Understanding 5Gs Signal-Processing Demands: Device Centric Network Cooperation for 5G and Beyond: Theory and Algorithms

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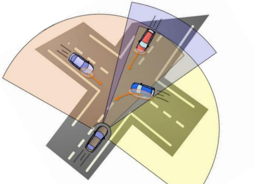
Network Coordination

Coordination and cooperation have emerged as central concepts in many types of networks

- Robots networks (autonomous drones, smart factory, plant probes, etc.)
- Transportation networks (driver less cars, truck trains, etc.)
- Sensor networks
- Processor networks
- Energy (Smart Grids) networks
- Wireless networks



Chalmers University project on self driving car safety

Cooperation Scenarios in Wireless Network (5G and beyond)

Cooperation turns a resource usage conflict into a system gain, for instance in following scenarios:

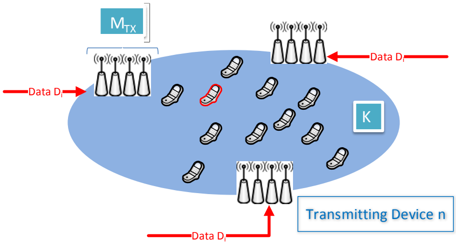
1. Coordinated Multipoint (CoMP) transmission
2. Power control for interference reduction
3. Spectrum sublicensing (coordinated cognitive radios)
4. Beam alignment for massive MIMO in mmwave bands
5. Dynamic content caching
6. Inter-cell Interference Coordination (ICIC and eICIC)
7. Coordinated power transfer for battery life extension (IoT)
8. and more...

Joint Processing CoMP

- n otherwise-interfering base stations jointly combine their nM_{TX} antenna elements over ideal backhaul
- K users are served simultaneously, free of interference (with K up to nM_{TX})

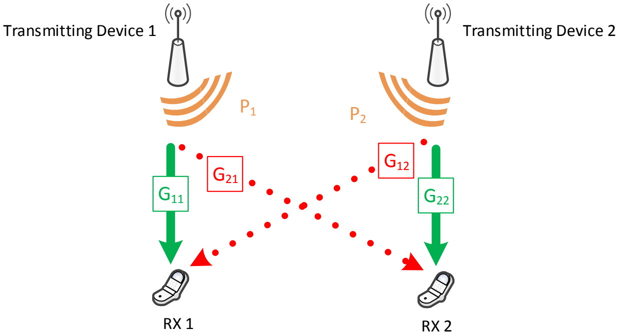
$$\text{Spatial Multiplexing Gain} = nM_{TX}$$

- **Challenges**:
  - All base stations must be synchronized and acquire knowledge of all served users' channels
  - All base stations must acquire knowledge of all served users' channels



Power Control for Interference Reduction

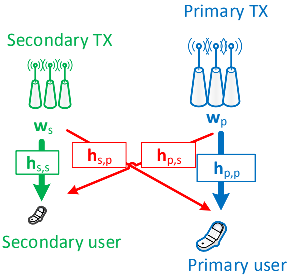
- Neighboring base stations interfere and coordinate their power control policies
- Power control is subject to a maximum power constraint
- Optimum policy aims at maximizing the overall throughput, i.e. just the right amount of interference is generated
- **Challenges**: Coordination requires knowledge of all channel strengths G_{ij}



Spectrum Sub-licensing using Cognitive Radio Beamforming

- A primary operator (p) is sub-licensing its spectrum to a secondary operator (s)
- Both operator base stations control a beamforming vector

$$\text{Maximize} \quad \underbrace{\mathbb{E}[R_s]}_{\text{Secondary}} \quad \text{subject to} \quad \underbrace{\mathbb{E}[R_p]}_{\text{Primary}} \geq \tau > 0$$

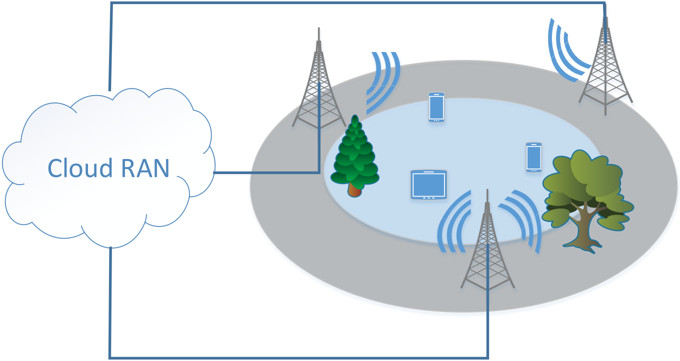


➥ Most common approach: Interference temperature constraint $I_{\text{primary}} \leq \tau$

- **Challenge**: Full beamforming coordination requires centralized knowledge of primary and secondary channels.

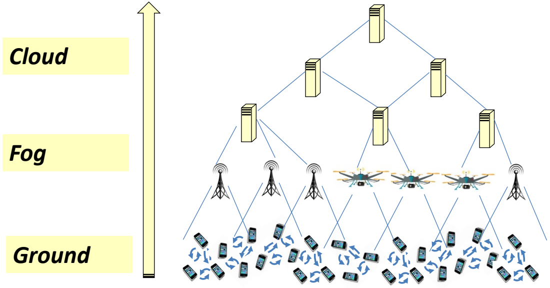
Centralized VS Decentralized Signal Processing Architectures in 5G and Beyond

- Cloud RAN is popular, pushes for more centralization
- Centralized decision making is conceptually simple
- Coordination is easy
- Mobile service providers love it



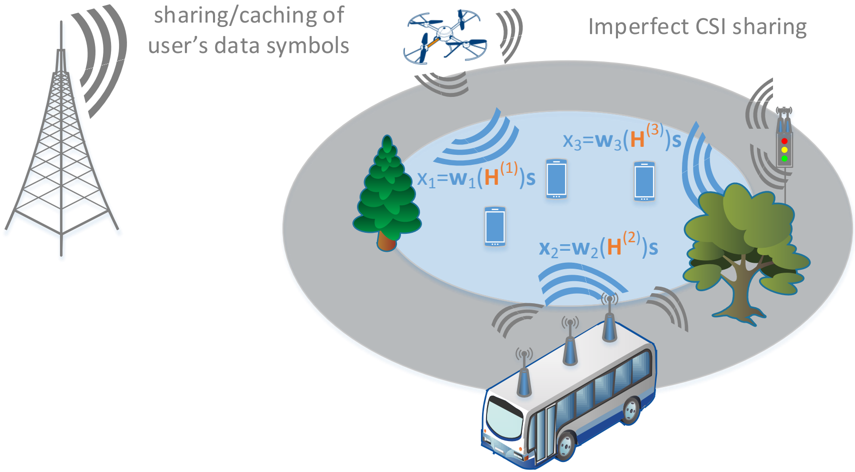
Centralized vs. Decentralized Signal Processing Architectures in 5G and Beyond

- Centralization leads to expensive deployment (road digging, fiber,..)
- Backhaul architectures can be of diverse nature
- Curse of dimension (IoT: billions of devices)
- More centralization increases latency, decreases timeliness of CSI



Centralization ↑ Backhaul ↑ latency ↑ timeliness ↓

Cooperation in LTE with Heterogeneous Backhaul: A Device Centric Perspective



CSI for Device-Centric Cooperation

- CSI affected by mobility, limited training and feedback
- CSI exchange is not free
  - ➥ Devices are myopic: They know better what is close
  - ➥ Need for local (device-centric) decision-making

CSI for Device-Centric Cooperation

- CSI affected by mobility, limited training and feedback
- CSI exchange is not free
  - ➡ Devices are myopic: They know better what is close
  - ➡ Need for local (device-centric) decision-making

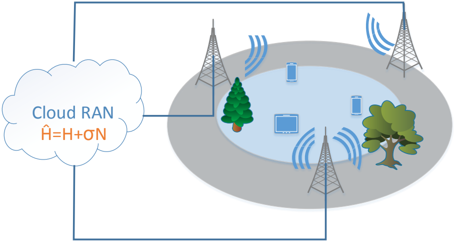
Today's questions:

1. Distributed information models?
2. Price of myopia?
3. Myopia-robust approaches?

Outline

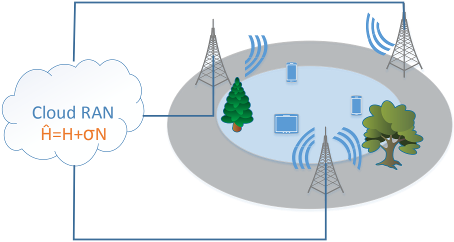
Centralized VS Distributed Channel State Information

- **Centralized (TX Independent)**

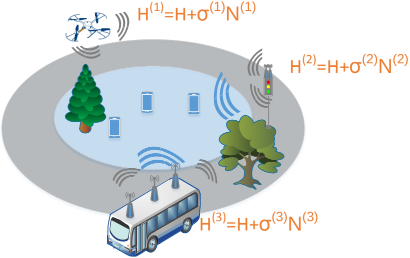


Centralized VS Distributed Channel State Information

- **Centralized (TX Independent)**



- **Distributed (TX Dependent)**



Outline

Device-centric Coordination $\Longleftrightarrow$ Team Decision

K devices cooperate to maximize network performance f

$$(\boldsymbol{s}_1^\star,\dots,\boldsymbol{s}_K^\star) = \underset{\boldsymbol{s}_1,\dots,\boldsymbol{s}_K}{\operatorname{argmax}}\, \mathbb{E}_{\boldsymbol{x},\boldsymbol{x}^{(1)},\dots,\boldsymbol{x}^{(K)}}\Big[f\big(\boldsymbol{x},\overbrace{\boldsymbol{s}_1}^{\text{Decision policy at device 1}}(\underbrace{\boldsymbol{x}^{(1)}}_{\text{Observation at device 1}}),\dots,\boldsymbol{s}_K(\boldsymbol{x}^{(K)})\big)\Big]$$

where

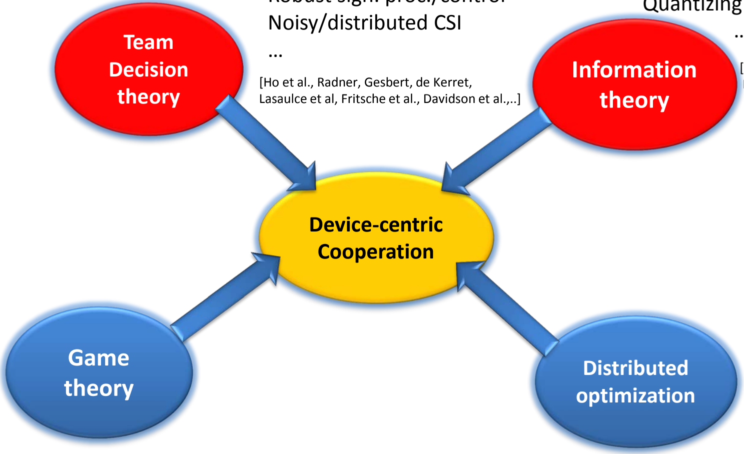
- $\boldsymbol{x} \in \mathbb{C}^m$: System State (for wireless: $\boldsymbol{x} = \mathbf{H}$)
- $\boldsymbol{x}^{(j)} \in \mathbb{C}^m$: Observation of the state of the world $\boldsymbol{x}$ at device j
- $\boldsymbol{s}_j : \mathbb{C}^m \to \mathcal{A}_j \subset \mathbb{C}^{d_j}$: Decision policy at device j
- $p_{\boldsymbol{x},\boldsymbol{x}^{(1)},\dots,\boldsymbol{x}^{(K)}}$: Joint probability distribution of the channel and the estimates

One-shot decision
Robust sign. proc./control
Noisy/distributed CSI
...

[Ho et al., Radner, Gesbert, de Kerret,
Lasaulce et al, Fritsche et al., Davidson et al.,..]

Capacity/DoF analysis
Coordination theory
Quantizing with side info.
...

[Larousse et al,Cuff et al,
Li et al, Grover, ...]



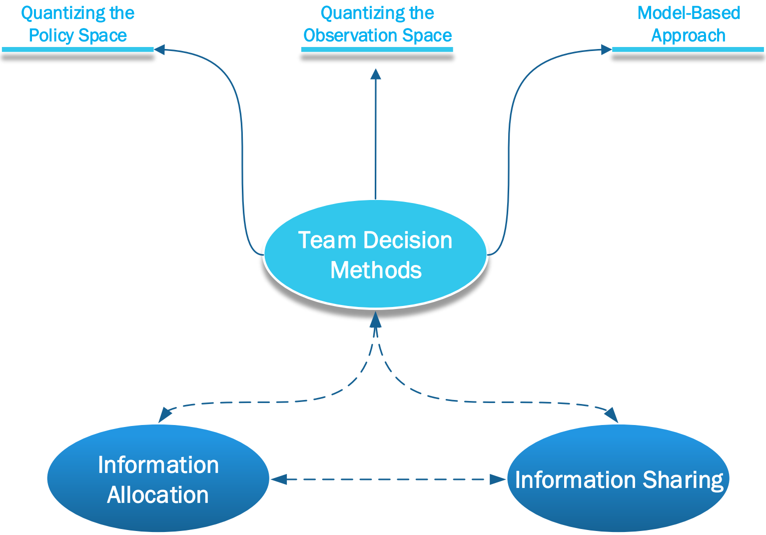
Study of equilibria
Selfish behavior
Convergence studies
...

[Saad et al, Han et al, McKenzie et al, Lasaulce et al,
Poor et al., Rose et al., Jorswieck et al.,..]

Complexity/Convergence studies
Consensus algorithms
Delay tolerant applications
...

[Boyd et al, Inalhan et al, Colorni et al, Rabbat et al, Chen et al., Johansson et al.,
Palomar et al., Scaglione et al., Scutari et al.]

One-Shot Team Decision: Algorithm Design



Outline

I/ First Application: Joint Processing CoMP

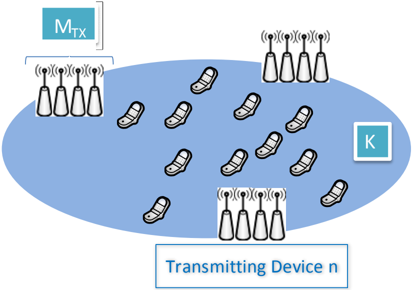
- Find precoders $\{\boldsymbol{w}_j\}_{j=1}^K$:

$$(\boldsymbol{w}_1^\star, \ldots, \boldsymbol{w}_K^\star) = \operatorname*{argmax}_{(w_1,\ldots,w_K)\in\mathcal{W}} \mathbb{E}[\mathrm{R}(\mathbf{H}, \boldsymbol{w}_1(\hat{\mathbf{H}}^{(1)}), \ldots, \boldsymbol{w}_K(\hat{\mathbf{H}}^{(K)}))]$$

  - $\boldsymbol{w}_j$ being the precoder at TX j

$$\boldsymbol{w}_j : \begin{array}{ccc} \mathbb{C}^{N_{\text{tot}} \times M_{\text{tot}}} & \rightarrow & \mathbb{C}^{M_j \times d_{\text{tot}}} \\ \hat{\mathbf{H}}^{(j)} & \mapsto & \boldsymbol{w}_j(\hat{\mathbf{H}}^{(j)}) \end{array}$$

$$\mathbf{T} = \begin{bmatrix} \mathbf{T}_1 & \ldots & \mathbf{T}_K \end{bmatrix} = \begin{bmatrix} \boldsymbol{w}_1(\hat{\mathbf{H}}^{(1)}) \\ \vdots \\ \boldsymbol{w}_K(\hat{\mathbf{H}}^{(K)}) \end{bmatrix}$$



K and M_{TX} grow large at the same rate $\beta \triangleq \lim_{M,K\to\infty} \frac{M}{K} \geq 1$: Asymptotic analysis

Large Random Matrix Theory in Wireless Networks [A Short Digression]

Example

Let $\mathbf{A}$ be the matrix of size $n \times n$ defined as

$$\mathbf{A} \triangleq \begin{bmatrix} 0 & \pm 1 & \pm 1 \\ \pm 1 & 0 & \pm 1 \\ \pm 1 & \pm 1 & 0 \end{bmatrix}$$

➥ Convergence of the eigenvalue distribution

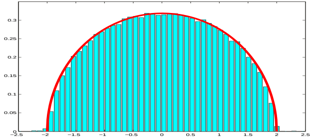


Fig. 1.4 The semicircle law density function (1.18) compared with the histogram of the average of 100 empirical density functions for a Wigner matrix of size $n = 100$.

Figure: from [Tulino and Verdu, 2004]

- Application to Wireless Networks for more than 10 years: Asymptotic expressions for SINR, rate, power, BER,...
  - ➥ Made more relevant by Massive MIMO technology!
- Many books and lecture notes [Tulino and Verdu, 2004] [Couillet and Debbah, 2011]

Model-Based Optimization: Introduction of Regularized Zero Forcing

Modelization of the precoder using Regularized Zero Forcing:

$$\boldsymbol{w}_j(\hat{\mathbf{H}}^{(j)}) = \underbrace{[\mathbf{0}_j, 1, \mathbf{0}_{M-j}]}_{\text{Selects the j th row}} \underbrace{\left((\hat{\mathbf{H}}^{(j)})^{\mathrm{H}}\hat{\mathbf{H}}^{(j)} + M\gamma^{(j)}\mathbf{I}_M\right)^{-1}(\hat{\mathbf{H}}^{(j)})^{\mathrm{H}}\frac{\sqrt{P}}{\sqrt{\Psi^{(j)}}}}_{\text{Robust channel inversion}}$$

- Intuition: Distributed (regularized) Channel Inversion
- Tikhonov Regularization of channel inversion [Golub et al., 2016], widely used [Shenouda and Davidson, 2006]

➥ How to find optimization parameter $\gamma^{(j)}$ at TX j?

Optimization of the Regularization Parameter $\gamma^{(j)}$

- Myopic regularization

$$\gamma^{(j),\mathrm{Myopic}} = \mathrm{argmax}_{\gamma\in\mathbb{R}}\mathbb{E}[\mathrm{R}(\hat{\mathbf{H}}^{(j)},\ldots,\hat{\mathbf{H}}^{(j)})]$$

- Team-Based regularization

$$(\gamma^{(1),\star},\ldots,\gamma^{(n),\star}) = \underset{(\gamma^{(1)},\ldots,\gamma^{(n)})}{\mathrm{argmax}}\ \mathbb{E}[\mathrm{R}(\hat{\mathbf{H}}^{(1)},\ldots,\hat{\mathbf{H}}^{(n)})].$$

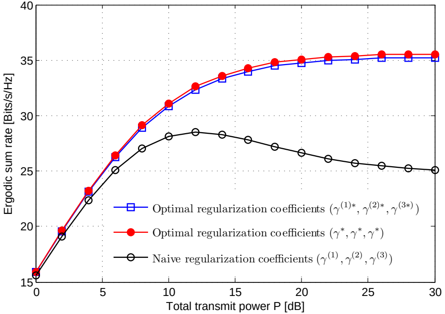
- Low Complexity Team-Based regularization (Equal coefficient at all TXs)

$$(\gamma^{\star},\ldots,\gamma^{\star}) = \underset{(\gamma,\ldots,\gamma)}{\mathrm{argmax}}\,\mathbb{E}[\mathrm{R}(\hat{\mathbf{H}}^{(1)},\ldots,\hat{\mathbf{H}}^{(n)})].$$

➥ RMT allows to get rid of the expectation operator in the optimization

Performance of CoMP Transmission with Distributed CSIT

Antenna Setting	n	3
	K	30
	M	30
Channel Modeling	Fading	Rayleigh
	Pathloss	Uniform
CSIT Configuration	$(\sigma_k^{(1)})^2$	0.01
	$(\sigma_k^{(2)})^2$	0.16
	$(\sigma_k^{(3)})^2$	0.49
	$\rho_k^{(j,j')}$	0.1



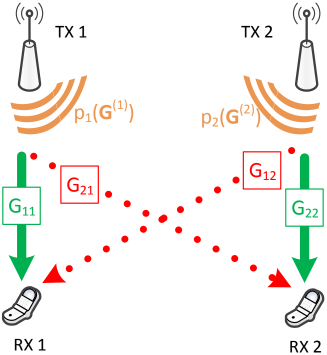
II/ Second Application: On-Off Power Control

- Power control to reduce interference of two interfering wireless links:

$$(p_1^\star, p_2^\star) = \underset{(p_1,p_2)\in\mathcal{P}}{\operatorname{argmax}} [R(p_1(\underbrace{\mathbf{G}^{(1)}}_{\text{Local Channel at device 1}}), p_2(\mathbf{G}^{(2)}))]$$

where p_j is the power control function

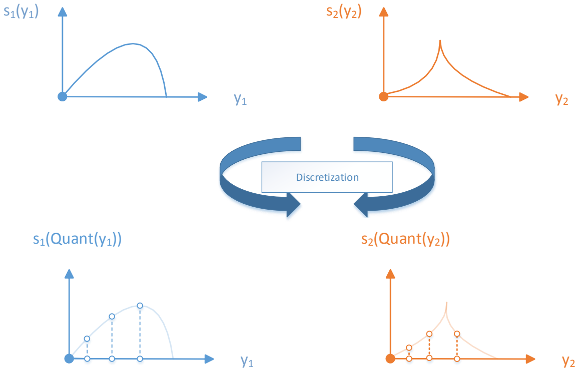
$$\begin{aligned} p_j : \quad \mathbb{R}_+^4 \quad &\rightarrow \quad \{P_j^{\min}, P_j^{\max}\} \\ \mathbf{G}^{(j)} \quad &\mapsto \quad p_j(\mathbf{G}^{(j)}) \end{aligned}$$



Discretization of the Observation Space [de Kerret and Gesbert, 2016, SPAWC]

- Replace the strategy $p_j(\hat{\mathbf{G}}^{(j)})$ by $p_j\left(\underbrace{\mathrm{Quant}(\hat{\mathbf{G}}^{(j)})}_{\text{belongs to a codebook of size } n}\right)$

➥ Optimizing a function over a discrete set is more easy than a continuous one



Best Response Optimization

- Solve iteratively
  - At TX 1, $\forall \mathbf{G}_i \in \{\mathbf{G}_1^{\mathrm{Quant}}, \ldots, \mathbf{G}_n^{\mathrm{Quant}}\}$,

$$p_1^{\mathrm{BR}} = \operatorname*{argmax}_{p_1} \mathbb{E}[\mathrm{R}(p_1(\mathbf{G}^{(1)}), p_2^{\mathrm{BR}}(\mathbf{G}^{(2)}))]$$

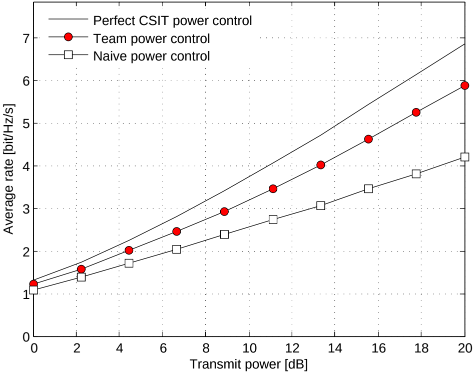
  - At TX 2, $\forall \mathbf{G}_i \in \{\mathbf{G}_1^{\mathrm{Quant}}, \ldots, \mathbf{G}_n^{\mathrm{Quant}}\}$,

$$p_2^{\mathrm{BR}} = \operatorname*{argmax}_{p_2} \mathbb{E}[\mathrm{R}(p_1^{\mathrm{BR}}(\mathbf{G}^{(1)}), p_2(\mathbf{G}^{(2)}))]$$

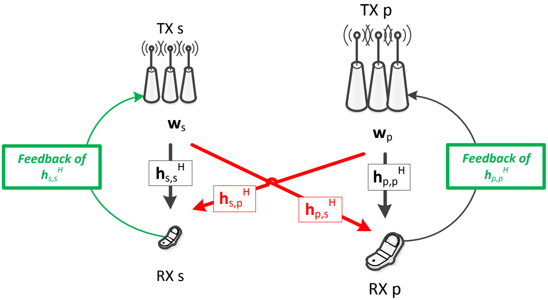
➥ Made possible by the discretization of the observation space

Simulations of On-Off Power Control with Local Feedback

Channel Modeling	Fading	Rayleigh
	Pathloss	Uniform
Algorithm parameters	Codebook size for quantization	10^4
	Number of Monte-Carlo runs	500
CSIT Configuration	$\sigma^{(1)}$	1
	$\sigma^{(2)}$	0



III/ Third Application: Cognitive Radio Beamforming with Local Feedback



$$\text{Maximize} \quad \underbrace{\mathbb{E}[R_s]}_{\text{Secondary}} \quad \text{subject to} \quad \underbrace{\mathbb{E}[R_p]}_{\text{Primary}} \geq \tau > 0$$

- CSI configuration
  - Primary TX only knows $\boldsymbol{h}_{p,p}$
  - Secondary TX only knows $\boldsymbol{h}_{s,s}$
- SOTA: Primary user is oblivious of the secondary user

Coordination scheme

Primary TX adapts without any exchange of instantaneous information

Robust Distributed Optimization

Optimization Problem (P)

$$(\boldsymbol{w}_p^\star, \boldsymbol{w}_s^\star) = \underset{(\boldsymbol{w}_p, \boldsymbol{w}_s)}{\operatorname{argmax}} \mathbb{E}\left[\mathrm{R}_s(\mathbf{w}_p(\mathbf{h}_{p,p}), \mathbf{w}_s(\mathbf{h}_{s,s}))\right]$$
$$\text{s. to} \quad \mathbb{E}\left[\mathrm{R}_p(\mathbf{w}_p(\mathbf{h}_{p,p}), \mathbf{w}_s(\mathbf{h}_{s,s}))\right] \geq \tau > 0, \qquad \text{(P)}$$

- $\boldsymbol{w}_p$ is the beamforming function at the primary TX

$$\begin{array}{rccc} \boldsymbol{w}_p : & \mathbb{C}^{M_p} & \rightarrow & \mathbb{C}^{M_p} \\ & \boldsymbol{h}_{p,p} & \mapsto & \boldsymbol{w}_p(\boldsymbol{h}_{p,p}) \end{array}$$

- $\boldsymbol{w}_s$ is the beamforming function at the secondary TX

$$\begin{array}{rccc} \boldsymbol{w}_s : & \mathbb{C}^{M_s} & \rightarrow & \mathbb{C}^{M_s} \\ & \boldsymbol{h}_{s,s} & \mapsto & \boldsymbol{w}_s(\boldsymbol{h}_{s,s}) \end{array}$$

Primary Friendly (PF) Strategy

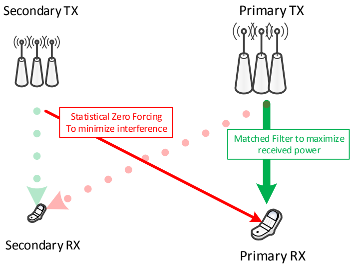
- Primary TX: uses Matched Filtering with full power $\bar{P}_p = P_p^{\max}$

$$\boldsymbol{u}_p^{(\mathrm{PF})} \triangleq \frac{\boldsymbol{h}_{p,p}}{\|\boldsymbol{h}_{p,p}\|}$$

- Secondary TX: uses the statistical Zero Forcing beamforming

$$\boldsymbol{u}_s^{(\mathrm{PF})} \triangleq \operatorname*{argmin}_{\boldsymbol{u}} \boldsymbol{u}^{\mathrm{H}} \mathbf{R}_{p,s} \boldsymbol{u}$$

and average transmit power $\bar{P}_s$ to fulfill the ergodic rate constraint



Secondary Friendly (SF) Strategy

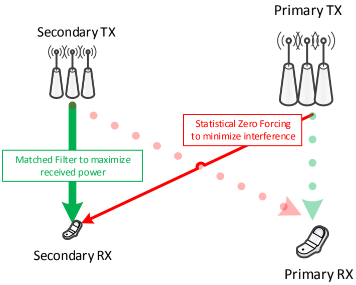
- Secondary TX: uses Matched Filtering with full power $\bar{P}_s = P_s^{\max}$

$$\boldsymbol{u}_s^{(\mathrm{SF})} \triangleq \frac{\boldsymbol{h}_{s,s}}{\|\boldsymbol{h}_{s,s}\|}$$

- Primary TX: uses the statistical Zero Forcing beamformer

$$\boldsymbol{u}_p^{(\mathrm{SF})} \triangleq \operatorname*{argmin}_{\boldsymbol{u}} \boldsymbol{u}^{\mathrm{H}} \mathbf{R}_{s,p} \boldsymbol{u}$$

and average transmit power $\bar{P}_p$ to fulfill the ergodic rate constraint



Quantizing the Policy Space [Filippou et al., 2016, TWC]

- Restrict to 2 strategies labeled Primary Friendly (PF) and Secondary Friendly (SF)

➥ Need good heuristic choices

Optimization Problem

$$(\boldsymbol{w}_p^\star, \boldsymbol{w}_s^\star) = \underset{(\boldsymbol{w}_p, \boldsymbol{w}_s)\in\mathcal{W}}{\operatorname{argmax}} \ \mathbb{E}\left[\mathrm{R}_s(\mathbf{w}_p(\mathbf{h}_{p,p}), \mathbf{w}_s(\mathbf{h}_{s,s}))\right]$$

$$\text{s. to } \ \mathbb{E}\left[\mathrm{R}_p(\mathbf{w}_p(\mathbf{h}_{p,p}), \mathbf{w}_s(\mathbf{h}_{s,s}))\right] \geq \tau > 0, \tag{P}$$

$$\mathcal{W} = \left\{ \underbrace{\left(\boldsymbol{w}_p^{(\mathrm{PF})}, \boldsymbol{w}_s^{(\mathrm{PF})}\right)}_{\text{First Strategy}}, \underbrace{\left(\boldsymbol{w}_p^{(\mathrm{SF})}, \boldsymbol{w}_s^{(\mathrm{SF})}\right)}_{\text{Second Strategy}} \right\}$$

Cognitive Radio with Local Feedback: Rate of the Secondary User

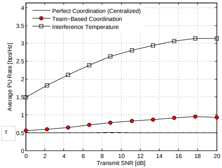


Figure: Ergodic rate of the Primary User

- $M_s = M_p = 3$ antennas per-TX
- Correlation matrices

$$\mathbf{R}_{p,p} = \mathbf{R}_{s,s} = \mathbf{I}_3,$$

$$\mathbf{R}_{p,s} = \mathbf{R}_{s,p} = \begin{bmatrix} 1 & \rho & \rho^2 \\ \rho & 1 & \rho \\ \rho^2 & \rho & 1 \end{bmatrix}$$

- Use in the following $\rho = 0.5$ and $\tau = 0.5$bps/Hz

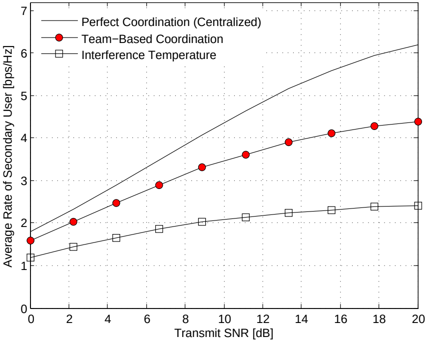
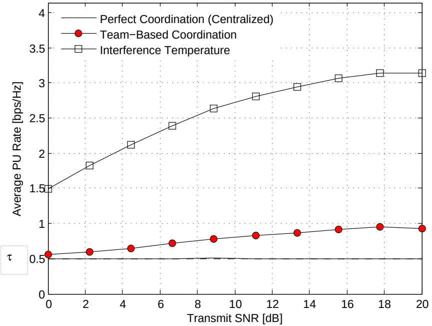


Figure: Ergodic rate of the Secondary User

Cognitive Radio with Local Feedback: Rate of the Primary User



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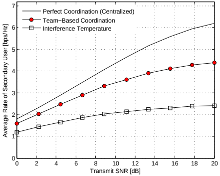

Figure: Ergodic rate of the Secondary User

Take home

- Device coordination is key to performance improvement in 5G and beyond
- Virtually all coordination schemes require extensive CSI acquisition and sharing among devices
- Coordination frameworks that are robust to CSI locality are desirable
- Several perspectives on the problem (i) control, (ii) signal processing, (iii) information theoretic

More applications (not covered here)

- Dynamic content caching at device side
- Coordinated beam alignment in millimeter wave Massive MIMO
- Coordinated power transfer for battery recharge in IoT networks
- More examples upon request

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References I

Romain Couillet and Merouane Debbah. *Random matrix methods for wireless Communications*. Cambridge University Press, 2011.

P. de Kerret and D. Gesbert. Quantized Team Precoding: A robust approach for network MIMO under general CSI uncertainties. In *Proc. IEEE International Workshop on Signal Processing Advances in Wireless Communications (SPAWC)*, 2016.

M. C. Filippou, P. de Kerret, D. Gesbert, T. Ratnarajah, A. Pastore, and G. A. Ropokis. Coordinated shared spectrum precoding with Distributed CSIT. *IEEE Trans. Wireless Commun.*, 15(8):5182–5192, Aug. 2016.

Gene H. Golub, Per Christian Hansen, and Dianne P. O'Leary. Tikhonov Regularization and Total Least Squares. *SIAM Journal on Matrix Analysis and Applications*, 21(1):185–194, 2016.

M. B. Shenouda and T. N. Davidson. Robust linear precoding for uncertain MISO Broadcast Channels. In *Proc. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2006.

A. Tulino and S. Verdu. *Random matrix theory and wireless communications*. Now Publisher Inc., 2004.