Distributed Censoring with Energy Constraint in Wireless Sensor Networks

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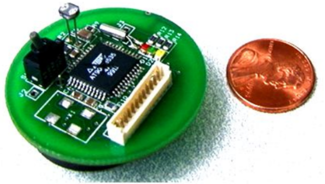
Outline

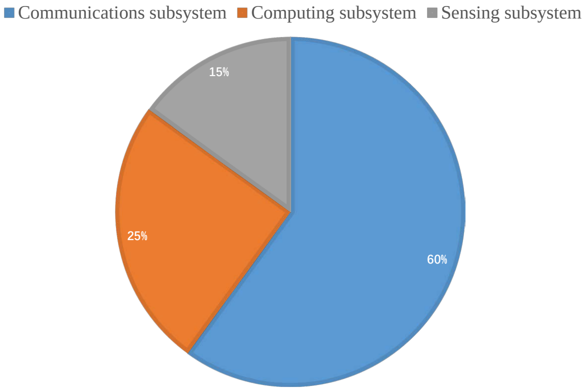
Wireless sensor networks

Wireless sensor node:

- Limited power supply
- Limited computation resource
- Limited communication ability



Energy consumption distribution [Priya'09]:



[1] S. Priya and D. J. Inman, *Energy harvesting technologies.* Springer, 2009, vol. 21.

Reducing data transmission

- Reducing data transmission can be an effective way to reduce the energy consumption

Techniques:

- Collaborative data covariance [Schizas'07]
- Measurement quantization [Gubner'93]
- Compressive sensing [Zymnis'10]

Disadvantages:

- Require collaboration among sensors
- Performance loss
- High computational complexity

- Censoring has recently been employed to select data in resource-constrained WSNs [Nevat'17]

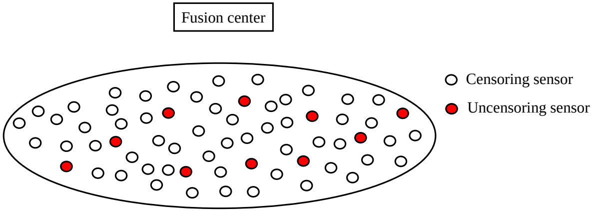
Data censoring

- **Key idea**: Reduce data transmission by only transmitting informative data [Zhu'17] [Berberidis'16]

Criterion

$$y_k = \begin{cases} \star, & y_k^* \in \mathcal{R}_k \\ y_k^*, & \text{otherwise} \end{cases} \quad (1)$$

- y_k^* denotes the measurement of sensor node k
- $\mathcal{R}_k$ denotes the censoring interval
- $\star$ denotes an unspecified value
- If $y_k^* \in \mathcal{R}_k$, y_k^* is censored; otherwise, $y_k = y_k^*$ is obtained



Distributed censoring problem

- **Key idea**: Select at most $\bar{K}$ measurements to fit $\{y_k^*\}_{k=1}^{K}$ best [Msechu'12]

Optimization problem

$$\boldsymbol{s}^* = \arg\min_{\boldsymbol{s}\in\{0,1\}^K} \sum_{k=1}^{K} (y_k^* - s_k \mathbf{h}_k^T \boldsymbol{\theta})^2 \tag{2a}$$

$$s.t. \sum_{k=1}^{K} s_k \leq \bar{K}, \tag{2b}$$

- This method does not consider the energy cost
- The efficiency in terms of selecting informative data depends on the initial LS estimation $\bar{\boldsymbol{\theta}} = \hat{\boldsymbol{\theta}}_{ls}(L)$ where $p < L \ll K$

Outline

System model

- Consider the WSN with K sensor nodes randomly deployed over a geographical area
- Unknown parameters $\boldsymbol{\theta} \in \mathbb{R}^p$, where p is the length of parameters
- The scalar measurement y_{tk}^* of sensor node k at time slot t is assumed to obey the model

Linear regression model [Msechu'12]

$$y_{tk}^* = \mathbf{h}_{tk}^T \boldsymbol{\theta} + v_{tk} \quad (3)$$

where $k = 1, 2, \ldots, K$, $t = 1, 2, \cdots, T$

- $\mathbf{h}_{tk}$ is known at fusion center
- v_{tk} denotes uncorrelated, zero-mean, Gaussian distributed noise

Energy model

- Assume that the data length is m bytes for both transmitter and receiver

The transmitting energy consumption is [Ye'08]

$$E_k = m\epsilon_{\text{elec}} + m\epsilon_{\text{amp}} d_k^2$$

The receiving energy consumption is

$$E_r = m\epsilon_{\text{elec}}$$

- To simplify notation, we normalize the energy in terms of receptions, then

$$E_k = 1 + \beta d_k^2 \tag{4}$$

where $\beta = \epsilon_{\text{amp}}/\epsilon_{\text{elec}} > 0$

Optimization problem

- During each time slot $t = 1, \cdots, T$, $\boldsymbol{s}_t^*$ is the selection vector at time slot t

Updated optimization problem

$$\boldsymbol{s}_t^* = \underset{\boldsymbol{s}_t \in \{0,1\}^K}{\arg\min} \sum_{k=1}^{K} \left[\alpha_{tk}(y_{tk}^* - s_{tk}\mathbf{h}_{tk}^T\boldsymbol{\theta})^2 + (1-\alpha_{tk})s_{tk}E_k\right] \tag{5a}$$

$$s.t. \sum_{k=1}^{K} s_{tk} \leq \bar{K}, \tag{5b}$$

- α_{tk} $(0 \leq \alpha_{tk} \leq 1)$ and $1 - \alpha_{tk}$ are the weights of estimation performance and transmission energy cost of sensor node k at time slot t, respectively
- If energy cost is not considered, i.e., $\alpha_{tk} = 1$, problem (5) reduces to the original censoring problem (2)

Optimal threshold

- The optimal threshold is given by

$$\tau_{tk}(\lambda_t^*) = \frac{(1-\alpha_{tk})E_k + \lambda_t^*}{2\alpha_{tk}|\mathbf{h}_{tk}^T\hat{\boldsymbol{\theta}}_{t-1}|} \tag{6}$$

- A one-dimensional grid search yields the desirable λ_t^* from

$$\begin{aligned}
&\sum_{k=1}^{K}\mathbb{E}[s_{tk}] = \sum_{k=1}^{K}\Pr[|y_{tk}^*| > \tau_{tk}(\lambda_t)] \\
&= K - \sum_{k=1}^{K} Q\left(\frac{-\tau_{tk}(\lambda_t) - \mathbf{h}_{tk}^T\boldsymbol{\theta}}{\sigma}\right) - Q\left(\frac{\tau_{tk}(\lambda_t) - \mathbf{h}_{tk}^T\boldsymbol{\theta}}{\sigma}\right) \\
&\leq \bar{K}
\end{aligned} \tag{7}$$

Distributed censoring

- Censoring can be implemented autonomously with the following rule

$$(y_{tk}, s_{tk}) = \begin{cases} (y^*_{tk}, 1), & \text{if } |y^*_{tk}| > \tau_{tk}(\lambda^*_t), \\ (\star, 0), & \text{otherwise.} \end{cases} \tag{8}$$

- Applying RLS algorithm in fusion center with the censoring rule, yields

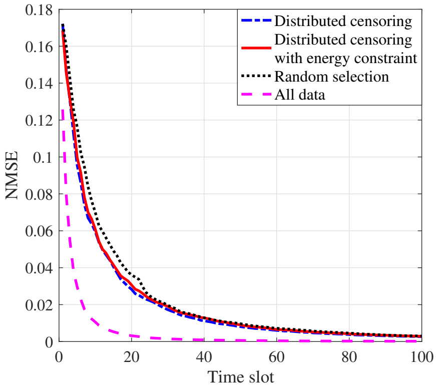
$$\mathbf{C}_n = \frac{n}{n-1}\left[\mathbf{C}_{n-1} - \frac{s_{tk}\mathbf{C}_{n-1}\mathbf{h}_{tk}\mathbf{h}_{tk}^T\mathbf{C}_{n-1}}{n-1+\mathbf{h}_{tk}^T\mathbf{C}_{n-1}\mathbf{h}_{tk}}\right], \tag{9a}$$

$$\hat{\boldsymbol{\theta}}_n = \hat{\boldsymbol{\theta}}_{n-1} + \frac{s_{tk}}{n}\mathbf{C}_n\mathbf{h}_{tk}(y_{tk} - \mathbf{h}_{tk}^T\hat{\boldsymbol{\theta}}_{n-1}), \tag{9b}$$

Outline

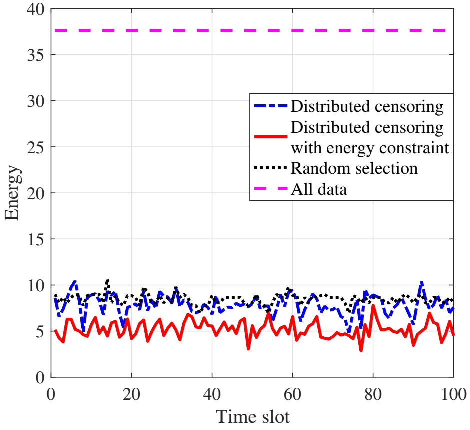
Convergence performance

- $K = 100$, $\bar{K} = 20$ and SNR=30 dB
- $\mathbf{h}_{tk}$ and $\boldsymbol{\theta}$ are picked uniformly over $[-1, 1]$ with dimension $p = 10$
- $\alpha_{tk} = 0.1$ is constant for each sensor node at each time slot



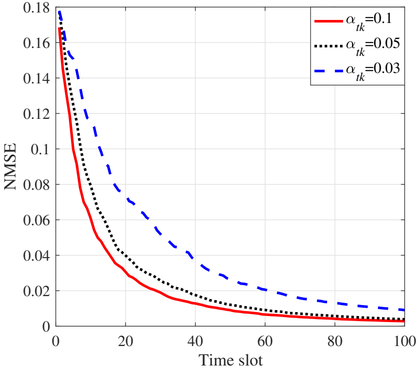
- $\text{NMSE} = ||\hat{\boldsymbol{\theta}}_t - \boldsymbol{\theta}||^2 / ||\boldsymbol{\theta}||^2$
- The proposed method performs slightly worse than distributed censoring but slightly better than randomly selected method

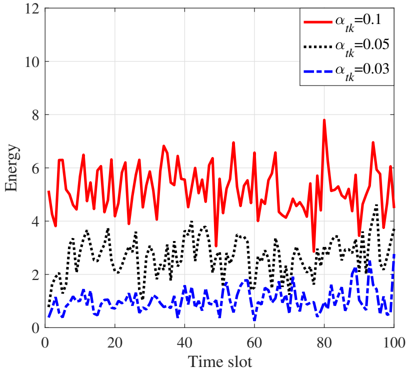
Energy consumption



- The method using all data has the largest energy consumption
- Energy consumptions of distributed censoring and random selection are basically the same
- The proposed method consumes the least energy than other methods

Robustness of the proposed method





a. Convergence performance

b. Energy consumption

- Appropriate choice of α_{tk} can achieve the trade-off between estimation performance and energy consumption

Outline

Conclusions

- The distributed censoring method with energy constraint for parameters estimation in WSNs is explored
- The energy cost is considered based on distributed censoring algorithm. The overall energy consumption of WSNs is reduced, with little estimation performance loss

Future work

- Maximize the network lifetime with the distributed censoring method
- Consider the data correlation in data censoring process

спасибо 谢谢

GRACIAS

THANK YOU

ありがとうございました MERCI

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