Cooperative Transmission in Small Cell Networks under Sparsity Constraints

Hwan-Joon (Eddy) Kwon

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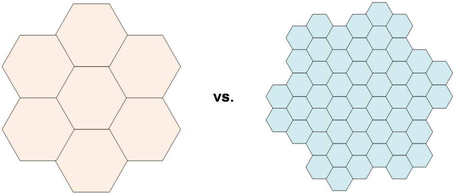
Outline

I. **Introduction**
  - **Communication in a Small Cell Network**
  - **Sparse Signal Recovery Techniques**

II. **Overview of a Relevant Paper**
"Joint BS Clustering and Beamformer Design for Partial Coordinated transmission in Heterogeneous Networks"

III. **Potential Study Items**

Communication in a Small Cell Network



- **To extend coverage and increase capacity, networks evolve to HetNet including small cells such as microcells, picocells, and femtocells.**
- **Interference becomes more significant in small cell networks**
  - INR $\gg$ 1 or SINR $\ll$ SNR
- **Two ways to overcome interference (can be used together)**
  - **Decode interference**: successive interference cancellation or simultaneous decoding of desired signal and interference (e.g., spatially-coupled LDPC codes)
  - **Avoid (or mitigate) interference**: via frequency/time/spatial/power resource allocation.
- **We consider the problem of cell association, beamforming, and power allocation assuming that interference is treated as noise.**

Sparse Signal Recovery Techniques

- **The problem of sparse signal recovery involves the estimation of a sparse signal $\mathbf{X}$ via linear measurements**

$$\mathbf{Y} = A\mathbf{X} + \mathbf{Z}$$

- **Goal: reconstruct the signal $\mathbf{X}$ from as few number of measurements as possible.**
- **Computationally efficient algorithms**
  - matching pursuit, orthogonal matching pursuit, LASSO, basis pursuit, FOCUSS, sparse Bayesian learning, finite rate of innovation, CoSaMP, and subspace pursuit.

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- **Block-sparse signals: nonzero entries of sparse signals take place in clusters.**
- **Group-LASSO: an extended version of LASSO taking into account block-sparsity**

$$\hat{\mathbf{X}}_\lambda = \arg\min_{\mathbf{x}} \left\{ \left\|\mathbf{Y} - A\mathbf{x}\right\|_2^2 + \lambda \sum_{i=1}^{\#\text{blocks}} \|\mathbf{x}_i\|_2 \right\}.$$

Paper Review:

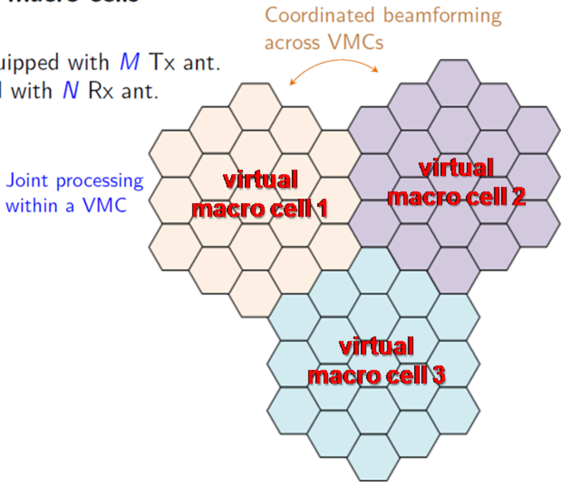
Joint BS Clustering and Beamformer Design for Partial Coordinated transmission in Heterogeneous Networks

- Mingyi Hong*, Ruoyu Sun*, Hadi Baligh**, Zhi-Quan Luo*
  - * University of Minnesota
  - ** Huawei Tech Canada

- To appear in IEEE JSAC, special issues on **Large-Scale Multiple-Antenna Systems**

System Model and Problem Definition

- **Downlink with $\mathcal{K}$ virtual macro cells**
- **In virtual macro cell k**
  - $\mathcal{Q}_k$ small cells, each equipped with M Tx ant.
  - $\mathcal{I}_k$ users, each equipped with N Rx ant.



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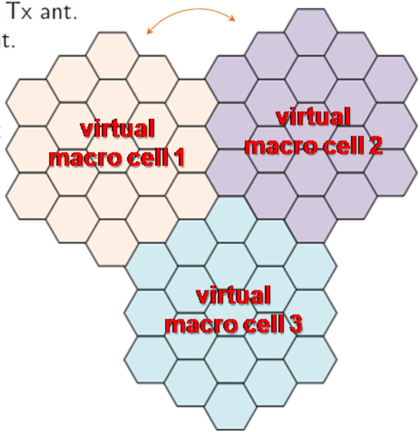

- **Determine**
  - Serving cells(SCs) for each user
  - Beamforming weights (including Tx power)
- **Objective**
  - Maximize the sum rate.

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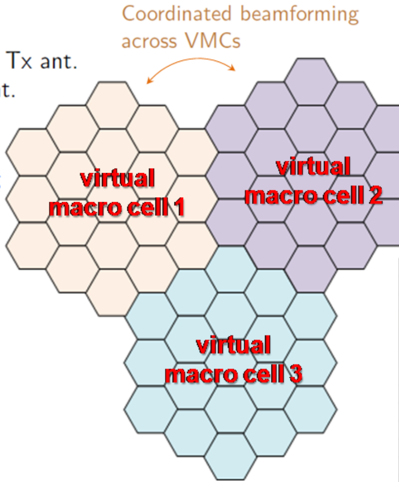


- **Determine**
  - Serving cells(SCs) for each user
  - Beamforming weights (including Tx power)
- **Objective**
  - Maximize the sum rate.
- **Constraints**
  - Average Tx power for each cell
  - **Keep # SCs small** (to reduce backhaul overhead) $\rightarrow$ **block-sparsity** (block size M) in each column of the beamforming matrix for each virtual macro cell

Problem Formulation

$$
\begin{aligned}
&\max_{\{\mathbf{v}_{i_k}^{q_k}\}} \sum_{k\in\mathcal{K}} \sum_{i_k\in\mathcal{I}_k} \left(u_{i_k}(R_{i_k}) - \lambda_k \sum_{q_k\in\mathcal{Q}_k} \|\mathbf{v}_{i_k}^{q_k}\| \right) \\
\text{s.t.} \quad & \sum_{i_k\in\mathcal{I}_k} (\mathbf{v}_{i_k}^{q_k})^H \mathbf{v}_{i_k}^{q_k} \le P_{q_k}, \ \forall\, q_k \in \mathcal{Q}_k, \ \forall\, k \in \mathcal{K}
\end{aligned}
$$

$$
\begin{aligned}
R_{i_k} = \log \Big| & \mathbf{I}_N + \mathbf{H}_{i_k}^{k} \mathbf{v}_{i_k} \mathbf{v}_{i_k}^H (\mathbf{H}_{i_k}^{k})^H \\
& \times \Big(\sum_{(\ell,j)\neq(k,i)} \mathbf{H}_{i_k}^{\ell} \mathbf{v}_{j_\ell} \mathbf{v}_{j_\ell}^H (\mathbf{H}_{i_k}^{\ell})^H + \sigma_{i_k}^2 \mathbf{I}_N \Big)^{-1} \Big| .
\end{aligned}
$$

- **Challenges**
  - With $\lambda_k = 0$, the problem is NP-hard for many utility functions.

Equivalent Problem

- Consider a simple case where $\mathcal{I}_k = 1$ and $u_{i_k}(R_{i_k}) = R_{i_k}$.

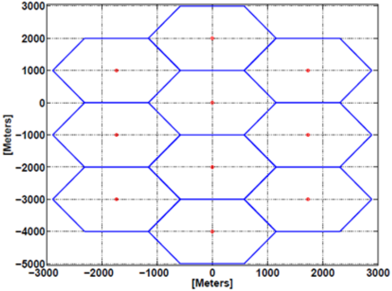
Original problem

$$\max_{\{\mathbf{v}_k^{q_k}\}} \sum_{k \in \mathcal{K}} \left(R_k - \lambda_k \sum_{q_k \in \mathcal{Q}_k} \|\mathbf{v}_k^{q_k}\| \right)$$
$$\text{s.t.} \quad (\mathbf{v}_k^{q_k})^H \mathbf{v}_k^{q_k} \le P_{q_k}, \ \forall\, q_k \in \mathcal{Q}_k, \ \forall\, k \in \mathcal{K}.$$

An equivalent problem

$$\min_{\{\mathbf{v}_k^{q_k}\},\{\mathbf{u}_k\},\{w_k\}} \sum_{k \in \mathcal{K}} \left(w_k e_k - \log(w_k) + \lambda_k \sum_{q_k \in \mathcal{Q}_k} \|\mathbf{v}_k^{q_k}\| \right)$$
$$\text{s.t.} \quad (\mathbf{v}_k^{q_k})^H \mathbf{v}_k^{q_k} \le P_{q_k}, \ \forall\, q_k \in \mathcal{Q}_k, \ \forall\, k \in \mathcal{K}$$

Numerical Results (1/3)



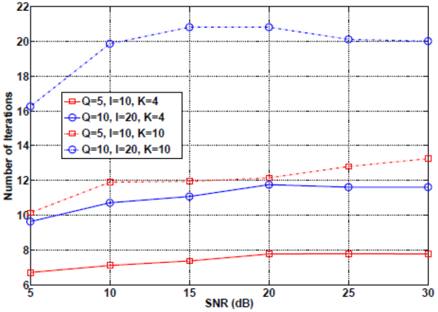


Fig. 3. Comparison of the number of iterations needed for convergence with different network sizes. $K = \{4, 10\}$, $M = 4$, $N = 2$, $\lambda_k = \frac{QK}{I\sqrt{\text{SNR}}}$, $\forall\, k$. The sum rate utility is used.

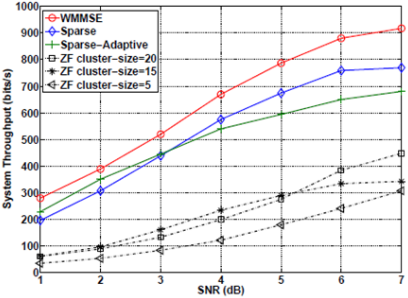


Fig. 4. Comparison of the system throughput achieved by different algorithms. $K = 4$, $M = 4$, $N = 2$, $|\mathcal{I}_k| = 40$, $|\mathcal{Q}_k| = 20$, the sum rate utility is used. For the S-WMMSE algorithm, $\lambda_k = \frac{QK}{I\sqrt{\text{SNR}}}$, $\forall\, k$.

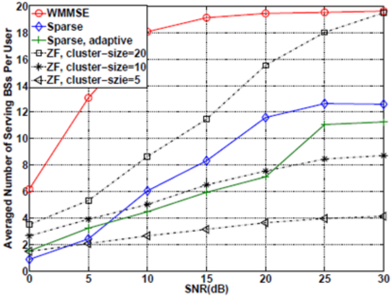


Fig. 5. Comparison of the averaged number of BSs serving each user for different algorithms. $K = 4$, $M = 4$, $N = 2$, $|\mathcal{I}_k| = 40$, $|\mathcal{Q}_k| = 20$, the sum rate utility is used. For the S-WMMSE algorithm, $\lambda_k = \frac{QK}{I\sqrt{\text{SNR}}}$, $\forall\, k$.

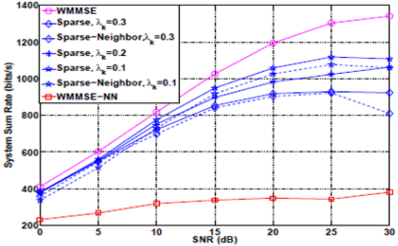


Fig. 6. Comparison of the system throughput achieved by different algorithms. $K = 10$, $M = 4$, $N = 2$, $|\mathcal{I}_k| = 20$, $|\mathcal{Q}_k| = 20$, the PF utility is used. λ_k is specified in the legend.

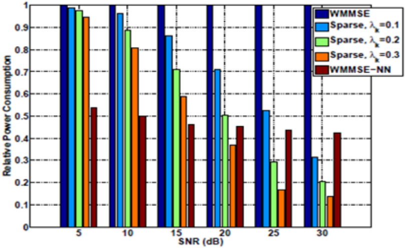


Fig. 7. Comparison of relative per-BS transmission power used (relative to the power consumption of WMMSE algorithm with full per-cell cooperation). $K = 10$, $M = 4$, $N = 2$, $|\mathcal{I}_k| = 20$, $|\mathcal{Q}_k| = 20$, PF utility is used. λ_k is specified in the legend.

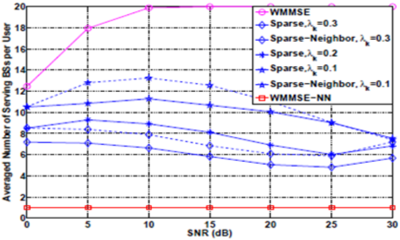


Fig. 8. Comparison of the averaged cluster sizes generated by different algorithms. $K = 10$, $M = 4$, $N = 2$, $|\mathcal{I}_k| = 20$, $|\mathcal{Q}_k| = 20$, PF utility is used. λ_k is specified in the legend.

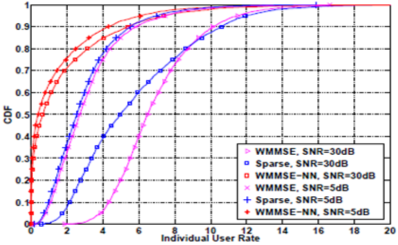


Fig. 9. Comparison of distribution of the users' individual transmission rates achieved by different algorithms. $K = 10$, $M = 4$, $N = 2$, $|\mathcal{I}_k| = 20$, $|\mathcal{Q}_k| = 20$, PF utility is used. For the S-WMMSE algorithm, $\lambda_k = 0.1$.

Potential Study Items

1. **Can we improve the tradeoff between sum rate and sparsity using penalizing techniques other than G-LASSO?**
2. **What happen if we allow spatial multiplexing (multi-streams) for a single-user?**
   - No interference among the streams (via either additional unitary precoding or MMSE+SIC decoder)
   - Will affect the beamforming matrix solution $\mathbf{V}$ and characteristics of it, since single-user MIMO will be preferred in many cases.
3. **(Semi-)static clustering vs. dynamic clustering?**
4. **Investigate other objective functions. For instance,**
   - Maximize min SINR, s.t. sparsity and an average power.
   - Minimize total power consumption, s.t. sparsity and a minimum SINR.
   - Minimize average # serving cells, s.t. a minimum SINR.