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Cooperative Sensing With Imperfect Reporting Channels: Hard Decisions or Soft Decisions?

Authors:

Sachin Chaudhari, Jarmo Lundn, Visa Koivunen, H. Vincent Poor

Aalto University of Electrical Engineering

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- Setup: Distributed detection, i.e., sensors and FC
 - Errors present in the reporting channels
 - Different average SNRs on listening channels
 - Hard decision and soft decision strategies are compared
 - HD: Each sensor transmits a 0/1 decision
 - ★ SD: Each sensor transmits a *D*-bit soft information
- Main Conclusions
 - There is a considerable performance gain in using SD based cooperative sensing even in the presence of reporting errors
 - Established that there is a BEP wall effect even for SD schemes but nothing to worry about as wall is quite high !!
- Other contributions:
 - Detection prob. for K-out-of-N fusion rule for HD in the presence of channel errors
 - Optimal fusion rule for SD based CS, etc.

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Optimal Topology Control and Power Allocation for Minimum Energy Consumption in Consensus Networks

Authors:

Stefania Sardellitti, Sergio Barbarossa and Ananthram Swami

Sapienza University of Rome

ARL

- Setup: Achievement of consensus in a WSN
 - Convergence rates of average consensus algo. is well understood
 - Lower bounded by algebraic connectivity, i.e., 2nd largest eig. of graph Laplacian
 - Topologies maximizing algebraic connectivity is also well understood
 - But for a WSN, the cost of establishing/maintaining topology needs to be accounted
- Main Contributions
 - Optimization problem is setup to minimize a performance metric that depends upon number of iterations required to reach consensus and total network power consumption required to maintain links in WSN
 - Topology, i.e. the active links, and the power per link is the output of above optimization problem
 - * For a given node, p_{ij} and a_{ij} are not independent
 - ★ Original opt. problem is hard to solve. So lot of relaxations and approximations are considered to make the problem tractable.
 - Both Deterministic and random graphs are considered

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Distributed Covariance Estimation in Gaussian Graphical Models

Authors: Ami Wiesel and Alfred O. Hero, III

The Hebrew University of Jerusalem

Univ of Michigan, Ann Arbor

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- Setup: Graphical Gaussian model
 - Nodes represent the joint Gaussian RVs.
 - Conditional independence structure is represented via graph topology.
 - Given the topology and multiple observations (at each node), how to compute the inverse of covariance matrix in distributed fashion.
- Estimation of required entries in the inverse using neighbor node information is well understood
- Collating information from different nodes makes the inverse matrix asymmetric
 - Two algorithms proposed to remove this asymmetry by exchanging information amongst neighbor nodes (message passing)

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Sensor-Centric Data Reduction for Estimation With WSNs via Censoring and Quantization

Authors: Eric J. Msechu and Georgios B. Giannakis

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- WSN with FC setup used to estimate some signal parameters
 - Data-reduction algorithms considered with no inter-sensor communication
 - Limited feedback from FC to nodes is assumed (to send CSI back to nodes)
- Data Censoring: Per node decision if the data is to be transmitted
 - Censoring rule arrived at by setting up an optimization problem that minimizes the least square fit error with a constraint on number of un-censored nodes.
 - Relaxations considered to reach at tractable censoring rule (thresholding)
 - ★ General intuition is to retain measurements that have large values of "regression functions" $(h_k^T \theta)$.
 - MLE with censored data
 - Need to find and maximize the joint pdf of received censored-data at FC
- Further data-reduction by quantizing un-censored data

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Reconciling Compressive Sampling Systems for Spectrally Sparse

Continuous-Time Signals Michael A. Lexa, Mike E. Davies and John S. Thompson The University of Edinburgh

Bit Allocation Laws for Multiantenna Channel Feedback Quantization:

Multiuser Case Authors: Behrouz Khoshnevis and Wei Yu Univ. of Toronto

Regularized Modified BPDN for Noisy Sparse Reconstruction With Partial Erroneous Support and Signal Value Knowledge Authors: Wei Lu and Namrata Vaswani Jowa State University, Ames

On the Achievability of CramerRao Bound in Noisy Compressed Sensing Authors: Rad Niazadeh. Massoud Babaie-Zadeh. and Christian Jutten

Entropy Minimization for Solving Sudoku Authors: Jake Gunther and Todd Moon