

Ultra-Low-Complexity Hybrid-Field Channel Estimation for XL-MIMO

Leandro Jacintho Freire, Victor Hugo de França Lima Souza, David William Marques Guerra and Daniel Pedro Bezerra Chaves

Abstract—This paper proposes an ultra-low-complexity hybrid-field orthogonal matching pursuit (ULC-HF-OMP) framework for channel estimation (CE) in extremely large-scale multiple-input multiple-output (XL-MIMO) systems. The proposed method combines a low-correlation optimized dictionary with an incremental scalar least-squares (LS) gain estimation strategy, enabling accurate support recovery with significantly reduced computational complexity. Unlike conventional approaches based on dense matrix operations, exhaustive searches, or prior knowledge of the sparsity level (L) and near-field/far-field ratio (γ), the proposed estimator operates adaptively through a residual-based stopping criterion while avoiding costly matrix inversions. In addition, the optimized HF dictionary improves atom selection reliability by reducing inter-atom correlation, leading to enhanced estimation accuracy. Numerical results demonstrate that the proposed method achieves superior NMSE and achievable rate performance while presenting the lowest runtime among the evaluated benchmark schemes, making it a promising solution for practical XL-MIMO implementations in future 6G systems.

Keywords—XL-MIMO, Hybrid-field, Channel estimation, Ultra-low-complexity.

I. INTRODUCTION

Extremely large-scale multiple-input multiple-output (XL-MIMO) is expected to play an important role in sixth-generation (6G) wireless communications by enabling highly directional transmissions and finer spatial discrimination capabilities [1]. Due to the very large antenna arrays employed in these systems, wave propagation can no longer be accurately represented only by conventional far-field (FF) planar-wave models, since spherical-wave effects may also become relevant [2]. As a result, both near-field (NF) and FF propagation mechanisms can coexist, giving rise to a hybrid-field (HF) communication environment. This propagation behavior increases the complexity of channel estimation (CE), while accurate channel state information (CSI) remains essential for exploiting the full potential of XL-MIMO systems [3], [4].

In this context, traditional FF Orthogonal Matching Pursuit (OMP) estimators, which rely solely on planar-wave dictionaries and matrix pseudo-inversions, fail to characterize the spherical components of the channel. Recent literature has addressed this by introducing hybrid models that utilize separate sparse representations: the angular domain for FF paths and the polar domain for NF paths [5]. Techniques such as HF-OMP and Support Detection OMP (SD-OMP)

attempt to estimate these components sequentially or through local atom refinement [6]. However, a significant limitation persists: these methods generally require prior knowledge of the ratio between NF and FF scatterers. Furthermore, even high-accuracy methods based on iterative refinement, such as the OMP-SSIGW and SGP-based methods proposed in [2] and [7] suffer from prohibitive complexity due to multi-dimensional gradient updates and matrix-based operations. Although these refinement stages are effective at mitigating grid mismatch, they add a heavy computational burden to the CE process. Consequently, there is a significant interest in developing optimized strategies capable of approaching the performance of high-accuracy refinement-based methods while preserving the lower computational burden of conventional OMP structures, particularly through improved support detection without exhaustive refinement procedures.

Related work: Various CE strategies for the HF scenario in XL-MIMO systems have been explored in recent literature. Algorithms based on Orthogonal Matching Pursuit (OMP), such as HF-OMP and Support Detection OMP (SD-OMP), employ angular and polar dictionaries to represent the channel; however, they suffer from the disadvantage of requiring prior knowledge of the ratio between NF and FF paths [1], [3]. Alternatives that seek to eliminate this dependency through exhaustive searches result in computational complexity that are infeasible for practical applications [6]. Furthermore, advanced sparse gradient projection and gridless refinement techniques frequently require information regarding the total sparsity level (L) and rely on complex matrix operations, which limits their scalability and efficiency in large-scale antenna arrays [2], [7].

Contribution: This work proposes a novel XL-MIMO CE framework tailored to the HF regime, with a strong emphasis on computational efficiency. In contrast to existing methods that depend on high-dimensional matrix operations and require prior knowledge of key parameters such as the sparsity level (L) [2] or the field ratio γ [3], [4], the proposed approach relies on a low-complexity incremental formulation based on single-column updates. A key aspect of the method is the use of an optimized dictionary with reduced inter-atom correlation, which enhances the reliability of the support detection and improves CE accuracy. In addition, an adaptive stopping criterion driven by the residual enables the algorithm to automatically determine the number of propagation paths, eliminating the need for prior information. The initial support is efficiently captured through a hybrid FF/NF dictionary structure [1], [5]. Numerical results show that the proposed method achieves an improved trade-off between estimation accuracy and computational complexity, demonstrating its suitability for practical

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XL-MIMO deployments in future 6G systems.

The remainder of this paper is organized as follows. Section II presents the system model and the proposed ULC-HF-OMP framework. Section III discusses the numerical results. Finally, Section IV concludes the paper.

II. SYSTEM MODEL

The system model for XL-MIMO networks in a HF regime is based on the premise that the massive physical dimension of the antenna array fundamentally alters the way waves propagate [8], [9]. In the considered uplink scenario, a single-antenna user ($N_u = 1$) communicates with a base station (BS) equipped with a uniform linear array (ULA) composed of N antenna elements. Unlike conventional systems, where all incoming waves are commonly modeled as planar wavefronts, the large array aperture in XL-MIMO systems leads to the co-existence of both FF and NF propagation components [8] [10]. This distinction is governed by the Rayleigh distance, defined as $D_{\text{Rayleigh}} = 2R^2/\lambda$, where R is the array aperture and λ is the wavelength. Scatterers located beyond this limit operate in the FF region, while those within this boundary belong to the NF regime [8].

The channel contribution associated with the FF propagation components depends exclusively on the azimuth angle θ_{ℓ_f} , since planar-wave propagation is assumed in this region. Accordingly, the corresponding channel can be modeled as

$$\mathbf{h}_F = \sqrt{\frac{1}{L_F}} \sum_{\ell_f=1}^{L_F} \alpha_{\ell_f} \mathbf{a}(\theta_{\ell_f}), \quad (1)$$

where L_F denotes the number of FF propagation paths, α_{ℓ_f} represents the complex gain of the ℓ_f -th path, and $\mathbf{a}(\theta_{\ell_f})$ corresponds to the associated steering vector.

In this case, the array response vector $\mathbf{a}(\theta_{\ell_f})$ assumes the conventional form based on linear phase shifts between the antenna elements:

$$\mathbf{a}(\theta_{\ell_f}) = \left[1, e^{-j\pi \sin(\theta_{\ell_f})}, \dots, e^{-j\pi(N-1) \sin(\theta_{\ell_f})} \right]^H, \quad (2)$$

with $\sin(\theta_{\ell_f}) \in (-1, 1)$. Given that the number of significant FF scatterers is generally much smaller than the array size N , the vector $\mathbf{h}_F$ exhibits sparsity in the angular domain. This property enables the factorization

$$\mathbf{h}_F = \mathbf{A}_{\text{FF}} \mathbf{h}_f, \quad (3)$$

in which $\mathbf{A}_{\text{FF}} \in \mathbb{C}^{N \times Q_F}$ is the angular-domain dictionary and $\mathbf{h}_f$ is a sparse coefficient vector. When $Q_F = N$, the matrix $\mathbf{A}_{\text{FF}}$ coincides with the N -point DFT matrix.

On the other hand, NF components must consider both the angle and the distance r_{ℓ_n} , since the wavefront is spherical. The model for these components is:

$$\mathbf{h}_N = \sqrt{\frac{1}{L_N}} \sum_{\ell_n=1}^{L_N} \alpha_{\ell_n} \mathbf{a}(\theta_{\ell_n}, r_{\ell_n}), \quad (4)$$

where L_N denotes the number of NF propagation paths, while α_{ℓ_n} , θ_{ℓ_n} , and r_{ℓ_n} correspond to the complex gain, azimuth angle, and reference distance associated with the ℓ_n -th NF component, respectively.

An analogous sparsity structure emerges when NF components are projected onto the polar domain, supporting the compact form

$$\mathbf{h}_N = \mathbf{A}_{\text{NF}} \mathbf{h}_n, \quad (5)$$

where $\mathbf{A}_{\text{NF}} \in \mathbb{C}^{N \times Q_N}$ being the polar-domain dictionary and $\mathbf{h}_n$ the associated sparse vector.

The response vector $\mathbf{a}(\theta_{\ell_n}, r_{\ell_n})$ takes into account the individual distance from each antenna element to the scatterer $r_{\ell_n}^{(n)}$:

$$\mathbf{a}(\theta_{\ell_n}, r_{\ell_n}) = \left[e^{-j\frac{2\pi}{\lambda}(r_{\ell_n}^{(1)} - r_{\ell_n})}, \dots, e^{-j\frac{2\pi}{\lambda}(r_{\ell_n}^{(N)} - r_{\ell_n})} \right]^H. \quad (6)$$

The term $\mathbf{h}_{\text{NLoS}}$ is the superposition of the FF and NF wavefronts, and the proportion between them is defined by $\gamma = L_F/L$, though neither γ nor L are required as inputs to the proposed CE algorithm.

$$\mathbf{h}_{\text{NLoS}} = \sqrt{\frac{1}{L}} \left(\sum_{\ell_f=1}^{\gamma L} \alpha_{\ell_f} \mathbf{a}(\theta_{\ell_f}) + \sum_{\ell_n=1}^{(1-\gamma)L} \alpha_{\ell_n} \mathbf{a}(\theta_{\ell_n}, r_{\ell_n}) \right). \quad (7)$$

For signal processing purposes, the HF channel is represented through a sparse formulation in the angular and polar domains using a complete dictionary $\mathbf{A}$, which combines the FF and NF bases. The resulting observation model can be expressed as

$$\mathbf{y}_t = \mathbf{A} \bar{\mathbf{h}} + \mathbf{q}_e, \quad (8)$$

where $\mathbf{A} = [\mathbf{A}_{\text{FF}}, \mathbf{A}_{\text{NF}}] \in \mathbb{C}^{N \times Q}$ denotes the complete HF dictionary composed of the FF and NF codebooks, with $Q = Q_F + Q_N$, while $\bar{\mathbf{h}} \in \mathbb{C}^{Q \times 1}$ represents the sparse channel coefficient vector associated with the sampled angular and polar domains. The term $\mathbf{q}_e$ models the residual approximation and quantization errors introduced by the discrete dictionary representation.

To estimate the HF channel, the single-antenna user transmits a pilot sequence $\Phi \in \mathbb{C}^{\tau \times 1}$ over τ pilot intervals, satisfying $\Phi^H \Phi = \tau$. After pilot transmission, the received signal matrix at the BS can be written as

$$\mathbf{Y} = \mathbf{h} \Phi^H + \mathbf{N}, \quad (9)$$

where $\mathbf{N} \in \mathbb{C}^{N \times \tau}$ is the additive white Gaussian noise (AWGN) matrix with entries distributed as $\mathcal{CN}(0, \sigma^2)$.

By correlating the received signal with the normalized pilot sequence $\Phi/\sqrt{\tau}$, the sufficient statistic used for channel estimation is obtained as

$$\mathbf{y}_t = \frac{1}{\sqrt{\tau}} \mathbf{Y} \Phi = \sqrt{\tau} \mathbf{h} + \mathbf{n}_t, \quad (10)$$

where $\mathbf{n}_t = \frac{1}{\sqrt{\tau}} \mathbf{N} \Phi \in \mathbb{C}^{N \times 1}$ denotes the equivalent noise vector after pilot correlation. Therefore, the CE problem can be reformulated as a sparse signal recovery task over the HF dictionary $\mathbf{A}$.

In this context, accurate CE is fundamental since the quality of the estimated channel directly impacts the achievable spectral efficiency (SE) of the system. Considering a single-antenna user scenario ($N_u = 1$) and linear combining at the

BS, the achievable rate can be expressed as

$$R = \mathbb{E} \left\{ \log_2 \left(1 + \frac{P_u |\mathbf{v}^H \mathbf{h}|^2}{\sigma_u^2 \|\mathbf{v}\|^2} \right) \right\}, \quad (11)$$

where P_u denotes the uplink transmit power, σ_u^2 is the noise variance, $\mathbf{h}$ represents the actual channel, and $\mathbf{v}$ denotes the combining vector employed at the BS.

Assuming maximum-ratio (MR) combining, the combining vector is directly obtained from the estimated channel, *i.e.*, $\mathbf{v} = \hat{\mathbf{h}}$. In this case, the achievable rate becomes

$$R = \mathbb{E} \left\{ \log_2 \left(1 + \frac{P_u |\hat{\mathbf{h}}^H \mathbf{h}|^2}{\sigma_u^2 \|\hat{\mathbf{h}}\|^2} \right) \right\}, \quad (12)$$

showing that the achievable rate is directly affected by the CE accuracy.

Therefore, improving the CE task not only reduces the estimation error but also directly enhances the achievable rate performance. This becomes particularly important in hybrid-field XL-MIMO systems, where accurate recovery of both FF and NF channel components is essential to fully exploit the spatial degrees of freedom provided by extremely large antenna arrays.

A. Proposed Low-Complexity HF-OMP Framework

To achieve low-complexity HF CE, we propose the Ultra-Low-Complexity HF-OMP (ULC-HF-OMP), a greedy framework using an optimized dictionary with reduced inter-atom correlation to improve support recovery. The algorithm iteratively constructs the active set and performs gain estimation via a scalar least-squares (LS) update. By avoiding matrix inversions, runtime is significantly reduced. The dictionary jointly spans the angular and polar domains through an adaptive angle-distance sampling strategy, providing an efficient and compact representation of both FF and NF components, which results in a less coherent dictionary.

The complete HF dictionary is given by $\mathbf{A} = [\mathbf{A}_{\text{FF}}, \mathbf{A}_{\text{NF}}]$, where $\mathbf{A}_{\text{FF}}$ is the DFT-based codebook and $\mathbf{A}_{\text{NF}}$ is obtained from the adaptive construction (see Algorithm 1).

In addition, the main steps of the CE procedure are summarized as follows.

Initialization. The active dictionary is initialized as $\hat{\mathbf{A}}^{[0]} = \emptyset$, and the residual is set to $\mathbf{r}^{[0]} = \mathbf{y}_t$.

(i) Atom selection. At iteration i , the atom that maximizes the correlation with the current residual is selected:

$$j^* = \arg \max_j |[\mathbf{A}^H \mathbf{r}^{[i]}]_j|, \quad \hat{\mathbf{a}}^{[i]} = \mathbf{A}_{(:,j^*)}. \quad (13)$$

The selected atom is then incorporated into the active set:

$$\hat{\mathbf{A}}^{[i]} = [\hat{\mathbf{A}}^{[i-1]}, \hat{\mathbf{a}}^{[i]}], \quad (14)$$

and the corresponding FF/NF parameters are initialized, *i.e.*, $\hat{\theta}_{\text{far}}^{[i]}$ or $(\hat{\theta}_{\text{near}}^{[i]}, \hat{r}_{\text{near}}^{[i]})$.

(ii) Incremental gain estimation. Let $\hat{\mathbf{A}}^{[i-1]}$ and $\bar{\mathbf{h}}^{[i-1]}$ denote the previously selected atoms and their gains. The residual can be written as

$$\mathbf{r} = \mathbf{y}_t - \hat{\mathbf{A}}^{[i-1]} \bar{\mathbf{h}}^{[i-1]}.$$

Algorithm 1 Optimized NF dictionary construction

Input: $N, d, \lambda, \eta, \rho_{\min}, \rho_{\max}$

Output: $\mathbf{A}_{\text{NF}}$

- 1: Define angular grid: $\theta_n = -1 + \frac{2n}{N}$, $n = 1, \dots, N$
- 2: Compute maximum distance:

$$Z_{\max} = \frac{(Nd)^2}{2\lambda\eta^2}$$

- 3: **for** $n = 1$ to N **do**

- 4: Compute angle-dependent scaling:

$$Z = Z_{\max}(1 - \theta_n^2)$$

- 5: Determine radial sampling range:

$$k_{\max} = \left\lfloor \frac{Z}{\rho_{\min}} \right\rfloor, \quad k_{\min} = \left\lfloor \frac{Z}{\rho_{\max}} \right\rfloor + 1$$

- 6: Generate distance samples:

$$r_1 = \frac{2(Nd)^2}{\lambda}, \quad r_k = \frac{Z}{k}, \quad k = k_{\min}, \dots, k_{\max}$$

- 7: **for** each r_k **do**

- 8: Compute NF steering vector:

$$\mathbf{a}(r_k, \theta_n) = \exp \left(-j \frac{2\pi}{\lambda} (r - r_k) \right)$$

- 9: Normalize: $\mathbf{a} \leftarrow \mathbf{a} / \|\mathbf{a}\|_2$

- 10: Append to dictionary $\mathbf{A}_{\text{NF}}$

- 11: **end for**

- 12: **end for**

Return: $\mathbf{A}_{\text{NF}}$

For the newly selected atom, the refinement reduces to a single-variable LS problem:

$$\min_{\bar{\mathbf{h}}^{[i]}, \hat{\theta}^{[i]}, \hat{r}^{[i]}} \|\mathbf{r} - \hat{\mathbf{a}}^{[i]} \bar{\mathbf{h}}^{[i]}\|_2^2. \quad (15)$$

Assuming normalized atoms, the optimal gain is obtained in closed form as

$$\bar{\mathbf{h}}^{[i]} = (\hat{\mathbf{a}}^{[i]})^H \mathbf{r}, \quad (16)$$

which corresponds to a simple inner product. This incremental update avoids matrix inversions, drastically reducing computational complexity.

(iii) Stopping criterion and reconstruction. The procedure is repeated until the MSE falls below a predefined threshold ϵ or the maximum number of iterations $\mathcal{I}_{\max}^{[i]}$ is reached. The final channel estimate is given by $\hat{\mathbf{h}} = \hat{\mathbf{A}}^{[i]} \bar{\mathbf{h}}^{[i]}$, as summarized in Alg. 2.

III. NUMERICAL RESULTS AND DISCUSSIONS

In this section, the proposed CE method is evaluated and compared with existing HF estimators. Simulations consider a carrier frequency of $f_c = 30$ GHz (*i.e.*, $\lambda = 0.01$ m), an HF channel with $L = 10$ propagation paths, and field ratio $\gamma = 0.5$. These parameters are used only for Monte Carlo channel generation, since the proposed ULC-HF-OMP does not require prior knowledge of the sparsity level or field ratio. The pilot length and stopping criterion are set to $\tau = 1$ and $\epsilon = \sigma^2$, respectively. An NLoS channel model is assumed, with path gains distributed as $\alpha_\ell \sim \mathcal{CN}(0, 1/L)$ and angular

Algorithm 2 Proposed ULC-HF-OMP CE scheme.

Input: $\mathbf{y}_t, \mathbf{A}, \epsilon, \mathcal{I}_{\max}$
Initialize: $i \leftarrow 0, \mathbf{r} \leftarrow \mathbf{y}_t, \mathcal{T}^{[i]} \leftarrow \emptyset, \hat{\mathbf{A}}^{[i]} \leftarrow \emptyset, \bar{\mathbf{h}}^{[i]} \leftarrow \emptyset, \text{MSE} \leftarrow \|\mathbf{r}\|_2^2/N$
 1: **while** $\text{MSE} > \epsilon$ **and** $i < \mathcal{I}_{\max}$ **do**
 2: $i \leftarrow i + 1$
 3: *// (i) Atom selection with low-correlation constraint*
 4: $\eta \leftarrow \arg \max_{j \notin \mathcal{T}^{[i-1]}} \|[\mathbf{A}^H \mathbf{r}]_j\|^2$
 5: $\hat{\mathbf{a}}^{[i]} \leftarrow \mathbf{A}_{(:,\eta)} / \|\mathbf{A}_{(:,\eta)}\|_2$
 6: $\mathcal{T}^{[i]} \leftarrow \mathcal{T}^{[i-1]} \cup \eta$
 7: $\hat{\mathbf{A}}^{[i]} \leftarrow [\hat{\mathbf{A}}^{[i-1]}, \hat{\mathbf{a}}^{[i]}$
 8: *// (ii) Incremental gain update (closed-form scalar)*
 9: $\bar{\mathbf{h}}^{[i]} \leftarrow (\hat{\mathbf{a}}^{[i]})^H \mathbf{r}$
 10: $\bar{\mathbf{h}}^{[i]} \leftarrow [\bar{\mathbf{h}}^{[i-1]}, \bar{\mathbf{h}}^{[i]}$
 11: *// (iii) Residual update*
 12: $\mathbf{r}_{\text{new}} \leftarrow \mathbf{r} - \hat{\mathbf{A}}^{[i]} \bar{\mathbf{h}}^{[i]}$
 13: $\mathbf{r} \leftarrow \mathbf{r}_{\text{new}}$
 14: $\text{MSE} \leftarrow \|\mathbf{r}\|_2^2/N$
 15: **end while**
Output: $\hat{\mathbf{h}} = \hat{\mathbf{A}}^{[i]} \bar{\mathbf{h}}^{[i]}$

components independently drawn from $\mathcal{U}[-1, 1]$. Additional simulation parameters are summarized in Table I. The NMSE is defined as

$$\text{NMSE} = \mathbb{E} \left\{ \frac{\|\hat{\mathbf{h}} - \mathbf{h}\|^2}{\|\mathbf{h}\|^2} \right\},$$

where $\mathbf{h}$ and $\hat{\mathbf{h}}$ denote the true and estimated HF channels, respectively. Results for NMSE and average achievable rate were obtained from 1000 independent Monte Carlo realizations. Simulations were carried out in GNU Octave 11.1.0 on a Windows 11 computer with an AMD Ryzen 5 5600 CPU and 32 GB DDR4 RAM.

TABLE I
SIMULATION PARAMETERS: ADOPTED VALUES

Parameter	Value	Parameter	Value
N	256	N_u	1
f_c	30 GHz	Q_F	256
Q_N	401	Q	657
ϵ	σ^2	$\mathcal{I}_{\max}$	20
L	10	γ	0.5
θ_{ℓ_f}	$\mathcal{U}[-1, 1]$	θ_{ℓ_n}	$\mathcal{U}[-1, 1]$

Fig. 1 shows the NMSE performance of the considered CE schemes for the NLoS HF scenario. As expected, the LS estimator presents the worst performance due to the absence of sparsity exploitation and statistical information. Although the MMSE estimator improves the estimation accuracy, its performance remains limited compared to HF sparse approaches.

The conventional FF OMP scheme exhibits a clear NMSE floor around 2.6 dB, which is mainly caused by the mismatch between the FF dictionary and the actual HF channel structure. In contrast, the HF-based estimators significantly improve the CE accuracy by jointly modeling FF and NF components.

Among the benchmark methods, the off-grid approaches outperform their on-grid counterparts, particularly in the high-SNR region, due to their ability to reduce basis mismatch effects. The HF SGP without γ achieves better performance than

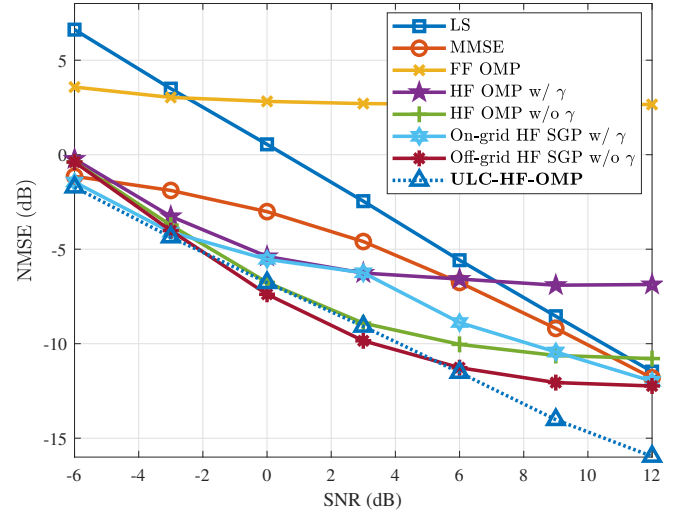


Fig. 1. NMSE vs. SNR of LS, MMSE, FF OMP, HF OMP variants, HF SGP with γ , HF SGP without γ , and the proposed HF OMP for NLoS channel.

the corresponding on-grid version, while HF OMP without γ also improves over the version assuming prior field-ratio information.

The proposed ULC-HF-OMP consistently achieves the best NMSE performance across the entire evaluated SNR range. In particular, the proposed method reaches approximately -11.5 dB at 6 dB SNR and nearly -16 dB at 12 dB SNR, outperforming the benchmark estimators in the high-SNR region. These gains are mainly associated with the optimized low-correlation dictionary, which improves support recovery reliability, and the incremental scalar LS update, which enables accurate gain estimation with reduced computational complexity. Therefore, these results demonstrate that the proposed ULC-HF-OMP provides an improved trade-off between estimation accuracy and computational efficiency for XL-MIMO HF CE.

Fig. 2 presents the achievable rate performance of the considered HF CE schemes under the NLoS scenario. As expected, the perfect CSI case provides the upper performance bound, while all practical estimators approach this limit as the SNR increases.

Among benchmarks, HF OMP with prior γ shows the lowest spectral efficiency (SE), while adaptive versions and off-grid HF SGP—due to its refinement capability—offer better performance.

The proposed ULC-HF-OMP consistently achieves the highest achievable rate among all practical estimators and remains very close to the perfect CSI performance. More specifically, the proposed method achieves approximately 9.83 bit/s/Hz at 6 dB SNR and nearly 11.87 bit/s/Hz at 12 dB SNR, while the perfect CSI case reaches about 11.91 bit/s/Hz.

The superior SE performance is mainly attributed to the optimized low-correlation dictionary, which improves atom selection reliability, and to the incremental scalar LS update, which enables efficient gain estimation with low computational complexity. These results confirm that the proposed ULC-HF-OMP achieves an excellent balance between spectral efficiency and computational efficiency, making it suitable for practical

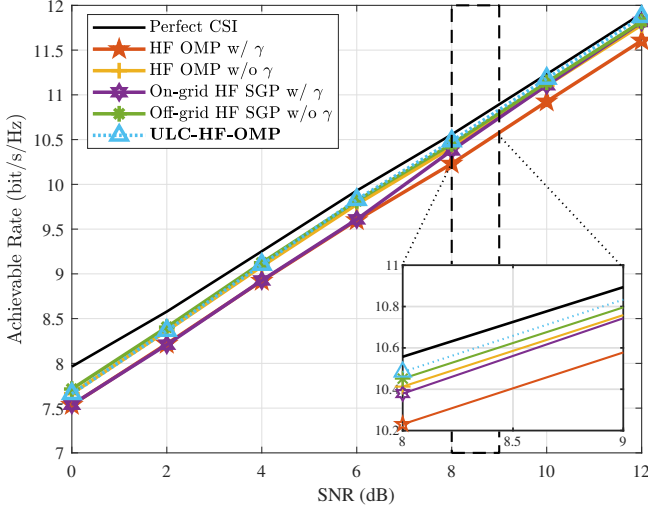


Fig. 2. Achievable rate vs. SNR for the considered HF CE schemes in the NLoS scenario, highlighting the performance of the proposed ULC-HF-OMP.

XL-MIMO HF systems.

Finally, Table II compares the computational complexity and average runtime of the considered HF CE schemes at 6 dB SNR. It can be observed that the proposed ULC-HF-OMP achieves the lowest runtime among all evaluated methods while maintaining a significantly reduced computational complexity.

TABLE II
COMPUTATIONAL COMPLEXITY AND AVERAGE RUNTIME OF HF CE
SCHEMES (AT SNR = 6 DB).

Scheme	Complexity	Runtime (ms)
HF OMP w/ γ [1]	$\mathcal{O}(N(Q_F L_F + L_F^2) + L_F^3 + N(Q_N L_N + L_N^2) + L_N^3)$	1.5525
HF OMP w/o γ [6]	$\mathcal{O}(NQ_F L + NL^2 + L^3 + N_\gamma(NQ_N + NL^2 + L^3 + N^2 L))$	14.1849
HF SGP w/ γ [7]	$\mathcal{O}(NL^2 + NL(Q_F + Q_N))$	16.6823
HF SGP w/o γ [7]	$\mathcal{O}(NQ_F L + NL^2 + N_\gamma(NQ_N + NL^2) + N_{\text{iter}}(N^2 + NL^2 + L^3 + N^2 L))$	18.6046
ULC-HF-OMP	$\mathcal{O}(iNQ)$	1.5114

The HF OMP scheme with prior knowledge of γ already presents relatively low execution time due to its simplified support recovery strategy, achieving an average runtime of approximately 1.55 ms. However, the proposed ULC-HF-OMP further reduces the runtime to nearly 1.51 ms by employing an incremental scalar LS update and an optimized low-correlation dictionary, which simplifies both the atom-selection and gain-estimation stages.

In contrast, the methods without prior knowledge of γ exhibit substantially higher computational complexity. In particular, HF OMP without γ requires approximately 14.18 ms due to the additional search procedures associated with adaptive field-ratio estimation. Similarly, the HF SGP approaches present the highest runtimes, especially the off-grid version, whose iterative refinement process increases the computational burden and leads to an average runtime of about 18.60 ms.

These results confirm that the proposed ULC-HF-OMP achieves a favorable trade-off between estimation accuracy and computational efficiency. Despite its low complexity, the proposed method still provides superior NMSE and achievable rate performance, demonstrating its suitability for practical XL-MIMO hybrid-field CE scenarios.

IV. CONCLUSIONS

This work proposed the ULC-HF-OMP framework for HF CE in XL-MIMO systems. The proposed method combines an optimized low-correlation dictionary with an incremental scalar LS update, enabling accurate support recovery while significantly reducing computational complexity.

Unlike conventional HF estimation approaches, the proposed method does not rely on prior knowledge of the sparsity level or field ratio and avoids costly matrix inversion operations. In addition, the optimized dictionary construction improves the reliability of the atom selection stage by reducing inter-atom correlation, leading to enhanced estimation accuracy. Simulation results demonstrated that the proposed ULC-HF-OMP consistently outperforms existing HF estimation schemes in terms of NMSE and achievable rate while also achieving the lowest runtime among the evaluated methods. In particular, the proposed approach closely approaches the perfect CSI performance in the high-SNR region while maintaining very low computational cost.

Overall, the obtained results confirm that the proposed ULC-HF-OMP provides an efficient trade-off between estimation performance and computational complexity, making it a promising solution for practical XL-MIMO HF communications in future 6G systems.

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