

Mobile Beamforming & Spatially Controlled Relay Communications

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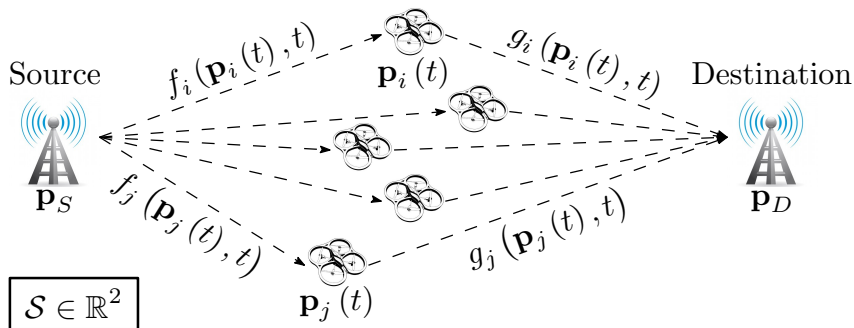
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- We consider **stochastic motion planning** in **single source/destination AF mobile relay beamforming networks**.
- Assumption: The wireless channel is a **spatiotemporal stochastic field**.
- We present a **2-stage stochastic programming formulation** for spatial relay control, such that
 - the **expected reciprocal of the total power at the relays is maximized**,
 - on the basis of **random causal CSI**.
- We propose a **lower bound relaxation** to the original problem.
 - This is equivalent to a set of simple tractable subproblems.
 - And results in spatial controllers with a predictive character.
- \Rightarrow Under this setting, the optimal control policy is **purely selective**:
 - **Only the “best” relay should move.**

Relay Beamforming (1)



- The network operates over a time horizon of N_T time slots in $[0, T]$.
- For later, let $\mathbf{p}(t) \triangleq [\mathbf{p}_1^T(t) \mathbf{p}_2^T(t) \dots \mathbf{p}_R^T(t)]^T$ (R : # of relays).
- Channels $\{f_i, g_i\}_{i \in \mathbb{N}_R^+}$ are modeled as random variables.
- Relays can exchange “small” messages locally.

Relay Beamforming (2)

- At each time instant, given **exact CSI** $\{f_i, g_i\}_{i \in \mathbb{N}_R^+}$, we would like to

$$\begin{aligned} & \underset{\mathbf{w}}{\text{maximize}} && \left(\mathbf{w}^H \mathbf{D} \mathbf{w} \right)^{-1} \\ & \text{subject to} && \frac{\mathbf{w}^H \mathbf{R} \mathbf{w}}{\sigma_D^2 + \mathbf{w}^H \mathbf{Q} \mathbf{w}} \geq \zeta, \end{aligned}$$

with (P_0 is trans power, σ^2/σ_D^2 are noise powers at relays/destination)

$$\mathbf{D} \triangleq P_0 \text{diag} \left(\left[|f_1|^2 \ |f_2|^2 \ \dots \ |f_R|^2 \right]^T \right) + \sigma^2 \mathbf{I}_R,$$

$$\mathbf{R} \triangleq P_0 \mathbf{h} \mathbf{h}^H \in \mathbb{S}_+^R, \text{ with } \mathbf{h} \triangleq [f_1 g_1 \ f_2 g_2 \ \dots \ f_R g_R]^T \text{ and}$$

$$\mathbf{Q} \triangleq \sigma^2 \text{diag} \left(\left[|g_1|^2 \ |g_2|^2 \ \dots \ |g_R|^2 \right]^T \right).$$

- The optimal value can be expressed as [Havary-Nassab et al., 2008]

$$V(\mathbf{p}(t), t) \equiv V \triangleq \frac{\lambda_{\max} \left(\mathbf{D}^{-1/2} (\mathbf{R} - \zeta \mathbf{Q}) \mathbf{D}^{-1/2} \right)}{\zeta \sigma_D^2} \triangleq \frac{\lambda_{\max}(\mathbf{B})}{\zeta \sigma_D^2}.$$

- At each t , V **depends on the positions of the relays.**

Mobile Beamforming? (1)

- Dependence of V on $\mathbf{p}(t)$ immediately generates a basic question:
 - **Given that we are at time $t - 1$** , can we **further increase $V(\mathbf{p}(t), t)$** by exploiting **relay mobility**?
 - What does it mean to **“further increase $V(\mathbf{p}(t), t)$ ”**?
 - On the basis of **what information** and **in which sense**?
- First, **“further increase $V(\mathbf{p}(t + 1), t + 1)$ ”** should mean that,
 - **at the new relay positions $\mathbf{p}(t + 1)$** ,
 - channels $\{f_i, g_i\}_{i \in \mathbb{N}_R^+}$ should be such **that we can beamform with smaller power** (can we do it the opposite way?).
- Then, we may agree on a basic *time division* protocol:
At each time interval
 - 1 **Beamforming.**
 - 2 **Relay steering** to the new positions (to be determined).

Mobile Beamforming? (2)

- Let $\{\mathcal{C}(\mathcal{T}_t)\}_{t \in \mathbb{N}_{N_T}^+}$ denote relay CSI, along the path of their trajectories

$$\mathcal{T}_i \triangleq \{\mathbf{p}(t)\}_{t \in \mathbb{N}_i^+}, i \in \mathbb{N}_{N_T}^+, \quad \text{where} \quad \mathcal{T}_t \equiv \{\mathcal{T}_{t-1}, \mathbf{p}(t)\}.$$

- Suppose that, at time slot $t-1$, **an oracle reveals** $\mathcal{C}(\mathcal{T}_t) \equiv \mathcal{C}(\{\mathcal{T}_{t-1}, \mathbf{p}(t)\})$, for each choice of $\mathbf{p}(t)$.
- Then, we could optimize $V(\mathbf{p}(t), t)$ with respect to $\mathbf{p}(t)$ deterministically, for each fixed channel realization the oracle has revealed.
- Such an oracle **does not exist** :(- **Choice of $\mathbf{p}(t)$ cannot be noncausal!**
- Approach: Stochastic Optimization**
 - Maximize $V(\mathbf{p}(t), t)$ **on average** with respect to $\mathbf{p}(t)$,
 - Taking into account **all the history of channel observations** $\{\mathcal{C}(\mathcal{T}_t)\}_{t \in \mathbb{N}_{N_T}^+}$.
 - \Rightarrow Systematically exploit **spatiotemporal statistical dependencies of** $\{f_i, g_i\}_{i \in \mathbb{N}_R^+}$.

Mobile Beamforming! (1)

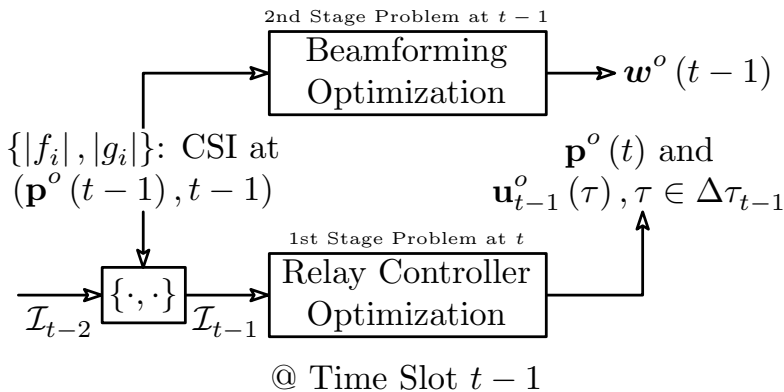
- We are then led to the **2-stage stochastic program** [Shapiro et al., 2009]

$$\begin{aligned} & \underset{\mathbf{p}(t)}{\text{maximize}} && \mathbb{E} \{ V(\mathbf{p}(t), t) \} \\ & \text{subject to} && \mathcal{C}(\mathbf{p}(t-1)) \ni \mathbf{p}(t) \equiv \mathbb{E} \{ \mathbf{p}(t) | \mathcal{C}(\mathcal{T}_{t-1}) \} \end{aligned} \text{ ,}$$

where $\mathcal{C}(\mathbf{p}(t-1))$ denotes a spatially feasible convex set.

- The **outer** one is called the **first stage problem**.
 - Take a **predictive** action.
- The **inner** problem whose value is V is called the **second stage problem**.
 - **Uncertainty is revealed**.
 - Take a “**recourse**” (**in a sense**) action.

Mobile Beamforming! (2)



Mobile Beamforming! (3)

- Using a generalized version of the *Fundamental Lemma of Stochastic Control*, the original 2-stage program stated above is equivalent to the **non-variational** problem

$$\underset{\mathbf{p}(t) \in \mathcal{C}(\mathbf{p}(t-1))}{\text{maximize}} \mathbb{E} \{ \lambda_{max} (\mathbf{B}(\mathbf{p}(t), t)) | \mathcal{C}(\mathcal{T}_{t-1}) \}$$

- However, $\mathbb{E} \{ \lambda_{max} (\mathbf{B}(\mathbf{p}(t), t)) | \mathcal{C}(\mathcal{T}_{t-1}) \}$ is **impossible to evaluate** :(
- \Rightarrow Therefore, we have to resort to some reasonable approximation.

Mobile Beamforming! (4)

- By Jensen's Inequality, we may consider the **lower bound relaxation**

$$\max_{\mathbf{p}(t) \in \mathcal{C}(\mathbf{p}(t-1))} \lambda_{max} (\mathbb{E} \{ \mathbf{B}(\mathbf{p}(t), t) | \mathcal{C}(\mathcal{T}_{t-1}) \}) \triangleq \lambda_{max} (\mathbf{E}(\mathbf{p}(t))).$$

- Under usual modeling assumptions concerning the small scale fading components of $\{f_i, g_i\}_{i \in \mathbb{N}_R^+}$, it is true that (drop the dependence on $(\mathbf{p}(t), t)$)

$$\mathbf{E} \equiv \text{diag}(\mathbf{E}_1 \mathbf{E}_2 \dots \mathbf{E}_R), \quad \text{with}$$
$$\mathbf{E}_i \triangleq \mathbb{E} \left\{ \frac{P_0 |f_i|^2 |g_i|^2 - \gamma \sigma^2 |g_i|^2}{P_0 |f_i|^2 + \sigma^2} \middle| \mathcal{C}(\mathcal{T}_{t-1}) \right\}, \quad i \in \mathbb{N}_R^+.$$

- Therefore, the relaxed problem is equivalent to

$$\max_{\mathbf{p}_i(t) \in \mathcal{C}(\mathbf{p}_i(t-1))} \left[\max_{i \in \mathbb{N}_R^+} \mathbf{E}_i(\mathbf{p}_i(t)) \right] \equiv \max_{i \in \mathbb{N}_R^+} \left[\max_{\mathbf{p}_i(t) \in \mathcal{C}(\mathbf{p}_i(t-1))} \mathbf{E}_i(\mathbf{p}_i(t)) \right]$$

and the challenge now is the evaluation of $\mathbf{E}_i(\mathbf{p}_i(t))$.

Mobile Beamforming! (5)

- Hereafter, we make the **high-SNR assumption**

$$\frac{1}{P_0 |f_i|^2 + \sigma^2} \approx \frac{1}{P_0 |f_i|^2}, \quad \forall i \in \mathbb{N}_R^+.$$

- Then,

$$\mathbf{E}_i = \mathbb{E} \left\{ |g_i|^2 \middle| \mathcal{C}(\mathcal{T}_{t-1}) \right\} - \frac{\gamma \sigma^2}{P_0} \mathbb{E} \left\{ |g_i|^2 |f_i|^{-2} \middle| \mathcal{C}(\mathcal{T}_{t-1}) \right\}.$$

- Final question: **Is it possible to evaluate \mathbf{E}_i in a reasonable manner so that we can at least maximize it locally?**
- **This depends heavily on channel modeling.**

Mobile Beamforming! (6) - On Channel Modeling

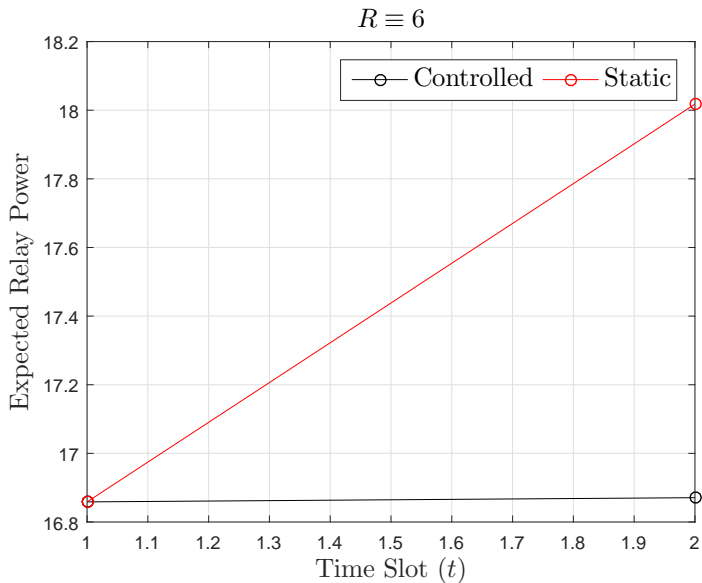
- An acceptable flat fading channel model (same for $g_i(\mathbf{p}_i(t), t)$)

$$f_i(\mathbf{p}_i(t), t) \equiv \underbrace{f^{PL}(\mathbf{p}_i(t))}_{\text{path loss}} \underbrace{f_i^{SH}(t)}_{\text{shadowing}} \underbrace{f_i^{MF}(t)}_{\text{fading}},$$

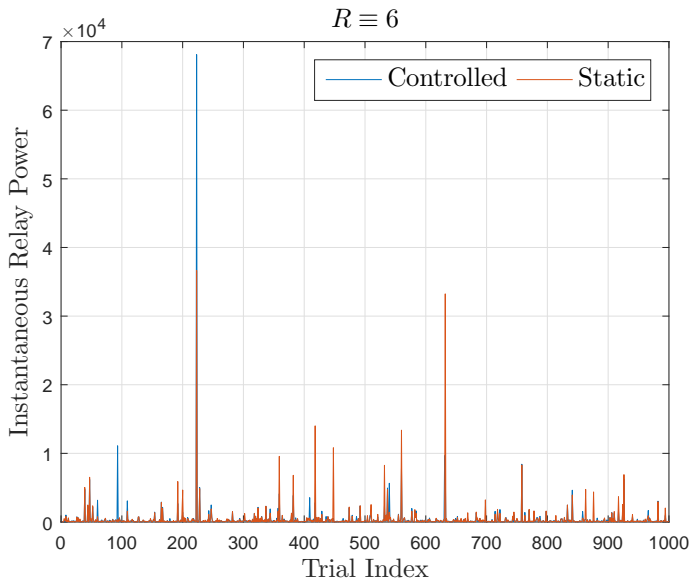
whose **squared magnitude in dB** can be well approximated by a **Gaussian random variable** [Malmirchegini and Mostofi, 2012], where:

- The path loss component is deterministic (conditioned on $\mathbf{p}_i(t)$).
- The fading component is *spatiotemporally white, and thus unpredictable*.
- Useful statistical dependencies are due to shadowing effects.
- Assuming **joint Gaussianity both spatially and temporally**, we end up with a well defined *spatiotemporal Gaussian random field*.
- Then, **E_i can be computed in closed form :)**

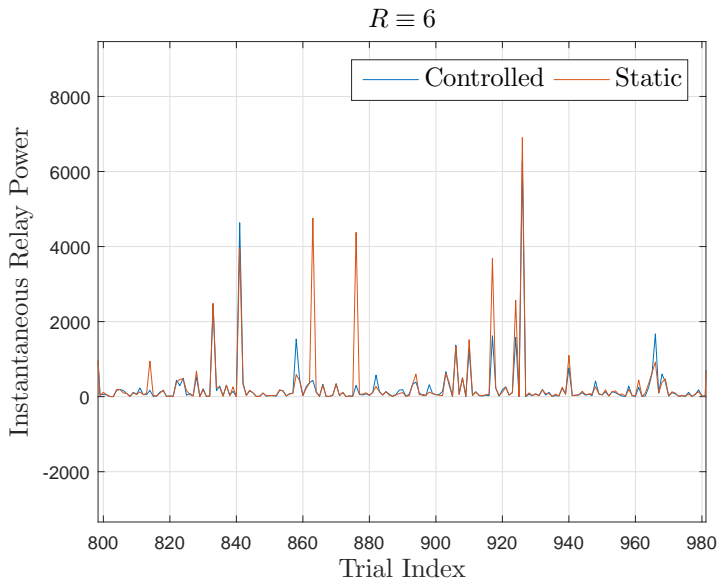
Some Numerical Simulations (1)



Some Numerical Simulations (2)



Some Numerical Simulations (3)



Conclusions

- We considered **stochastic motion planning** in **single source/destination AF mobile relay beamforming networks**.
- We formulated a **2-stage stochastic program** for spatial relay control
- We showed that **beamforming can indeed be benefited by exploiting relay mobility**.
- However, although the proposed solution
 - is **power efficient**,
 - it produces **quite conservative results**. :(
- Topics for future research:
 - Tighter relaxations to the *expected maximum eigenvalue maximization*.
 - Alternative *wireless channel modeling* assumptions.
 - Extensions to *other beamforming problems* (e.g. multiuser networks).
 - And many more!

THANK YOU!

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