

Multiple Bits Distributed Moving Horizon State Estimation for Wireless Sensor Networks

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Outline

- Background
- Problem Statement
- Main Results
- Simulation Study
- Conclusion

Background

- Wireless sensor network (WSN) could be used to perform advanced signal processing tasks such as distributed detection and estimation.
- Environment monitoring and target tracking.
- Under bandwidth constraints——→quantization, only quantized observations are communicated.
- Dynamic systems state estimation.

Deterministic parameter estimators

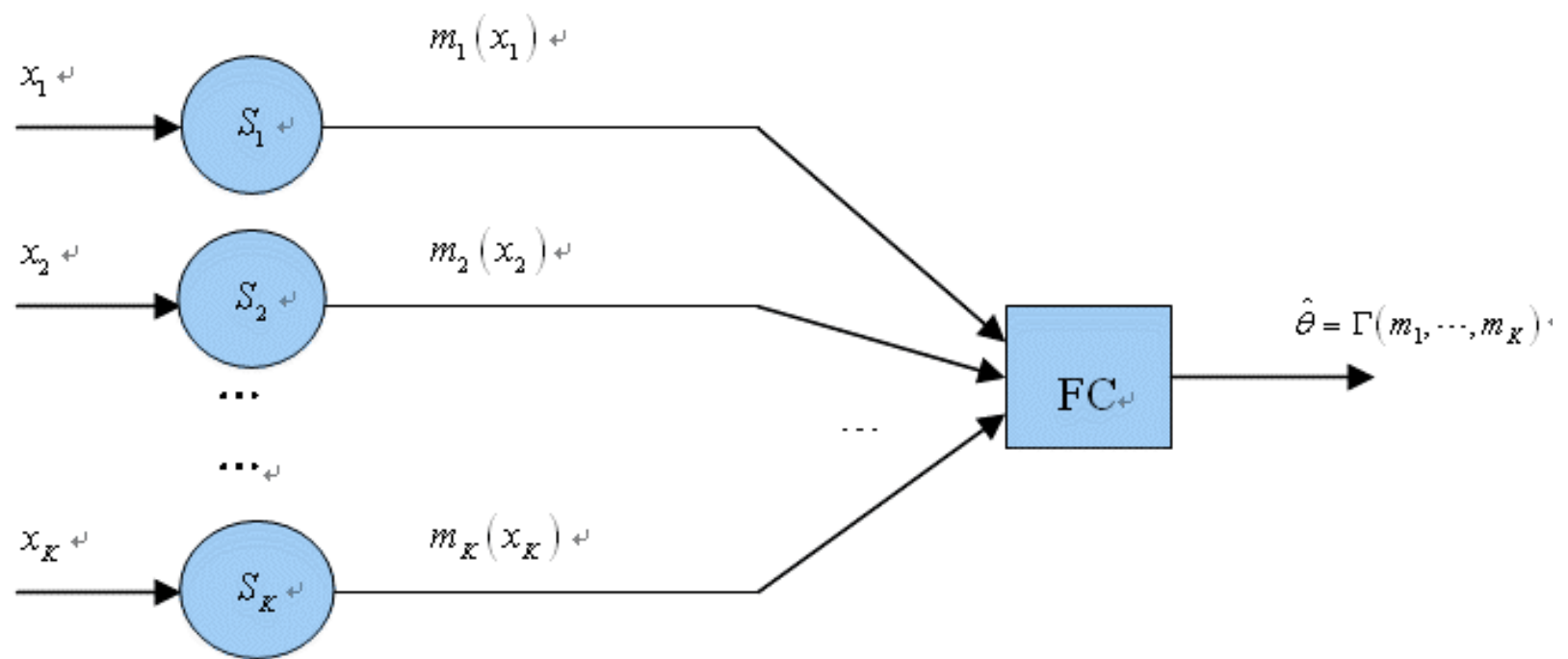
- Ribeiro and Giannakis etc. studied problems of maximum likelihood estimation under various noise assumption and signal and noise ratio (SNR) condition.
- Xiao and Luo etc. designed decentralized linear estimation schemes that do not require the knowledge of noise pdf, the estimator can be used in large scale WSN.

Distributed estimation framework

- Consider a generic distributed estimation problem using a WSN with an fusion center (FC)

$$x_k = \Phi_k(\theta) + w_k, \quad k = 1, \dots, K$$

where $\Phi_k : \mathbb{R}^p \rightarrow \mathbb{R}$ is generally a nonlinear function and the noise terms $w_k, k = 1, \dots, K$ are zero-mean independent random variables.



Distributed estimation setup.

If there is no quantization

- Consider the simple signal model:

$$x_k = \theta + w_k \quad k = 1, \dots, K$$

- The best linear unbiased estimator (BLUE):

$$\hat{\theta}_{BLUE} = \frac{\sum_{k=1}^K x_k / \sigma_k^2}{\sum_{k=1}^K 1 / \sigma_k^2}$$

- Mean-square error (MSE):

$$E \left\{ \left(\hat{\theta}_{BLUE} - \theta \right)^2 \right\} = \left(\sum_{k=1}^K 1 / \sigma_k^2 \right)^{-1}$$

- Especially, when $\sigma_k^2 = \sigma^2$, $\hat{\theta}_{BLUE} = \sum_{k=1}^K x_k / K$, whose MSE is known to be σ^2 / K .

Example I : ε -estimator

- Consider a set of K distributed sensors with observations

$$x_k = \theta + w_k \quad k = 1, \dots, K$$

- Let noise w_k be uniform over $[-U, U]$
- Local message functions are **binary**.

$$m_k(x_k) = \begin{cases} 1, & x_k \in S_k \\ 0, & x_k \notin S_k \end{cases}$$

where $S_k = \square^+$.

- An ε -estimator of θ : $\hat{\theta} = \Gamma(m_1, \dots, m_K)$ with

$$E\left(\left|\hat{\theta} - \theta\right|^2\right) \leq \varepsilon$$

- We have $P(m_k = 1) = \frac{U + \theta}{2U}$, $P(m_k = 0) = \frac{U - \theta}{2U}$,

$$E(m_k) = \frac{U + \theta}{2U}, \quad \forall k = 1, \dots, K$$

- Choose the final fusion function Γ as

$$\hat{\theta} = \Gamma(m_1, \dots, m_K) = -U + \frac{2U}{K} \sum_{k=1}^K m_k$$
$$E(\hat{\theta}) = \theta, \quad E(\hat{\theta} - \theta)^2 \leq U^2/K$$

- Requiring a total of $K = U^2/\varepsilon$ sensors to compute an ε -estimator for θ

Example II: A decentralized estimation scheme (DES) for the known sensor variances case

- Assume that fusion center knows sensor noise variances $\sigma_k^2, k=1, \dots, M$.
- Let $\alpha_k' = \sigma_k / \sigma_f$ and write $\alpha_k' = \beta_k + \gamma_k$ where β_k and γ_k are the integer and decimal parts of α_k' .
- Construct sensor k 's message function as

$$z_k = \beta_k + \gamma_k + \eta_k$$
 where η_k is a 0–1 binary random variable with

$$P(\eta_k = 1) = \gamma_k, P(\eta_k = 0) = 1 - \gamma_k$$

- The final estimator of θ at the fusion center is:

$$\hat{\theta} = \sum_{i=1}^M \left[\frac{1}{\sigma_i^2} \left(\hat{\theta}_i - \theta_0 \right) \right] \left[\sum_{i=1}^M \frac{1}{\sigma_i^2} \right]^{-1} + \theta_0$$

- $\hat{\theta}$ is an unbiased estimator of θ , and the MSE

$$E \left[\left(\hat{\theta} - \theta \right)^2 \right] = \left[\sum_{i=1}^M \frac{1}{\sigma_i^2} \right]^{-1}$$

Moving Horizon State Estimation

Consider a joint density over N states:

$$\{x^*(n-N+1), \dots, x^*(n)\} = \arg \max_{\{x(m)\}_{m=n-N+1}^n} p(x(n-N+1), \dots, x(n) | y(0), \dots, y(n))$$

Equivalent optimization:

$$\min_{x(n-N), \{w(m)\}_{m=n-N}^{n-1}} \sum_{m=n-N}^{n-1} \left(\|w(m)\|_{Q^{-1}}^2 + \|v(m)\|_{R^{-1}}^2 \right) + \underline{Z_{n-N}(x(n-N))}$$

prior information
arrival cost

subject to model:

$$x(n+1) = f(x(n)) + w(n)$$

$$y(n) = h(x(n)) + v(n)$$

$$w(n) \in W, v(n) \in V, x(n) \in X$$

What can moving horizon state estimation do?

Linear model
Gaussian noise
Stability



nonlinear model
Gaussian noise



Linear model
General noise
Inequality constraints
stability



nonlinear model
general noise
inequality constraints
stability

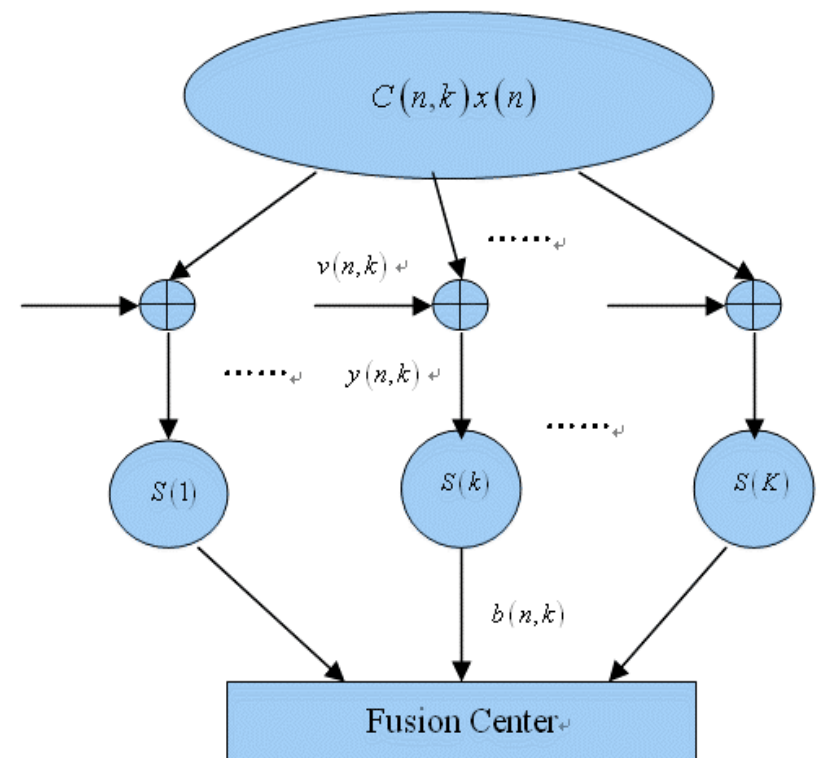


online “solution” to quadratic/nonlinear program

Problem Statement

- Let us consider a WSN with a fusion center
- ■ distributed sensors deployed with the objective of tracking a real random vector

$$x(n) \in \mathbb{R}^{p \times 1}$$



- The underlying system and sensor nodes observing processes can be modeled as

$$x(n) = A(n)x(n-1) + w(n) \quad n = 0, 1, 2, \dots$$

$$y(n, k) = C(n, k)x(n) + v(n, k) \quad k = 1, \dots, K$$

where

$$\begin{aligned} &A(n) = \begin{bmatrix} a_{11}(n) & \dots & a_{1M}(n) \\ \vdots & \ddots & \vdots \\ a_{M1}(n) & \dots & a_{MM}(n) \end{bmatrix}, \quad w(n) = \begin{bmatrix} w_1(n) \\ \vdots \\ w_M(n) \end{bmatrix}, \\ &C(n, k) = \begin{bmatrix} c_{1k}(n) & \dots & c_{1M}(n) \\ \vdots & \ddots & \vdots \\ c_{Mk}(n) & \dots & c_{MM}(n) \end{bmatrix}, \quad v(n, k) = \begin{bmatrix} v_{1k}(n) \\ \vdots \\ v_{Mk}(n) \end{bmatrix}, \\ &w(n) \sim \mathcal{N}(0, Q), \quad v(n, k) \sim \mathcal{N}(0, R_k), \quad Q, R_k \text{ are positive semi-definite matrices.} \end{aligned}$$

Assumption

- This communication takes place over the shared wireless channel that we will assume can afford transmission of a single packet per time slot .
- Leading to a one-to-one correspondence between time n and sensor index t and allowing us to drop the sensor index t .
- Which sensor is active at time n depends on the underlying scheduling algorithm.

Quantization

- Observation model:

$$y(n) = C(n)x(n) + v(n)$$

- Define a set of thresholds $\{\tau_i, i \in \mathbb{N}\}$, $\tau = \tau_i - \tau_{i-1}$

$$b_i(n) = \begin{cases} 1 & y(n) > \tau_i \\ 0 & y(n) \leq \tau_i \end{cases}$$

- Each $b_i(n)$ is a Bernoulli random variable with parameter

$$q_i(g(n)) = \Pr\{b_i(n) = 1\} = F(\tau_i - C(n)x(n)) = F(\tau_i - g(n)) \quad i \in \mathbb{N}$$

where $v(n) \sim \mathcal{N}(0, \sigma^2)$

- Sensor obtains total binary observation at time n :

$y_n = [y_{n,1}, y_{n,2}, \dots, y_{n,K}]$

- Without loss of generality, we will assume that $y_{n,i} \in \{0, 1\}$, when $y_{n,i} = 1$, $y_{n,i}$ can only take on realizations $y_{n,i} = [y_{n,i,1}, y_{n,i,2}, \dots, y_{n,i,K_i}]$ when $y_{n,i} = 0$, $y_{n,i}$

Main results

- If there is no quantization, we can obtain the estimate of state by



- Methods
 - Batch filter
 - Kalman filter
 - Moving horizon estimate
 - Particle filter etc.

State estimation using quantized observations

- Consider a joint density over N states:

$$p(\mathbf{x}_1, \dots, \mathbf{x}_N) = \prod_{i=1}^N p(\mathbf{x}_i) \prod_{i=1}^{N-1} p(\mathbf{x}_{i+1} | \mathbf{x}_i)$$

- Approximate optimization:

$$\min_{\mathbf{x}_1, \dots, \mathbf{x}_N} \sum_{i=1}^N \sum_{j=1}^M \sum_{k=1}^M \mathbb{1}_{\{y_{i,j} \neq k\}} \quad \text{subject to } p(\mathbf{x}_1, \dots, \mathbf{x}_N) > 0$$

where

$$\mathbb{1}_{\{y_{i,j} \neq k\}} = \begin{cases} 1 & \text{if } y_{i,j} \neq k \\ 0 & \text{otherwise} \end{cases}$$

- Online “solution” to nonlinear program**

- If $\mathbf{y} = [y_1, y_2, \dots, y_n]$, then $\mathbf{y} = \mathbf{A}\mathbf{x}$, the thresholds are $\mathbf{t} = [t_1, t_2, \dots, t_n]$, the binary observations are $\mathbf{z} = [z_1, z_2, \dots, z_n]$
- Approximate optimization is :

$$\mathbf{z} = \mathbf{A}\mathbf{x} + \mathbf{e}$$

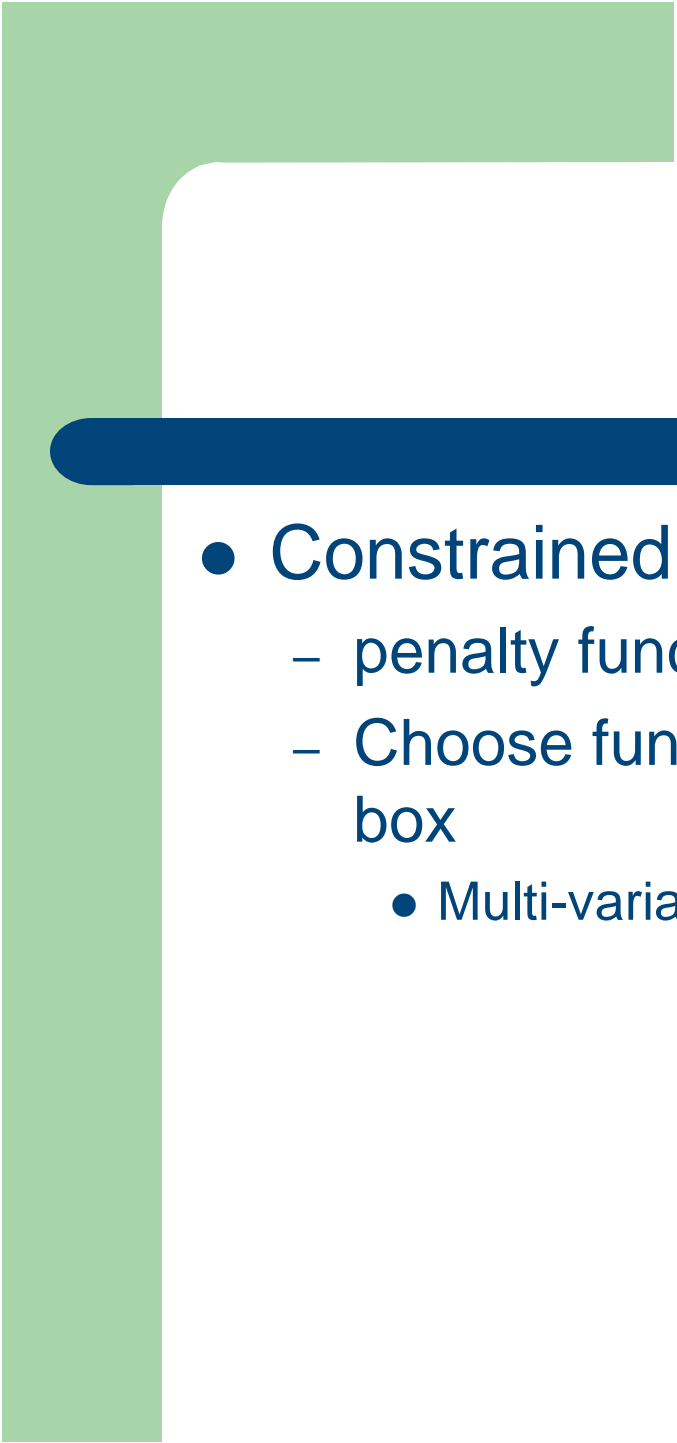

$$z_i = \sum_{j=1}^m a_{ij}x_j + e_i$$

Solution steps of moving horizon state estimation for WSN

- Initialization
- At time n \longrightarrow $\hat{x}_{n|n}$, by using state transfer equation $\hat{x}_{n+1|n} = A_n \hat{x}_{n|n} + B_n u_n$, obtain $\hat{x}_{n+1|n}$.
- Only $\hat{x}_{n+1|n}$ reserve as final estimate at time $n+1$.
- At time $n+1$, obtain $\hat{x}_{n+2|n+1}$.
- Only $\hat{x}_{n+2|n+1}$ reserve as final estimate at time $n+2$.

Matlab toolbox

- Unconstrained nonlinear programming
 - halver method
 - Newton method
 - Choose functions of MATLAB optimization toolbox
 - One variable: `fminbnd`, `fminsearch`, `fminunc`
 - Multi-variable: `fminsearch`, `fminunc`

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- Constrained nonlinear programming
 - penalty function method
 - Choose functions of MATLAB optimization tool box
 - Multi-variable : fmincon

The application of Multi-bit DMHE in target tracking

- Consider N sensors randomly and uniformly deployed in a square region of 100×100 meters and suppose that sensor positions are known



- New observation equation obtained by DES method

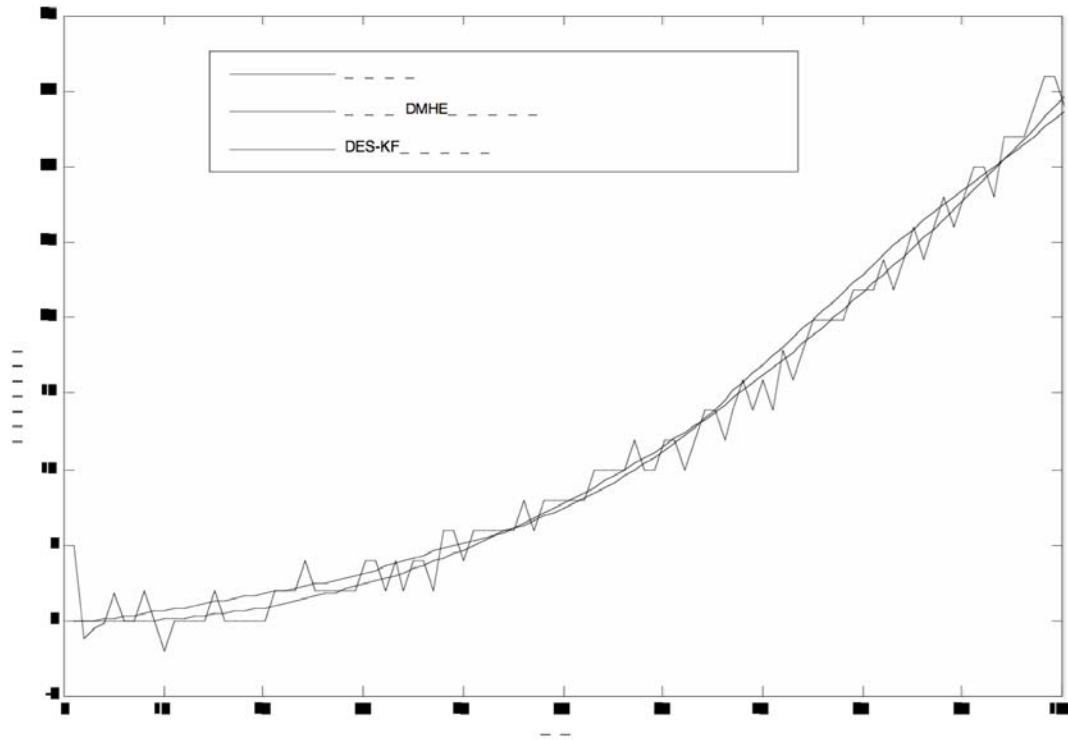
$$z_k = \begin{bmatrix} x_k \\ y_k \end{bmatrix} + \begin{bmatrix} v_{k1} \\ v_{k2} \end{bmatrix}$$

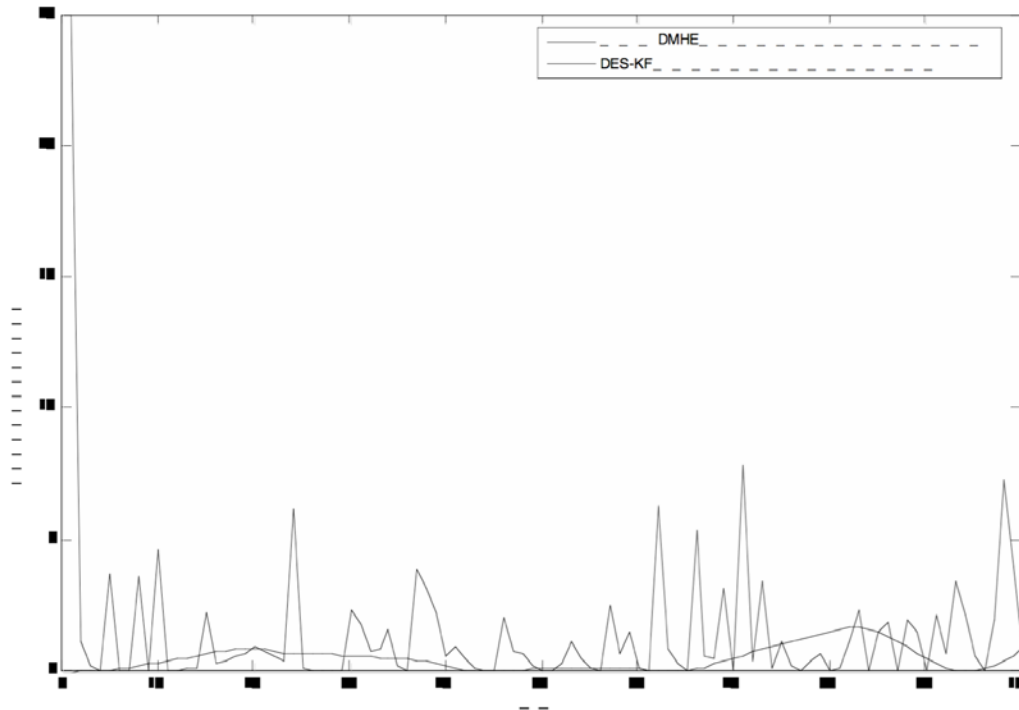
with distribution $v_k \sim \mathcal{N}(\mathbf{0}, R)$

- Suppose only one sensor node works at a time slot, then the observations are given by



Items / Methods	The number of sensors sending information	The most bits transmitted by one node		Threshold changes or not	Estimation performance $J = \sum_{n=1}^{100} (x(1,n) - \hat{x}(1,n))^2$
DES-KF	K=1	5.9149		No	147.4031
	K=5	5.9149		No	34.0500
	K=10	5.9149		No	15.7701
Multi-bit DMHE (N=3)	K=1	$\tau = 1$	6.6439	Yes	38.0754
		$\tau = 0.8$	6.9149	Yes	18.3789
		$\tau = 0.5$	7.6439	Yes	12.1556





Conclusion

- An important problem of wireless sensor network signal processing is that bandwidth is limited, quantization of observations is necessary.
- A dynamic state estimation problem in the context of WSN has been considered.
- Develop a moving horizon state estimation method based on several quantized data for WSN.



Thanks!