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Broadband Channel Estimation for Intelligent Reflecting Surface Aided mmWave Massive MIMO Systems

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1 System Model

- Intelligent Reflecting Surface (IRS) aided massive MIMO systems [1]-[4]
  - The broadband (frequency-selective fading) property is seldom considered for IRS.
- BS and IRS are equipped with UPAs with M and N antennas, resp., to serve multiple single-antenna users;
- IRS is passive without any RF chains;
- BS is of fully-connected hybrid architecture [5] with $N_{RF} << M$ RF chains;

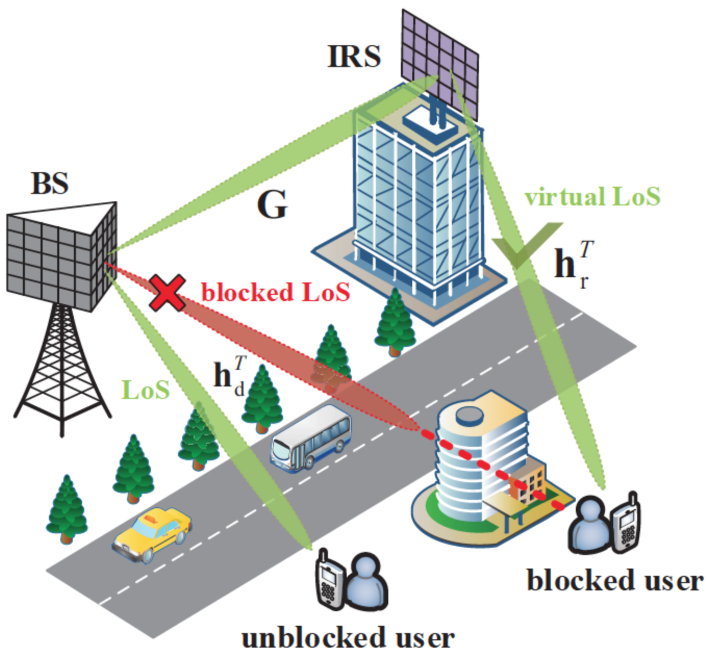

Fig. 1: IRS-aided mmWave massive MIMO systems.

System Model

- The downlink BS-IRS delay-domain channel with one LoS path and L_{g} NLoS paths:

Steering vectors with AoA and AoD

Pulse shaping filter with delay offset

$$\mathbf{G}(\tau)=\frac{\alpha_{\mathrm{g},0}}{\rho_{\mathrm{g},0}}\boxed{\mathbf{a}_N(\theta^{\mathrm{r}}_{\mathrm{g},0},\varphi^{\mathrm{r}}_{\mathrm{g},0})\mathbf{a}_M^H(\theta^{\mathrm{t}}_{\mathrm{g},0},\varphi^{\mathrm{t}}_{\mathrm{g},0})}\times\boxed{p(\tau-\tau_{\mathrm{g},0})}$$
$$+\sum_{l=1}^{L_{\mathrm{g}}}\frac{\alpha_{\mathrm{g},l}}{\rho_{\mathrm{g},l}}\mathbf{a}_N(\theta^{\mathrm{r}}_{\mathrm{g},l},\varphi^{\mathrm{r}}_{\mathrm{g},l})\mathbf{a}_M^H(\theta^{\mathrm{t}}_{\mathrm{g},l},\varphi^{\mathrm{t}}_{\mathrm{g},l})\times p(\tau-\tau_{\mathrm{g},l}),\quad (1)$$

- OFDM system with K subcarriers, N_{CP} cyclic prefix, and sampling space T_{s} is adopted. The corresponding frequency-domain channel in the k-th subcarrier is:

$$\mathbf{G}_k=\sum_{d=0}^{N_{\mathrm{CP}}-1}\mathbf{G}(dT_s)e^{j\frac{2\pi(k-1)}{K}d}$$ (DFT to convert delay-domain to frequency-domain)

$$=\underbrace{g_{\mathrm{g},0,k}\mathbf{a}_N(\theta^{\mathrm{r}}_{\mathrm{g},0},\varphi^{\mathrm{r}}_{\mathrm{g},0})\mathbf{a}_M^H(\theta^{\mathrm{t}}_{\mathrm{g},0},\varphi^{\mathrm{t}}_{\mathrm{g},0})}_{\mathbf{G}_{\mathrm{L},k}}+\underbrace{\sum_{l=1}^{L_{\mathrm{g}}}g_{\mathrm{g},l,k}\mathbf{a}_N(\theta^{\mathrm{r}}_{\mathrm{g},l},\varphi^{\mathrm{r}}_{\mathrm{g},l})\mathbf{a}_M^H(\theta^{\mathrm{t}}_{\mathrm{g},l},\varphi^{\mathrm{t}}_{\mathrm{g},l})}_{\mathbf{G}_{\mathrm{N},k}},\qquad(3)$$

LoS part

NLoS part

- The BS-user channel, $\mathbf{h}^T_{\mathrm{d},k}$, and IRS-user channel, $\mathbf{h}^T_{\mathrm{r},k}$ can be similarly modeled.

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2.A Downlink pilot transmission

- To conduct downlink CE, BS broadcast the pilot signals $\mathbf{s}_{i,k} \in \mathbb{C}^{M\times 1}$ in the *k*-th subcarrier and *i*-th time slot. At the user, the received pilot signals can be written as

Direct BS-user transmission

$$y_{i,k} = \boxed{\mathbf{h}_{\mathrm{d},k}^T \mathbf{s}_{i,k}} + \boxed{\mathbf{h}_{\mathrm{r},k}^T \boldsymbol{\Theta}_i \mathbf{G}_k \mathbf{s}_{i,k}} + n_{i,k}$$

Pilot signals reflected by IRS

$$= [\mathbf{h}_{\mathrm{d},k}^T, \mathbf{h}_{\mathrm{r},k}^T] \begin{bmatrix} \mathbf{s}_{i,k} \\ \boldsymbol{\Theta}_i \mathbf{G}_k \mathbf{s}_{i,k} \end{bmatrix} + n_{i,k}, \qquad (6)$$

where $\boldsymbol{\Theta}_i = \mathrm{diag}(\boldsymbol{\theta}_i) \in \mathbb{C}^{N\times N}$ are the phase-shifts imposed by IRS.

- Collecting $\{y_{i,k}\}_{i=1}^{N_\mathrm{P}}$ in N_P successive OFDM symbols, we have

$$\mathbf{y}_k = \boldsymbol{\Phi}_k \mathbf{h}_{\mathrm{eff},k} + \mathbf{n}_k, \quad (8) \quad \begin{cases} \mathbf{y}_k = [y_{1,k}, \ldots, y_{N_\mathrm{p},k}]^T \\ \mathbf{n}_k = [n_{1,k}, \ldots, n_{N_\mathrm{p},k}]^T \\ \boldsymbol{\Phi}_k = \begin{bmatrix} \mathbf{s}_{1,k} & \cdots & \mathbf{s}_{N_\mathrm{p},k} \\ \boldsymbol{\Theta}_1 \mathbf{G}_k \mathbf{s}_{1,k} & \cdots & \boldsymbol{\Theta}_{N_\mathrm{p}} \mathbf{G}_k \mathbf{s}_{N_\mathrm{p},k} \end{bmatrix}^T \\ \mathbf{h}_{\mathrm{eff},k} = [\mathbf{h}_{\mathrm{d},k}^T, \mathbf{h}_{\mathrm{r},k}^T]^T \text{ is the channel to be estimated} \end{cases}$$

- Assume the LoS part of $\mathbf{G}_k$ is known, and treat the NLoS part as minor interferences.

$$\mathbf{y}_k = \boxed{\boldsymbol{\Phi}_{\mathrm{L},k}} \mathbf{h}_{\mathrm{eff},k} + \boxed{\bar{\mathbf{n}}_k}, \qquad (10)$$

The pre-known measurement matrix

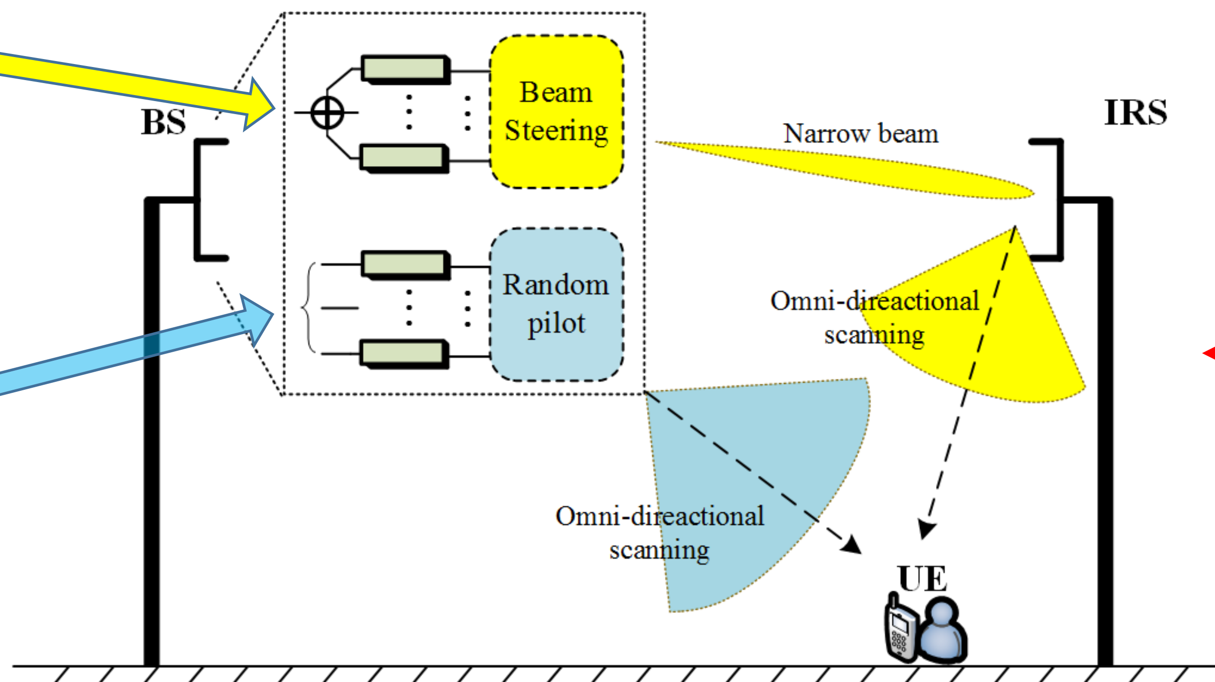
Effective noise containing the interference from the NLoS part of $\mathbf{G}_k$

2.B Pilot design

	Challenge(s)	Solution(s)
BS-user channel	The locations of users (w.r.t. BS) are unknown.	Random pilot at the BS to realize omni-directional detection [5].
BS-IRS-user channel	① The locations of users (w.r.t. IRS) are unknown; ② Severely high path loss due to long transmission distance.	① Random pilot at the IRS; ② Beam steering at the BS towards the LoS direction of IRS.

Dedicated to sounding the IRS-user channels

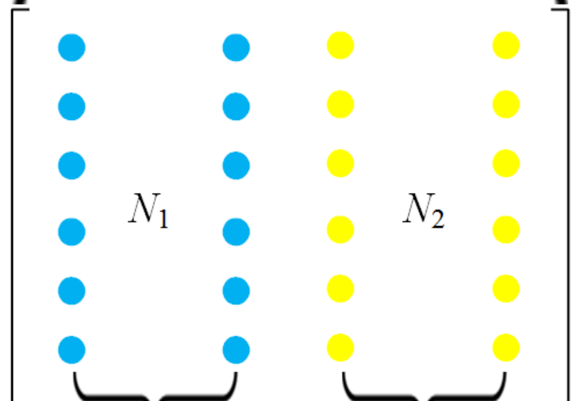
Dedicated to sounding the BS-user channels



2.B Pilot design

- The design at the BS:

$$\mathbf{S}_{i,k} = \overbrace{\left[\underbrace{\qquad}_{N_1}\ \underbrace{\qquad}_{N_2}\right]}^{\mathbf{F}_{\mathrm{RF},i}} \cdot \overbrace{\sqrt{\frac{P_{\mathrm{Tx}}}{N_{\mathrm{RF}}}}\mathbf{1}}^{\mathbf{f}_{\mathrm{BB},i,k}}$$



$$N_{\mathrm{RF}} = N_1 + N_2$$

The first N_1 columns as random pilot.
Each entry is: $\frac{1}{M}e^{jf}$, $\phi \sim \mathcal{U}[0,2\pi)$

The last N_2 columns as beam steering.
All columns share identical value:
$\mathbf{a}_M\left(q_{\mathrm{LoS}}, j_{\mathrm{LoS}}\right)$

$$\mathbf{a}_M(\theta,\varphi) = \frac{1}{\sqrt{M}}[1, e^{j\pi\sin\theta}, \ldots, e^{j\pi(M_x-1)\sin\theta}]^T \otimes [1, e^{j\pi\cos\theta\sin\varphi}, \ldots, e^{j\pi(M_y-1)\cos\theta\sin\varphi}]^T, \quad (2)$$

- The design at the IRS:

$$\boldsymbol{\Theta}_i = \mathrm{diag}\left(\boldsymbol{\theta}_i\right)$$

$$\left|[\boldsymbol{\theta}_i]_n\right| = e^{j\phi}, \quad \phi \sim \mathcal{U}[0,2\pi)$$

Compressive sensing-based CE solution

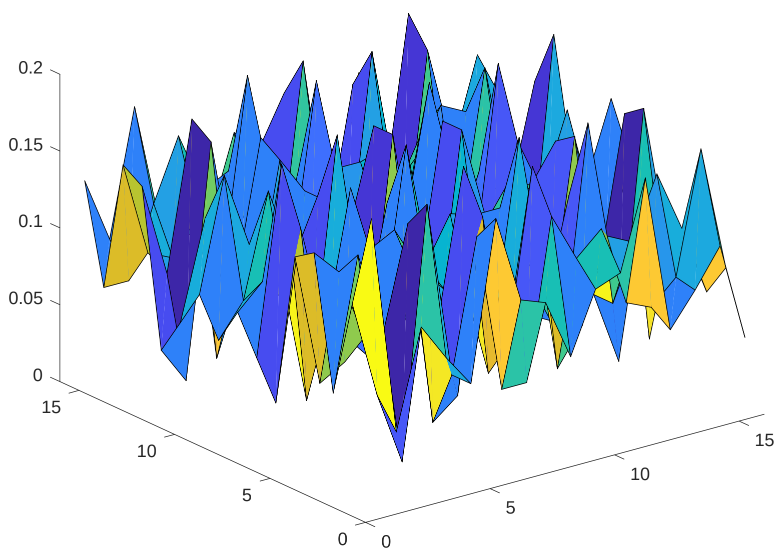
$$\mathbf{y}_k = \mathbf{\Phi}_{\mathrm{L},k}\mathbf{h}_{\mathrm{eff},k} + \bar{\mathbf{n}}_k, \tag{10}$$

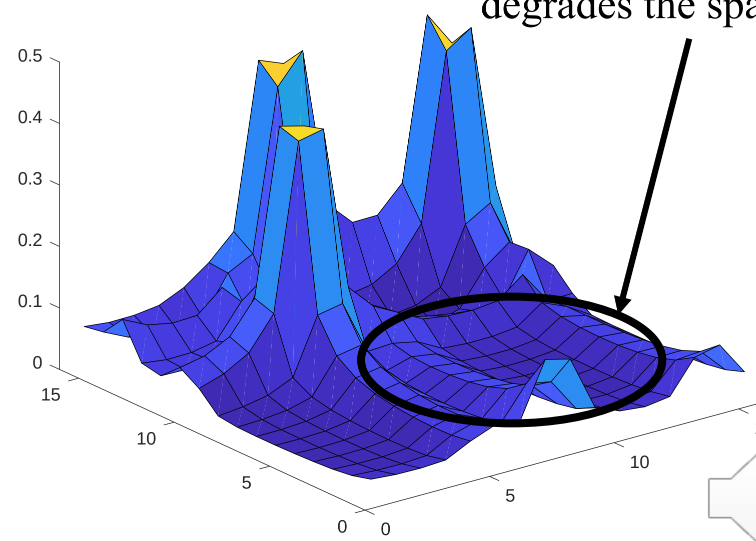
- Large-scale arrays at both the BS and IRS → Extremely large dimension of channels → Unaffordable pilot overhead in traditional algorithms.
- Compressive sensing [4]-[8]: leveraging the angular sparsity of mmWave channels to significantly reduce the pilot overhead in channel estimation.

$$\mathbf{h}_{\mathrm{d},k}^T = \mathbf{h}_{\mathrm{da},k}^T \mathbf{A}_{\mathrm{d}}^H + \mathbf{e}_{\mathrm{d},k}^T, \tag{16}$$

$$\mathbf{h}_{\mathrm{r},k}^T = \mathbf{h}_{\mathrm{ra},k}^T \mathbf{A}_{\mathrm{r}}^H + \mathbf{e}_{\mathrm{r},k}^T. \tag{17}$$

spatial-domain → angular-domain



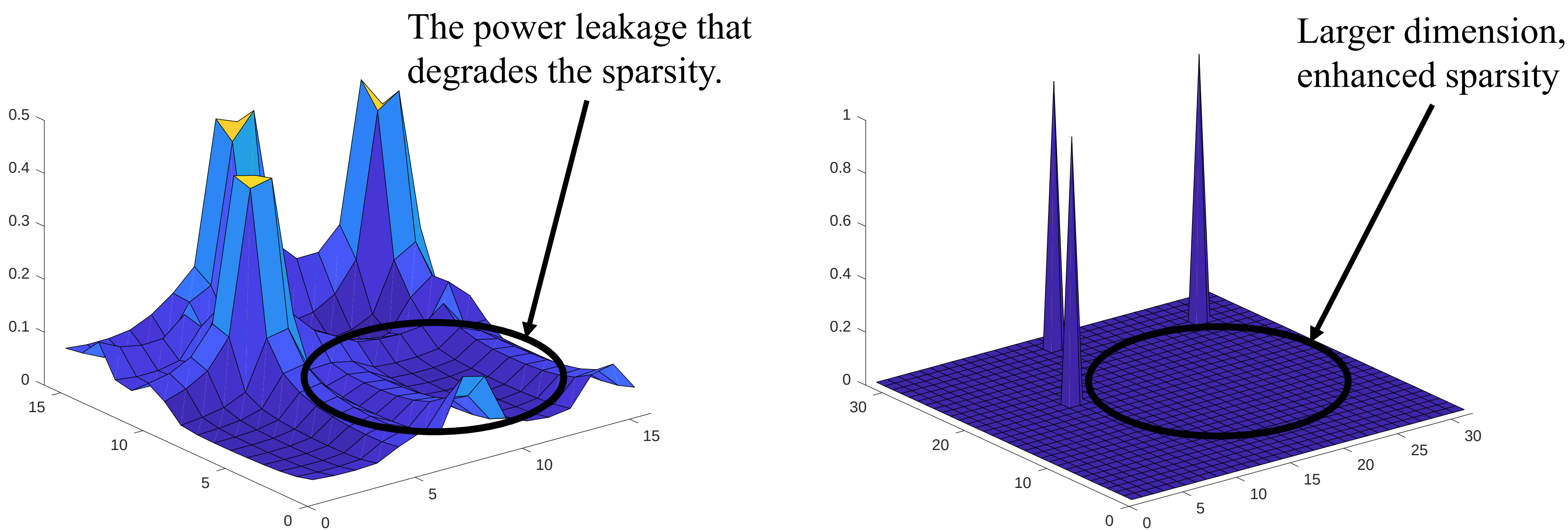


The power leakage that degrades the sparsity.

Compressive sensing-based CE solution

- Redundant dictionary [8]: trading off the complexity and estimation performance.

angular-domain channel with unitary dictionary 16×16 → angular-domain channel with redundant dictionary 32×32



- According to CS theory [6], with enhanced sparsity of channels, the improved performance of the CS-based CE is expected.

Compressive sensing-based CE solution

- Standard form of sparse signal recovery problem:

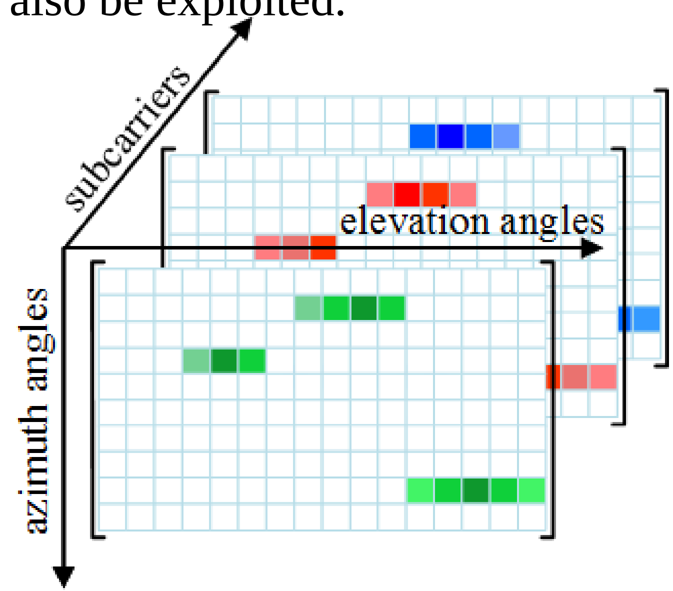
$$
\begin{aligned}
\mathbf{y}_k &= \boldsymbol{\Phi}_{\mathrm{L},k}\left([\mathbf{h}_{\mathrm{da},k}^T\mathbf{A}_{\mathrm{d}}^H, \mathbf{h}_{\mathrm{ra},k}^T\mathbf{A}_{\mathrm{r}}^H]^T + [\mathbf{e}_{\mathrm{d},k}^T, \mathbf{e}_{\mathrm{r},k}^T]^T\right) + \bar{\mathbf{n}}_k \\
&= \boldsymbol{\Phi}_{\mathrm{L},k} \underbrace{\begin{bmatrix} \mathbf{A}_{\mathrm{d}}^H & \\ & \mathbf{A}_{\mathrm{r}}^H \end{bmatrix}^T}_{\boldsymbol{\Psi}} \underbrace{[\mathbf{h}_{\mathrm{da},k}^T, \mathbf{h}_{\mathrm{ra},k}^T]^T}_{\mathbf{h}_{\mathrm{effa},k}} + \mathbf{n}_{\mathrm{eff},k} \\
&= \boldsymbol{\Phi}_{\mathrm{L},k} \boxed{\boldsymbol{\Psi}}\boxed{\mathbf{h}_{\mathrm{effa},k}} + \mathbf{n}_{\mathrm{eff},k}, \qquad (18)
\end{aligned}
$$

Dictionary matrix

Sparse angular-domain channel vector

- The structure of channels in broadband system [5][7] can also be exploited.

$$\mathrm{supp}(\mathbf{h}_{\mathrm{effa},1}) = \dots = \mathrm{supp}(\mathbf{h}_{\mathrm{effa},K}). \qquad (19)$$



Compressive sensing-based CE solution

- Distributed Orthogonal Matching Pursuit (DOMP) to solve sparse signal recovery problem with structure.

Algorithm 1 Distributed OMP algorithm

Input: The noise-polluted measurements $\mathbf{y}_k$, the sensing matrices $\mathbf{\Phi}_{\mathrm{L},k}\mathbf{\Psi}$, and the threshold ε for the stop criterion.

Output: The estimated channels $\hat{\mathbf{h}}_{\mathrm{d},k}$ and $\hat{\mathbf{h}}_{\mathrm{r},k}$.

1: Initialization: $\mathcal{I}$ = empty set, $\mathbf{r}_k = \mathbf{y}_k$ and $\hat{\mathbf{h}}_{\mathrm{effa},k} = \mathbf{0}$.

2: **while** $\frac{1}{KN_{\mathrm{P}}}\sum_{k=1}^{K}\|\mathbf{r}_k\|_2^2 > \varepsilon$, **do**

3: $\quad i^* = \boxed{\arg\max_i \sum_{k=1}^{K}\left|\left[\left(\mathbf{\Phi}_{\mathrm{L},k}\mathbf{\Psi}\right)^H \mathbf{r}_k\right]_i\right|}$;

4: $\quad \mathcal{I} = \mathcal{I} \cup \{i^*\}$;

5: $\quad \hat{\mathbf{h}}_k = [\mathbf{\Phi}_{\mathrm{L},k}\mathbf{\Psi}]_{\mathcal{I}}^{\dagger}\mathbf{y}_k$;

6: $\quad \mathbf{r}_k = \mathbf{y}_k - [\mathbf{\Phi}_{\mathrm{L},k}\mathbf{\Psi}]_{\mathcal{I}}\hat{\mathbf{h}}_k$;

7: **end while**

8: $\left[\hat{\mathbf{h}}_{\mathrm{effa},k}\right]_{\mathcal{I}} = \hat{\mathbf{h}}_k$;

9: Decompose $\hat{\mathbf{h}}_{\mathrm{effa},k}$ as $\hat{\mathbf{h}}_{\mathrm{effa},k} = [\hat{\mathbf{h}}_{\mathrm{da},k}^T, \hat{\mathbf{h}}_{\mathrm{ra},k}^T]^T$;

10: $\hat{\mathbf{h}}_{\mathrm{d},k}^T = \hat{\mathbf{h}}_{\mathrm{da},k}^T\mathbf{A}_{\mathrm{d}}^H$, $\hat{\mathbf{h}}_{\mathrm{r},k}^T = \hat{\mathbf{h}}_{\mathrm{ra},k}^T\mathbf{A}_{\mathrm{r}}^H$

DOMP is the extension of multi-measurement vector (MMV) in CS model, also known as general MMV (GMMV) [7]

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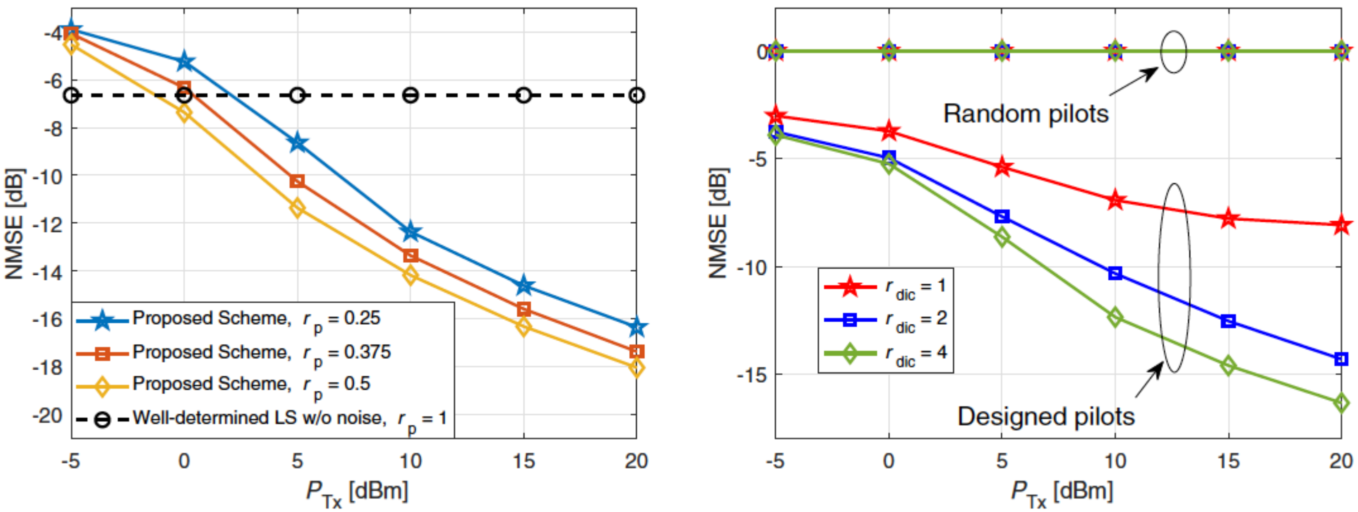
3 Simulation Results

Simulation Parameters

- $M = N = 256$, $N_{\mathrm{RF}} = 2$, $N_1 = N_2 = 1$;
- $K = N_{\mathrm{CP}} = 64$;
- 3GPP mmWave channel model [9]
- $r_{\mathrm{p}} = N_{\mathrm{P}} / (M + N)$: pilot overhead;
- $r_{\mathrm{dic}} = G / (M + N)$: redundant dictionary.

Benchmark 1: Well-determined LS [3] with unaffordable pilot overhead $N_{\mathrm{P}} = M + N$;
Benchmark 2: Completely random pilot design [5] to meet the RIP in CS;
Benchmark 3: Unitary dictionary [7] with degraded sparsity in angular-domain



(a) (b)

- **The CS-based CE scheme outperforms traditional algorithm with much less pilot overhead**
- **The proposed pilot design and redundant dictionary outperform their counterparts**

Fig. 3: NMSE performances of estimating $\mathbf{h}_{\mathrm{r},k}$ for the blocked users. (a) r_{dic} is fixed as 4; (b) r_{p} is fixed as 0.25.

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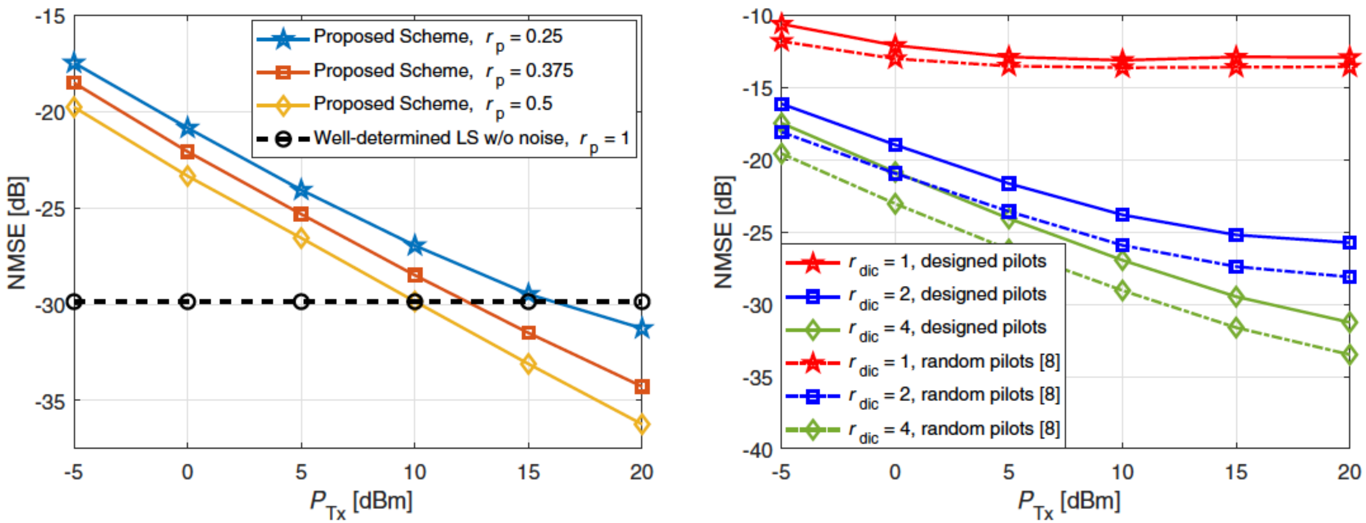

(a) (b)

- **For estimating the BS-user channels, the proposed pilot design has a minor negative effect, because it decreases the power of pilot signals transmitted directly to users**

Fig. 4: NMSE performances of estimating $\mathbf{h}_{\mathrm{d},k}$ for the un-blocked users. (a) r_{dic} is fixed as 4; (b) r_{p} is fixed as 0.25.

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Thanks for your listening!

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