FDD-Based Cell-Free Massive MIMO Systems

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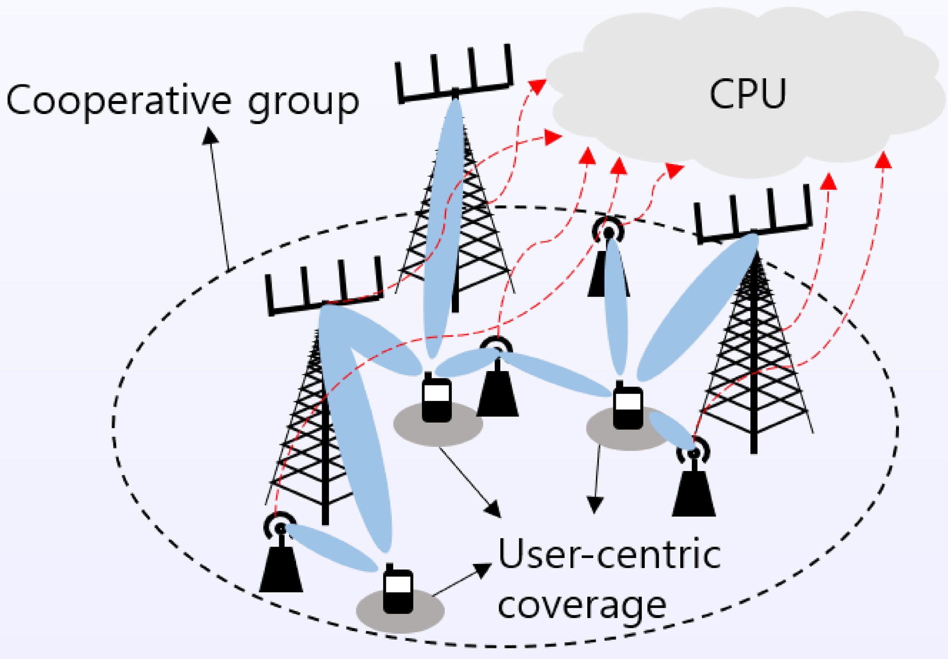
Motivation

- Cell-free massive MIMO system is a promising technology that provide a user-centric coverage to the user.



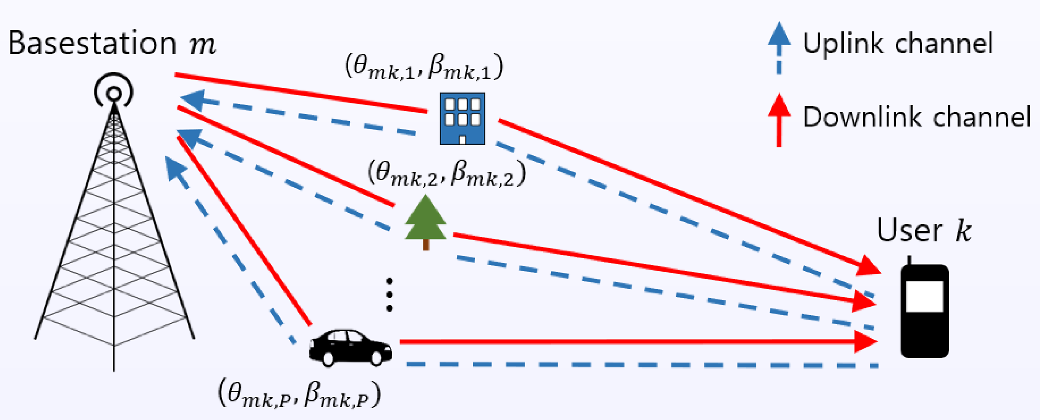
- In the cell-free massive MIMO systems, more than one basestations cooperatively serve multiple users.
- In the FDD systems, CSI acquisition and feedback overhead are serious concerns when the number of antennas and basestations are large.
- Most prior works on the cell-free massive MIMO systems assume TDD systems, although FDD systems dominate the current wireless communications.

Key Idea

- To address these problems, we use the property that the uplink and downlink multipath components are similar, so-called *angle reciprocity*.
- The key idea behind the proposed scheme is to extract the multipath components used for the basestation cooperation from the uplink pilot signal.

System Model

- Geometric one-ring scattering model

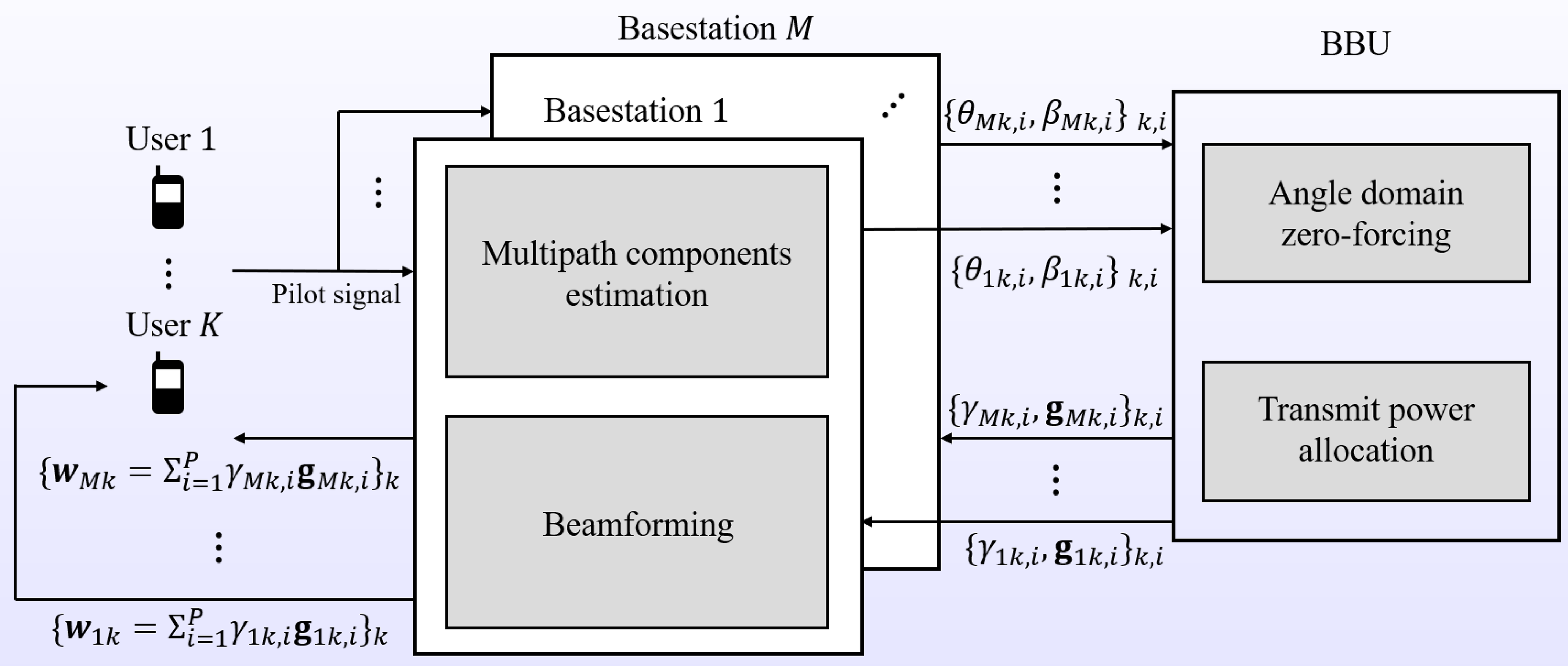


- Uplink and downlink channel model

$$\mathbf{h}^l = \sum_{i=1}^{P} \sqrt{\beta_i} g_i^l \mathbf{a}(\theta_i, \lambda^l), \ \ l \in \{\text{UL}, \text{DL}\}$$

- The AoA θ_i and large-scale fading coefficient β_i which are independent of frequency are similar for the uplink and downlink channels.
- To model a realistic system, we assume that the differences between uplink and downlink multipath components, $\tilde{\theta}_i$ and $\tilde{\beta}_i$, are i.i.d random variables with zero mean and variance $\sigma_\theta^2, \sigma_\beta^2 \ll 1$

Block Diagram



Multipath Component Estimation

- When the number of antennas is very large, the conventional MUSIC or ESPRIT algorithms are computational burdensome.
- The proposed method maximizes the likelihood function using the gradient descent method.
- Likelihood function maximization

$$\hat{\boldsymbol{\theta}} = \text{argmin tr}\left(\mathbf{P}_{\bar{\mathbf{A}}}^{\perp} \bar{\mathbf{Y}} \bar{\mathbf{Y}}^H\right)$$

- Update equation and gradient function

$$\boldsymbol{\theta}_{(n)} = \boldsymbol{\theta}_{(n-1)} - \alpha_n \nabla_{\boldsymbol{\theta}} f(\boldsymbol{\theta}_{(n-1)})$$

$$\nabla_{\boldsymbol{\theta}} f = \text{Im}\left(\text{diag}\left(\mathbf{C}\mathbf{A}^H \mathbf{E} \mathbf{P}_{\bar{\mathbf{A}}}^{\perp} \bar{\mathbf{Y}} \bar{\mathbf{Y}}^H \mathbf{A}(\mathbf{A}^H \mathbf{A})^{-1}\right)\right)$$

- Large-scale fading coefficient estimation

$$\hat{\boldsymbol{\beta}} = \frac{1}{T} \text{diag}((\hat{\mathbf{A}}^H \hat{\mathbf{A}})^{-1} \hat{\mathbf{A}}^H \bar{\mathbf{Y}} \bar{\mathbf{Y}}^H \hat{\mathbf{A}} (\hat{\mathbf{A}}^H \hat{\mathbf{A}})^{-1})$$

Angle-based ZF precoding

- The key idea is to make the precoding vector orthogonal to all the other array steering vectors.

$$\hat{\mathbf{G}}_m = [\hat{\mathbf{G}}_{m1}, \cdots, \hat{\mathbf{G}}_{mK}] = \hat{\mathbf{A}}_m \left(\hat{\mathbf{A}}_m^H \hat{\mathbf{A}}_m\right)^{-1}$$

- The angle-based ZF precoding vector

$$\hat{\mathbf{w}}_{mk} = \hat{\mathbf{G}}_{mk} \boldsymbol{\gamma}_{mk}$$

- **Theorem 1** *The approximated closed-form expression of achievable rate R_k for the user k is*

$$\log_2\left(1 + \frac{\sum_{m=1}^{M}\left(\|\mathbf{B}_{mk}\boldsymbol{\gamma}_{mk}\|_2^2 + \sigma_\theta^2 \|\mathbf{B}_{mk}\mathbf{C}_{mk}\hat{\mathbf{Q}}_{mkk}\boldsymbol{\gamma}_{mk}\|_2^2\right)}{\sigma_\theta^2 \sum_{m=1}^{M}\sum_{j\neq k}^{K} \|\mathbf{B}_{mk}\mathbf{C}_{mk}\hat{\mathbf{Q}}_{mkj}\boldsymbol{\gamma}_{mj}\|_2^2 + 1}\right)$$

where $\hat{\mathbf{Q}}_{mkj} \in \mathbb{C}^{P\times P}$ *is a submatrix of* $\hat{\mathbf{Q}}_m = \hat{\mathbf{A}}_m^H \mathbf{E} \hat{\mathbf{A}}_m (\hat{\mathbf{A}}_m^H \hat{\mathbf{A}}_m)^{-1}$.

Transmit Power Allocation

- Since each propagation path has different path gain, proper allocation of $\{\gamma_{mk,i}\}$ is important to improve the energy efficiency.
- Power allocation problem

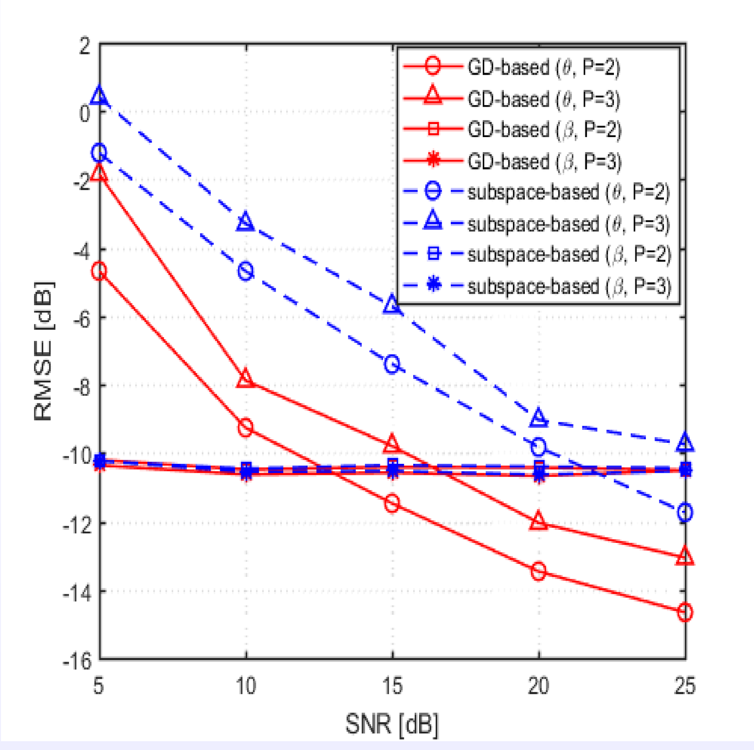
$$\min_{\{\boldsymbol{\gamma}_{mk}\}} \sum_{m=1}^{M} \sum_{k=1}^{K} \|\hat{\mathbf{G}}_{mk} \boldsymbol{\gamma}_{mk}\|_2^2$$

$$\text{s.t.} \ \frac{\sum_{m=1}^{M}\left(\|\mathbf{B}_{mk}\boldsymbol{\gamma}_{mk}\|_2^2 + \sigma_\theta^2 \|\mathbf{B}_{mk}\mathbf{C}_{mk}\hat{\mathbf{Q}}_{mkk}\boldsymbol{\gamma}_{mk}\|_2^2\right)}{\sigma_\theta^2 \sum_{m=1}^{M}\sum_{j\neq k}^{K} \|\mathbf{B}_{mk}\mathbf{C}_{mk}\hat{\mathbf{Q}}_{mkj}\boldsymbol{\gamma}_{mj}\|_2^2 + 1} \geq \xi_k, \forall k$$

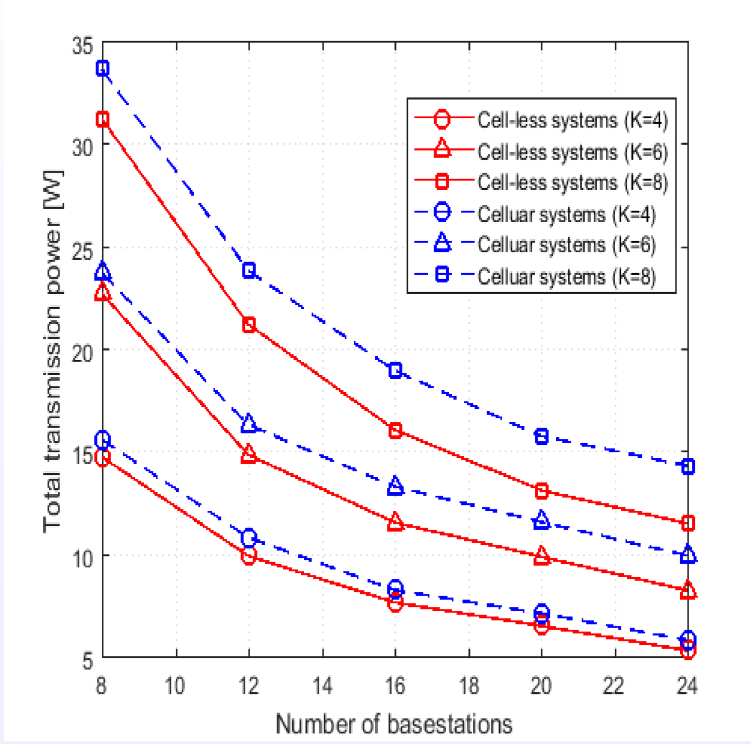
$$\sum_{k=1}^{K} \|\hat{\mathbf{G}}_{mk} \boldsymbol{\gamma}_{mk}\|_2^2 \leq 1, \ \forall m,$$

- This problem is a non-convex QCQP which can be relaxed into a convex SDP using the semi-definite relaxation.

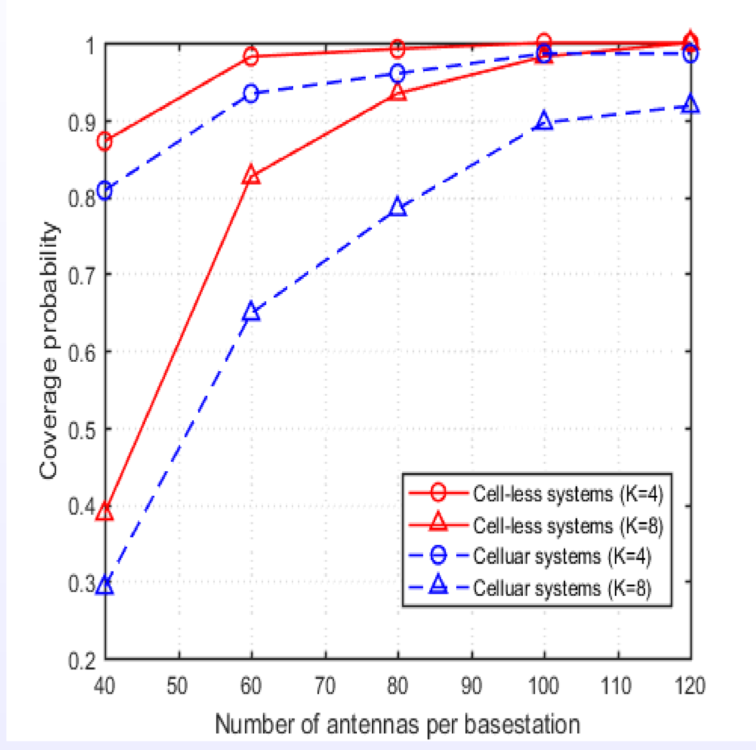
Simulation Result



The RMSE performance of the multipath component estimation versus SNR for $N = 32$



The total transmission power versus the number of basestations for $N = 512$ and $P = 4$



The coverage probability versus the number of antennas per basestation for $M = 8$ and $P = 2$

- We demonstrate that the proposed FDD-based cell-free massive MIMO systems save approximately 19% of transmission power over the conventional cellular systems and also improve the coverage probability by the amount of 22%.