

Parametric Frugal Sensing of Moving Average Power Spectra

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Collaborative Moving Average Spectrum Estimation

- Crowdsourced spectrum sensing: Exploit spatial diversity in distributed sensors to avoid hidden terminal problem, mitigate fading, and enhance spectrum estimation reliability
- Classical spectrum estimation techniques not suitable in distributed sensing scenarios
- Sending analog or finely quantized signal samples creates a heavy burden in terms of communication overhead and battery lifetime \rightarrow send one (few) bits/sensor: Frugal Sensing [Mehanna *et al.*, 2013]
- Assumption: primary signal admits a Moving Average (MA) parametrization (e.g., FIR pulse-shaping of digital communication signals)

Challenge: collaborative MA spectrum estimation using low-end sensors with limited communication capabilities

Quadratically Constrained Quadratic Programming (QCQP) Formulation

Constraints

- Assume single threshold: $t_m = t$
- Define sets $\mathcal{M}_a := \{m : b_m = 1\}$,
 $\mathcal{M}_b := \{m : b_m = -1\}$,
 $|\mathcal{M}_a| + |\mathcal{M}_b| = M$
- Received bits: $b_m = 1 \Rightarrow \mathbf{h}^H \mathbf{C}_m \mathbf{h} \geq t, \forall m \in \mathcal{M}_a$
 $b_m = -1 \Rightarrow \mathbf{h}^H \mathbf{C}_m \mathbf{h} < t, \forall m \in \mathcal{M}_b$

Cost function

- Average signal power: $\mathbb{E}[|x(n)|^2] = r_x(0) = \mathbf{h}^H \mathbf{h} = \|\mathbf{h}\|_2^2$

QCQP formulation

$$(P) \min_{\mathbf{h} \in \mathbb{C}^{p+1}} \|\mathbf{h}\|_2^2$$

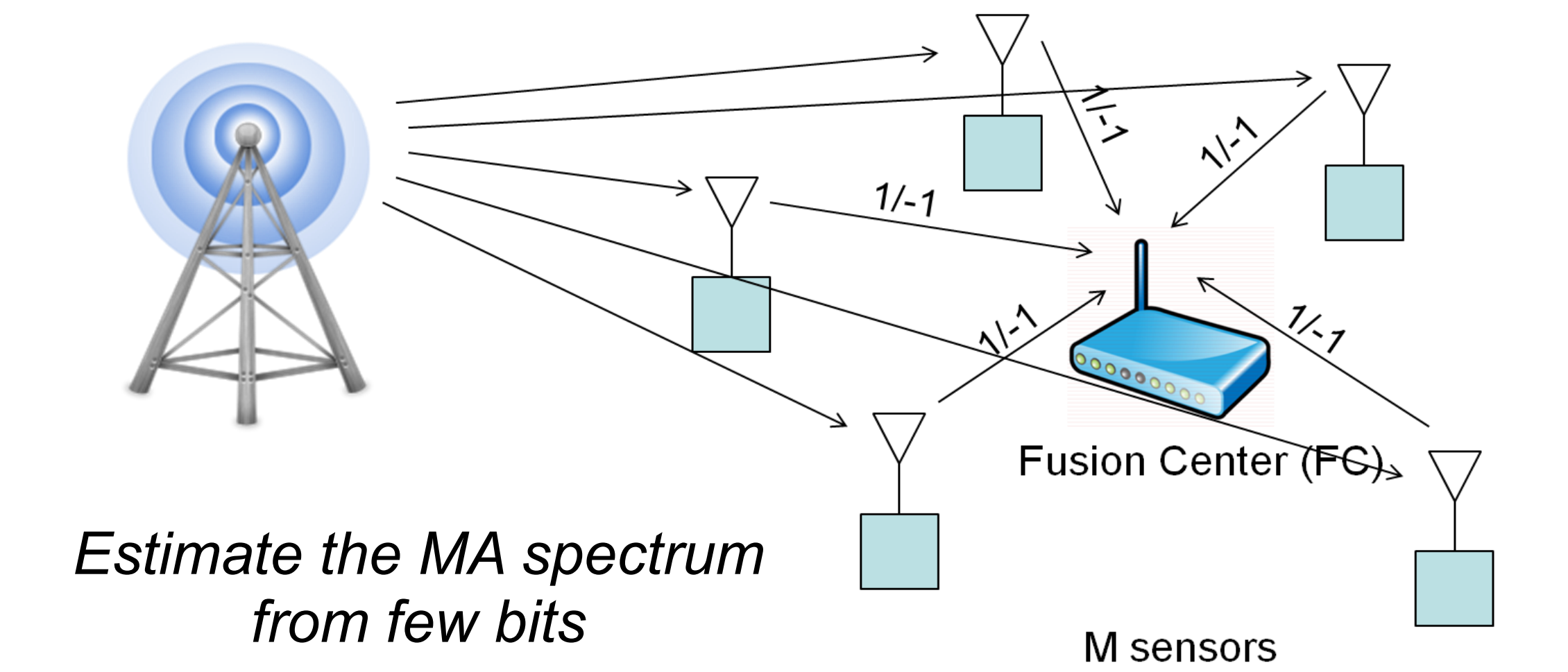
$$\text{s.t. } \mathbf{h}^H \mathbf{C}_m \mathbf{h} \geq t, m \in \mathcal{M}_a$$

$$\mathbf{h}^H \mathbf{C}_m \mathbf{h} < t, m \in \mathcal{M}_b$$

Non-convex problem, known to be NP-Hard in general

MA power spectrum: $S_x(e^{j\omega}) = |\sum_{n=0}^q h(n)e^{-j\omega n}|^2$

Frugal Sensing



MA Signal Model

$$x(n) = \sum_{k=0}^q h(k)w(n-k)$$

MA parameters Complex WGN

Signal Autocorrelation

$$r_x(k) = \begin{cases} \sum_{i=0}^{q-|k|} h^*(i)h(i+|k|) & : |k| \leq q \\ 0 & : |k| > q \end{cases}$$

$$= \begin{cases} \mathbf{h}^H \mathbf{\Theta}_k^{(q+1)} \mathbf{h} & : |k| \leq q \\ 0 & : |k| > q \end{cases}$$

Power Measurement

$$\hat{\alpha}_m = \mathbb{E}[|z_m|^2] = \mathbb{E}[\mathbf{g}_m^H \mathbf{x}^2] = \mathbf{g}_m^H \mathbf{R}_x \mathbf{g}_m \rightarrow \text{Linear in the auto-correlation}$$

$$\mathbf{g}_m^H \mathbf{R}_x \mathbf{g}_m = \mathbf{g}_m^H \left(r_x(0) \mathbf{\Theta}_0^K + \sum_{k=1}^{\min(K-1,q)} (r_x(k) \mathbf{\Theta}_k^K + r_x^*(k) \mathbf{\Theta}_{-k}^K) \right) \mathbf{g}_m$$

$$= \mathbf{g}_{m,0}^H \mathbf{\Theta}_0^K \mathbf{g}_{m,0} r_x(0) + \sum_{k=1}^{\min(K-1,q)} \left(\mathbf{g}_{m,k}^H \mathbf{\Theta}_k^K \mathbf{g}_{m,k} r_x(k) + \mathbf{g}_{m,-k}^H \mathbf{\Theta}_{-k}^K \mathbf{g}_{m,-k} r_x^*(k) \right)$$

$$= c_{m,0} r_x(0) + \sum_{k=1}^{\min(K-1,q)} (c_{m,k} r_x(k) + c_{m,-k} r_x^*(k))$$

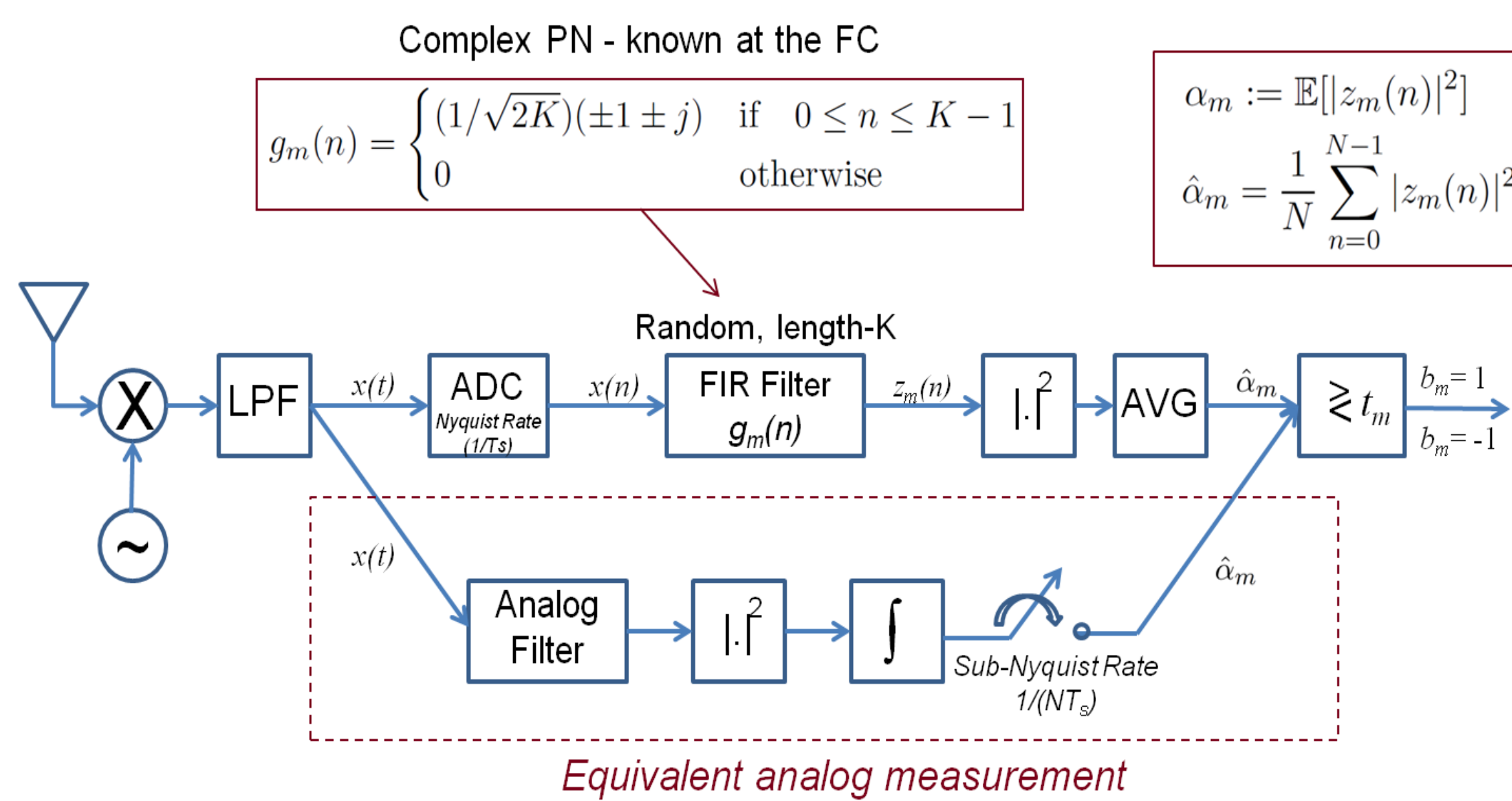
$$= \mathbf{h}^H \left(c_{m,0} \mathbf{\Theta}_0^{(q+1)} + \sum_{k=1}^{\min(K-1,q)} (c_{m,k} \mathbf{\Theta}_k^{(q+1)} + c_{m,-k} \mathbf{\Theta}_{-k}^{(q+1)}) \right) \mathbf{h}$$

$$= \mathbf{h}^H \mathbf{C}_m \mathbf{h} \rightarrow \text{Quadratic in the MA parameters}$$

1-Bit Measurement

$$b_m = \text{sign}(\mathbf{h}^H \mathbf{C}_m \mathbf{h} - t_m)$$

Goal: Estimate \mathbf{h} from $\{b_m\}_{m=1}^M$



Semidefinite Programming (SDP) Relaxation and other approaches

Equivalent Rank Constrained SDP formulation

➢ Define $\mathbf{H} := \mathbf{h}\mathbf{h}^H$

$$\min_{\mathbf{H} \in \mathbb{C}^{(p+1) \times (p+1)}} \text{Trace}(\mathbf{H})$$

$$\text{s.t. } \text{Trace}(\mathbf{C}_m \mathbf{H}) \geq t, m \in \mathcal{M}_a$$

$$\text{Trace}(\mathbf{C}_m \mathbf{H}) < t, m \in \mathcal{M}_b$$

$$\mathbf{H} \succeq \mathbf{0},$$

$$\text{rank}(\mathbf{H}) = 1$$

Rank Relaxation

SDP Relaxation

$$\min_{\mathbf{H} \in \mathbb{C}^{(p+1) \times (p+1)}} \text{Trace}(\mathbf{H})$$

$$\text{s.t. } \text{Trace}(\mathbf{C}_m \mathbf{H}) \geq t, m \in \mathcal{M}_a$$

$$\text{Trace}(\mathbf{C}_m \mathbf{H}) < t, m \in \mathcal{M}_b$$

$$\mathbf{H} \succeq \mathbf{0}$$

Lagrangian bi-dual of (P)

Randomization Algorithm

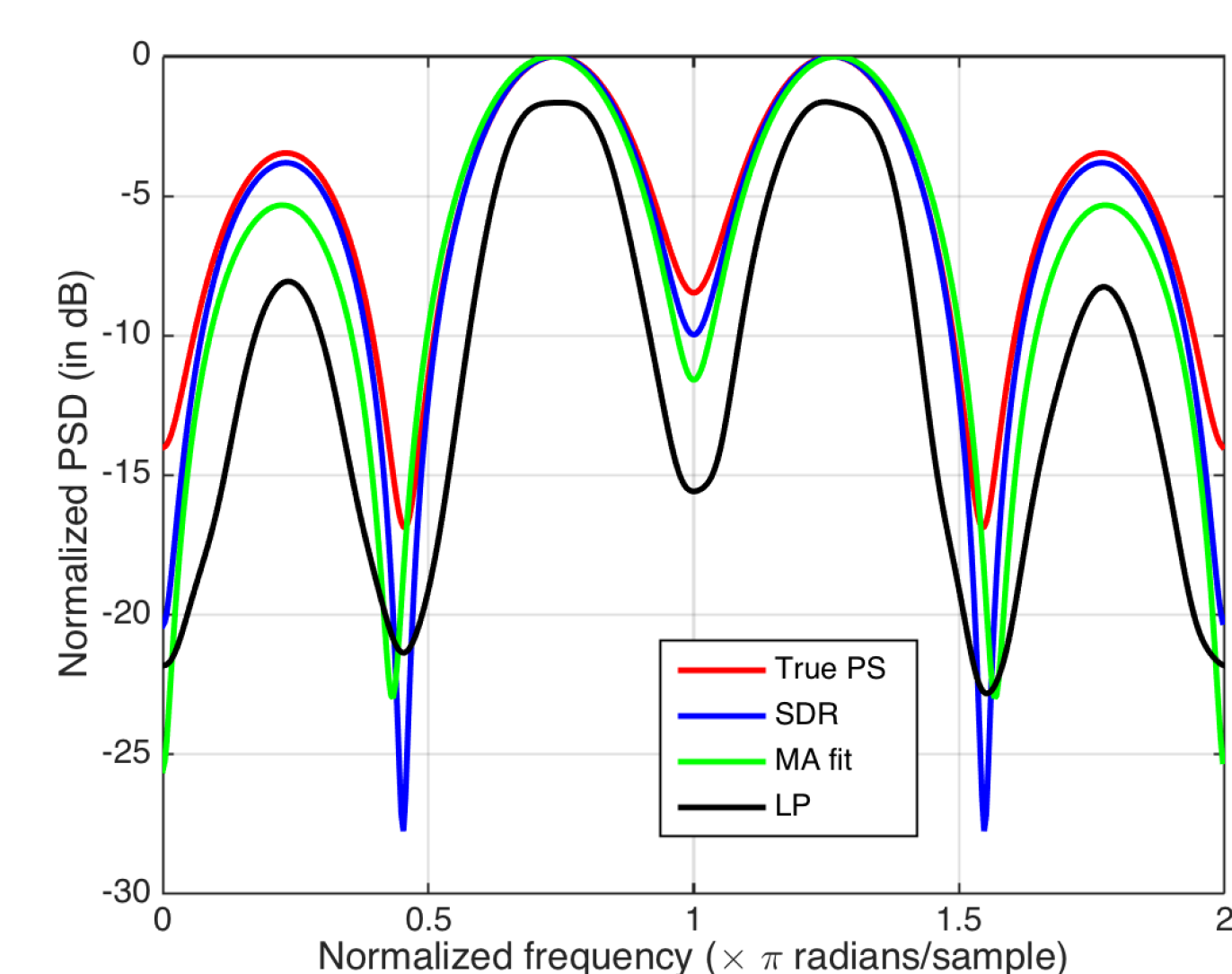
- If solution of SDP relaxation is rank-1, then global optimum achieved
- Randomization Approach
 - Scale principal component of SDP solution to be feasible for
 - Employ *Gaussian Randomization* to obtain feasible solution (P)
 - If randomization fails to produce a feasible solution,
 - Scale principal component/use Gaussian Randomization to obtain feasible solutions for \mathcal{M}_a only
 - Justification: \mathcal{M}_a is the activity detection set, MVDR interpretation
- Randomization algorithm fails to yield feasible solution in most cases (observed from simulations)
- Interestingly, fall-back procedure still yields good quality estimates in many cases

Current State-of-the-Art

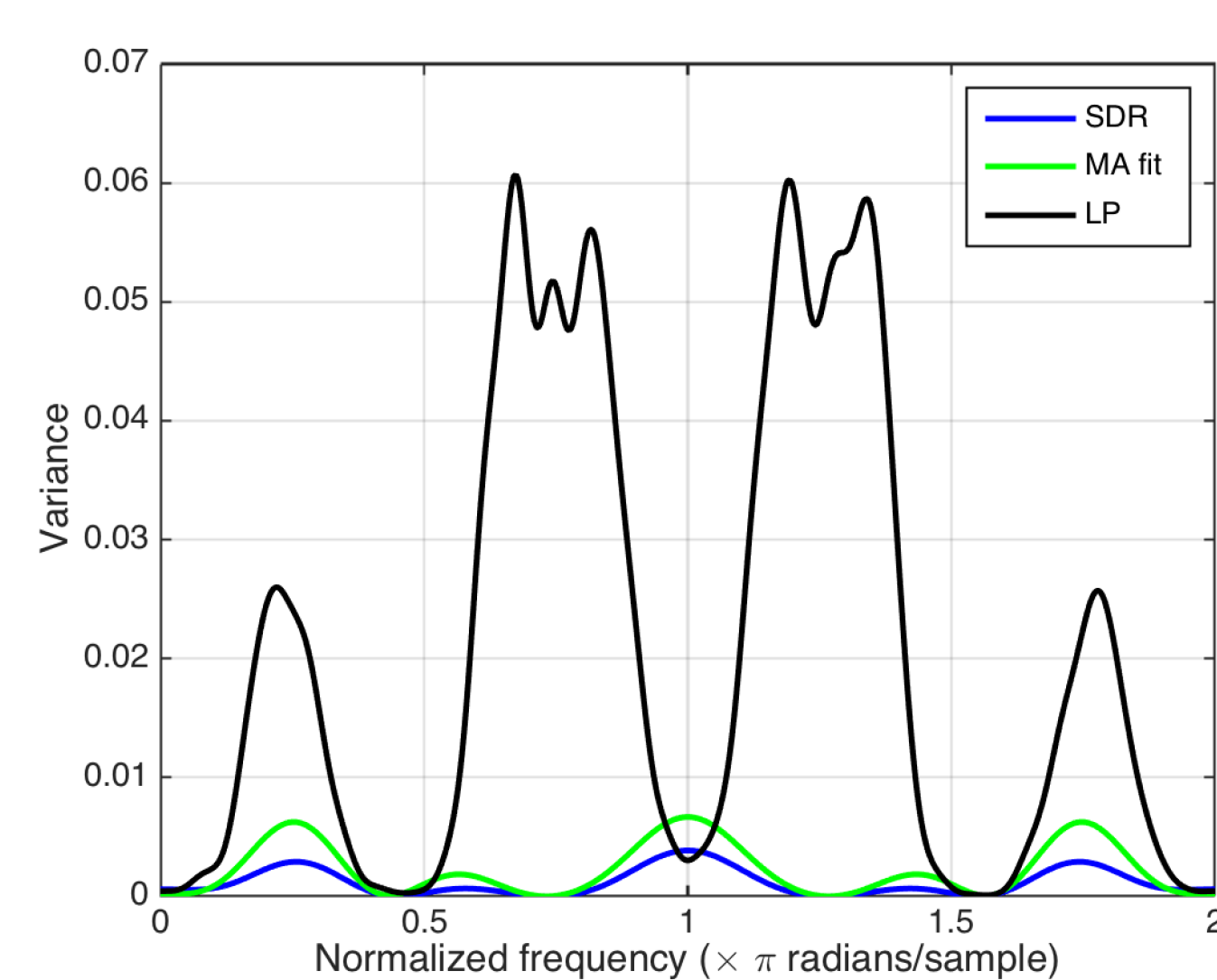
- Non parametric Linear Programming (LP) approach (Ref: O. Mehanna and N. D. Sidiropoulos, "Frugal Sensing: Wideband Power Spectrum Sensing from few bits", *IEEE TSP*, May 2013)
- Classical MA spectrum estimation tools (Ref: P. Stoica and R. L. Moses, "Spectral Analysis of Signals")
- SDP relaxation + Spectral Factorization. Solves (P) to global optimality in polynomial time! (Ref: A. Konar and N. D. Sidiropoulos, "Hidden Convexity in QCQP with Toeplitz-Hermitian Quadratics", *IEEE SPL*, Oct. 2015)

Numerical Results

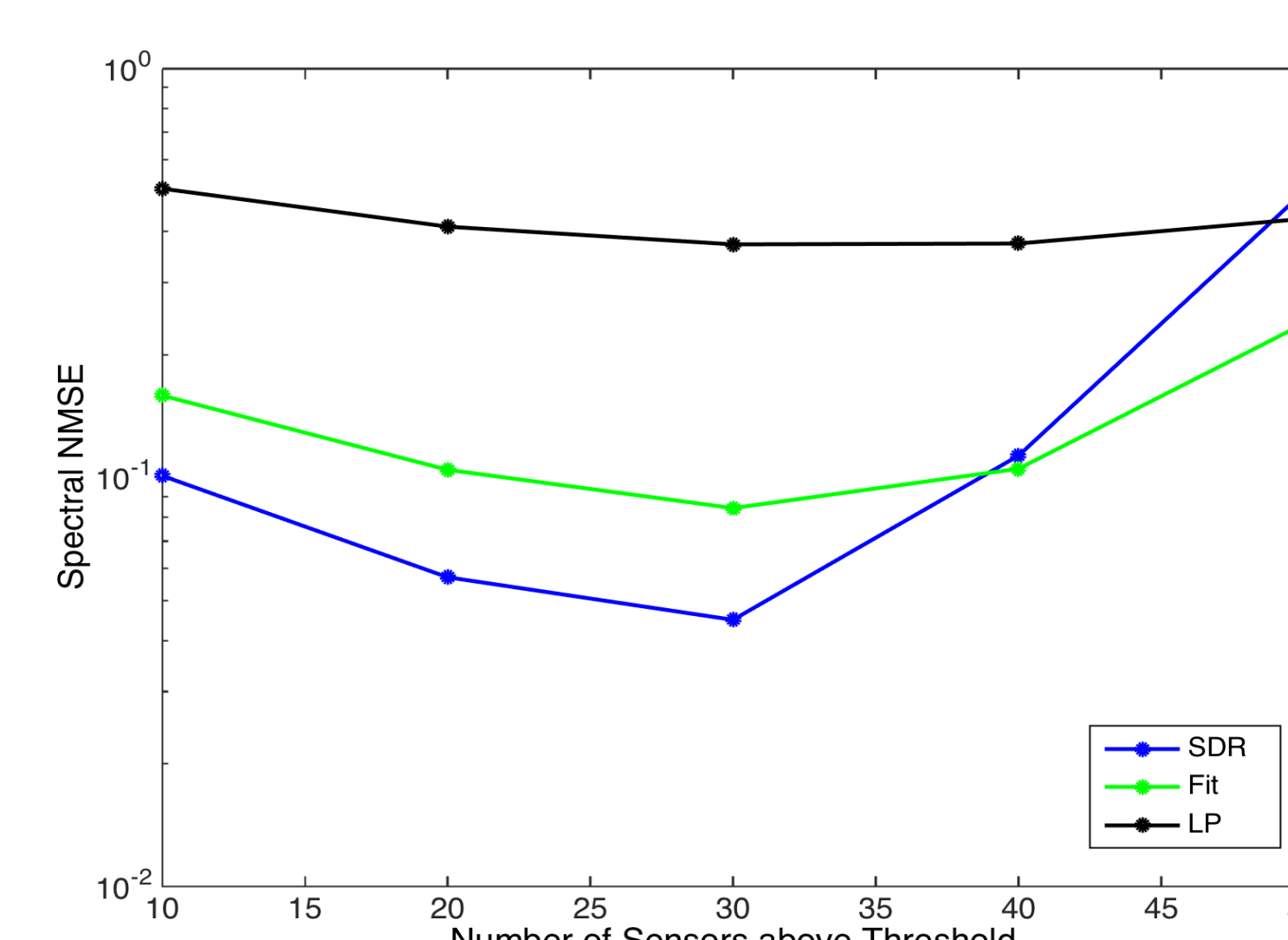
Normalized mean spectra for a real MA(5) model



Variance of Normalized spectra for a real MA(5) model



Spectral NMSE vs number of sensors above threshold for MA(9) models



Conclusions

- Adequate wideband MA spectrum estimation possible from few bits.
- Exploiting underlying MA structure produces more accurate estimation results as compared to non-parametric approaches