Leveraging Channel Knowledge Map for ISTA based Channel Estimation

Muhammad Awais[‡], Mubasher Ahmed Khan[‡],and Yun Hee Kim[‡†]

{mawais, mubasher, yheekim}@khu.ac.kr

[†] Dept. of Electronic Engineering, [‡] Dept. of Electronics and Information Convergence, Kyung Hee University.

Abstract

Future 6G and beyond communication networks are expected to deploy a large number of antennas to meet growing communication demands. Recently, the channel knowledge map (CKM) has been proposed to store channel parameters, enabling channel estimation with few or no pilots. In this work, we use the CKM to construct the steering matrix from the provided angles and distances and estimate the near-field channel, which is then iteratively refined using the iterative shrinkage-thresholding algorithm (ISTA). Simulation results show that the proposed framework achieves improved channel estimation performance across all signal-to-noise ratios.

Ⅰ. Introduction

Sixth-generation and beyond communication systems are expected to operate at high frequencies and employ extremely large antenna arrays to support high data rates and massive connectivity. However, the use of large-scale arrays introduces significant challenges for accurate channel state information (CSI) estimation due to increased system complexity, high pilot overhead, and the presence of near-field propagation effects [1]. In such scenarios, conventional pilot-based channel estimation methods become inefficient and may fail to scale with the array size.

Recently, the channel knowledge map (CKM) has been proposed as a promising solution to alleviate these challenges by storing location-specific channel parameters in a database [2]. When the base station (BS) has access to the user's location, prior information such as multipath angles and distances can be extracted from the CKM and exploited for channel estimation or beamforming, thereby reducing the required training overhead. To further enable CKM-based processing in both near-field and far-field regions, a database known as the channel distance angle map (CADM) was introduced in [3]. The CADM provides multipath angles and distances for different locations, facilitating more accurate channel modeling and improved estimation performance across diverse propagation conditions.

Ⅱ. System Model

We consider a near-field orthogonal frequency division multiplexing (OFDM) system in which the BS is equipped with M antennas and serves K users with single antenna [3] as illustrated in Fig. 1. For near-field distance range uniform spherical wave (USW) model is adopted when users and BS are located in (x,y) coordinates. The received signal $\boldsymbol{y}_{s,p}$ at BS for s-th subcarrier during the p-th pilot transmission is

$$\boldsymbol{y}_{s,p} = \boldsymbol{W}_p \boldsymbol{h}_s x_{m,p} + \boldsymbol{W}_p \boldsymbol{n}_{s,p}, \qquad (1)$$

where $\boldsymbol{W}$ is combining matrix with normalized unit modulus constraint, and $\boldsymbol{n}$ is Gaussian complex noise with zero mean and σ variance and $x_{m,p}=1$ is known transmitted pilot. Near-field channel is expressed as

$$\boldsymbol{h}_s = \sqrt{\frac{M}{L}} \sum_{l=1}^{L} e^{-j\frac{2\pi f_s}{c} r_l} g_l \boldsymbol{b}(\theta_l, r_l), \qquad s = 1,2,\cdots,S \qquad (2)$$

where L is number of multiple paths g_l is path gain and $\boldsymbol{b}$ is steering vector for θ_l angle and r_l distance for l-th path.

In our considered system as in Fig. 1 CADM is at BS and for given user location $\boldsymbol{q}$, we can get angles and distances from CADM for all L paths from which corresponding steering vector can be calculated. In [3], the CADM-LS method directly retrieves angles and distances from the CADM database to estimate the channel, while the CADM-LBFGS approach further refines the channel estimation by iteratively updating the angles and distances of all propagation paths using an quasi-Newton algorithm called limited-memory BFGS (L-BFGS).

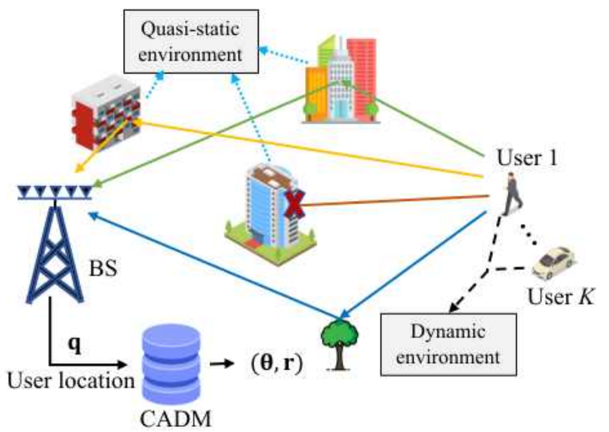

Fig. 1. System model having CADM database in BS which maps multipath angles and distances.

Ⅲ. Proposed Method

In literature iterative shrinkage-thresholding algorithm for group row-sparse (ISTA-GS) is used to solved sparse channel in polar domain but it need significant number of iterations for solution. In [4] problem is formulated in angular domain with steering matrix $\boldsymbol{B}$ so that dictionary information can be utilized which provide better channel update and by using leaning based updates complexity can be reduced. In [4] initial $\boldsymbol{B}$ was randomly taken which can result in more number of iteration for solution convergence. As by leveraging CADM we can have very good initial $\boldsymbol{B}$ therefore in our work instead of random $\boldsymbol{B}$, we use initial CADM database and CADM-LBFGS based optimization to calculate steering matrix $\boldsymbol{B}$ based on provided angles and distances. Hence final ISTA-GS in angular domain for this work is provided in matrix format as

$$\boldsymbol{H}_{t+1} = \boldsymbol{B} \cdot \eta_{\theta_t}\left[\boldsymbol{B}^{-1}\boldsymbol{H}_t + \frac{1}{\lambda}(\boldsymbol{WB})^H(\boldsymbol{Y} - \boldsymbol{WH}_t)\right], \tag{3}$$

where $\boldsymbol{H}_{t+1}$ is updated channel in t-th iteration, $\boldsymbol{Y}$ is received signal in matrix format for all total P pilots. λ is maximum eigenvalue of from $\boldsymbol{WB}^H\boldsymbol{WB}$, and η_θ is given as

$$\eta_\theta(\boldsymbol{H}^p(m,:)) = \max\left\{0, \frac{\|\boldsymbol{H}^p(m,:)\|_2 - \theta}{\|\boldsymbol{H}^p(m,:)\|_2}\right\}\boldsymbol{H}^p(m,:), \tag{4}$$

where $\boldsymbol{H}^p$ represents channel for m-th row in polar domain and $\theta = 0.01$ is thershold parameter.

Ⅳ. Results

Using same simulation parameters as [3], we use ISTA-GS iterations with $t = 5$. While $\boldsymbol{B}$ is calculated based on (θ_l, r_l) pair for all $\hat{L} = 12$ paths obtained from CADM while actual channel has $L = 6$. Impact on performance for different $\hat{L}$ values for different signal-to-noise ratios (SNRs) was evaluated in [5]. In our simulation CADM was contructed using $\hat{P} = 64$ while live pilot training contains $P = 32$. Results are compared against benchmarks of polar domain simultaneous orthogonal matching pursuit (P-SOMP) and CADM-LS which is channel estimation based on stored angles and distances using least squres (LS). We also compare CADM-LBFGS method in which angles and distances are optimized then channel is estimated.

In Fig. 2 we obtained normalized mean square error (MSE) performance against SNR values form which it is observed that our proposed method to use CADM based $\boldsymbol{B}$ and updating using ISTA-GS results in better performance than compared benchmarks. In ISTA-CADM-LS, $\boldsymbol{B}$ was calculated using initial CADM and initial $\boldsymbol{H}_0$ is taken using CADM-LS while in ISTA-CADM-LBFGS, $\boldsymbol{B}$ was calculated using refined angles and distances from CADM-LBFGS and initial $\boldsymbol{H}_0$ is taken from final estimation of CADM-LBFGS.

This work can be further extended by incorporating learning-based optimization techniques (I.e. deep unfolding) that are initialized using the CADM provided parameters. By leveraging accurate initial values such as angles and distances from the database, only a lightweight learning model is required for parameter refinement, significantly reducing training complexity and computational cost compared to fully data driven approaches used in previous methods.

Ⅴ. Conclusion

The CKM-based CADM database is exploited to construct the near-field steering matrix using the obtained multipath angles and distances. This steering matrix provides an informed initial representation of the channel structure and is subsequently leveraged within an ISTA-GS based iterative refinement framework to progressively update the channel estimates. By incorporating prior spatial information from the database and exploiting the inherent sparsity of the channel, the proposed method achieves superior channel estimation performance across all SNR regimes.

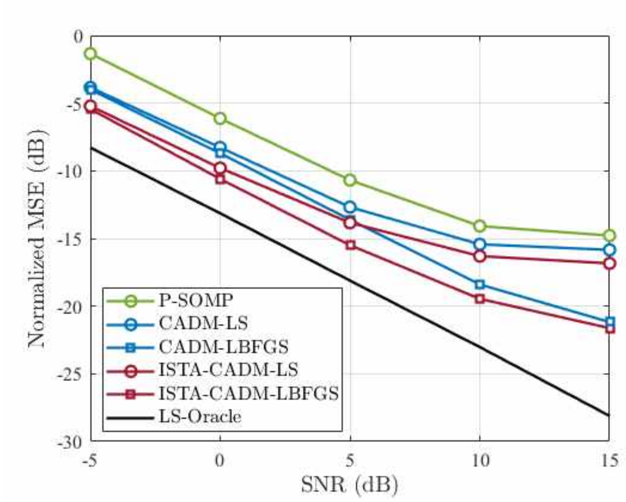

Fig. 2. Normalized MSE (dB) versus SNR (dB) in a near-field scenario with user distances ranging from 5 m to 10 m.

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