Journal Watch On
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Harish V

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- The field Wireless Comm has major number of papers: 32 (probably the reason for a dedicated publication of WC Letters!)
- A number of interesting papers. Can carry over to one more journal watch.
- We see 4 specific papers from the interesting pool of papers from the issue.

Distribution of Diagonal Elements of A General Central Complex Wishart Matrix

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  - The mean vector ($\underline{\mu}$)
  - The covariance matrix or correlation matrix ($K \triangleq \mathbb{E}[XX^*]$)
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  - The pseudo-covar. matrix or relation matrix ($C \triangleq \mathbb{E}[XX^T]$)
- In case of circular Gaussians, $C = 0$ and $\underline{\mu} = 0$.

Background-Random Matrices

- Random Matrices with Gaussian elements (correlated or uncorrelated elements).
- Columns are mutually independent.
- Each column is Complex Gaussian (correlated elements within)
- Simplification: "Circularly Gaussian".
- Reduces a lot of complexity.
- Wide literature on this assumption.

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- Importance: Characterize effective SNR in MIMO, under various Tx policies.
- Lot of works devoted to such analysis on diagonals of Wishart matrices.

- Practical random matrices are seen to contain non-circularly symmetric elements.
- An active area of research. Many new distributions and models are being proposed in this direction.
- This paper:
  - Non-circularly symmetric elements for Random matrix X.
  - Characterizing $diag(Z)$ completely.
  - Derived: PDF,CDF and MGF.
  - Complex enough expressions with lot of special functions & multi-level summations, products.

A New Power Allocation Method for Parallel AWGN Channels in the Finite Block Length Regime

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Korea Advanced Institute of Science Technology (KAIST), Korea.

Main Arguments

- Achieving Capacity of Parallel Gaussian Channels: Waterfilling.
- Capacity maximization (vs) Achievable-rate maximization
- The block length constraint
- Series of papers by Polyanskiy on achievable rates for finite blocklengths.

The Contributions

- Maximization of latest lower bounds on achievable rate of a Gaussian channel with finite block length.
- For a given power allocation p the achievable rate is [Polyanski etal],

$$R(p) = C(p) - \sqrt{V(p)}\frac{Q^{-1}(\zeta)}{\sqrt{n}} + \frac{O(\log_b n)}{n}$$

where, $C(p)$ waterfilling capacity,

ζ is the desired codeword error prob,

n is block length.

- A non-convex optimization formulation using a lowerbound of R(p)
- A new *modified* waterfilling power-allocation scheme.

Optimality of Homogeneous Sensing Range Assignment in Large-Scale Wireless Sensor Network Deployments

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October 14, 2012

THE PROBLEM

- Sensor deployment scenario
- Coverage problem with total power constraint
- Optimal coverage subject to an overall power constraint in the network.
- Does diversity in sensing ranges of sensor nodes help??

- The deployment(location of sensors) follows a Poisson point process.
- From stochastic geometry results for the popular *boolean model*, the fraction of area not covered by any sensor is given by: $\exp\left(-\alpha \sum_{i=1} N p_i \pi r_i^2\right)$
- Two optimization problems are formed:

1) Minimizing uncovered area under power constraint,

$$\begin{aligned} \text{minimize} \quad & \exp\left(-\alpha \sum_i p_i \pi r_i^2\right) \\ \text{subject to} \quad & \sum_i p_i = 1, \\ & \alpha \sum_i p_i r_i^\eta \leq \beta \\ & r_i \geq 0, p_i \geq 0 \text{ for } i = 1, ..., N. \end{aligned}$$

2) Power minimization under coverage area constraint,

$$\begin{aligned} \text{minimize} \quad & \alpha \sum_i p_i r_i^{\eta} \\ \text{subject to} \quad & \sum_i p_i = 1, \\ & \exp\left(-\alpha \sum_i p_i \pi r_i^2\right) \leq \theta \\ & r_i \geq 0, p_i \geq 0 \text{ for } i = 1, ..., N. \end{aligned}$$

- From KKT conditions, optimality is achieved when each $r_i = r$ for both the problems.

- If all sensors deployed have the same sensing range then
  - The uncovered area is minimized for a power constraint
  - The overall power is minimized for a coverage constraint
- Optimum sensing range depends on the density of deployment α as well as the parameters β, η and θ

Sub-Modularity and Antenna Selection in MIMO Systems

Rahul Vaze[1] and Harish Ganapathy[2]

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[2] Dept of ECE,
University of Texas, Austin.

Sub-modularity

Definition: [Nemhauser etal., 1958]

Let N be a set and f a real-valued function defined on the set of sub-sets of N. Then f is called *sub-modular* if:

$$f(S) + f(T) \geq f(S \cup T) + f(S \cap T), \quad \forall S, T \subseteq N$$

or, equivalently:

$$f(S \cup \{a\}) - f(S) \geq f(T \cup \{a\}) - f(T), \\ \forall S \subseteq T \subseteq N, \quad \forall a \in N$$

- Sub-modular functions are studied a while ago.
- Such functions can be optimized (sub-optimally) by simple iterative Greedy algorithms with theoretical *guarantees*. Hence are of interest.

Receive Antenna Selection Problem:

$$\underset{R_L \subset \{1,2,...,N_r\};|R_L|=L}{\text{maximize}} \quad C(R_L)$$

where,

$$C(R_L) \triangleq \log\det\left(I + \frac{P}{N_t} H_{R_L} H_{R_L}^*\right)$$

- Select an optimum subset of antennas $R_L \subset \{1,2,...,N_t\}$ such that it maximizes the capacity over that set of antennas.
- No elegant solution.
- Bruteforce search requires $\mathcal{O}(N_r^L)$ MIMO capacity computations.

Results

1. Proves that $C(R_L)$ is a monotonic, sub-modular function over sub-sets of $\{1, 2, ..., N\}$
2. Proposes a simple greedy iterative search algorithm to solve antenna selection problem.
   - Starting with a null-set, at each iteration, add that specific antenna from the remaining antennas, which maximizes the Capacity.
   - Stop when L antennas are selected.
3. Main result:

If S is the set output by above algorithm, and S^* is the optimal subset then

$$C(S) \geq (1 - \frac{1}{e})C(S^*)$$

4. First algorithm with theoretical guarantees.
5. Extension to 'Relay selection problem' in a network of relays, where the similar approach infact gives precisely *optimal* performance.