Ph.D Dissertation Defense

Design of Hybrid Analog and Digital Precoding in Large-scale MIMO System

Research Advisor

Prof. Suk Chan Kim

Ph.D Candidate

Yongpan Feng

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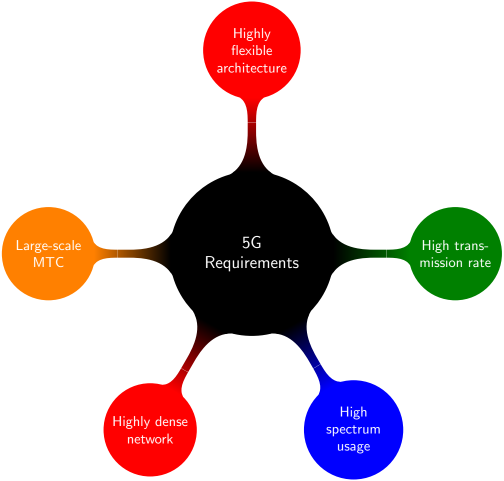
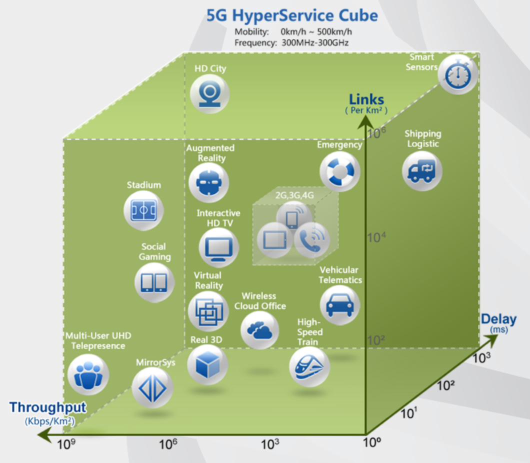
Contents

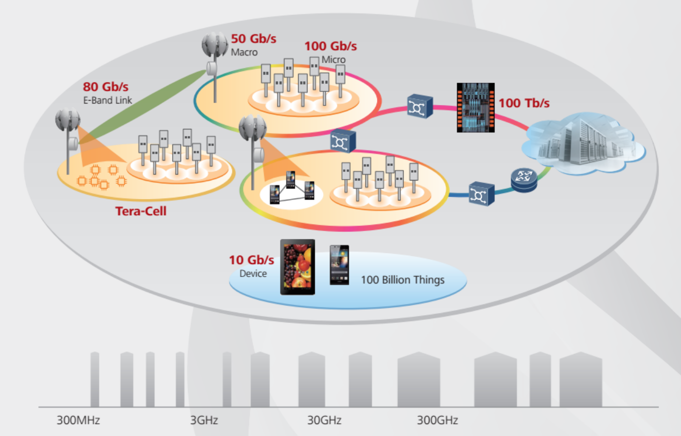
Overview of 5G



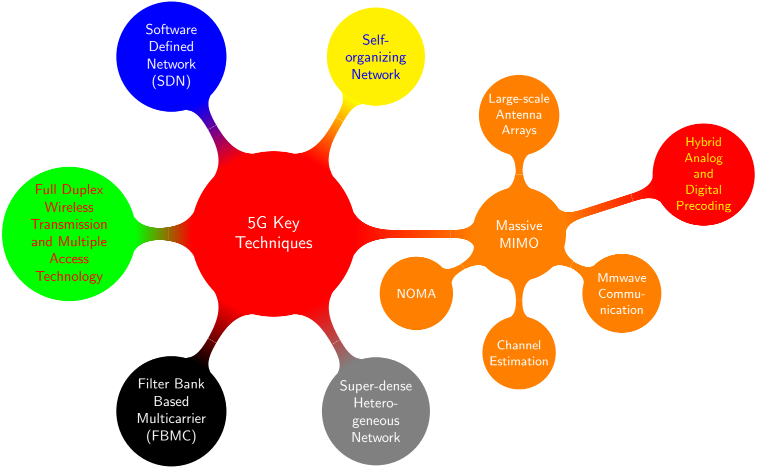
Overview of 5G



Overview of 5G



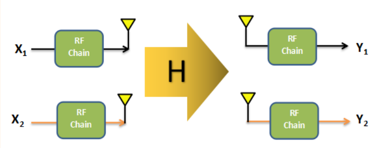
Overview of 5G



Traditional Precoding

What is precoding and why we need it?

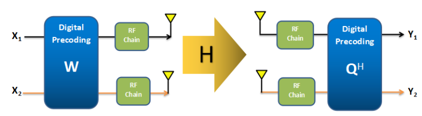
2x2 P2P MIMO



$$\mathbf{y} = \mathbf{H}\mathbf{x}$$

Precoding

$$\mathbf{H} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^H \Rightarrow \mathbf{y} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^H\mathbf{x}$$



$$\mathbf{y} = \mathbf{Q}^H\mathbf{H}\mathbf{W}\mathbf{x} = \mathbf{Q}^H\mathbf{U}\mathbf{\Sigma}\mathbf{V}^H\mathbf{W}\mathbf{x}$$

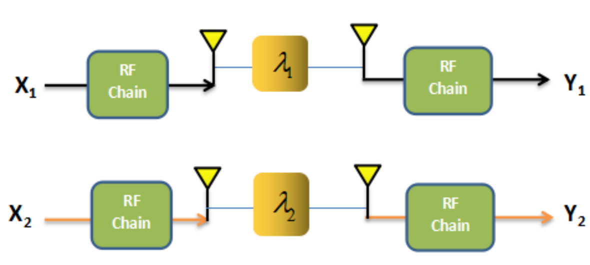
Traditional Precoding

Equivlent Model

$$\mathbf{y} = \mathbf{Q}^H \mathbf{H} \mathbf{W} \mathbf{x} = \mathbf{Q}^H \mathbf{U} \mathbf{\Sigma} \mathbf{V}^H \mathbf{W} \mathbf{x}$$

Set $\mathbf{Q} = \mathbf{U}, \mathbf{V} = \mathbf{W}$, we have

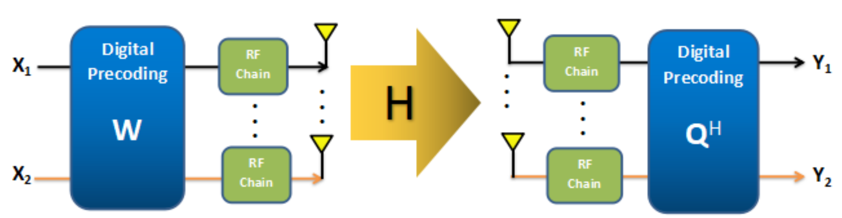
$$\mathbf{y} = \mathbf{\Sigma} \mathbf{x}.$$



Problem

What will happen when antenna number greatly increases ($10^2 \sim 10^3$ order)?
Array gain but also cost.

We note that conventional MIMO precoding requires a dedicated radio frequency (RF) chain for each antenna element, which is prohibitive cost and power consumption for massive MIMO.

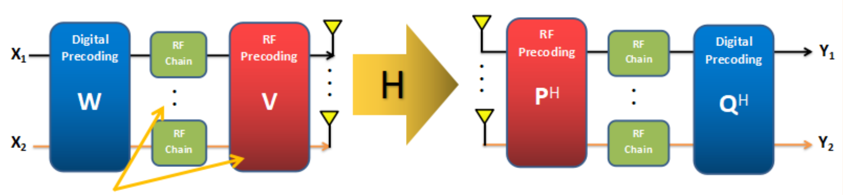


Note: a RF chain includes digital-to-analog conversion, signal mixing and power amplifying.

Hybrid Precoding

To solve this problem, the hybrid analog and digital precoding is proposed [Alkhateeb13, El14, Sohrabi16].

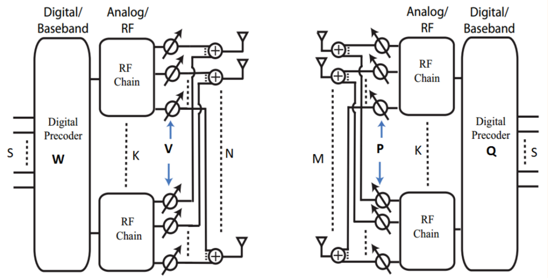
Hybrid Precoding



Hybrid Precoding

Requirement: RF Precoder should be realized only with phase-shifter!

Example: N $\times$ M P2P MIMO

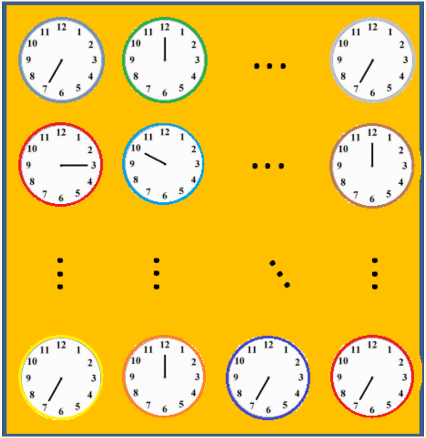


Note

- $S \ll K \ll N$
- $M \gg K \gg S$
- $|V_{ij}| = const$
- $|P_{ij}| = const$

Objective

RF precoder: phase-clock array



Objective

- Find the optimal phase combination of RF precoder
- Find the optimal digital precoder

Challenges

- Large-scale array variables
- Non-convex optimization problem
- Large-scale non-linear constraints
- Inner-interference elimination
- Quantized Phase-shifter in practical implementation
- Spectral efficiency matches that of fully digital precoding

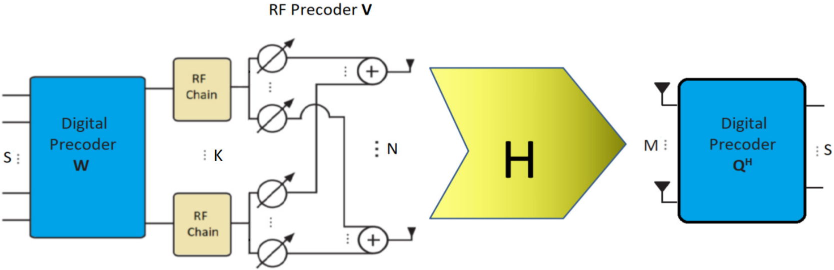
The State of the Art

High Cited Existing Works

- Liang14 proposed a low-complexity RF precoding scheme, which has a poor performance
- Alkhateeb15 developed iterative algorithms based on Macthing Pursuit (MP), which only limited a certain channel model
- Sohrabi16 raised another iterative algorithm, however it is element-wise updating method, which greatly consume time.

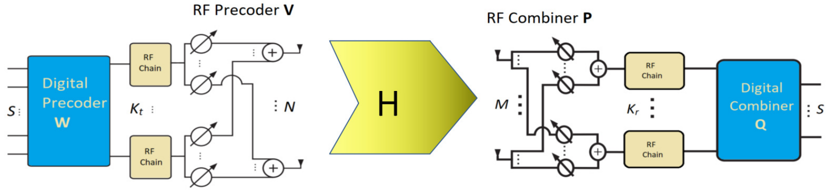
Overview of the Previous Defense

P2P MIMO Hybrid Precoding (I)



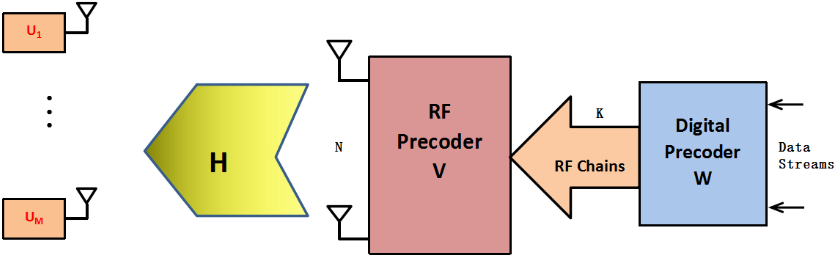
Overview of the Previous Defense

P2P MIMO Hybrid Precoding (II)



Overview of the Previous Defense

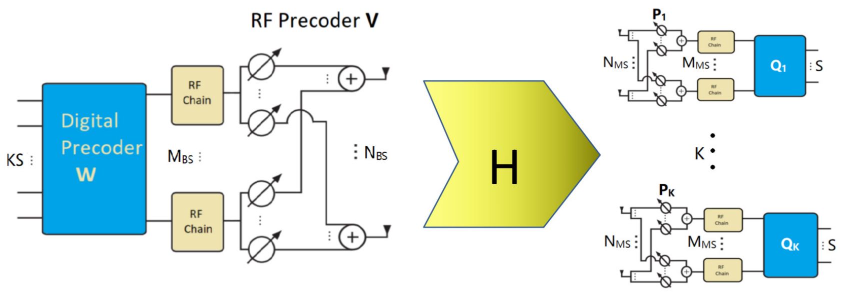
MU-MISO Hybrid Hybrid Precoding



Contents

System Model

System Model



System Model

The combined signal at the kth MS can be expressed as

System Model

$$\tilde{\mathbf{y}}_k = \mathbf{Q}_k^H \mathbf{P}_k^H \mathbf{H}_k \mathbf{V} \mathbf{W} \mathbf{s} + \mathbf{Q}_k^H \mathbf{P}_k^H \mathbf{n}_k, \quad k = 1, \cdots, K, \tag{1}$$

- $\mathbb{E}[\mathbf{s}\mathbf{s}^H] = \frac{P}{SK} \mathbf{I}_{SK}$
- $\mathbf{H}_k \in \mathbb{C}^{N_{MS} \times N_{BS}}$ is the channel matrix
- $\mathbf{n}_k \in \mathbb{R}^{N_{MS} \times 1}$ is i.i.d. additive complex Gaussian noise

Spectrum Efficiency

The sum spectral efficiency of the whole system can be expressed as

Spectrum Efficiency

$$R = \sum_{k=1}^{K} \log_2 \left(\left| \mathbf{I}_S + \frac{P}{SK} \mathbf{R}_i^{-1} \mathbf{Q}_k^H \bar{\mathbf{H}}_k \mathbf{W}_k \mathbf{W}_k^H \bar{\mathbf{H}}_k^H \mathbf{Q}_k \right| \right), \qquad (2)$$

- $\mathbf{R}_i = \frac{P}{SK} \sum_{i \neq k}^{K} \mathbf{Q}_k^H \bar{\mathbf{H}}_k \mathbf{W}_i \mathbf{W}_i^H \bar{\mathbf{H}}_k^H \mathbf{Q}_k + \sigma^2 \mathbf{Q}_k^H \mathbf{P}_k^H \mathbf{P}_k \mathbf{Q}_k$
- $\bar{\mathbf{H}} = [\bar{\mathbf{H}}_1^T, \cdots, \bar{\mathbf{H}}_K^T]^T$
- $\bar{\mathbf{H}}_k = \mathbf{P}_k^H \mathbf{H}_k \mathbf{V}, \quad k = 1, 2, \cdots, K.$

Additional Constraints

In order to eliminate inter-user interference, we imposes the constraints of

Imposed Constraints

$$\bar{\mathbf{H}}_k \mathbf{W}_i = \mathbf{0}, \quad \forall i \neq k \tag{3}$$

Hybrid Precoding

Then, we have the optimization problem of hybrid precoding optimization problem as follows:

Optimization Problem

$$\max_{\{\mathbf{P}_k\},\{\mathbf{W}_k\},\mathbf{V}} \quad R = \sum_{k=1}^{K} R_k \tag{4a}$$

$$s.t. \quad \bar{\mathbf{H}}_k \mathbf{W}_i = \mathbf{0}, \quad \forall i \neq k \tag{4b}$$

$$tr(\mathbf{V}\mathbf{W}\mathbf{W}^H\mathbf{V}^H) \leq P, \tag{4c}$$

$$|\mathbf{V}(n,m)| = 1/\sqrt{N_{BS}}, \forall n, m \tag{4d}$$

$$|\mathbf{P}_k(p,q)| = 1/\sqrt{N_{MS}}, \forall p, q. \tag{4e}$$

and $\mathbf{R}_i$ is simplied as $\mathbf{R}_i = \sigma^2 \mathbf{Q}_k^H \mathbf{P}_k^H \mathbf{P}_k \mathbf{Q}_k$.

Hybrid Precoding

Consider (4) as a distributed optimization problem, we can transfer it as follows

Optimization Problem

$$\max_{\substack{\{\mathbf{P}_k\},\{\mathbf{W}_k\},\\ \mathbf{V},\{\mathbf{V}_k\}}} \quad \hat{R} = \sum_{k=1}^{K} \hat{R}_k \tag{5a}$$

$$s.t. \quad \bar{\mathbf{H}}_k \mathbf{W}_i = \mathbf{0}, \quad \forall i \neq k \tag{5b}$$

$$tr(\mathbf{V}\mathbf{W}\mathbf{W}^H\mathbf{V}^H) \leq P, \tag{5c}$$

$$\mathbf{V}_k = \mathbf{V}, \forall k \tag{5d}$$

$$|\mathbf{V}(n,m)| = 1/\sqrt{N_{BS}}, \forall n, m \tag{5e}$$

$$|\mathbf{P}_k(p,q)| = 1/\sqrt{N_{MS}}, \forall p, q. \tag{5f}$$

- $\hat{R}_k = \log_2(|\mathbf{I}_S + \mathbf{R}_i^{-1}\mathbf{Q}_k^H\bar{\mathbf{H}}_k\mathbf{W}_k\mathbf{W}_k^H\bar{\mathbf{H}}_k^H\mathbf{Q}_k|)$
- $\bar{\mathbf{H}}_k = \mathbf{P}_k^H\mathbf{H}_k\mathbf{V}_k$

Hybrid Precoding

For each kth separable sub-problem in (5), the alternating direction method of multipliers (ADMM) can be derived directly from the augmented Lagrangian method as follows

Optimization Problem

$$\min_{\substack{\mathbf{P}_k, \mathbf{W}_k, \\ \mathbf{V}, \mathbf{V}_k, \mathbf{A}_k}} L_c^k = -\hat{R}_k + \Re tr[\mathbf{A}_k(\mathbf{V}_k - \mathbf{V})] + \frac{c}{2}||\mathbf{V}_k - \mathbf{V}||_F^2 \tag{6a}$$

$$s.t. \quad \bar{\mathbf{H}}_k \mathbf{W}_i = \mathbf{0}, \quad \forall i \neq k \tag{6b}$$

$$tr(\mathbf{V}\mathbf{W}\mathbf{W}^H\mathbf{V}^H) \leq P, \tag{6c}$$

$$|\mathbf{V}(n,m)| = 1/\sqrt{N_{BS}}, \forall n, m \tag{6d}$$

$$|\mathbf{P}_k(p,q)| = 1/\sqrt{N_{MS}}, \forall p, q \tag{6e}$$

where $\mathbf{A}_k$ is Lagrange multiplier matrix, c is called the penalty parameter.

ADMM Algorithm for (6)

Require: $\mathbf{P}_k^0, \mathbf{W}^0, \mathbf{V}_k^0, \mathbf{A}_k^0, \mathbf{V}^0, c$

1: **while** not reach stopping condition **do**

2: 1.$\mathbf{V}_k^{t+1} = \arg\min -\hat{R}_k(\mathbf{P}_k^t, \mathbf{W}^t, \mathbf{V}_k^t) + \Re tr(\mathbf{A}_k^t \mathbf{V}_k^t) + \frac{c}{2}||\mathbf{V}_k^t - \mathbf{V}^t||_F^2$
s.t. $|\mathbf{V}_k(n,m)| = 1/\sqrt{N_{BS}}, \forall n, m$

3: 2. $\mathbf{V}^{t+1} = \arg\min -\sum_{k=1}^{K} \Re tr(\mathbf{A}_k^t \mathbf{V}^t) + \frac{c}{2}\sum_{k=1}^{K} ||\mathbf{V}_k^{t+1} - \mathbf{V}^t||_F^2$
s.t. $\mathbf{V}(n,m) = 1/\sqrt{N_{BS}}, \forall n, m$

4: 3. $\mathbf{P}_k^{t+1} = \arg\min -\hat{R}_k(\mathbf{P}_k^t, \mathbf{W}^t, \mathbf{V}_k^{t+1})$
s.t. $\mathbf{P}_k(p,q) = 1/\sqrt{N_{MS}}, \forall p, q$

5: 4. $\mathbf{A}_k^{t+1} = \mathbf{A}_k^t + c(\mathbf{V}_k^{t+1} - \mathbf{V}^{t+1})$

6: 5. $\mathbf{W}^{t+1} = \arg\min -\sum_{k=1}^{K} \hat{R}_k(\mathbf{P}_k^{t+1}, \mathbf{W}^t, \mathbf{V}_k^{t+1})$
s.t. $\bar{\mathbf{H}}_k \mathbf{W}_i^t = \mathbf{0}$, and $tr[\mathbf{V}^{t+1}\mathbf{W}^t(\mathbf{W}^t)^H(\mathbf{V}^{t+1})^H] \leq P, \forall i \neq k$

7: **end while**

Update of $\mathbf{V}_k$

Now we revisit the first problem as follows,

Optimization of $\mathbf{V}_k$

$$\min_{\mathbf{V}_k} \quad g_k(\mathbf{V}_k) = -\hat{R}_k(\mathbf{V}_k) + \Re tr(\mathbf{A}_k \mathbf{V}_k) + \frac{c}{2}||\mathbf{V}_k - \mathbf{V}||_F^2 \tag{7a}$$

$$s.t. \quad |\mathbf{V}_k(n, m)| = 1/\sqrt{N_{BS}}. \tag{7b}$$

Update of $\mathbf{V}_k$

By the proposed matrix complex exponential learning (MCXL), we have the following update equations for (7):

Update of $\mathbf{V}_k$

$$\mathbf{\Phi}_k^{n+1} = \mathbf{\Phi}_k^n + \gamma_k^n \frac{\mathbf{D}_{g_k}(\mathbf{\Phi}_k^n)}{||\mathbf{D}_{g_k}(\mathbf{\Phi}_k^n)||_F}, \tag{8a}$$

$$\mathbf{V}_k^{n+1} = \exp(i\mathbf{\Phi}_k^{n+1})/\sqrt{N_{BS}}, \tag{8b}$$

where:
1) $\mathbf{\Phi}_k \in \mathbb{R}^{N_{BS} \times M_{BS}}$ is an auxiliary matrix which represents the phase matrix of the RF precoder $\mathbf{V}_k$,
2) $\mathbf{D}_{g_k} \equiv \mathbf{D}_{g_k}(\mathbf{\Phi}_k)$ denotes the real part of the matrix derivative of g_k with respect to the phase matrix of $\mathbf{V}_k$:

$$\mathbf{D}_{g_k}(\mathbf{\Phi}_k) = -\Re\nabla_{\mathbf{\Phi}_k} g_k, \tag{9}$$

3) γ_k^n is the nth step for the $\mathbf{\Phi}_k$,
4) $i = \sqrt{-1}$,
5) $||\cdot||_F$ denotes Frobenius norm.

To obtain $\mathbf{D}_{g_k}(\boldsymbol{\Phi}_k)$, we explore a proposition as follow

Proposition 1

Suppose $f : \mathbb{C}^{n\times m} \rightarrow \mathbb{R}$ is a function that takes as input the matrix $\mathbf{A} \in \mathbb{C}^{n\times m}$ and produces as the output $f(\mathbf{A}) \in \mathbb{R}$, while $\mathbf{A} = \exp(i\mathbf{X})$, where $\mathbf{X} \in \mathbb{R}^{n\times m}$ is a real matrix. If the derivative of $f(\mathbf{A})$ with respect to $\mathbf{A}$ is (see Appendices)

$$\nabla_{\mathbf{A}} f = \mathbf{D},$$

then, the derivative of f with respect to $\mathbf{X}$ is (Appendix A)

$$\nabla_{\mathbf{X}} f = i\mathbf{D}^* \circ \mathbf{A}.$$

where $\circ$ is the Hadamard (elementwise) product and $(\cdot)^*$ denotes conjugate. $\square$

Update of $\mathbf{V}_k$

According to Proposition 1, the (8) can be rewritten as

Update of $\mathbf{V}_k$

$$\mathbf{\Phi}_k^{n+1} = \mathbf{\Phi}_k^n + \gamma_k^n \frac{i\mathbf{D}_{g_k}(\mathbf{V}_k^n)^* \circ \mathbf{\Phi}_k^n}{||\mathbf{D}_{g_k}(\mathbf{V}_k^n)^* \circ \mathbf{\Phi}_k^n||_F}, \tag{10a}$$

$$\mathbf{V}_k^{n+1} = \exp(i\mathbf{\Phi}_k^{n+1})/\sqrt{N_{BS}}, \tag{10b}$$

where

$$\mathbf{D}_{g_k}(\mathbf{V}_k) = -\Re\nabla_{\mathbf{V}_k} g_k. \tag{11}$$

Proposition 2

Complex Gradient Matrix: If f is a real function of a complex matrix $\mathbf{Z}$, then the complex gradient matrix is given by (Anemuller03)

$$\begin{aligned}\nabla_{\mathbf{Z}} f(\mathbf{Z}) &= 2\frac{df(\mathbf{Z})}{d\mathbf{Z}^*} \\ &= \frac{\partial f(\mathbf{Z})}{\partial \Re \mathbf{Z}} + i\frac{\partial f(\mathbf{Z})}{\partial \Im \mathbf{Z}}.\end{aligned} \tag{12}$$

□

Update of $\mathbf{V}_k$

After several derivations, the derivative of g_k with respect to $\mathbf{V}_k$ can be obtained as follows (see Appendices)

$$
\begin{aligned}
\nabla_{\mathbf{V}_k} g_k &= 2\frac{\partial g_k}{\partial \mathbf{V}_k^*} = \frac{\partial g_k}{\partial \Re \mathbf{V}_k} + i\frac{\partial g_k}{\partial \Im \mathbf{V}_k} \\
&= -\frac{2}{\sigma^2 \ln 2}\mathbf{H}_k^H \mathbf{P}_k (\mathbf{I} + \frac{1}{\sigma^2}(\mathbf{P}_k^H \mathbf{P}_k)^{-1} \bar{\mathbf{H}}_k \mathbf{W}\mathbf{W}^H \bar{\mathbf{H}}_k^H)^{-1} \\
&\quad \cdot (\mathbf{P}_k^H \mathbf{P}_k)^{-1} \bar{\mathbf{H}}_k \mathbf{W}\mathbf{W}^H + \mathbf{A}_k^* + c(\mathbf{V}_k - \mathbf{V}).
\end{aligned} \tag{13}
$$

Derivative of g_k w.r.t $\mathbf{V}_k$

We repeat the the objective function as follows,

$$g_k = -\hat{R}_k + \Re tr(\mathbf{A}_k \mathbf{V}_k) + \frac{c}{2}||\mathbf{V}_k - \mathbf{V}||_F^2, \tag{14}$$

where

$$\hat{R}_k = \log_2 |\mathbf{I} + \frac{1}{\sigma^2}(\mathbf{P}_k^H \mathbf{P}_k)^{-1} \mathbf{P}_k^H \mathbf{H}_k \mathbf{V}_k \mathbf{W}_k \mathbf{W}_k^H \mathbf{V}_k^H \mathbf{H}_k^H \mathbf{P}_k|.$$

We will find the derivative of the three terms in (14) with respect to $\mathbf{V}_k$ in sequence.
First, we find the partial differential of $\hat{R}_k$ with respect to $\mathbf{V}_k$ as

$$\begin{aligned}
\partial \hat{R}_k &= \frac{1}{\sigma^2 \ln 2} tr[(\mathbf{I} + \frac{1}{\sigma^2}(\mathbf{P}_k^H \mathbf{P}_k)^{-1} \bar{\mathbf{H}}_k \mathbf{W}_k \mathbf{W}_k^H \bar{\mathbf{H}}_k^H)^{-1} \cdot \partial (\mathbf{P}_k^H \mathbf{P}_k)^{-1} \mathbf{P}_k^H \mathbf{H}_k \mathbf{V}_k \mathbf{W}_k \mathbf{W}_k^H \mathbf{V}_k^H \mathbf{H}_k^H \mathbf{P}_k] \\
&= \frac{1}{\sigma^2 \ln 2} tr[(\mathbf{I} + \frac{1}{\sigma^2}(\mathbf{P}_k^H \mathbf{P}_k)^{-1} \bar{\mathbf{H}}_k \mathbf{W}_k \mathbf{W}_k^H \bar{\mathbf{H}}_k^H)^{-1} (\mathbf{P}_k^H \mathbf{P}_k)^{-1} \mathbf{P}_k^H \mathbf{H}_k \cdot \partial \mathbf{V}_k \cdot \mathbf{W}_k \mathbf{W}_k^H \mathbf{V}_k^H \mathbf{H}_k^H \mathbf{P}_k \\
&+ (\mathbf{I} + \frac{1}{\sigma^2}(\mathbf{P}_k^H \mathbf{P}_k)^{-1} \bar{\mathbf{H}}_k \mathbf{W}_k \mathbf{W}_k^H \bar{\mathbf{H}}_k^H)^{-1} (\mathbf{P}_k^H \mathbf{P}_k)^{-1} \mathbf{P}_k^H \mathbf{H}_k \mathbf{V}_k \mathbf{W}_k \mathbf{W}_k^H \cdot \partial \mathbf{V}_k^H \cdot \mathbf{H}_k^H \mathbf{P}_k].
\end{aligned} \tag{15}$$

The derivative of $\hat{R}_k$ with respect to the real part of $\mathbf{V}_k$ can be obtained as

$$\begin{aligned}
\frac{\partial \hat{R}_k}{\partial \Re \mathbf{V}_k} &= \frac{1}{\sigma^2 \ln 2} [(\mathbf{W}_k \mathbf{W}_k^H \mathbf{V}_k^H \mathbf{H}_k^H \mathbf{P}_k (\mathbf{I} + \frac{1}{\sigma^2}(\mathbf{P}_k^H \mathbf{P}_k)^{-1} \bar{\mathbf{H}}_k \mathbf{W}_k \mathbf{W}_k^H \bar{\mathbf{H}}_k^H)^{-1} (\mathbf{P}_k^H \mathbf{P}_k)^{-1} \mathbf{P}_k^H \mathbf{H}_k)^T \\
&+ \mathbf{H}_k^H \mathbf{P}_k (\mathbf{I} + \frac{1}{\sigma^2}(\mathbf{P}_k^H \mathbf{P}_k)^{-1} \bar{\mathbf{H}}_k \mathbf{W}_k \mathbf{W}_k^H \bar{\mathbf{H}}_k^H)^{-1} (\mathbf{P}_k^H \mathbf{P}_k)^{-1} \mathbf{P}_k^H \mathbf{H}_k \mathbf{V}_k \mathbf{W}_k \mathbf{W}_k^H].
\end{aligned} \tag{16}$$

Derivative of g_k w.r.t $\mathbf{V}_k$

The derivative of $\hat{R}_k$ with respect to the image part of $\mathbf{V}_k$ can be obtained as

$$
\begin{aligned}
i\frac{\partial \hat{R}_k}{\partial \Im \mathbf{V}_k} = &-\frac{1}{\sigma^2 \ln 2}[(\mathbf{W}_k\mathbf{W}_k^H\mathbf{V}_k^H\mathbf{H}_k^H\mathbf{P}_k(\mathbf{I}+\frac{1}{\sigma^2}(\mathbf{P}_k^H\mathbf{P}_k)^{-1}\bar{\mathbf{H}}_k\mathbf{W}_k\mathbf{W}_k^H\bar{\mathbf{H}}_k^H)^{-1}(\mathbf{P}_k^H\mathbf{P}_k)^{-1}\mathbf{P}_k^H\mathbf{H}_k)^T \\
&+\mathbf{H}_k^H\mathbf{P}_k(\mathbf{I}+\frac{1}{\sigma^2}(\mathbf{P}_k^H\mathbf{P}_k)^{-1}\bar{\mathbf{H}}_k\mathbf{W}_k\mathbf{W}_k^H\bar{\mathbf{H}}_k^H)^{-1}(\mathbf{P}_k^H\mathbf{P}_k)^{-1}\mathbf{P}_k^H\mathbf{H}_k\mathbf{V}_k\mathbf{W}_k\mathbf{W}_k^H].
\end{aligned}
\tag{17}
$$

Hence, the derivative of $\hat{R}_k$ with respect to $\mathbf{V}_k$ can be obtained as

$$
\begin{aligned}
\nabla_{\mathbf{V}_k}\hat{R}_k &= \frac{\partial \hat{R}_k}{\partial \Re \mathbf{V}_k} + i\frac{\partial \hat{R}_k}{\partial \Im \mathbf{V}_k} \\
&= \frac{2}{\sigma^2 \ln 2}\mathbf{H}_k^H\mathbf{P}_k(\mathbf{I}+\frac{1}{\sigma^2}(\mathbf{P}_k^H\mathbf{P}_k)^{-1}\bar{\mathbf{H}}_k\mathbf{W}_k\mathbf{W}_k^H\bar{\mathbf{H}}_k^H)^{-1}(\mathbf{P}_k^H\mathbf{P}_k)^{-1}\mathbf{P}_k^H\mathbf{H}_k\mathbf{V}_k\mathbf{W}_k\mathbf{W}_k^H.
\end{aligned}
\tag{18}
$$

Then, we study the derivative of the second term in (14) with respect to $\mathbf{V}_k$. The second term can be reformulated as

$$
\begin{aligned}
\Re tr(\mathbf{A}_k\mathbf{V}_k) &= \Re tr[(\Re\mathbf{A}_k + i\Im\mathbf{A}_k)(\Re\mathbf{V}_k + i\Im\mathbf{V}_k)] \\
&= tr[\Re\mathbf{A}_k\Re\mathbf{V}_k - \Im\mathbf{A}_k\Im\mathbf{V}_k].
\end{aligned}
\tag{19}
$$

Derivative of g_k w.r.t $\mathbf{V}_k$

The derivative of the second term with respect to the real part of $\mathbf{V}_k$ can be got as

$$\frac{\partial \Re tr(\mathbf{A}_k \mathbf{V}_k)}{\partial \Re \mathbf{V}_k} = \Re \mathbf{A}_k^T. \tag{20}$$

The derivative of the second term with respect to the image part of $\mathbf{V}_k$ can be got as

$$i \frac{\partial \Re tr(\mathbf{A}_k \mathbf{V}_k)}{\partial \Im \mathbf{V}_k} = -\Im \mathbf{A}_k^T. \tag{21}$$

Hence, the derivative of the second term with respect to $\mathbf{V}_k$ can be got as

$$\begin{aligned} \nabla_{\mathbf{V}_k} \Re tr(\mathbf{A}_k \mathbf{V}_k) &= \frac{\partial \Re tr(\mathbf{A}_k \mathbf{V}_k)}{\partial \Im \mathbf{V}_k} + i \frac{\partial \Re tr(\mathbf{A}_k \mathbf{V}_k)}{\partial \Im \mathbf{V}_k} \\ &= \mathbf{A}_k^*, \end{aligned} \tag{22}$$

where $\mathbf{A}_k^*$ is the conjugate of $\mathbf{A}_k$.
Similarly, the derivative of the third term in (14) with respect to $\mathbf{V}_k$ can be obtained as

$$\nabla_{\mathbf{V}_k} ||\mathbf{V}_k - \mathbf{V}||_F^2 = 2(\mathbf{V}_k - \mathbf{V}). \tag{23}$$

According to the above we can know the derivative of g_k with respect to $\mathbf{V}_k$ can be obtained as

$$\begin{aligned} \nabla_{\mathbf{V}_k} g_k &= -\nabla_{\mathbf{V}_k} \hat{R}_k + \nabla_{\mathbf{V}_k} \Re tr(\mathbf{A}_k \mathbf{V}_k) + \frac{c}{2} \nabla_{\mathbf{V}_k} ||\mathbf{V}_k - \mathbf{V}||_F^2 \\ &= -\frac{2}{\sigma^2 \ln 2} \mathbf{H}_k^H \mathbf{P}_k (\mathbf{I} + \frac{1}{\sigma^2} (\mathbf{R}_k^H \mathbf{P}_k)^{-1} \bar{\mathbf{H}}_k \mathbf{W} \mathbf{W}^H \bar{\mathbf{H}}_k^H)^{-1} \\ &\cdot (\mathbf{P}_k^H \mathbf{P}_k)^{-1} \bar{\mathbf{H}}_k \mathbf{W} \mathbf{W}^H + \mathbf{A}_k^* + c(\mathbf{V}_k - \mathbf{V}). \end{aligned} \tag{24}$$

Learning Rate

To speed the iteration efficiency in (8), we should carefully choose the learning rate γ_k^n. In this study, we employ an adaptive method named backtracking line search (BLS) based on Armijo-Goldstein condition to obtain the step size [Michael10].

For simplicity, we define the normalized descent direction matrix of the nth $\mathbf{\Phi}_k$ as

$$\bar{\mathbf{D}}_{g_k}(\mathbf{\Phi}_k^n) = \frac{\mathbf{D}_{g_k}(\mathbf{\Phi}_k^n)}{||\mathbf{D}_{g_k}(\mathbf{\Phi}_k^n)||_F}. \tag{25}$$

Starting with a maximum candidate step size value $\gamma_k^0 > 0$, using search control parameter $\rho \in (0,1)$ and $\alpha \in (0, 0.5)$, the BLS can be expressed as following process.

BLS

While the Armijo-Goldstein condition is not met as follows

$$g_k(\mathbf{\Phi}_k + \gamma \mathbf{D}_{g_k}) > g_k(\mathbf{\Phi}_k) + \gamma\alpha \Re tr(\mathbf{D}_{g_k}^T \nabla_{\mathbf{\Phi}_k} g_k), \tag{26}$$

repeatedly set $\gamma = \rho\gamma$ until Armijo-Goldstein condition is fulfilled.
Stopping criteria:

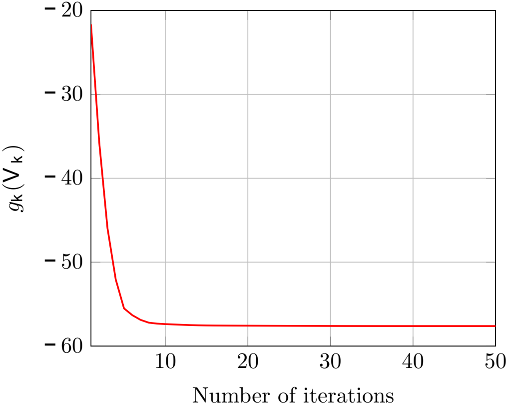
$$n > N_{threshold}, \tag{27a}$$

$$||\bar{\mathbf{D}}_{g_k}(\mathbf{\Phi}_k^n)||_F < \epsilon. \tag{27b}$$

where $N_{threshold} \in \mathbb{Z}^+$ is the number of desired threshold and $\epsilon \in \mathbb{R}^+$ is the matrix tolerance error.

Learning Rate

Consider a MU-MIMO system of a BS and $K = 2$ MSs. Each MS in the system is supported by $S = 2$ data streams and equipped with $N_{MS} = 16$ antennas and $M_{MS} = S$ RF chains. The BS is equipped with $N_{BS} = 128$ antennas and $M_{BS} = KS$ RF chains. We set parameters as: SNR=0 dB, $c = 10, \mu = 100, \gamma_k^0 = 10, \rho = 0.25$.



In brief, the update of $\mathbf{V}_k, \mathbf{V}, \mathbf{P}_k$ (similar optimization problems) can be summarized as follows:

Algorithm of Update $\mathbf{V}_k$

Require: $\mathbf{P}_k^0, \mathbf{W}^0, \mathbf{V}_k^0, \mathbf{A}_k^0, \mathbf{V}^0, \mathbf{\Phi}_k^0, c, \gamma_k^0, \rho$

1: **while** $n \leq N_{threshold}$ and $||\bar{\mathbf{D}}_{g_k}(\mathbf{\Phi}_k^n)||_F \geq \varepsilon$ **do**

2: Calculate $\mathbf{D}_{g_k}(\mathbf{V}_k^n) = -\Re\nabla_{\mathbf{V}_k^n} g_k$.

3: Calculate $\mathbf{D}_{g_k}(\mathbf{\Phi}_k^n) = i\mathbf{D}_{g_k}(\mathbf{V}_k^n)^* \circ \mathbf{\Phi}_k^n$.

4: Initialize $\gamma_k^n = \gamma_k^0$.

5: **while** $g_k(\mathbf{\Phi}_k^n + \gamma_k^n \bar{\mathbf{D}}_{g_k}(\mathbf{\Phi}_k^n)) > g_k(\mathbf{\Phi}_k^n) + \gamma_k^n \alpha \Re tr((\bar{\mathbf{D}}_{g_k}(\mathbf{\Phi}_k^n))^T \nabla_{\mathbf{\Phi}_k^n} g_k)$ **do**

6: $\gamma_k^n = \rho\gamma_k^n$

7: **end while**

8: Update $\mathbf{\Phi}_k^{n+1} = \mathbf{\Phi}_k^n + \gamma_k^n \bar{\mathbf{D}}_{g_k}(\mathbf{\Phi}_k^n)$.

9: Update $\mathbf{V}_k^{n+1} = \exp(i\mathbf{\Phi}_k^{n+1})/\sqrt{N_{BS}}$.

10: Update $n \leftarrow n + 1$.

11: **end while**

Algorithm of Update $\mathbf{V}$

Require: $\mathbf{V}, \mathbf{A}^0, \mathbf{V}^0, \gamma^0, \rho$

while $n \leq N_{threshold}$ and $||\bar{\mathbf{D}}_g(\mathbf{\Phi}^n)||_F \geq \varepsilon$ **do**

  Calculate $\mathbf{D}_g(\mathbf{V}^n) = -\Re\nabla_{\mathbf{V}^n} g$.

  Calculate $\mathbf{D}_g(\mathbf{\Phi}^n) = i\mathbf{D}_g(\mathbf{V}^n)^* \circ \mathbf{\Phi}^n$.

  Initialize $\gamma^n = \gamma^0$.

  while $g(\mathbf{\Phi}^n + \gamma^n \bar{\mathbf{D}}_g(\mathbf{\Phi}^n)) > g(\mathbf{\Phi}^n) + \gamma^n \alpha \Re tr((\bar{\mathbf{D}}_g(\mathbf{\Phi}^n))^T \nabla_{\mathbf{\Phi}^n} g)$ **do**

    $\gamma^n = \rho\gamma^n$

  end while

  Update $\mathbf{\Phi}^{n+1} = \mathbf{\Phi}^n + \gamma^n \bar{\mathbf{D}}_g(\mathbf{\Phi}^n)$.

  Update $\mathbf{V}^{n+1} = \exp(i\mathbf{\Phi}^{n+1})/\sqrt{N_{BS}}$.

  Update $n \leftarrow n + 1$.

end while

Algorithm of Update $\mathbf{P}_k$

Require: $\mathbf{P}_k^0, \mathbf{W}^0, \mathbf{\Psi}_k^0, \delta_k^0, \rho$

while $n \leq N_{threshold}$ and $||\bar{\mathbf{D}}_{h_k}(\mathbf{\Psi}_k^n)||_F \geq \varepsilon$ **do**

  Calculate $\mathbf{D}_{h_k}(\mathbf{P}_k^n) = -\Re\nabla_{\mathbf{P}_k^n} h_k$.

  Calculate $\mathbf{D}_{h_k}(\mathbf{\Psi}_k^n) = i\mathbf{D}_{h_k}(\mathbf{P}_k^n)^* \circ \mathbf{\Psi}_k^n$.

  Initialize $\delta_k^n = \delta_k^0$.

  while $h_k(\mathbf{\Psi}_k^n + \delta_k^n \bar{\mathbf{D}}_{h_k}(\mathbf{\Psi}_k^n)) > h_k(\mathbf{\Psi}_k^n) + \delta_k^n \alpha \Re tr((\bar{\mathbf{D}}_{h_k}(\mathbf{\Psi}_k^n))^T \nabla_{\mathbf{\Psi}_k^n} h_k)$ **do**

    $\delta_k^n = \rho\delta_k^n$

  end while

  Update $\mathbf{\Psi}_k^{n+1} = \mathbf{\Psi}_k^n + \delta_k^n \bar{\mathbf{D}}_{h_k}(\mathbf{\Psi}_k^n)$.

  Update $\mathbf{P}_k^{n+1} = \exp(i\mathbf{\Psi}_k^{n+1})/\sqrt{N_{MS}}$.

  Update $n \leftarrow n + 1$.

end while

ADMM Algorithm for (6)

Require: $\mathbf{P}_k^0, \mathbf{W}^0, \mathbf{V}_k^0, \mathbf{A}_k^0, \mathbf{V}^0, c$

while not reach stopping condition **do**

$$1. \mathbf{V}_k^{t+1} = \arg\min -\hat{R}_k(\mathbf{P}_k^t, \mathbf{W}^t, \mathbf{V}_k^t) + \Re tr(\mathbf{A}_k^t \mathbf{V}_k^t) + \frac{c}{2}||\mathbf{V}_k^t - \mathbf{V}^t||_F^2$$
$$\text{s.t. } |\mathbf{V}_k(n,m)| = 1/\sqrt{N_{BS}}, \forall n, m$$

$$2. \ \mathbf{V}^{t+1} = \arg\min -\sum_{k=1}^K \Re tr(\mathbf{A}_k^t \mathbf{V}^t) + \frac{c}{2}\sum_{k=1}^K ||\mathbf{V}_k^{t+1} - \mathbf{V}^t||_F^2$$
$$\text{s.t. } \mathbf{V}(n,m) = 1/\sqrt{N_{BS}}, \forall n, m$$

$$3. \ \mathbf{P}_k^{t+1} = \arg\min -\hat{R}_k(\mathbf{P}_k^t, \mathbf{W}^t, \mathbf{V}_k^{t+1})$$
$$\text{s.t. } \mathbf{P}_k(p,q) = 1/\sqrt{N_{MS}}, \forall p, q$$

$$4. \ \mathbf{A}_k^{t+1} = \mathbf{A}_k^t + c(\mathbf{V}_k^{t+1} - \mathbf{V}^{t+1})$$

$$5. \ \mathbf{W}^{t+1} = \arg\min -\sum_{k=1}^K \hat{R}_k(\mathbf{P}_k^{t+1}, \mathbf{W}^t, \mathbf{V}_k^{t+1})$$
$$\text{s.t. } \bar{\mathbf{H}}_k \mathbf{W}_i^t = \mathbf{0}, \text{ and } tr[\mathbf{V}^{t+1}\mathbf{W}^t(\mathbf{W}^t)^H(\mathbf{V}^{t+1})^H] \leq P, \forall i \neq k$$

end while

Digital Precoding

We repeat the optimization problem of digital precoding as follows

Optimization of **W**

$$\min_{\mathbf{W}} \quad \hat{R}(\mathbf{W}) = -\sum_{k=1}^{K} \hat{R}_k(\mathbf{W}) \tag{28a}$$

$$s.t. \quad \bar{\mathbf{H}}_k \mathbf{W}_i = 0, \forall i \neq k \tag{28b}$$

$$tr(\mathbf{V}\mathbf{W}\mathbf{W}^H\mathbf{V}^H) \leq P. \tag{28c}$$

Digital Precoding

To remove the constraints of IUI in (28b), we first construct an incomplete equivalent channel matrix as follows

$$\tilde{\bar{\mathbf{H}}}_k = [\bar{\mathbf{H}}_1^T, \cdots, \bar{\mathbf{H}}_{k-1}^T, \bar{\mathbf{H}}_{k+1}^T, \cdots, \bar{\mathbf{H}}_K^T]^T. \quad (29)$$

It is advantageous for $\mathbf{W}_k$ to lie in the null space of $\tilde{\bar{\mathbf{H}}}_k$ so that the constraints of (28b) can be satisfied.

$$\tilde{\bar{\mathbf{H}}}_k = \tilde{\mathbf{U}}_k \tilde{\mathbf{\Sigma}}_k [\tilde{\mathbf{V}}_k^{(1)}, \tilde{\mathbf{V}}_k^{(0)}]^H \quad (30)$$

Hence, it is easy to know that

$$\bar{\mathbf{H}}_i \tilde{\mathbf{V}}_k^{(0)} = \mathbf{0}, \quad \forall i \neq k. \quad (31)$$

Digital Precoding

Then, the matrix of block diagonalization (BD), performed on the equivalent channel, can be defined as

Block Diagonalization Matrix

$$\begin{aligned}\bar{\mathbf{H}}_{BD} &= \bar{\mathbf{H}}[\tilde{\mathbf{V}}_1^{(0)}, \cdots, \tilde{\mathbf{V}}_K^{(0)}] \\ &= \begin{bmatrix} \bar{\mathbf{H}}_1\tilde{\mathbf{V}}_1^{(0)} & & 0 \\ & \ddots & \\ 0 & & \bar{\mathbf{H}}_K\tilde{\mathbf{V}}_K^{(0)} \end{bmatrix}\end{aligned} \tag{32}$$

where

$$\bar{\mathbf{H}} = [\bar{\mathbf{H}}_1^T, \cdots, \bar{\mathbf{H}}_K^T]^T. \tag{33}$$

Digital Precoding

To eliminate the internal interference of each MS through a secondary SVD method, which can be expressed as

$$\check{\bar{\mathbf{H}}}_k = \bar{\mathbf{H}}_k \tilde{\mathbf{V}}_k^{(0)} = \check{\mathbf{U}}_k \check{\mathbf{\Sigma}}_k \check{\mathbf{V}}_k^H. \tag{34}$$

Hence, without considering power allocation,

$$\bar{\mathbf{W}}_k = \tilde{\mathbf{V}}_k \check{\mathbf{V}}_k^{(S)}, \tag{35}$$

has the properties of eliminating the inter and inner interference for each MS and data stream.

Digital Precoding

Then, the digital precoder at the kth MS $\mathbf{Q}_k$ can be designed by the first S columns of $\check{\mathbf{U}}_k$, i.e., $\mathbf{Q}_k = \check{\mathbf{U}}_k$. And, the digital precoder at the BS can be obtained by

$$\mathbf{W} = \bar{\mathbf{W}} \boldsymbol{\Lambda}^{1/2}, \tag{36}$$

where $\bar{\mathbf{W}} = [\bar{\mathbf{W}}_1, \cdots, \bar{\mathbf{W}}_K]$ and $\boldsymbol{\Lambda}$, a diagonal matrix, is used for the power allocation for all the streams of the whole system.

The Algorithm of Update Λ

Require: $\bar{\mathbf{\Lambda}}^0, \delta^0, \rho, l$

while $n \leq N_{threshold}$ and $||\bar{\mathbf{D}}_f(\bar{\mathbf{\Lambda}}^n)||_F \geq \varepsilon$ **do**
    Calculate $\nabla_{\bar{\mathbf{\Lambda}}^n} f$.
    Calculate $\bar{\mathbf{D}}_f(\bar{\mathbf{\Lambda}}^n) = -\frac{\nabla_{\bar{\mathbf{\Lambda}}^n} f}{||\nabla_{\bar{\mathbf{\Lambda}}^n} f||_F}$.
    Initialize $\delta^n = \delta^0$.
    while $f(\bar{\mathbf{\Lambda}}^n + \delta^n \bar{\mathbf{D}}_f(\bar{\mathbf{\Lambda}}^n)) > f(\bar{\mathbf{\Lambda}}^n) + \delta^n \alpha tr(\bar{\mathbf{D}}_f(\bar{\mathbf{\Lambda}}^n) \nabla_{\bar{\mathbf{\Lambda}}^n} f)$ **do**
        $\delta^n = \rho \delta^n$
    end while
    Update $\bar{\mathbf{\Lambda}}^{n+1} = \bar{\mathbf{\Lambda}}^n + \delta^n \bar{\mathbf{D}}_f(\bar{\mathbf{\Lambda}}^n)$.
    Update $n \leftarrow n + 1$.
end while

Simulations: SNR

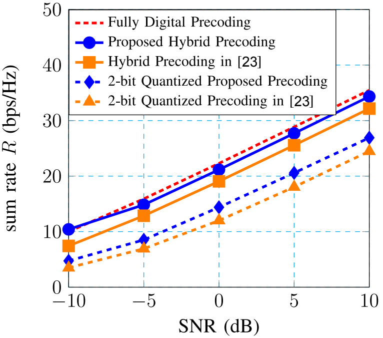


Figure: Sum spectral efficiency in 128×16 2-user MU-MIMO system.

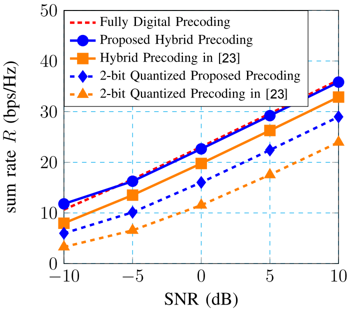


Figure: Sum spectral efficiency in 128×32 2-user MU-MIMO system.

[23]:[Ni16]

Simulations: N_{MS}

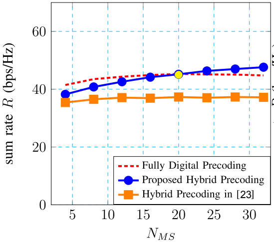


Figure: Sum spectral efficiency achieved by different schemes in 3-user MU-MIMO system under different N_{MS} where $N_{BS} = 128$.

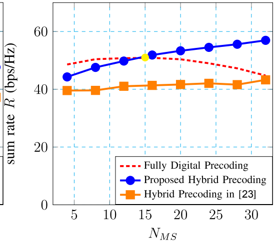


Figure: Sum spectral efficiency achieved by different schemes in 4-user MU-MIMO system under different N_{MS} where $N_{BS} = 128$.

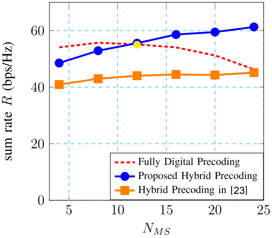


Figure: Sum spectral efficiency achieved by different schemes in 5-user MU-MIMO system under different N_{MS} where $N_{BS} = 128$.

Constraint of the Cross Point

$$N_{BS} \approx 2KN_{MS}. \tag{37}$$

Simulations: N_{BS}

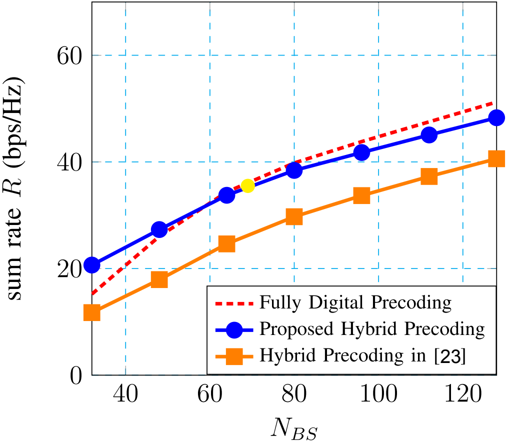


Figure: Sum spectral efficiency achieved by different schemes in 4-user MU-MIMO system under different N_{BS} where $N_{MS} = 8$.

Simulations: K, S

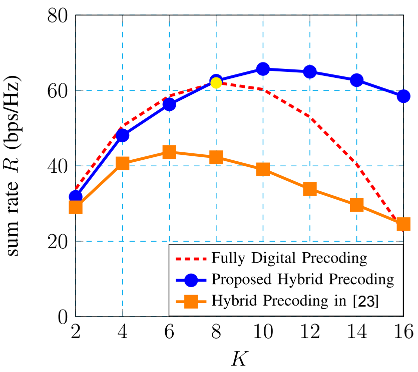


Figure: Sum rate achieved by different schemes in 128×8 4-user MU-MIMO under different number of MSs K.

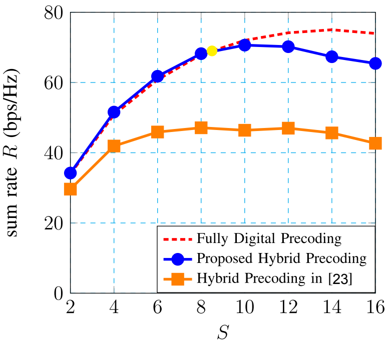


Figure: Sum rate achieved by different schemes in 128×16 4-user MU-MIMO under different number of data streams S.

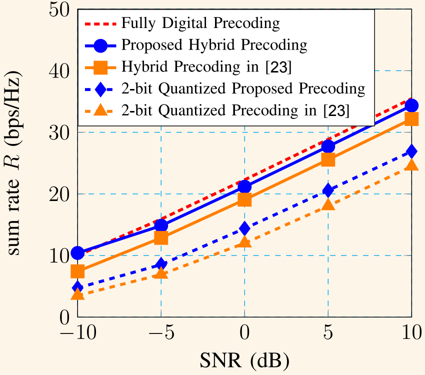
Summary

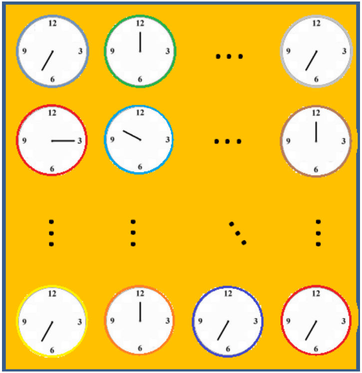
- Considered the system of MU-MIMO
- Generalized ZF based on BD was applied to the equivalent channel
- Algorithm of MCXL was designed to get the optimal RF precoder
- Higher spectral efficiency than the traditional hybrid precoding
- Lower computational complexity

Contents

Low Performance in Quantized Precoder

2-bit Quantized Phase-shifter





- Limited phase set
- Constant modulus constraints

Double-RF Hybrid Precoding

To break the above limitations, we proposed a new structure of hybrid precoding as follows,

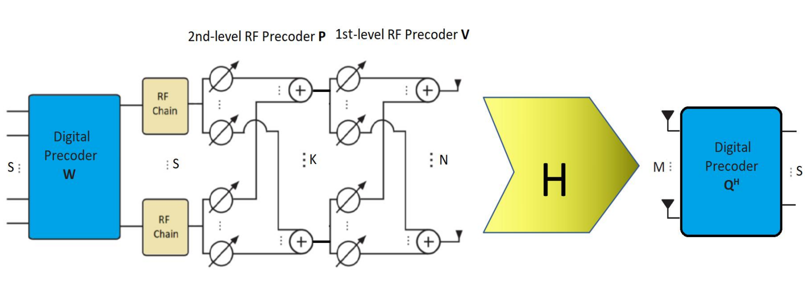


Figure: Block diagram of the P2P system with the double-RF hybrid precoding architecture.

Double-RF Hybrid Precoding

The precoder design problem for the BS can be expressed as

Optimization Problem

$$\max_{\mathbf{Q},\mathbf{V},\mathbf{P},\mathbf{W}} \quad \log_2 \left|\mathbf{I} + \frac{1}{\sigma^2}\mathbf{Q}(\mathbf{Q}^H\mathbf{Q})^{-1}\mathbf{Q}^H\mathbf{H}\mathbf{V}\mathbf{P}\mathbf{W}\mathbf{W}^H\mathbf{P}^H\mathbf{V}^H\mathbf{H}^H\right| \tag{38a}$$

$$s.t. \quad |V_{n,k}| = 1, \forall n, k \tag{38b}$$

$$|P_{k,s}| = 1, \forall k, s \tag{38c}$$

$$tr(\mathbf{V}\mathbf{P}\mathbf{W}\mathbf{W}^H P^H V^H) \leq P, \tag{38d}$$

where P is the power budget for the transmitting system.

Double-RF Hybrid Precoding

With the following algorithms discussed previously,

- matrix complex exponential learning (MCXL)
- alternating direction method of multipliers (ADMM)
- backtracking line search (BLS)
- water-filling (WF)

we directly give the algorithms of (38) as follows.

update of $\mathbf{V}$

Require: $\mathbf{P}_0, \mathbf{W}_0, \mathbf{V}_0, \boldsymbol{\Phi}_0, \delta_0, \rho$

while $n \leq N_{threshold}$ and $||\bar{\mathbf{D}}_{R_{RF}}(\boldsymbol{\Phi}_n)||_F^2 \geq \varepsilon$ **do**
    Calculate $\mathbf{D}_{R_{RF}}(\mathbf{V}_n) = \Re \nabla_{\mathbf{V}_n} R_{RF}$.
    Calculate $\mathbf{D}_{R_{RF}}(\boldsymbol{\Phi}_n) = i\mathbf{D}_{R_{RF}}(\mathbf{V}_n)^* \circ \boldsymbol{\Phi}_n$.
    Initialize $\delta_n = \delta_0$.
    while $R_{RF}(\boldsymbol{\Phi}_n + \delta_n \bar{\mathbf{D}}_{R_{RF}}(\boldsymbol{\Phi}_n)) <$ $R_{RF}(\boldsymbol{\Phi}_n) + \delta_n \alpha \Re tr((\bar{\mathbf{D}}_{R_{RF}}(\boldsymbol{\Phi}_n))^T \nabla_{\boldsymbol{\Phi}_n} R_{RF})$ **do**
        $\delta_n = \rho \delta_n$
    end while
    Update $\boldsymbol{\Phi}_{n+1} = \boldsymbol{\Phi}_n + \delta_n \bar{\mathbf{D}}_{R_{RF}}(\boldsymbol{\Phi}_n)$.
    Update $\mathbf{V}_{n+1} = \exp(i\boldsymbol{\Phi}_{n+1})$.
    Update $n \leftarrow n + 1$.
end while

$$\nabla_{\mathbf{V}} R_{RF} = \frac{1}{\sigma^2 \ln 2} \left(\mathbf{P}\mathbf{W}\mathbf{W}^H\mathbf{P}^H\mathbf{V}^H\mathbf{H}^H \cdot (\mathbf{I} + \frac{1}{\sigma^2}\mathbf{H}\mathbf{V}\mathbf{P}\mathbf{W}\mathbf{W}^H\mathbf{P}^H\mathbf{V}^H\mathbf{H}^H)^{-1}\mathbf{H} \right)^T \tag{39}$$

update of $\mathbf{P}$

Require: $\mathbf{P}_0, \mathbf{W}_0, \mathbf{V}, \mathbf{\Psi}_0, \delta_0, \rho$

while $n \leq N_{threshold}$ and $||\bar{\mathbf{D}}_{R_{RF}}(\mathbf{\Psi}_n)||_F^2 \geq \varepsilon$ **do**

  Calculate $\mathbf{D}_{R_{RF}}(\mathbf{P}_n) = \Re\nabla_{\mathbf{P}_n} R_{RF}$.

  Calculate $\mathbf{D}_{R_{RF}}(\mathbf{\Psi}_n) = i\mathbf{D}_{R_{RF}}(\mathbf{P}_n)^* \circ \mathbf{\Psi}_n$.

  Initialize $\delta_n = \delta_0$.

  while $R_{RF}(\mathbf{\Psi}_n + \delta_n \bar{\mathbf{D}}_{R_{RF}}(\mathbf{\Psi}_n)) <$ $R_{RF}(\mathbf{\Psi}_n) + \delta_n \alpha \Re tr((\bar{\mathbf{D}}_{R_{RF}}(\mathbf{\Psi}_n))^T \nabla_{\mathbf{\Psi}_n} R_{RF})$ **do**

    $\delta_n = \rho\delta_n$

  end while

  Update $\mathbf{\Psi}_{n+1} = \mathbf{\Psi}_n + \delta_n \bar{\mathbf{D}}_{R_{RF}}(\mathbf{\Psi}_n)$.

  Update $\mathbf{P}_{n+1} = \exp(i\mathbf{\Psi}_{n+1})$.

  Update $n \leftarrow n + 1$.

end while

$$\nabla_{\mathbf{P}} R_{RF} = \frac{1}{\sigma^2 \ln 2}\left(\mathbf{W}^H\mathbf{P}^H\mathbf{V}^H\mathbf{H}^H \cdot (\mathbf{I} + \frac{1}{\sigma^2}\mathbf{HVPWW}^H\mathbf{P}^H\mathbf{V}^H\mathbf{H}^H)^{-1}\mathbf{HVP}\right)^T \tag{40}$$

Digital Precoding

Define the effective channel $\tilde{\mathbf{H}}$ as

$$\tilde{\mathbf{H}} = \mathbf{HVP}, \tag{41}$$

The digital precoder design problem can be rewritten as follows

$$\begin{aligned} \max_{\mathbf{W}} \quad & \log_2 |\mathbf{I} + \frac{1}{\sigma^2} \tilde{\mathbf{H}} \mathbf{W} \mathbf{W}^H \tilde{\mathbf{H}}^H| \\ s.t. \quad & tr(\mathbf{VPWW}^H \mathbf{P}^H \mathbf{V}^H) \leq P \end{aligned} \tag{42}$$

By the waterfilling method, we have

$$\mathbf{W} = \mathbf{U}\boldsymbol{\Gamma} \tag{43}$$

and $\mathbf{Q}$ can be set as the first S left singular vectors of $\tilde{\mathbf{H}}$.

Simulations: SNR

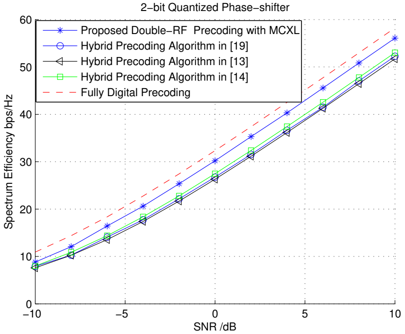


Figure: Spectral efficiency in 128 × 8 P2P MIMO with 2-bit quantized RF precoder.

[13]: [Liang14], [14]: [Sohrabi16], [19]: [Feng17]

Simulations: K

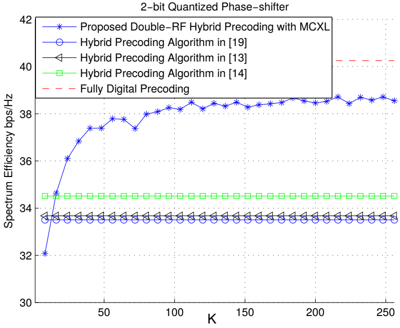


Figure: Spectral efficiency in 256×8 P2P MIMO with 2-bit quantized RF precoder.

Simulations: Multiples

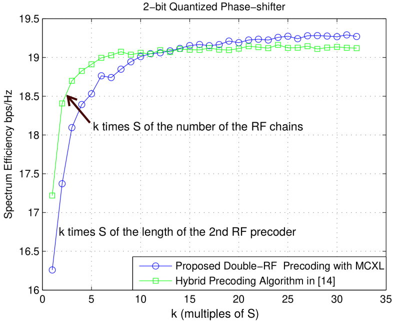


Figure: Spectral efficiency in 128 $\times$ 4 P2P MIMO with 2-bit quantized RF precoder.

The performance of double-RF precoding with $k \times S$ length of the second-level RF precoder requires the conventional hybrid precoding with $k \times S$ RF cl

Summary

- Proposed a new structure of double-RF precoder
- Employed algorithms of MCXL, ADMM and WF
- Lower cost than the traditional hybrid precoding
- Lower computational complexity

Contents

Main Work of the Thesis

- Designed the one side hybrid precoder in P2P MIMO
- Designed the two sides hybrid precoders in P2P MIMO
- Designed an efficient algorithm of hybrid precoders in MU-MISO
- Designed an efficient algorithm for hybrid precoders in MU-MIMO
- Proposed an innovative structure of double-RF hybrid precoder

Main Algorithms in the Work

- Solved five non-convex optimization problems with large-scale nonlinear constraints
- Proposed an innovative core algorithm of MCXL
- Proposed two propositions of complex matrix derivations
- Deduced the derivative of spectral efficiency w.r.t. phase matrix of RF precoder in P2P MIMO, MU-MISO and MU-MIMO
- Designed algorithms of hybrid precoding with MCXL, ADMM, BLS, WF, ALM, BD, ZF and SVD
- Employed the distributed optimization and the alternating direction strategies

Main Performances of the Algorithms

- Higher spectral efficiency than existing works
- Lower computational complexity than existing works
- Lower cost than existing works
- Can be applied in any channel model
- High robustness in quantized phase-shifter array

Contents

Publications

Journal Papers

[1] **Y. Feng**, and S. C. Kim, "Hybrid precoding in point-to-point massive multiple-input multiple-output systems based on normalised matrix adaptive method," *IET Communications*, vol. 11, no. 12, pp. 1882-1885, 2017. (SCI)
[2] **Y. Feng**, and S. C. Kim, "Hybrid Precoding Based on Matrix-adaptive Method for Multiuser Large-scale Antenna Arrays,", *PLoS ONE*, vol. 12, no. 12, Dec, 2017. (SCI)
[3] **Y. Feng**, and S. C. Kim, "Hybrid Analog and Digital Precoding Based on Adaptive Method in P2P Massive MIMO," *Wireless Personal Communications*, vol. 99, no. 12, pp. 953-964, Mar, 2018. (SCI)
[4] **Y. Feng**, and S. C. Kim, "Hybrid Precoding Design for Multiuser MIMO Based on Matrix Complex Exponential Learning,", *IEEE Transactions on Wireless Communications*.(under reviewing)
[5] **Y. Feng**, and S. C. Kim, "Double-RF Hybrid Precoding Design in Large-scale P2P MIMO,", *IEEE Wireless Communications Letters*.(submitted)

Publications

Conference Papers

[1] **Y. Feng**, H. J. Choi, and S. C. Kim, "Elimination of Pilots Contamination Based on Power Coding,", *The 26th Joint Conference on Communications and Information (JCCI2016)*, vol. 26, no. 81, 2016
[2] S.Y. Yu, **Y. Feng**, M.K. Kim, S.C. Kim, "Performance analysis of subcarrier index modulation-OFDM in Doppler spread environments,", *Intelligent Systems, Modelling and Simulation (ISMS)*, pp. 380-382, 2016
[3] H. J. Choi, **Y. Feng**, S. Jeong, D. H. Yi, and S. C. Kim, "Bluetooth Beacon Based Cell-ID Positioning Technique using Median Filter,", *The Academic Conference of Korean Communication in 2017 (KICS2017)*, vol. 2017, no. 1, pp. 382-383, 2017 (Best Paper Award)
[4] **Y. Feng**, S. Jeong, D. H. Yi, and S. C. Kim, "Analogue-to-information conversion using random sub-Nyquist sampler,", *The Academic Conference of Korean Communication in 2017 (KICS2017)*, vol. 2017, no. 6, 2017

Lectures in PNU

년도	학기	교과구분	교과목명	학점	성적등급	비고
2014	2	외국인공통	한국어초급	0	S	
2014	2	전공	수치해석및프로그래밍	3	A+	
2014	2	전공	응용대수학	3	A0	
2014	신청학점: 6.0 취득학점: 6.0 평균평점: 4.25 총평점: 25.50					
2015	1	외국인공통	한국어중급	0	S	
2015	1	전공	논문연구	3	A+	
2015	1	전공	연구윤리및연구관리	0	S	
2015	1	전공	적응신호처리	3	A0	
2015	1	전공	확률및랜덤프로세스	3	A0	
2015	신청학점: 9.0 취득학점: 9.0 평균평점: 4.17 총평점: 37.50					
2015	2	전공	논문연구	3	A+	
2015	2	전공	비선형시스템	3	B+	
2015	2	전공	웨이브렛변환이론및응용	3	A0	

2015	신청학점: 9.0 취득학점: 9.0 평균평점: 4 총평점: 36.00					
2016	1	전공	논문연구	3	A0	
2016	1	전공	영상처리	3	A+	
2016	1	전공	통신시스템	3	B+	
2016	신청학점: 9.0 취득학점: 9.0 평균평점: 4 총평점: 36.00					
2016	2	전공	기계학습	3	A0	
년도	학기	교과구분	교과목명	학점	성적등급	비고
2016	신청학점: 3.0 취득학점: 3.0 평균평점: 4 총평점: 12.00					
총신청학점: 36.0 총취득학점: 36.0 총평균평점: 4.08 총총평점: 147.00 백분환산율: 95/100 전체석차: 1/1						

Self-study Courses

- Compressive Sensing
- Convex Optimization
- Deep Learning
- Particl Filter

Awards in PNU

제 2018-1 호

우수연구상

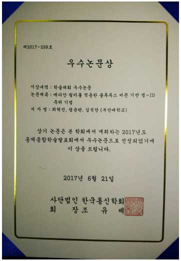
대상

박사과정 Yongpan Feng

위 사람은 부산대학교 전기전자컴퓨터공학과 대학원의 발전과 BK21 PLUS IT기반 융합산업 창의인력양성 사업단 성과에 기여한 공로로 이에 상장과 상금을 수여합니다.

2018년 02월 20일

부산대학교 BK21 PLUS
IT기반 융합산업 창의인력양성 사업단장
김 성 신



제2017-299호

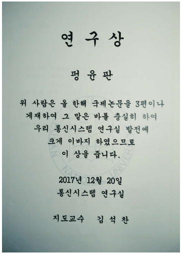
우수논문상

시상내역 : 학술대회 우수논문
논문제목 : 메디안 필터를 적용한 블루투스 비콘 기반 셀-ID 측위 기법
저 자 명 : 최혁진, 평윤판, 김석찬 (부산대학교)

상기 논문은 본 학회에서 개최하는 2017년도 동계종합학술발표회에서 우수논문으로 선정되었기에 이 상을 드립니다.

2017년 6월 21일

사단법인 한국통신학회
회 장 조 유 제



연 구 상

평 윤 판

위 사람은 올 한해 국제논문을 3편이나
게재하여 그 맡은 바를 충실히 하여
우리 통신시스템 연구실 발전에
크게 이바지 하였으므로
이 상을 줍니다.

2017년 12월 20일
통신시스템 연구실

지도교수 김 석 찬

Scholarships

BK scholarship for every semester since Sep. 2014.

Start of the New Journey