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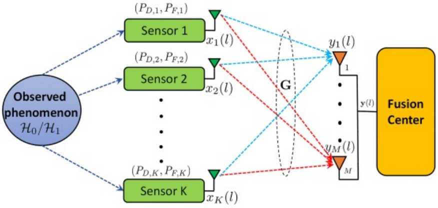
Distributed Detection in Massive MIMO Wireless Sensor Networks Under Perfect and Imperfect CSI - Apoorva Chawla, Adarsh Patel, Aditya K. Jagannatham, Pramod K. Varshney



Contributions

- Fusion rules for the low channel SNR regime derived based on linear filtering at the FC which also incorporates the P_D and P_{FA} for local sensor decisions.
- Close-form expressions for P_D, P_{FA} for both perfect and imperfect CSI.
- Asymitodic system performance for the large antenna regime.
- The signaling matrices are derived for the WSN to maximize the detection performance at the FC.

System Model

- The WSN consists of K single antenna sensors, based on local decision, the kth sensor transmits $x_k(1), x_k(2), \ldots, x_k(L)$ over L time instants to a fusion centre having M antennas such that $M \gg K$.

$$\mathbf{y}(l) = \sqrt{p_u}\mathbf{G}\mathbf{x}(l) + \mathbf{n}(l),$$

where, $n(l) \sim \mathcal{CN}(0, \sigma_n^2 I_M)$, $y(l) \in \mathbb{C}^{M\times 1}$ is the signal recieved by FC at lth time instant. The channel coefficient between the mth antenna and kth sensor is given by $g_{mk} = h_{mk}\sqrt{\beta_k}$. The resulting channel matrix can be written as $G = HD^{1/2}$ and the recieved signal $Y = \left[y(1), y(2), \ldots, y(L)\right] \in \mathbb{C}^{M\times L}$

$$\mathbf{Y} = \sqrt{p_u}\mathbf{G}\mathbf{X} + \mathbf{N}$$

$$\frac{1}{M}\mathbf{G}^H\mathbf{G} \approx \mathbf{D}, \quad \text{for } M \gg K.$$

Fusion Rule with Perfect CSI

$$\mathbf{Z} = \mathbf{G}^H\mathbf{Y} = \sqrt{p_u}\mathbf{G}^H\mathbf{G}\mathbf{X} + \tilde{\mathbf{N}},$$

$$\mathbf{z}_k = \sqrt{p_u}M\beta_k\mathbf{x}_k + \tilde{\mathbf{n}}_k.$$

$$T(\mathbf{Z}) = \ln\left[\frac{p(\mathbf{Z}|\mathcal{H}_1)}{p(\mathbf{Z}|\mathcal{H}_0)}\right] = \ln\left[\prod_{k=1}^{K}\frac{p(\mathbf{z}_k|\mathcal{H}_1)}{p(\mathbf{z}_k|\mathcal{H}_0)}\right],$$

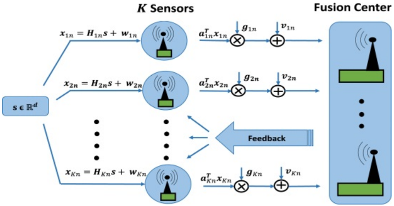
Antipodal Signalling

$$T_{\mathrm{A}}(\mathbf{Z}) = \sum_{k=1}^{K}\ln\left[\frac{P_{D,k}\exp\left(-\frac{\|\mathbf{z}_k-\sqrt{p_u}M\beta_k\mathbf{u}_k\|^2}{M\beta_k\sigma_n^2}\right)+(1-P_{D,k})\exp\left(-\frac{\|\mathbf{z}_k+\sqrt{p_u}M\beta_k\mathbf{u}_k\|^2}{M\beta_k\sigma_n^2}\right)}{P_{F,k}\exp\left(-\frac{\|\mathbf{z}_k-\sqrt{p_u}M\beta_k\mathbf{u}_k\|^2}{M\beta_k\sigma_n^2}\right)+(1-P_{F,k})\exp\left(-\frac{\|\mathbf{z}_k+\sqrt{p_u}M\beta_k\mathbf{u}_k\|^2}{M\beta_k\sigma_n^2}\right)}\right]$$

$$T_{\mathrm{A}}(\mathbf{Z}) = \sum_{k=1}^{K}a_k\Re(\mathbf{z}_k^H\mathbf{u}_k)\underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}}\gamma_{\mathrm{AP}},$$

where, $a_k = P_{D,k} - P_{F,k}$

Online Design of Optimal Precoders for High Dimensional Signal Detection - Prashant Khanduri, Lakshmi Narasimhan Theagarajan, Pramod K. Varshney



Contributions

- An online algorithm to design precoders (both scalar and vector precoding) for WSNs that perform distributed detection of high-dimensional unknown deterministic signals using spatio-temporal data.
- Analytical expressions for the error exponents of the distributed detector for the proposed precoder design and other state-of-the-art precoder design strategies and show that the proposed precoders are asymptotically optimal.

System Model

- WSN with K sensors. Detect the presence or absence of an uknown signal $s \in \mathbb{R}^d$.
- Each sensor observes and forwards a precoded version of the observations to a FC at each time instant (N time instants).

$$\begin{aligned} \mathcal{H}_0: \ \mathbf{x}_{kn} &= \mathbf{w}_{kn}, \\ \mathcal{H}_1: \ \mathbf{x}_{kn} &= \mathbf{H}_{kn}\mathbf{s} + \mathbf{w}_{kn} \\ \mathbf{y}_{kn} &= \mathbf{G}_{kn}\mathbf{A}_{kn}\mathbf{x}_{kn} + \mathbf{v}_{kn}, \end{aligned}$$

where, $\mathbf{H}_{kn} \in \mathbb{R}^{l_k \times d}$ is the observation matrix, $\mathbf{G}_{kn} \in \mathbb{R}^{q_k \times q_k}$ is the wireless fading channel matrix and $\mathbf{A}_{kn} \in \mathbb{R}^{q_k \times l_k}$ denotes the precoding matrix.

$$\mathbb{P}(\mathbf{y}_{kn}|\mathcal{H}_i) \sim \mathcal{N}(\boldsymbol{\mu}_{kn}, \boldsymbol{\Sigma}_{kn})$$

$$\boldsymbol{\mu}_{kn} = \begin{cases} 0 & \text{under } \mathcal{H}_0 \\ \mathbf{T}_{kn}\mathbf{s} & \text{under } \mathcal{H}_1 \end{cases}, \qquad \mathbf{T}_{kn} \triangleq \mathbf{G}_{kn}\mathbf{A}_{kn}\mathbf{H}_{kn}$$

$$\text{and } \boldsymbol{\Sigma}_{kn} = \boldsymbol{\Sigma}_{v_{kn}} + \mathbf{G}_{kn}\mathbf{A}_{kn}\boldsymbol{\Sigma}_{w_{kn}}\mathbf{A}_{kn}^T\mathbf{G}_{kn}^T.$$

The ML estimate of s is given by-

$$\hat{\mathbf{s}} = \left(\sum_{k=1}^{K} \sum_{n=1}^{N} \mathbf{T}_{kn}^T \boldsymbol{\Sigma}_{kn}^{-1} \mathbf{T}_{kn} \right)^{\dagger} \left(\sum_{k=1}^{K} \sum_{n=1}^{N} \mathbf{T}_{kn}^T \boldsymbol{\Sigma}_{kn}^{-1} \mathbf{y}_{kn} \right). \tag{6}$$

The probability of detection is computed as below -

$$\beta_D = \mathcal{Q}\left(\frac{\sqrt{2d}\,\mathcal{Q}^{-1}(\alpha) - \Lambda_{KN}}{\sqrt{2d + 4\Lambda_{KN}}}\right). \tag{14}$$

where,

$$\Lambda_{KN} = \mathbf{s}^T \left(\sum_{k=1}^{K}\sum_{n=1}^{N} \mathbf{T}_{kn}^T \mathbf{\Sigma}_{kn}^{-1} \mathbf{T}_{kn}\right) \mathbf{s}. \tag{10}$$

Scalar Case

$$\mathbf{a}_{kn} = \left(\sigma_{v_{kn}}^2 \mathbf{I}_d + \mathbf{\Sigma}_{w_{kn}}\right)^{-1} \mathbf{s}/c, \tag{20}$$

With each received sample, the ML estimation error decreases, i.e., $s^n \xrightarrow{P} s$ in probability as $N \to \infty$.

$$\mathbf{a}_{kn} = \left(\sigma_{v_{kn}}^2 \mathbf{I}_d + \mathbf{\Sigma}_{w_{kn}}\right)^{-1} \hat{\mathbf{s}}_{n-1}/c$$

$$\hat{\mathbf{s}}_n = \left(\sum_{k=1}^{K}\sum_{i=1}^{n} \mathbf{a}_{ki}\left(\sigma_{v_{ki}}^2 + \mathbf{a}_{ki}^T \mathbf{\Sigma}_{w_{ki}} \mathbf{a}_{ki}\right)^{-1} \mathbf{a}_{ki}^T\right)^{\dagger} \left(\sum_{k=1}^{K}\sum_{i=1}^{n} \mathbf{a}_{ki}\left(\sigma_{v_{ki}}^2 + \mathbf{a}_{ki}^T \mathbf{\Sigma}_{w_{ki}} \mathbf{a}_{ki}\right)^{-1} \mathbf{y}_{ki}\right)$$

Simultaneous Safe Feature and Sample Elimination for Sparse Support Vector Regression - Hongmei Wang, Xianli Pan, Yitian Xu

Goal & Contributions

- To reduce the computation complexity of Sparse Support Vector Regression (SSVR) by identifying the inactive features and samples.
- A safe Feature and Sample Screening Rule (FSSR1) is proposed for accelerating the SSVR. Through FSSR1 most inactive features and samples can be discarded before training the model.
- FSSR2 is proposed to to continuously discard the remained inactive features and samples during the reduced model training process.

System Model Given training set $T = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$, where $x_i \in \mathbb{R}^p$ and $y_i \in \mathbb{R}$
The formulation of SSVR is displayed as follows :

$$\min_{w} P_{\alpha,\beta}(w) = \frac{\alpha}{2}\|w\|_2^2 + \beta\|w\|_1 + \frac{1}{n}\sum_{i=1}^{n} l(x_i^T w - y_i), \tag{1}$$

$$l(t) = \begin{cases} 0, & \text{if } |t| < \epsilon, \\ \frac{1}{2\gamma}(|t| - \epsilon)^2, & \text{if } \epsilon \le |t| \le \epsilon + \gamma, \\ |t| - \epsilon - \frac{\gamma}{2}, & \text{if } |t| > \epsilon + \gamma, \end{cases}$$

$$\min_{w,z} P_{\alpha,\beta}(w) = \frac{\alpha}{2}\|w\|_2^2 + \beta\|w\|_1 + \frac{1}{n}\sum_{i=1}^{n} l(z_i)$$

$$\text{s.t.} \quad z = Xw - Y.$$

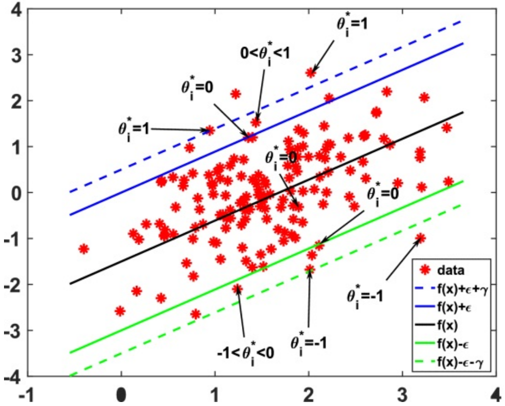
$$L = \frac{\alpha}{2}\|w\|_2^2 + \beta\|w\|_1 + \frac{1}{n}\sum_{i=1}^{n} l(z_i) + \frac{1}{n}\langle z - Xw + Y, \theta\rangle$$

By differentiating w.r.t w and equating to 0 -

$$w_j = \frac{1}{\alpha}\begin{cases} \frac{1}{n}\langle x^j, \theta\rangle - \beta, & \text{if } \frac{1}{n}\langle x^j, \theta\rangle > \beta, \\ 0, & \text{if } |\frac{1}{n}\langle x^j, \theta\rangle| \leq \beta, \\ \frac{1}{n}\langle x^j, \theta\rangle + \beta, & \text{if } \frac{1}{n}\langle x^j, \theta\rangle < -\beta. \end{cases}$$

By differentiating w.r.t z and equating to 0 -

$$\theta_i = \begin{cases} 1, & \text{if } z_i < -\epsilon - \gamma, \\ -\frac{1}{\gamma}(z_i + \epsilon), & \text{if } -\epsilon - \gamma \leq z_i \leq -\epsilon, \\ 0, & \text{if } -\epsilon < z_i < \epsilon, \\ -\frac{1}{\gamma}(z_i - \epsilon), & \text{if } \epsilon \leq z_i \leq \epsilon + \gamma, \\ -1, & \text{if } z_i > \epsilon + \gamma, \end{cases}$$


θ*i=1
0<θ*i<1
θ*i=0
θ*i=1
θ*i=0
θ*i=0
θ*i=-1
-1<θ*i<0
θ*i=-1
data
f(x)+ϵ+γ
f(x)+ϵ
f(x)
f(x)-ϵ
f(x)-ϵ-γ

Other Interesting Papers

- Self-Tuning Algorithms for Multisensor-Multitarget Tracking Using Belief Propagation.
- Asymptotic Task-Based Quantization With Application to Massive MIMO
- Energy Efficiency Optimization in MIMO Interference Channels: A Successive Pseudoconvex Approximation Approach.
- Nonsubsampled Graph Filter Banks: Theory and Distributed Algorithms.
- Truncated Sequential Non-Parametric Hypothesis Testing Based on Random Distortion Testing.