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Iterative Channel Estimation Using Virtual Pilot Signals for MIMO-OFDM Systems

Authors : S. Park, B. Shim, and J. W. Choi Objective : To analyze the optimal data tone selection criterion for

new decision directed channel estimation technique.

- Since soft estimates are required Iterative detection and decoding is used.
- Interstream interference is cancelled.
- MSE Metric

$$\phi(n) = E \| \begin{bmatrix} h_{r,t} \\ g_n^{(r,t)} \end{bmatrix} - \begin{bmatrix} \hat{h}_{r,t} \\ \hat{g}_n^{(r,t)} \end{bmatrix} \|^2$$

- Using Pilots and virtual pilots, channel is re-estimated using MMSE.
- Run maximum seven outer iteration but stop if packet passes the CRC check or no improvement in the channel estimation quality at pilot tones is observed.

Massive MIMO for Wireless Sensing With a Coherent Multiple Access Channel

Authors : F. Jiang, J. Chen, A. L. Swindlehurst, and J. A. Lpez-Salcedo Objective : Find optimal values for the sensor transmission gains.

- Assumes Coherent Multiple access, Multiple Antenna at FC and Rayleigh Fading channel.
- NP detector, requires CSI

$$\max_{p} g(\mathbf{a}) = \mathbf{a}^{H} H^{H} (HDVD^{H}H^{H} + \sigma_{n}^{2}\mathbf{I}_{M})^{-1} H\mathbf{a}$$

s.t. $\mathbf{a}^{H}\mathbf{a} = P$

By taking $M \to \infty$ and using the result that $H^*H \to diag$ matrix. Water filling solution for low power regime is obtained. Benefit of multiple antennas at the FC disappears as the transmit power grows.

Massive MIMO for Wireless Sensing With a Coherent Multiple Access Channel

Energy detector, does not require CSI Test Statistic is

$$T = \frac{1}{M} \sum_{i=1}^{M} \frac{\lambda_i}{2} \chi_i^2(2)$$

As $M \rightarrow \infty$ normal distribution can not provide a good approximation.

Metric used is Deflection

$$D(T) = \frac{(E[T/H_1] - E[T/H_0])^2}{var[T/H_0]}$$

Maximisation is a QCRQ problem.

Upper bounded it and as $M \rightarrow \infty$ this bound is tight.

Solved it for upper bound as this can be converted in the convex optimisation problem.

Social Learning With Bayesian Agents and Random Decision Making

Authors : Y. Wang and P. M. Djuri c Objective : Study the effect of randomness in the decision making of agents on social learning.

$$\alpha_n \sim Ber(\beta_n)$$

Social belief :

$$\pi_n = p(H_1/\alpha_{1:n})$$

Action Likelihood :

$$I_n^{(k)} = p(\alpha_n = 1 | \alpha_{1:n-1}, H_k)$$

where β_n is private belief.

- Prevents herd behavior and information cascading even if the log-likelihood ratio is bounded.
- ► Convergence in probability to the true hypothesis.

A Novel Statistical Model for Distributed Estimation in Wireless Sensor Networks

Authors : H. Leung, C. Seneviratne, and M. Xu Objective : Give statistic of the proposed model and analyse the power scheduling.

At kth node : $s_k = \theta + n_k$ Quantised value : $x_k = \theta + n_k + w_k$

$$E[x_k] = \theta,$$
 $var[x_k] = \sigma_k^2 + \delta_k^2$

Recieved signal can be modeled as : $\hat{x}_k = (1 - 2p_k)\theta + \gamma_k$ where $E[\gamma_k] = 0$ and $var[\gamma_k] = var[\hat{x}_k]$

$$L_k = ceiling[log_2(\frac{W}{\sigma_k})]$$

• Gives unbiased estimate of θ

A Novel Statistical Model for Distributed Estimation in Wireless Sensor Networks

Power scheduling :

$$min||\mathbf{P}||_2$$
 s.t. $MSE_{(Achieved)} \leq MSE_{(Targate)}$

where

$$\mathbf{P} = (P_1, P_2, \dots, P_K)$$

- ► *P_k* is average transmission power consumption of node k.
- Gives improved closed form expression for power scheduling.

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Some other papers

- L0 Sparse Inverse Covariance Estimation G. Marjanovic and A. O. Hero.
- Estimating Localized Sources of Diffusion Fields Using Spatiotemporal Sensor Measurements - J. Murray-Bruce and P. L. Dragotti.
- Regularized Robust Estimation of Mean and Covariance Matrix Under Heavy-Tailed Distributions - Y. Sun, P. Babu, and D. P. Palomar.

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