

Journal Watch

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Sanjeev G.
SPC Lab,
Dept. of ECE, IISc.

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Partially Linear Estimation with Application to Sparse Signal Recovery From Measurement Pairs

Tomer Michaeli, Daniel Sigalov, and Yonina C. Eldar
Technion - Israel Institute of Technology

- PLMMSE estimation of X from two sets of measurements Y and Z . $\hat{X} = \mathbf{A}Y + b(Z)$.
- Closed form for \hat{X} (requires $\text{cov}(X)$, $\text{cov}(X, Y)$, $\mathbb{E}(X|Z)$, and F_{YZ}).
- PLMMSEE is **minimax-optimal** (worst case MSE over all feasible distributions complying with given knowledge).
- Case studies: sparse signal recovery from noisy observations and a filtered version (static and dynamic).
- Performance of PLMMSEE is comparable with state of the art algorithms, and is faster.

A General Class of Outage Error Probability Lower Bounds in Bayesian Parameter Estimation

Tirza Routtenberg, and Joseph Tabrikian
Ben-Gurion University of the Negev Beer-Sheva, Israel

- Outage error probability = $\Pr \left\{ |\theta - \hat{\theta}| > h \right\}$. Min out. err. prob. is related to the MAP estimate
- A general class of lower bounds is of the form $\Pr \left\{ |\theta - \hat{\theta}| > h/2 \right\} \geq \mathcal{B} (f_{(\theta|x)}, g(\theta, h, x), \rho)$, where $g(\cdot, \cdot, \cdot)$ and $\rho > 1$ are free parameters
- It is necessary and sufficient that g is periodic in θ with a period h
- Ziv-Zakai lower bounds are shown to be a subclass. The corresponding choice $g(\theta, h, x)$ is given
- It is shown that if the posterior is a) unimodal, then the bound coincides with the actual minimum value b) symmetric and unimodal, then the tightest MSE bound in the class coincides with MSE and ZZLB
- Several examples (including time-delay estimation) are considered

Geolocation Performance With Biased Range Measurements

Ning Liu, Zhengyuan Xu, and Brian M. Sadler

University of California–Riverside, Tsinghua University–Beijing, Army
Research Laboratory–Adelphi

- Localization of a source at $p_s = [x_s y_s]^T$ K sensors at known locations $p_i = [x_i y_i]^T$
- Assuming non-line of sight environment, the range measurement $r_i = d_i + b_i + n_i$
- For a deterministic (random) b_i , the geolocation problem is solved as a WLS (MLE). In both cases, it is shown that the error is biased, based on perturbation analysis.
- In the random bias case, b_i is modeled as exponential, uniform and maxwell distributed.
- For $b_i = 0$, a localization CRLB is derived. Through simulations, it is shown that the performance of WLS and MLE are close to CRLB in some cases (depending on b_i, σ_n^2).

Distributed Spectrum Sensing With Sequential Ordered Transmissions to a Cognitive Fusion Center

Laila Hesham, Ahmed Sultan, Mohammed Nafie, and Fadel
Digham

Nile University, Alexandria University, Cairo University and National
Telecommunications Regulatory Authority, Egypt

- Sensors take measurements and transmit their LLRs in descending order of their magnitude. Sequential detection at the FC
- First method is an improvement over Blum-Sadler's scheme
- Second method finds threshold to maximize a cost function (related to primary and secondary throughputs)
- Also extend these works with for a fading channel between the sensors and FC

Exact Reconstruction Conditions for Regularized Modified Basis Pursuit

Wei Lu and Namrata Vaswani
Iowa State University

- Sufficient conditions are derived for exact recovery of regularized modified BP and it is discussed when the conditions are weaker compared to BP and mod-CS.
- In reg-mod-BP, the erroneous estimates of signal support (T) and signal values on T (μ_T) are assumed to be known.
- BP - $\min_{\beta} \|\beta\|_1$ s.t. $y = A\beta$
 mod-CS - $\min_{\beta} \|\beta_{T^c}\|_1$ s.t. $y = A\beta$
 reg-mod-BP - $\min_{\beta} \|\beta_{T^c}\|_1$ s.t. $y = A\beta$, and
 $\|\beta_T - \mu_T\|_{\infty} \leq \rho$