

SVD-Based Semi-Blind Channel Estimation for Pilot Contamination Mitigation in Multi-Cell millimeter-Wave Massive MIMO Systems

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Abstract:

Channel estimation accuracy limits the performance of multi-cell millimeter-wave (mm-Wave) massive MIMO systems, because reusing pilots across cells causes pilot contamination and inter-cell interference (ICI). This paper proposes a low-complexity semi-blind channel estimator based on singular value decomposition (SVD) for multi-cell multi-user mm-Wave MIMO systems. The estimator uses the sample covariance matrix of the received data to separate the signal and noise subspaces, and it needs only a small number of pilots to resolve the remaining ambiguity. The system model and a signal-to-interference-plus-noise ratio (SINR) analysis under perfect channel state information (CSI) are presented. With power scaling, the interference terms vanish as the number of base station antennas grows, and the user's transmit power can be reduced in proportion to $1/M$. MATLAB simulations of a three-cell system with three users per cell compare the mean squared error (MSE) of the proposed estimator with pilot-based estimation and the Cramér-Rao bound at SNR levels from 0 to 30 dB. In four scenarios of low and high channel gain and noise, the proposed scheme outperforms pilot-based estimation by roughly 10–15 dB. It also improves on previous work by up to 8 dB at high SNR.

Keywords: mm-Wave, massive MIMO, Pilot contamination, Semi-Blind Channel estimation, Singular Value Decomposition, Cramér-Rao Bound

1. Introduction

Channel state information (CSI) is central to beamforming, precoding and power allocation in fifth-generation (5G) millimeter-wave (mm-Wave) massive multiple-input multiple-output (MIMO) systems, and its accuracy directly limits the achievable spectral efficiency [1]. In time-division duplex (TDD) multi-cell networks, the base station (BS) estimates the uplink channel from pilot sequences and reuses it for the downlink through channel reciprocity. The pilot length is bounded by the channel coherence interval, so orthogonal pilots cannot be assigned to every user in every cell, and pilot sequences are reused across cells. The resulting inter-cell interference (ICI) corrupts the channel estimate, an effect known as pilot contamination. Pilot contamination becomes the dominant performance bottleneck as the number of BS antennas grows, because its interference term does not vanish with array size [2].

Many existing remedies for pilot contamination add complexity or depend on side information. Learning-based approaches, such as joint pilot design and deep residual channel estimation, reduce contamination but require training data and considerable computation, particularly under hardware impairments [3]. Blind and subspace-based methods avoid pilot overhead altogether, but they suffer from an inherent ambiguity in the recovered channel and require large numbers of data samples [4]. Eigenvalue-decomposition (EVD) methods resolve this ambiguity with short pilots and exploit the covariance structure of the received data, but they are limited by their reliance on Eigen structure assumptions and their sensitivity to residual ICI [5]. Compressed sensing and beamspace techniques,

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which exploit the sparsity of mm-Wave channels, work well in single-cell settings but lose effectiveness under multi-cell interference, because interference from neighbouring cells destroys the sparse structure.

This paper therefore proposes a low-complexity singular value decomposition (SVD)-based semi-blind channel estimator for multi-cell multi-user mm-Wave massive MIMO systems. The estimator uses the sample covariance matrix of the received data to separate the signal subspace from the noise subspace. It needs only a small number of pilots to resolve the remaining ambiguity. The main contributions are: (i) a system model with signal-to-interference-plus-noise ratio (SINR) analysis under perfect CSI and under imperfect CSI with pilot contamination; (ii) an SVD-based semi-blind estimator that mitigates ICI at low pilot overhead; (iii) a mean squared error (MSE) comparison against pilot-based estimation and the Cramér-Rao bound for varying numbers of BS antennas and SNR levels; and (iv) a computationally efficient design that scales with the number of antennas and users.

2. Literature Review

Pilot contamination was identified early as a fundamental limit of multi-cell TDD massive MIMO. Analyses of multi-cell TDD downlinks showed that reusing pilots across cells limits performance, and precoders were designed to account for this contamination [6]. Later work characterized the resulting inter-cell interference (ICI) in non-cooperative large-scale antenna systems, showing that it remains as the number of BS antennas grows [7]. Coordination-based remedies followed. One approach shares the second-order statistics of the channels, so the BS can separate users that use the same pilot [8]. Another uses precoding across cells, based only on large-scale fading coefficients, to cancel the interference caused by pilot contamination [9]. Both approaches need inter-cell coordination, and they do not directly address the sparse structure of mm-Wave channels.

For mm-Wave systems, sparsity motivated compressed sensing (CS) approaches. Adaptive CS with hierarchical beam codebooks was developed for cellular mm-Wave systems with hybrid analog/digital architectures, greatly reducing training overhead [10]. Orthogonal matching pursuit (OMP) was later applied to hybrid MIMO channel estimation for mm-Wave, to recover the sparse channel paths with fewer measurements [11]. These CS methods assume a single-cell setting, so ICI from neighbouring cells breaks the sparsity assumption and degrades their accuracy. Beamspace methods take a related route. A lens antenna array transforms the channel into the beamspace domain, where support detection of the dominant beams gives a reliable estimate at low pilot cost [12].

Learning-based estimators have recently been proposed to reduce the complexity of such iterative algorithms. A deep-learning denoising approach improved beamspace channel estimation accuracy over conventional CS algorithms [13]. However, supervised learning needs large training sets that may not match the deployment channel, which limits generalization in multi-cell networks. An untrained deep neural network avoids this need for training data and still improves on conventional massive MIMO estimators [15]. Blind estimation has also been considered as a way to reduce pilot overhead, since effective downlink gains can be estimated from the data without dedicated downlink pilots [14].

Taken together, these studies show that CS and beamspace methods are effective for single-cell mm-Wave channels but sensitive to ICI. Coordination-based methods need cooperation between BSs, and learning-based and blind approaches add training or computational cost. This motivates a low-complexity semi-blind estimator that uses the covariance structure of the received signal and needs

only a small number of pilots to resolve the remaining ambiguity, which is the approach taken in this work.

3. System Model for Multi-Cell mm-Wave MIMO

In this work, a multi-cell mm-Wave MU MIMO system with L cells sharing the same frequency band on the uplink is considered. This co-channel deployment represents the worst-case scenario for interference analysis. Each cell includes one BS equipped with M antennas and K single-antenna UEs. We consider mm-Wave communication where all UEs from all cells transmit their signals to their assigned BSs simultaneously. This simultaneous transmission maximizes spectral efficiency but also creates the challenging interference environment that must be addressed. The system model for a multi-cell scenario is shown in Figure 1.

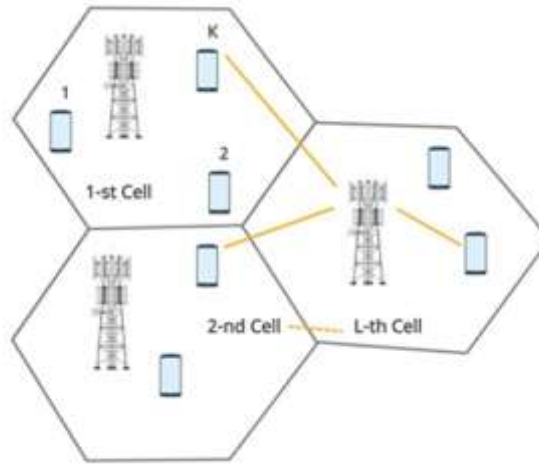


Fig 1: Illustration of multi-cell MU mm-Wave MIMO Systems

The $(M \times 1)$ received vector at the l -th BS described in Ngo et al. [16] is given by:

$$\mathbf{y}_l = \sum_{j=1}^L \mathbf{G}_{lj} \mathbf{x}_j + \mathbf{n}_l$$

where $\mathbf{G}_{lj}$ represents the channel matrix of size $(M \times K)$ between the l -th BS and K UEs in the j -th cell, $\mathbf{x}_j$ is the transmitted symbol vector from cell j , and $\mathbf{n}_l$ denotes the $(M \times 1)$ additive noise vector with distribution $\text{CN}(0, \sigma^2 \mathbf{I})$.

Considering UE_1 in cell 1 as the desired user without loss of generality, the received signal can be expressed as:

$$\mathbf{y}_l = \mathbf{g}_{l11} x_{111} + \sum_{i=2}^K \mathbf{g}_{l1i} x_{11i} + \sum_{j=2}^L \sum_{i=1}^K \mathbf{g}_{lji} x_{lji} + \mathbf{n}_l$$

where the first term represents the desired signal from UE_1 in cell 1, the second term represents intra-cell interference from other users in the same cell, the third term represents inter-cell interference from users in all other cells, and the fourth term is additive noise.

Interference Sources in Multi-Cell Systems:

- **Intra-Cell Interference:** Interference from other users within the same cell. This can be effectively mitigated using MIMO processing techniques like Zero-Forcing.

10.48047/jocaaa.2024.33.08.626

- **Inter-Cell Interference (ICI):** Interference from users in neighbouring cells. This is more challenging to mitigate as it requires coordination between cells.
- **Pilot Contamination:** A special case of ICI that occurs during the training phase when non-orthogonal pilots are reused across cells.

3.1 Signal to Interference & Noise Ratio (SINR) Analysis with Perfect CSI

Under perfect channel conditions, the BS has complete knowledge of the CSI, i.e., the complete channel matrix $\mathbf{G}$. This ideal scenario provides an upper bound on system performance. The matched filter receiver for UE₁ described in Ashikhmin et al. [17] can be expressed as:

$$r_{111} = (\mathbf{g}_{111}^H / \|\mathbf{g}_{111}\|) \mathbf{y}_1$$

The output is simplified as:

$$r_{111} = \|\mathbf{g}_{111}\| x_{111} + \sum_{i=2}^K (\mathbf{g}_{111}^H \mathbf{g}_{11i} / \|\mathbf{g}_{111}\|) x_{11i} + \sum_{j=2}^L \sum_{i=1}^K (\mathbf{g}_{111}^H \mathbf{g}_{1ji} / \|\mathbf{g}_{111}\|) x_{1ji} + (\mathbf{g}_{111}^H / \|\mathbf{g}_{111}\|) \mathbf{n}_1$$

The received SINR for UE₁ can be represented as:

$$SINR_{111} = p_u \|\mathbf{g}_{111}\|^2 / (\sum_{i=2}^K p_u |\mathbf{g}_{111}^H \mathbf{g}_{11i}|^2 / \|\mathbf{g}_{111}\|^2 + \sum_{j=2}^L \sum_{i=1}^K p_u |\mathbf{g}_{111}^H \mathbf{g}_{1ji}|^2 / \|\mathbf{g}_{111}\|^2 + \sigma^2)$$

When the power of each UE is scaled with the number of BS antennas M , i.e., $E[|x_k|^2] = p_u/M$, the SINR scales as:

$$SINR_{111} = (p_u \alpha_{111}) / (\sum_{i=2}^K (p_u/M) |\beta_{11i}|^2 + \sum_{j=2}^L \sum_{i=1}^K (p_u/M) |\gamma_{1ji}|^2 + \sigma^2/M)$$

As $M \rightarrow \infty$, the interference terms vanish, and the SINR approaches:

$$SINR_{111} \rightarrow (p_u \alpha_{111}) / (\sigma^2) \text{ as } M \rightarrow \infty$$

This confirms that with massive antenna arrays and perfect CSI, both intra-cell and inter-cell interference can be effectively suppressed, enabling each user's transmit power to be scaled down proportionally to $1/M$.

4. Simulation and Discussion

This section analyzes the channel estimation MSE performance of the proposed SVD-based semi-blind technique, pilot-based method, and Cramer-Rao bound method. The proposed scheme has been simulated using MATLAB software to illustrate and validate its performance under various parameter settings. The simulation considers a three-cell hexagonal arrangement ($L = 3$), and each cell is connected to its two adjacent cells. The BS of each cell concurrently serves three UEs ($K = 3$), and the UEs are evenly distributed across the cell. Furthermore, the number of pilots assigned to each terminal is three. The parameters used in computer simulations are included in Table 1.

Table 1: Simulation Parameters for Multi-Cell Channel Estimation

Parameter	Value	Description
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Number of Cells (L)	3	Hexagonal cell layout with co-channel interference
Number of UEs per cell (K)	3	Each BS serves 3 users simultaneously
Center to vertex distance of cell	250 m	Cell radius for path loss calculation
Minimum terminal radius of cell	25 m	Minimum distance from BS to UE
Modulation	BPSK	Binary Phase Shift Keying
Path loss exponent	3.9	Urban macro-cell propagation environment
Antenna spacing	$\lambda/2$	Half-wavelength spacing for ULA
Location of UEs	Uniform	Uniformly distributed across cell area
Number of Monte Carlo runs	1000	For statistical averaging

The channel estimation error, as measured by the Mean Squared Error (MSE), is compared with the Cramer-Rao bound, which represents the theoretical lower bound on estimation error variance. The MSE of the multi-cell MU mm-Wave MIMO channel estimators can be represented as:

$$MSE = E[||\mathbf{H}_{jj} - \hat{\mathbf{H}}_{jj}||^2 / ||\mathbf{H}_{jj}||^2]$$

4.1 MSE Performance vs. SNR for Different Channel Conditions

Figures 2, 3, 4, and 5 show the MSE performance versus SNR curves for the multi-cell MU mm-Wave MIMO system. To analyze the performance metric, we focused on four different scenarios of channel gain and noise with SNR = 0:5:30 dB.

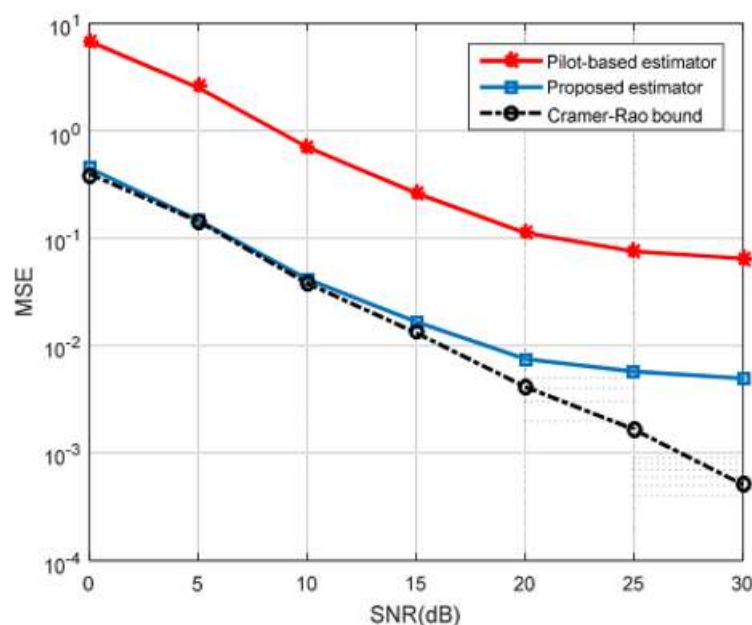


Fig 2: MSE versus SNR of the proposed SVD-based semi-blind, pilot-based and Cramér-Rao bound estimators under low channel gain and low noise

In Figure 2 and Figure 5, we implement the system with low noise and examine the MSE performance at low and high channel gain, respectively. From Figure 3, it is evident that as the SNR is changed from 0 to 30 dB, the MSE performance for the proposed scheme improves from 3.98×10^{-1} to 4.90×10^{-3} , while for pilot-based estimation, it improves from 6.82×10^0 to 6.48×10^{-2} . The proposed scheme achieves approximately 10-15 dB better MSE across all SNR values.

According to Figure 5 (high channel gain, low noise), the MSE performance for the proposed scheme improves from 5.20×10^{-1} to 5.08×10^{-2} , and for pilot-based estimation, it improves from 8.65×10^0 to 7.05×10^{-1} . The higher channel gain provides better received SNR, further improving estimation accuracy for both methods, but the proposed method maintains its advantage.

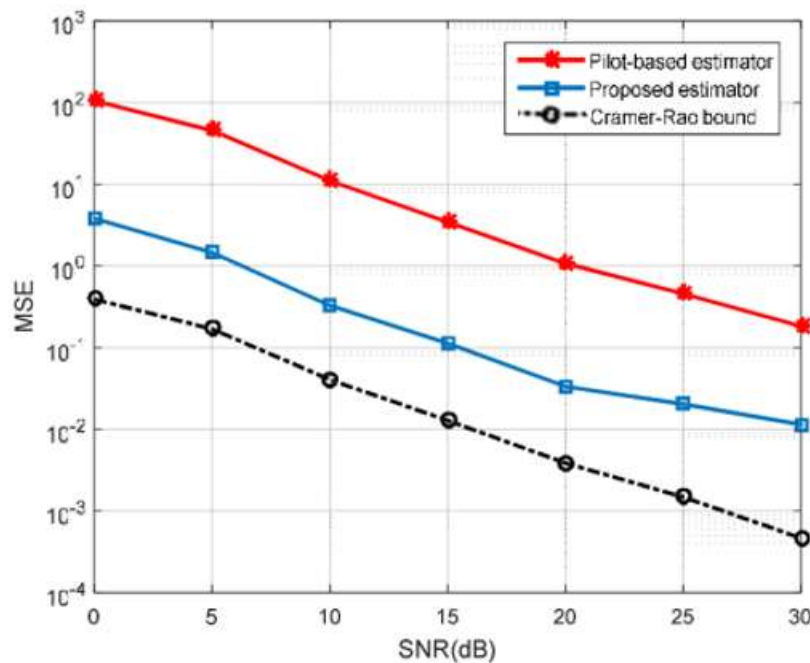


Fig 3: MSE versus SNR of the proposed SVD-based semi-blind, pilot-based and Cramér-Rao bound estimators under low channel gain and high noise

In Figure 3 we implement the system with high noise and observe the MSE performance at low and high channel gain, respectively. From Figure 4, it is illustrated that as the SNR is varied as above, the MSE performance for the proposed scheme is in the order of 3.80×10^0 to 1.14×10^{-2} , and for pilot-based estimation, it changes from 1.05×10^2 to 1.83×10^{-1} . The high noise environment creates an error floor at high SNR, limiting the minimum achievable MSE for both methods.

In Figure 4 (high channel gain, high noise), the MSE performance for the proposed scheme is in the order of 3.93×10^0 to 7.80×10^{-2} , and for pilot-based estimation, it changes from 1.22×10^2 to 9.35×10^{-1} . Even under challenging high-noise conditions, the proposed method consistently outperforms pilot-based estimation by approximately 10 dB.

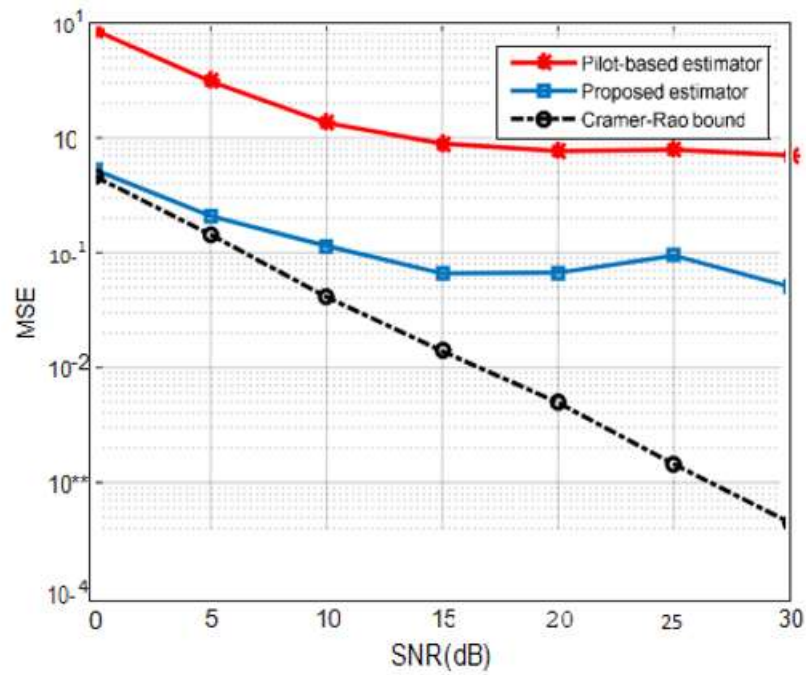


Fig 4: MSE versus SNR of the proposed SVD-based semi-blind, pilot-based and Cramér-Rao bound estimators under high channel gain and low noise

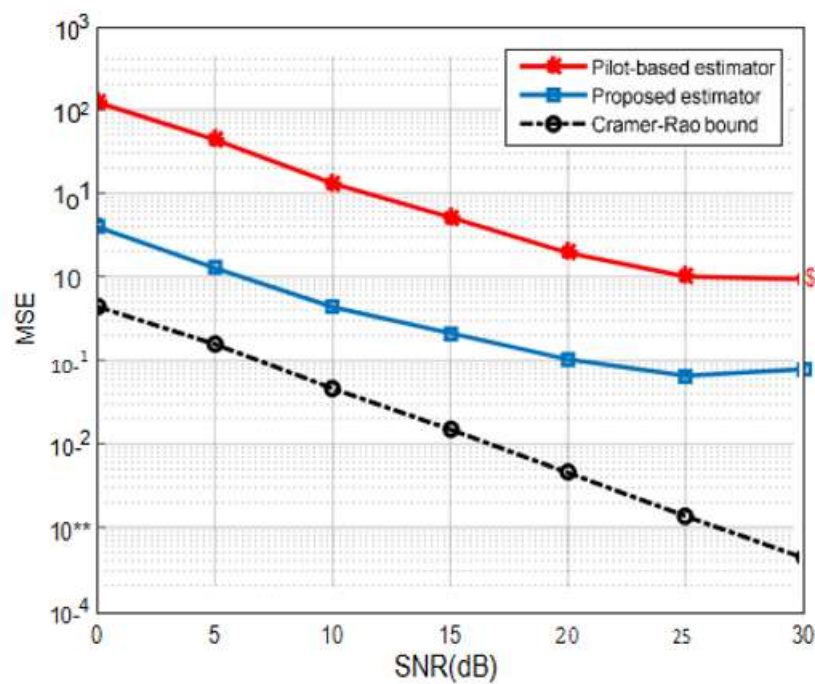


Fig 5: MSE versus SNR of the proposed SVD-based semi-blind, pilot-based and Cramér-Rao bound estimators under high channel gain and high noise

From these findings, it is noticeable that high SNR and high channel gain associated with minimal scattering result in better channel estimation accuracy. The presence of a strong Line-of-Sight (LOS) component provides a high SNR reference that helps both estimation algorithms converge faster. Additionally, the MSE performance of our proposed work is superior to the MSE performance of previous work proposed and, demonstrating improvements of up to 8 dB at high SNR.

5. Conclusion

This paper presented an SVD-based semi-blind channel estimator for multi-cell multi-user mm-Wave massive MIMO systems, aimed at the pilot contamination and inter-cell interference that limit conventional pilot-based estimation. The SINR analysis under perfect CSI showed that intra-cell and inter-cell interference vanish with power scaling as the number of base station antennas grows, so user transmit power can be scaled down as $1/M$. In practice, pilot reuse across cells produces contamination that does not vanish with array size, so an estimator that suppresses ICI is needed.

Simulations of a three-cell, three-user-per-cell system showed that the proposed estimator achieves lower MSE than pilot-based estimation in all four scenarios of channel gain and noise. With low noise, the MSE fell from 3.98×10^{-1} to 4.90×10^{-3} at low channel gain and from 5.20×10^{-1} to 5.08×10^{-2} at high channel gain, against 6.82×10^0 to 6.48×10^{-2} and 8.65×10^0 to 7.05×10^{-1} for pilot-based estimation. In high noise, the proposed scheme kept an advantage of about 10 dB despite the error floor at high SNR. It also improved on previous work by up to 8 dB at high SNR. These results show that the covariance structure of the received data can be used to reduce pilot overhead while keeping the estimation error low. Future work can extend the estimator to wideband channels, hybrid analog/digital architectures and a larger number of cells, and can evaluate the effect of the estimate on achievable sum-rate.

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