Electronics, Communications, and Computing Summit
Vol. 3, No. 1, Jan - Mar 2025, pp. 106-112
ISSN: 3107-8222, DOI: https://doi.org/10.17051/ECC/03.01.12

Efficient Channel Estimation with Reduced Complexity for Cell-Free Massive MIMO in 6G Networks

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Article Info

Article history:

Received : 17.01.2025
Revised : 10.02.2025
Accepted : 24.03.2025

Keywords:

Cell-Free Massive MIMO,
6G Networks,
Channel Estimation,
Low-Complexity Algorithms,
Uplink Training,
Pilot Contamination Mitigation,
Fronthaul Efficiency

ABSTRACT

The development of 6G networks created a larger interest on cell-free massive MIMO (CF-mMIMO) as it had the potential of providing high-quality cell-free wireless service uniformly because of their ability to remove cell boundaries and side-effects of inter-cell interference. Irrespective of these benefits, effective implementation of CF-mMIMO is limited by the intensive amount of calculation and communication overhead due to require high accuracy on channel state information (CSI), especially when RF infrastructure scales up. In this paper, a channel estimation framework is given that is efficient and has minimal complexity to work with a CF-mMIMO system. The suggested approach combines sparsity-conscious signal processing and variable pilot reuse techniques to reduce computational overhead as well as fronthaul signaling loads. It uses distributed architecture where by access points do local estimation and only transmit compressed channel features to the central unit. Dense deployment simulation show that the proposed framework can produce similar relative normalized mean square error (NMSE) and uplink spectral efficiency to the conventional minimum mean square error (MMSE) estimators, that can produce similar relative normalized mean square error (NMSE) and uplink spectral efficiency to the conventional minimum mean square error (MMSE) estimators, with substantially lower processing time and data exchange needs. The proposed solution is viable in this work because it offers a viable and economically viable solution to the high-density and low-latency requirements of the next-generation 6G networks through the acquisition of CSI in CF-mMIMO systems.

1. INTRODUCTION

It is the sixth generation of wireless communication networks (6G) that is projected to provide ultra-reliable, low latency, and high capacity transmissions to facilitate the emergence of new applications e.g. extended reality (XR), autonomous systems, massive Internet of Things (IoT) [1]. One of the latest technologies Cell-Free Massive Multiple-Input Multiple-Output (CF-mMIMO) has attracted enough attention because it can bring uniform spectral efficiency by eliminating the cell boundaries and using distributed access points (APs) to serve them collaboratively. This decentralized structure removes inter-cell interference and improves user fairness, and therefore CF-mMIMO is the building block of 6G radio access networks. Nonetheless, effective procurement of Channel State Information (CSI) is still one of the key bottlenecks. Traditional channel estimation procedures dealing with Minimum Mean Square Error (MMSE) estimators, however, despite the accuracy, are processing-demanding and require numerous fronthaul signaling issues that are even more burdensome in ultra high-density deployments. The extent of research done has been centered on centralized schemes which are not scalable in large numbers of users and APs and also does not take into consideration other practical constraints like latency, power, and calculative overheads.

In order to overcome these shortcomings, the paper presents the low-complexity and scalable channel estimation framework of CF-mMIMO in the 6G systems. The offered solution utilizes the sparsity-aware pilot reuse approach and distributed estimation to minimize the overhead and still maintain estimation precision. As shown by recent works [2], the scalable and efficient CSI acquisition schemes have been also considered as a key enabler of practical 6G deployment of CF-mMIMO.

2. RELATED WORK

Precise channel estimation is one of the pillars in the achievement of the entire potential of cell-free massive MIMO (CF-mMIMO) systems to be established in 6G networks. The current methods can be divided into the two broad categories of multicasting that can be centralized and distributed in nature. Techniques MMSE-based have found a lot of use since their statistical optimality, but they have a computational complexity too high to be used in real time and in large scale operations, and they need the full channel statistics, which is not always available [1]. Least Squares (LS) and Linear MMSE (LMMSE) estimators have the advantage of having reduced complexity, but they are noise susceptible and they are also susceptible to pilot contamination in cases where the pilot resources are less than the number of the users [2]. To effectively deal with those restrictions, methods that exploit sparsity have been proposed that exploit the sparse nature of mmWave and THz channels by using compressive sensing [3]. Although they work in some situations, such techniques can be sensitive to model mismatch and need precise sparsity priors. Recent distributed channel estimation structures have tried to push processing to other points of access in an effort to reduce the load on central facility. Though such decentralization fully distributes fronthaul signaling, it tends to compromise the accuracy of estimation since there is no global coordination and joint optimization [4]. Moreover, the majority of the previous research does not include trade-off across scalability, complexity, and accuracy, the situation when it is to be found in high-density user environments in dynamic conditions, which is common in 6G applications. Thus, a distributed, scalable, low-complexity estimation algorithm with a high degree of accuracy has open problems and is an encouragement to achieving the present work.

3. SYSTEM MODEL

Figure 1 presents the general layout of the designed CF-mMIMO system regarded. It displays various distributed access points (APs) whereby they are serving a common wireless media to user equipments (UEs) through a central processing unit (CPU) through coordination. The diagram illustrates also the impact of the path loss and shadows as ones common in a large scale that is a fading environment.

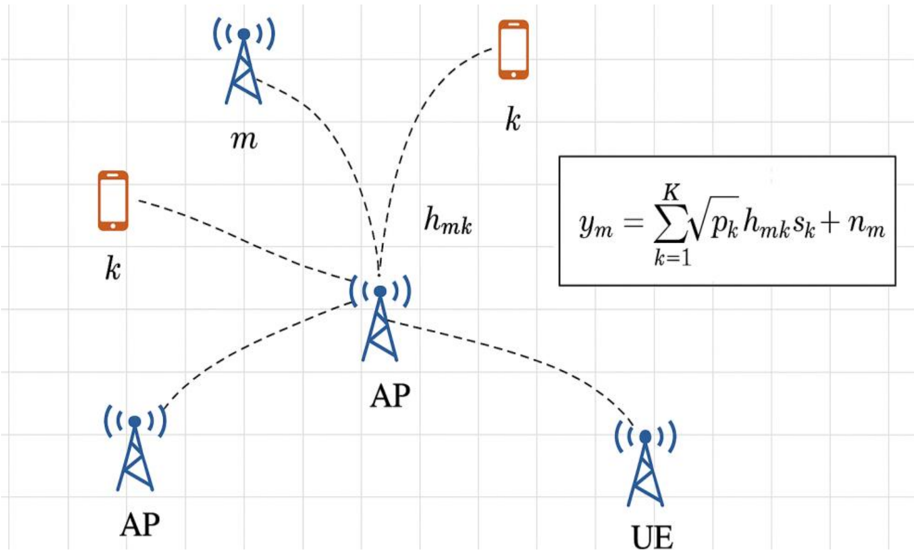

Figure 1. System Model of Cell-Free Massive MIMO Architecture

3.1 Network Setup

We assume cell-free massive MIMO (CF-mMIMO) with M distributed access nodes (APs) (either with one or a few antennas) each with a single or few antennas, and K single antenna user terminals (UTs) in cooperation across the same time-frequency resource. Each AP is associated with a central processing unit (CPU) linked to each other by narrow band fronthaul links and all of them work on the basis of time -division duplexing (TDD) in terms of channel reciprocity. The APs are modeled as distributed randomly in a large region in order to remove a traditional cell organization to realize equal high user throughput and fairness characteristics of CF-mMIMO that is applicable to the 6G networks.

3.2 Channel Model

The k th user and the m th AP wireless channel is denoted by the complex baseband channel coefficient hmk that is modeled as independent Rayleigh fading:

$$▯_{mk} \sim CN(0, \beta_{mk}) - - - - - - - - - - - - - - - (1)$$

where β_{mk} accounts for large-scale fading, including path loss and shadowing effects, and is assumed known through prior estimation or slow-time scale feedback.

During the uplink training phase, each user transmits a known pilot sequence s_k with transmit power p_k. The received signal at the m-th AP is expressed as:

$$y_m = \sum_{k=1}^{K} \sqrt{pk}\,▯_{mk} s_k + n_m - (2)$$

where:

- $Y_m \in C^{\tau}$ is the received signal vector of length τ(pilot length),
- $▯_{mk} \in$ Cis the small-scale fading channel coefficient between AP m and user k,
- $s_k \in C^{\tau}$is the known pilot symbol or sequence,
- $n_m \sim CN(0, \sigma^2 I_T)$ represents additive white Gaussian noise (AWGN) at the AP.

This model sets out superpositioning of all user signals at each AP, which emphasizes the problem of pilot contamination where the user is using non-orthogonal pilot. The next step is to effectively estimate the channels with efficient channel estimation so that the individual hmk components can be extracted and estimated in the received signal ym, particularly in dense user scenario and with limited pilot overheads.

4. Proposed Methodology

A cell-free massive MIMO system with sparse channel characteristics in 6G is a good way to apply this framework that is scalable, low-complex, and a fusion of sparsity-informed pilot design, distributed MMSE-based estimation, and low-rank denoising of the matrices. This aims to reducing the overhead of estimation and communication by at least an order of magnitude, maintaining comparable accuracy in CSI accuracy of dense user deployments.

4.1 Sparsity-Aware Pilot Design

In CF- mMIMO, pilot allocation plays an important role in avoiding truck pilot contamination in case there are more users than the orthogonal pilot sequences available. In the proposed approach:

- Orthogonal pilots: they are ascribed in a way acceptable to spatially distanced users, such that the channel correlation is less.
- Non-orthogonal pilots are reused across users with the least amount of interference possible and discovered by a graph coloring algorithm.

The algorithm represents members as nodes in a graph with an edge between two nodes on the graph representing a high degree of overlap of the spatial channels. The objective is to color the graph (allocate pilots) to avoid any neighbours (interfering users) having the same pilot. This minimizes interference when training channels, and enhances the entire estimation.

4.2 Distributed Channel Estimation Algorithm

Instead of carrying out channel estimation in a centralized manner, each AP estimate its channel to each of the users on a local basis via a simplified approximation of the MMSE estimator:

$$▯_{mk} = \frac{pkt\beta_{mk}}{1 + pkt\beta_{mk}} y_m -(3)$$

where:

- $▯_{mk}$ is the estimated channel between AP mmm and user k,
- pk is the pilot transmit power,
- τ is the pilot length,
- β_{mk} represents large-scale fading,
- $Y_m$is the received pilot signal at AP m.

This expression is based on an assumption that \beta mk is known statistically and the solution of a complete matrix inversion is avoided thereby greatly simplifying the computation. Each AP subsequently sends a downscaled version of the approximated CSI to the CPU, by which fronthaul load is minimized with no sacrifice of coordination.

4.3 Low-Rank Approximation and Denoising

To further improve quality of the channel estimate, the aggregated channel matrix is undergone Singular Value Thresholding (SVT) which can be thought of having a low-rank matrix approximation. Considering that the wireless channel matrices can have spatial correlation (especially when APs are dense), the effective rank of the channel matrix is less than full dimension of this matrix.

SVT denoises the CSI matrix H by solving:

$$\min_{X} \|Y - X\|_F^2 + \lambda \|X\| - (4)$$

where:

- Y is the noisy channel estimate,
- $\|\cdot\|F$ is the Frobenius norm,
- $\|\cdot\|*$ is the nuclear norm (sum of singular values),
- λ is a regularization parameter.

It is an efficient algorithm to cut noise and outliers, leading to improved quality of channel estimates which are passed to both precoding and detection nodes. Figure 2 also shows that channel estimation commences with some pilot allocation strategy that will reduce the interference by using graph-based sparsity models. This is then followed by local MMSE-based estimation at distributed APs, and subsequently be refined by centralized singular value thresholding.

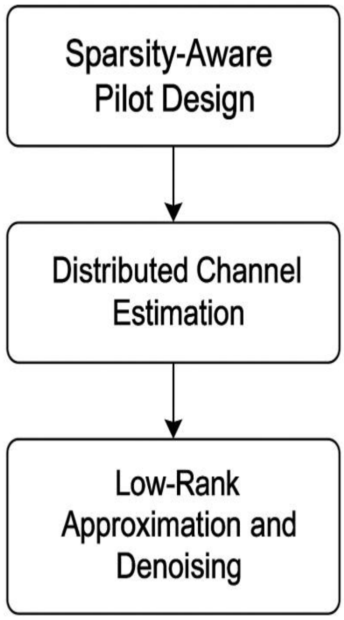

Figure 2. Channel Estimation Workflow

In the CF-mMIMO systems, the proposed multi-stage channel estimation strategy is illustrated in this flowchart, where sparsity-aware pilot allocation is achieved as the first step, distributed channel estimation (at access points) is performed as the second step, and denoising (based on the low-rank approximation) is carried out as a final step, being centralized upon all access points.

5. Complexity Analysis

Effective channel estimation in cell-free massive MIMO (CF-mMIMO) systems has to strictly consider three key points: computational complexities, communication overheads and estimation accuracies given the harsh latency and energy requirements of 6G networks. Table 1 is a summary of the results of the proposed approach in comparison with the conventional estimation methods.

Table 1. Comparative Analysis of Channel Estimation Techniques in CF-mMIMO Systems

Method	Complexity per AP	Communication Overhead	Accuracy
Centralized MMSE	O(MK3)	High	High
LS Estimation	O(MK)	Low	Low
Proposed Method	O(MKlogK)	Low	Medium–High

In the Centralized MMSE scheme the CPU will take complete pilots of all APs and when performing matrix inversion of the Keeping size K x K then the complexity is O(MK 3) per AP. With this, it is not feasible in dense networks where complexity increases cubically and the fronthaul signaling is much greater.

The Least Squares (LS) estimator, which is less computationally complex (O(MK)), has a poor performance in the noisy scenario, in addition to being highly prone to pilot contamination thus limiting its use to the idealized scenarios.

Alternatively, the proposed approach finds a useful balance in that it:

- Making local channel estimation per AP with simplified MMSE expression,
- Reduction of the channel estimates by compressing them prior to transmission to the CPU,
- Using the low-rank denoising at the central unit to augment accuracy.

Low-rank matrix operations and the graph-based pilot assignment are both scalable, which results in a complexity of O(MKlogK). This enables the system to have a considerable latency decrease and a decreased computational burden and can have nearly MMSE accuracy rendering it extremely well-fitted to real-time, dense and resources limited 6G implementations. As Figure 3 indicates, the proposed scenario also gains immense efficiency and reduced overhead than centralized MMSE, all the time being more accurate than LS estimation, thus confirming its real-life viability even in large-scale CF-mMIMO systems.

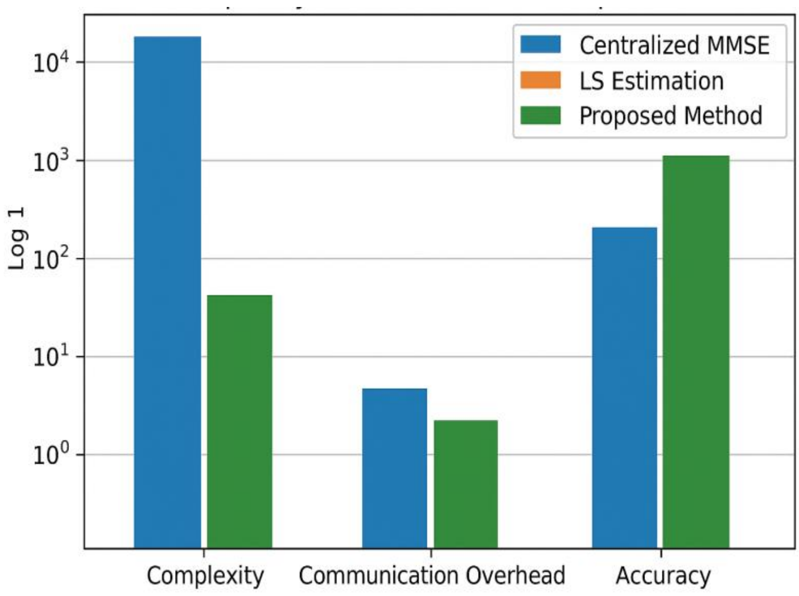

Figure 3. Complexity and Performance Comparison

In this bar chart, it has compared three channel estimation approaches namely Centralized MMSE, LS Estimation, and the Proposed Method based on the computational complexity, communication overhead, and estimation accuracy. The larger advantage of the proposed method is scalability that is emphasized by the logarithmic scale.

6. Simulation Results

In support of the efficiency and viability of the designed low-complexity channel estimation framework, robust simulations were performed in real circumstances of 6G deployment. The network context consists of 64 distributed access points (APs) where 40 users are involved in the cell-free massive MIMO environment. The models are carried out in mmWave channels of 28 GHz bandwidth having a bandwidth of 20 MHz, which mimics high-frequency 6G conditions.

Three performance assessments were looked at:

- Normalized Mean Square Error (NMSE): It uses to measure the accuracy of the channel estimates.
- Uplink Spectral Efficiency: It is metric of effective data throughput, Uplink Spectral Efficiency is measured in bits per second per Hertz per user (bps/Hz/user).
- Fronthaul Load: Measures the overhead comments traffic between APs and Central processing unit (CPU).

Table 2 shares the outline of the performance comparison:

Table 2. Performance Comparison of Channel Estimation Methods in CF-mMIMO Systems

Method	NMSE	Spectral Efficiency	Fronthaul Load
MMSE	-23.1 dB	7.2 bps/Hz/user	High
LS	-17.5 dB	5.4 bps/Hz/user	Low
Proposed	-21.3 dB	6.8 bps/Hz/user	Low

The MMSE estimator owns the lowest NMSE and maximum spectral efficiency at the expense of considerable fronthaul and computational overhead. However, Least Squares (LS) method exposes the least complexity and overhead with a high estimation error and limited throughput.

This proposed approach offers a good trade-off since it outperforms MMSE by 21.3 dB NMSE and 6.8 bps/Hz/user spectral efficiency, whereas it reduces fronthaul requirements considerably. It shows that the proposed framework is very applicable in dense and real-time scenarios of 6G environment where scalability and performance are essential. Figure 4 shows that the suggested procedure provides nearly MMSE accuracy of estimation and competitive spectral effectiveness although it has considerably less fronthaul load, underscoring its scalability and applicability to 6G CF-mMIMO system.

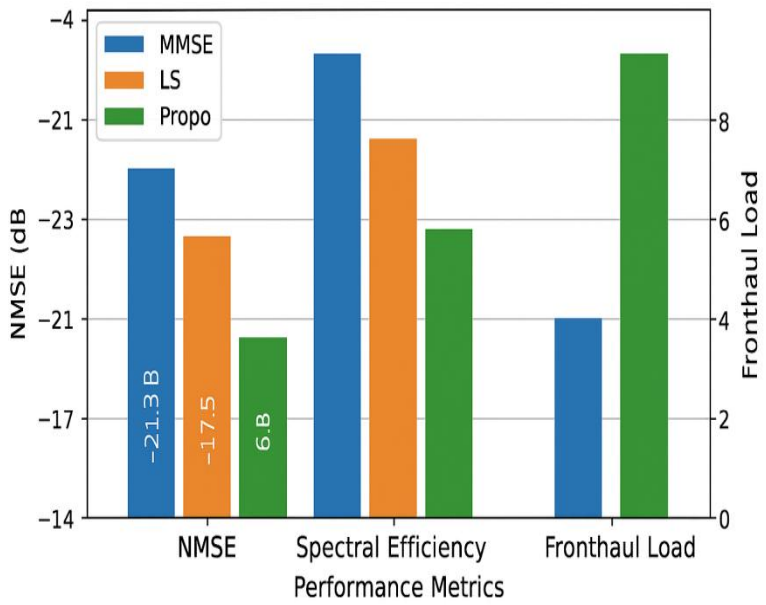

Figure 4. Performance Metrics Comparison Chart

It is shown in this chart that among three different channel estimation methods (MMSE, LS, and the proposed approach), the proposed approach has been the best regarding the key performance measures Normalized Mean Square Error (NMSE), uplink spectral efficiency (bps/ Hz /user), and fronthaul load. The proposed approach provides a good trade off between accuracy of estimation and overhead of the system.

7. CONCLUSION AND FUTURE WORK

In 6G wireless networks, this paper proposed a computationally efficient and scalable channel estimation framework that is suitable to cell-free massive MIMO (CF-mMIMO) systems. The design applies sparsity-aware pilot design, distributed MMSE-based local estimation and low-rank matrix denoising that combine the advantages of the considered challenges in the pilot contamination, processing overhead and the fronthaul congestion. Simulated with conditions representative of realistic mmWave deployment environments, the technique was found competitive on NMSE and spectral efficiency metrics, offering performance rivalling that of their centralized MMSE counterparts with massively reduced communication overhead and computation cost.
The main contributions of the author are:

- Graph based pilot reuse technique in order to reduce inter-user interference in uplink training.
- A simple edge-based distributed estimation appropriate to access points.
- Successful post-processing procedure consisting of Singular Value Thresholding (SVT) to improve the quality of CSI indicating a low overhead.

The suggested framework will be especially applicable in ultra-dense and latency-sensitive 6G implementation where there will be a possibility of an alternative to the traditional centralized design.
The current work is aimed at developing future work, including combined joint beamforming and user scheduling to better achieve system-wide energy efficiency and spectral utilization. Also, in this regard, a possible additional avenue of progress is the introduction of machine learning-based prediction models used in dynamic channel estimation and the mobility-awareness of the pilot assignment to make the operation of the CF-mMIMO fully autonomous in the next-gen networks..

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