Sensor Selection in Energy Harvesting Wireless Sensor Networks

Miguel Calvo-Fullana, Javier Matamoros and Carles Antón-Haro

Centre Tecnològic de Telecomunicacions de Catalunya (CTTC)

December 14th, 2015

Outline

Introduction

System Model

Numerical Results

Conclusions

Wireless Sensor Networks

A Wireless Sensor Network (WSN) typically consists of

- A Fusion Center (FC).
- Large number of sensor nodes.

With the goal being to estimate an underlying parameter, we might want to select a subset of sensor to perform this task

- Due to e.g., available bandwidth or interference.

This is referred to as the *sensor selection problem*.

Energy Harvesting Wireless Sensor Networks

Sensor nodes:

- Low complexity, power and cost.
- Long operational lifetime.
- Batteries can be difficult to replace.

Energy Harvesting:

- Collect energy from the environment (solar, thermal, RF, etc).
- Random nature of the energy supply.
- Potentially unlimited sensor lifetime.

Outline

System Model

Wireless Sensor Network:

- One fusion center and M sensor nodes $\mathcal{M} = \{1, \ldots, M\}$.
- Time-slotted communication $\mathcal{T} = \{1, \ldots, T\}$.
- Selected sensors in time slot t, $\mathcal{Z}_t \subseteq \mathcal{M}$, where $|\mathcal{Z}_t| \leq k$.

Underlying source

- $\mathbf{x} \in \mathbb{R}^m$, with $\mathbf{x} \sim \mathcal{N}(0, \mathbf{\Sigma}_x)$.

At time slot t, source x produces an i.i.d. sequence of n samples

- $\{\mathbf{x}^{(k)}[t]\}_{k=1}^{n} = \left\{\mathbf{x}^{(1)}[t], \ldots, \mathbf{x}^{(n)}[t]\right\}$.

Measurement Model

Sensor measurements from source samples follow a linear model.

$$y_i^{(k)}[t] = \mathbf{a}_i^T \mathbf{x}^{(k)}[t] + w_i^{(k)}[t], \qquad \begin{array}{l} k = 1, \ldots, n \\ i \in \mathcal{Z}_t, \end{array}$$

- Observation noise $w_i^{(k)}[t]_{k=1}^n \sim \mathcal{N}(0, \mathbf{\Sigma}_w)$.
- Linear combination coefficients $\mathbf{a}_i$ at sensor i.

Measurements are then encoded into codewords

$$u_i^{(k)}[t] = y_i^{(k)}[t] + q_i^{(k)}[t], \qquad \begin{array}{l} k = 1, \ldots, n \\ i \in \mathcal{Z}_t, \end{array}$$

- Encoding noise $q_i^{(k)}[t] \sim \mathcal{N}\left(0, \sigma_{q_i}^2[t]\right)$.

Source-Channel Coding

We assume separability of source-channel coding.

Source coding by a rate-distortion optimal encoder.

$$R_i[t] \geq I(y_i[t]; u_i[t]) = \frac{1}{2} \log \left(1 + \frac{\mathbf{a}_i^T \mathbf{\Sigma}_x \mathbf{a}_i + \sigma_w^2}{\sigma_{q_i}^2[t]} \right)$$

Channel coding by Shannon's capacity.

$$R_i[t] = \frac{1}{2} \log(1 + h_i[t] p_i[t])$$

Encoding noise is then given by

$$\sigma_{q_i}^2[t] = \frac{\mathbf{a}_i^T \mathbf{\Sigma}_x \mathbf{a}_i + \sigma_w^2}{h_i[t] p_i[t]}, \quad i \in \mathcal{Z}_t.$$

Estimation

Minimum Mean Square Error (MMSE) estimator at the FC.
The average (MSE) distortion in time slot $t \in \mathcal{T}$ is given by

$$D(\mathbf{x}[t];\mathbf{z}[t]) = \mathrm{tr}\left(\sum_{i=1}^{M} \frac{z_i[t]}{\sigma_w^2 + \sigma_{q_i}^2[t]} \mathbf{a}_i \mathbf{a}_i^T + \mathbf{\Sigma}_x^{-1}\right)^{-1}$$

- Sensor selection vector $\mathbf{z}[t] = [z_1[t], \ldots, z_M[t]]^T$.
- $z_i[t] = \begin{cases} 1 & \text{if } i \in \mathcal{Z}_t \\ 0 & \text{otherwise} \end{cases}$

Optimal Power Allocation and Sensor Selection

$$\underset{\mathbf{z}[t],\mathbf{s}[t],\mathbf{p}[t]}{\text{minimize}} \quad \sum_{t=1}^{T} \operatorname{tr}\left(\sum_{i=1}^{M} s_i[t]\mathbf{a}_i\mathbf{a}_i^T + \mathbf{\Sigma}_x^{-1}\right)^{-1} \tag{1a}$$

$$\text{subject to} \quad s_i[t] \leq \frac{h_i[t]p_i[t]}{\mathbf{a}_i^T\mathbf{\Sigma}_x\mathbf{a}_i + \sigma_w^2(1 + h_i[t]p_i[t])} z_i[t], \quad \forall t \in \mathcal{T}, \forall i \in \mathcal{M} \tag{1b}$$

$$T_s \sum_{l=1}^{t} p_i[l] \leq \sum_{l=1}^{t} E_i[l], \forall t \in \mathcal{T}, \forall i \in \mathcal{M} \tag{1c}$$

$$\mathbf{1}^T\mathbf{z}[t] = k, \quad \forall t \in \mathcal{T} \tag{1d}$$

$$\mathbf{z}[t] \in \{0,1\}^M, \quad \forall t \in \mathcal{T} \tag{1e}$$

$$\mathbf{p}[t] \geq \mathbf{0}, \quad \forall t \in \mathcal{T} \tag{1f}$$

$$\mathbf{s}[t] \geq \mathbf{0}, \quad \forall t \in \mathcal{T}. \tag{1g}$$

Optimal Power Allocation for a Given Sensor Selection

$$\underset{\mathbf{s}[t],\mathbf{p}[t]}{\text{minimize}} \quad \sum_{t=1}^{T} \operatorname{tr}\left(\sum_{i\in\mathcal{Z}_t} s_i[t]\mathbf{a}_i\mathbf{a}_i^T + \mathbf{\Sigma}_x^{-1}\right)^{-1} \tag{2a}$$

$$\text{subject to} \quad s_i[t] \leq \frac{h_i[t]p_i[t]}{\mathbf{a}_i^T\mathbf{\Sigma}_x\mathbf{a}_i + \sigma_w^2(1+h_i[t]p_i[t])}, \quad \forall t \in \mathcal{T}, \forall i \in \mathcal{Z}_t \tag{2b}$$

$$T_s \sum_{l=1}^{t} p_i[l] \leq \sum_{l=1}^{t} E_i[l], \forall t \in \mathcal{T}, \forall i \in \mathcal{Z}_t \tag{2c}$$

$$\mathbf{p}[t] \geq \mathbf{0}, \quad \forall t \in \mathcal{T} \tag{2d}$$

$$\mathbf{s}[t] \geq \mathbf{0}, \quad \forall t \in \mathcal{T} \tag{2e}$$

Sensor Selection Policy

Without energy harvesting constraints

$$\begin{aligned} \underset{\mathbf{z}}{\text{minimize}} \quad & \operatorname{tr}\left(\sigma_w^{-2}\sum_{i=1}^{M} z_i \mathbf{a}_i \mathbf{a}_i^T + \boldsymbol{\Sigma}_x^{-1}\right)^{-1} \\ \text{subject to} \quad & \mathbf{1}^T\mathbf{z} = k, \\ & \mathbf{z} \in [0,1]^M. \end{aligned}$$

- The k largest values of the optimal $\mathbf{z}^\star$ are taken.

With energy harvesting constraints

$$\begin{aligned} \underset{\mathbf{s}[t],\mathbf{p}[t]}{\text{minimize}} \quad & \sum_{t=1}^{T} \operatorname{tr}\left(\sum_{i\in\mathcal{Z}_t} s_i[t]\mathbf{a}_i\mathbf{a}_i^T + \boldsymbol{\Sigma}_x^{-1}\right)^{-1} \\ \text{subject to} \quad & s_i[t] \leq \frac{h_i[t]p_i[t]}{\mathbf{a}_i^T\boldsymbol{\Sigma}_x\mathbf{a}_i + \sigma_w^2(1+h_i[t]p_i[t])}, \\ & \forall t \in \mathcal{T}, \forall i \in \mathcal{Z}_t \\ & T_s\sum_{l=1}^{t} p_i[l] \leq \sum_{l=1}^{t} E_i[l], \forall t \in \mathcal{T}, \forall i \in \mathcal{Z}_t \\ & \mathbf{p}[t] \geq \mathbf{0}, \quad \forall t \in \mathcal{T} \\ & \mathbf{s}[t] \geq \mathbf{0}, \quad \forall t \in \mathcal{T} \end{aligned}$$

- Let $\mathcal{Z}_t = \mathcal{M}$ and take the k largest values of the optimal $\mathbf{s}[t]^\star$.

Outline

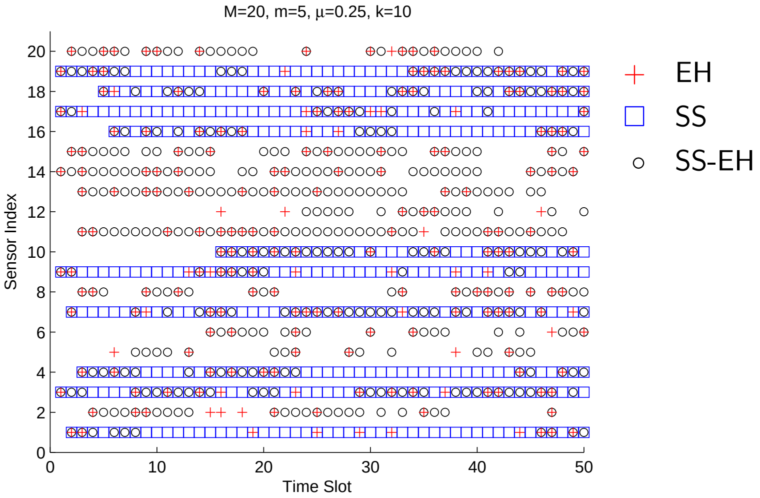
Introduction

System Model

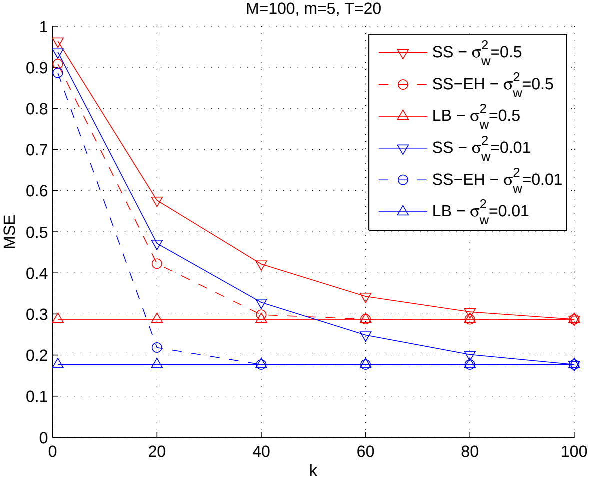
Numerical Results

Conclusions

Numerical Results



Numerical Results



Outline

Conclusions

Contribution

- We formulated the sensors selection problem with energy harvesting constraints.
- We proposed an heuristic EH-aware sensor selection algorithm.

Why choose this heuristic?

- Deriving the optimal power allocation leads to two-dimensional directional waterfilling interpretations.
- Easy to derive good performing online policies.
- The solution can be used as an initial feasible point to find a stationary solution to the (nonconvex) original problem.

Thank You!
Q&A

Miguel Calvo-Fullana

miguel.calvo@cttc.cat

Centre Tecnològic de Telecomunicacions de Catalunya (CTTC)

Castelldefels, Barcelona, Spain

December 14th, 2015