Energy-Aware Distributed Tracking in Wireless Sensor Networks

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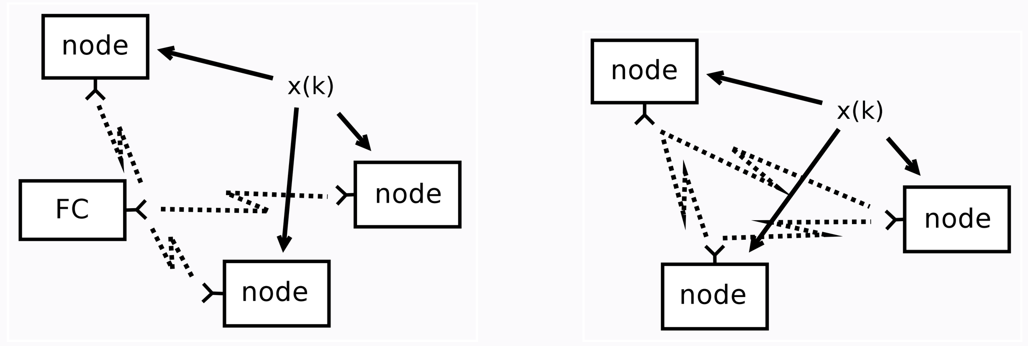
Abstract

This work [1,2] considers centralized distributed estimation in wireless sensor networks (WSN).

- Fusion center (FC) uses BLUE with estimate uncertainty dependent on the transmit energy and quantization levels
- Energy and bandwidth critically constrained resources in WSNs
- A convex program approximates the underlying non-convex MINLP and incorporates the node operating states into the resource allocation to prolong network lifetime

Background



Centralized Decentralized

Advantages of Wireless Networks for Sensing

- Robust to indiv. failure, reliable, inexpensive
- Geographically distributed
- Reduce fusion node computation

Challenging Limitations

- Energy resources ⇒ *battery powered*
- Transmit energy ⇒ *channel noise*
- Network bandwidth ⇒ *quantization noise*

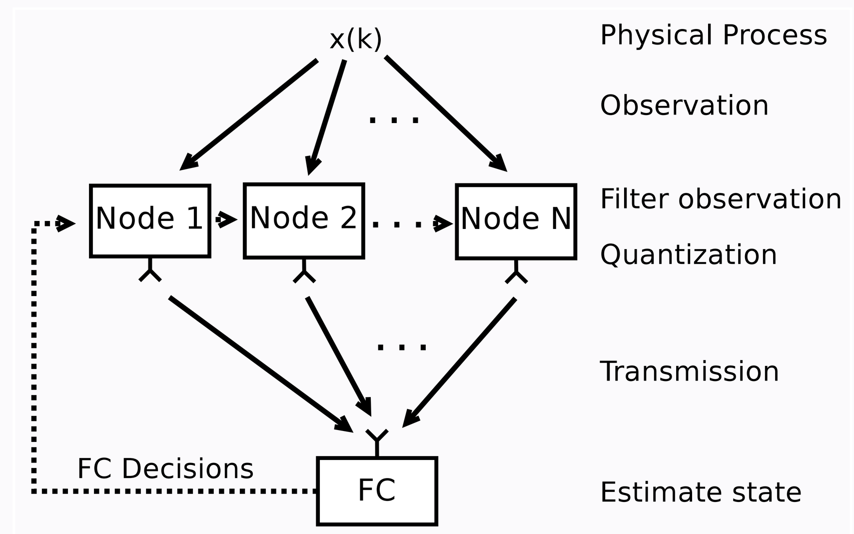
Prior Work

Decentralized	Speyer '79, Willsky '82
Centralized-nonlinear	Castanon '85
Measurement noise*	Willsky '82, Castanon '85
Quantization*	Ayanoğlu '90, Gubner '93, Lam '93
BLU Estimation*	Luo '05
Channel, quant., & meas. noise† *	Xiao '04
Network lifetime analyzed‡	Cardei '05, Li '08
Distributed tracking	Balasubramanian '05†, Williams '07†, Varshney '09§
Channel, quant., & meas. noise and node operating states*	Krishnan '08

†primarily consider sensor selection and scheduling, ‡no communication noise considered, §filtering is done at fusion node, *primarily focus on estimation for a single time instance

System Model

- We consider the task of assigning bit and transmission energy levels *after* sensor **selection and scheduling** has been completed.



- Node estimate and covariance after the **Kalman filter update**

$$\{\hat{\mathbf{x}}_n(k|k), \mathbf{P}_n(k|k)\}$$

- Received data corrupted by channel and quantization noise

$$\tilde{\mathbf{x}}_n(k|k) = \hat{\mathbf{x}}_n(k|k) + \mathbf{n}_n^q(k) + \mathbf{n}_n^c(k) \quad (1)$$

- $n_n^{q,i}(k) \sim \mathcal{N}(0, r_n^{q,i})$ and $n_n^{c,i}(k) \sim \mathcal{N}(0, r_n^{c,i})$; $\mathbf{P}_n^{(i,i)}(k|k)$, $r_n^{q,i} = \sigma_{q,i}^2(k), r_n^{c,i}(k) = \sigma_{c,i}^2$ variances of $\tilde{x}_n^i(k|k)$ estimate
- **BPSK / flat Rayleigh fading** produces channel noise variance

$$r_n^{c,i}(k) = \frac{4W^2}{3}\left(1 - \sqrt{\frac{0.5\Gamma_n^i}{1 + 0.5\Gamma_n^i}}\right) \quad (2)$$

- **Uniform quantization** noise variance is

$$r_n^{q,i}(k) = \frac{W^2}{3(2^{b_n^i(k)} - 1)^2} \quad (3)$$

Assumption. *Make normal simplifying assumptions about noise processes: white, zero mean, uncorrelated; spatially and in time.*

Optimization Problem Formulation

- Minimize the estimation error variance: use **Best Linear Unbiased Estimator (BLUE)**

$$D_i(k) = E[(x^i(k) - \hat{x}^i_{BLUE}(k))^2] = \left(\sum_{n=1}^N \frac{1}{V_n^i(k)}\right)^{-1}$$

Resulting in the estimate

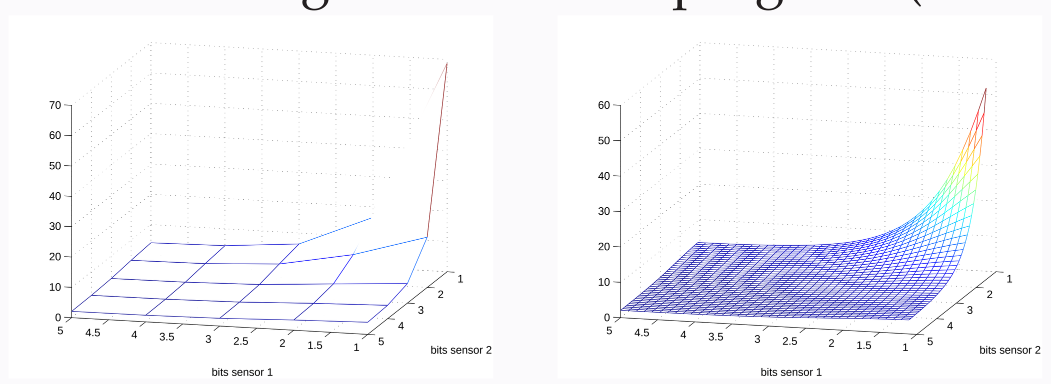
$$\hat{x}^i_{BLUE}(k) = \left(\sum_{n=1}^N \frac{1}{V_n^i(k)}\right)^{-1} \cdot \sum_{n=1}^N \frac{\tilde{x}_n^i(k|k)}{V_n^i(k)} \quad (4)$$

with $V_n^i(k) = E[(x_n^i(k|k) - \tilde{x}_n^i(k|k))^2] = \mathbf{P}_n^{(i,i)}(k|k) + r_n^{c,i}(k) + r_n^{q,i}(k)$, dependent on variables $b_n^i(k)$ and $p_n^i(k)$.

- Expression for the **optimization problem**:

$$\begin{aligned}
&\textit{minimize } D(k) = \sum_{i=1}^d \left(\sum_{n=1}^N \frac{1}{V_n^i(k)}\right)^{-1} \\
&\quad \textit{subject to} \qquad\qquad\qquad\qquad \text{(Global)} \\
&\quad \text{C1:} \quad \sum_{i=1}^d \sum_{n=1}^N b_n(k) \le BW \\
&\quad \text{C2:} \quad \sum_{i=1}^d p_n^i(k) b_n^i(k) \le p_n^{rem}(k) \\
&\quad \text{C3:} \quad 1 \le b_n^i(k) \\
&\quad \text{C4:} \quad p_n^i(k) \le p_n^{max} \qquad \forall\, n = 1, \ldots, N \\
&\quad \text{C5:} \quad p_n^{min} \le p_n^i(k) \qquad i = 1, \ldots, d
\end{aligned}$$

- A mixed-integer non-linear program (MINLP)



Approx. & Energy-Awareness

- Minimize $D_i(k)$ by minimizing $-D_i^{-1}(k)$
- Approximation: solve a **(integer-)relaxed epigraph form** by substituting $y_n^i(k) = \mathbf{P}_n^{(i,i)}(k|k) + r_n^{c,i}(k) + r_n^{q,i}(k)$ and rewriting the problem as

$$\begin{aligned}
&\textit{minimize } \sum_{i=1}^d \sum_{n=1}^N y_n^i(k) \\
&\quad \textit{subject to} \qquad\qquad \text{(LCVX)} \\
&\quad y_n^i(k) - \mathbf{P}_n^{(i,i)}(k|k) + r_n^{c,i}(k) + r_n^{q,i}(k) = 0
\end{aligned}$$

and still subject to constraints C1-C5.

- Relax the epigraph equality constraint to an inequality constraint

$$\mathbf{P}_n^{(i,i)}(k|k) + r_n^{c,i}(k) + r_n^{q,i}(k) - y_n^i(k) \le 0 \quad (5)$$

This inequality constraint is always tight

- Use Sequential Quadratic Programming (SQP); **computational cost** is $O(km^2)$, k variables, m constraints

"Worst-case" approximation

$$\begin{aligned}
&\textit{minimize } d\sum_{n=1}^N y^n(k) \\
&\quad \textit{subject to} \qquad\qquad \text{(WC)} \\
&\quad \max_i\{\mathbf{P}_n^{(i,i)}(k|k)\} + r_c^n(k) + r_q^n(k) - y^n(k) \le 0
\end{aligned}$$

and still subject to C1-C5. Reduces no. of variables by $N(d-1)$ and no. of constraints by $6N(d-1)$.

Energy-Aware Heuristic

- Dynamically update the allowable resource usage of each node based on operating state
- As a heuristic, update ($\forall\, n = 1, \ldots, N$)

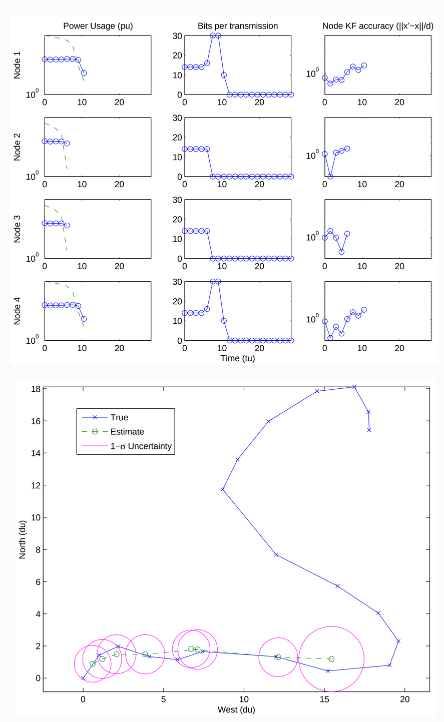
$$\Lambda_n(k) = \frac{1}{\alpha + (1-\alpha)\cdot \frac{p_n^{rem}(k)}{p^{init}}} \quad (6)$$

- Use above to replace constraint C2 with

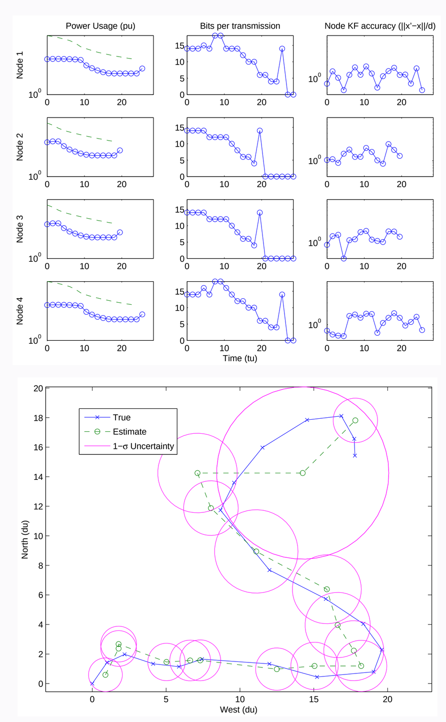
$$\Lambda_n(k) \cdot \sum_{i=1}^d p_n^i(k) b_n^i(k) < p_n^{rem}(k) \quad (7)$$

Results

Time-based single runs for scenario with differing initial energy resources



Non-Energy-Aware



Energy-Aware

Single instance comparison of approx. and exact objective values

- Case A: easy scenario
- Case B: energy-sensitive scenario

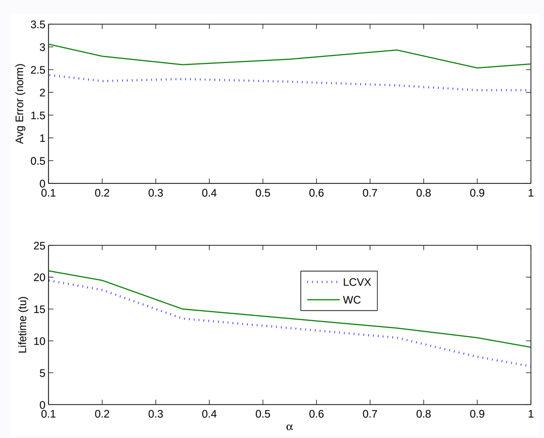
	WC		LCVX		Global
	rlxd	int	rlxd	int	
Case A	6.53	7.52	5.49	6.04	3.59
Case B	10.67	11.21	9.32	9.21	5.67

Discussion of Results

- Solution is approximate, as table of objective values reveal
- Fair results, lifetime can be poor
- Energy-aware heuristic improves network lifetime by 150% on average
- Trade-off of estimation performance, 25% error increase for smallest α tested

Monte Carlo Runs

- Executed 50 MC runs
- Varied lifetime parameter $\alpha \in [0.1,\ 1]$
- Sensitivity tests showed small changes for perturbations of the filter covariance



Error (top) & Lifetime (bottom) vs. α

Acknowledgements

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Future Work

- Dual problem, i.e. optmz. network lifetime
- Decentralized formulation (indep. but co-op.)
- Scheduling and selection for WSN estimation
- Effect on optimal network lifetime of adding energy harvesting systems to current model

References

References in *Prior Work* can be found in:

[1] N. Roseveare and B. Natarajan, "Energy-Aware Distributed Tracking in Wireless Sensor Networks," IEEE WCNC, 2011.

[2] N. Roseveare and B. Natarajan, "Distributed Tracking with Energy Management in Wireless Sensor Networks," Submitted: IEEE TAES, 2011.

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