

# Cramer-Rao Bounds for Distributed System Size Estimation Using Consensus Algorithms

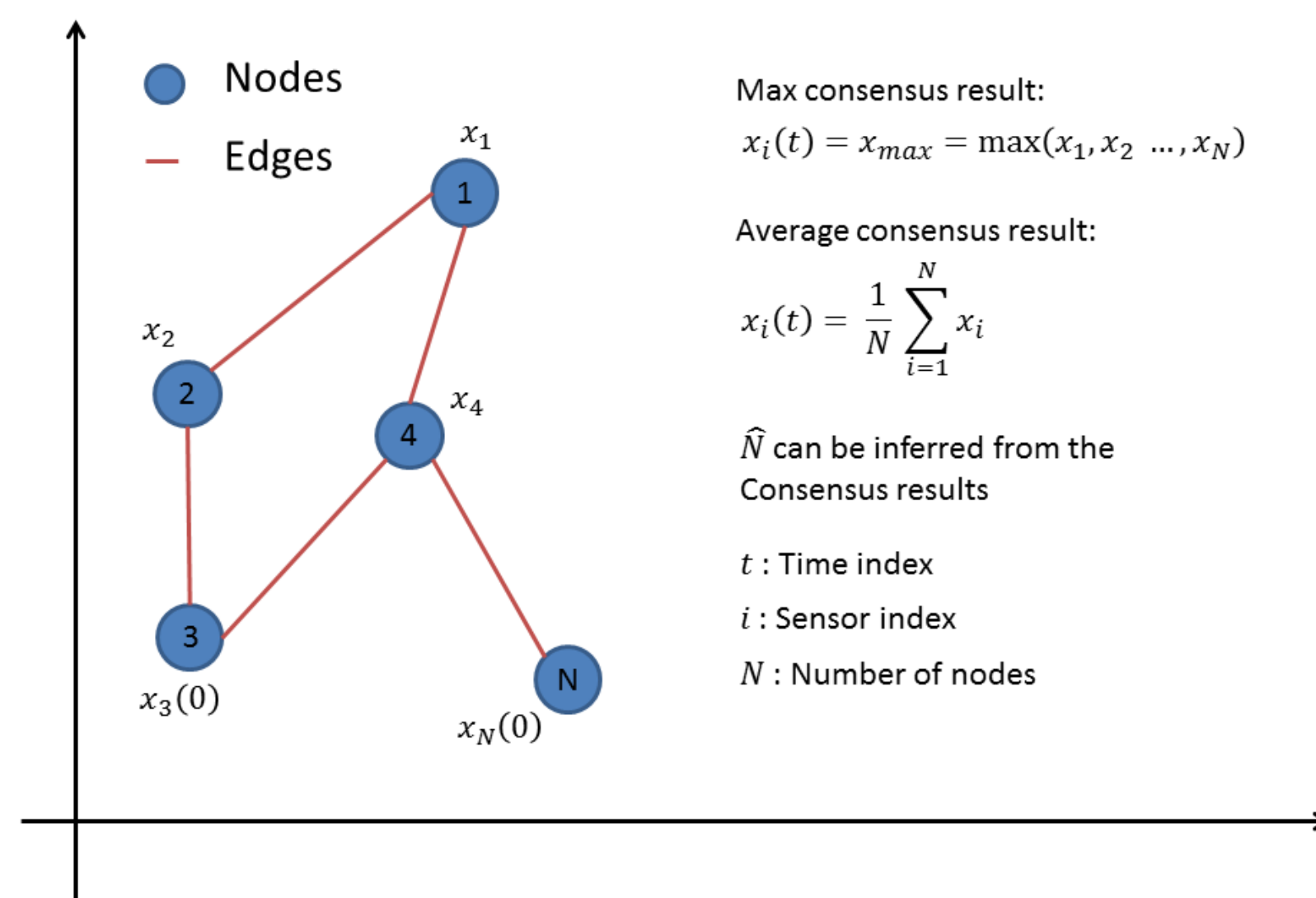
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## INTRODUCTION AND MOTIVATION

- Wireless sensor networks (WSNs) with no fusion center
- Estimate the system size (total number of sensors) of WSNs
- Applications: network maintenance, detect nodes join or leave the network

## PROBLEM STATEMENT

- Count number of nodes using consensus
- Random initial values,  $x_i$  generated at nodes
- Different consensus algorithms:
  - Max consensus
 
$$x_i(t+1) = \max \left\{ x_i(t), \max_{j \in \mathbb{N}_i} x_j(t) \right\}$$
  - Average consensus
 
$$x_i(t+1) = W_{ii}x_i(t) + \sum_{j \in \mathbb{N}_i} W_{ij}x_j(t)$$
- System size inferred from the consensus results
- Problem: performance is affected by:
  - Types of consensus algorithm
  - Initial values,  $x_i$
- Performance analysis: Fisher information (FI) and Cramer-Rao bounds (CRBs)



## RESULTS: FI AND CRBS UNDER DIFFERENT CASES

### Max Consensus in the Absence of Noise

#### Theorem

Assume the initial values at nodes  $x_i$  are i.i.d. with PDF  $f(x)$  and CDF  $F(x)$ , and  $f(x)$  is differentiable. When max consensus is used, the Fisher information for estimate of system size  $N$  is,

$$\mathcal{I}_{\max} = \frac{1}{N^2}.$$

The CRB is the inverse of the Fisher information, and a lower bound on the estimation variance can be expressed as

$$\text{Var}[\hat{N}] \geq N^2.$$

The distribution of the initial values at nodes does not affect the Fisher information and CRB.

### Average Consensus in the Absence of Noise

#### Theorem

Assume the initial values at nodes  $x_i$  are i.i.d. with mean  $\mu$  and variance  $\sigma^2$ . Also assume that  $N$  is large. When average consensus is used, the Fisher information for estimate of system size  $N$  is

$$\mathcal{I}_{\text{avg}} = \frac{1}{2N^2}.$$

The CRB is the inverse of the Fisher information, and a lower bound on the estimation variance can be expressed as

$$\text{Var}[\hat{N}] \geq 2N^2.$$

### Max Consensus with Noise

#### Theorem

Assume the initial values at nodes  $x_i$  have exponential tail and its tail PDF  $\lambda e^{-\lambda x}$ . The distribution of the max of the initial values can be approximated using Gumbel distribution. Assume that the final error at nodes is Gaussian distributed  $e \sim \mathcal{N}(\mu_e, \sigma_e^2)$ . The Fisher information for estimate of system size  $N$  is bounded by

$$\mathcal{I}_{\text{nmax}} \leq \left( \frac{1}{N^2} \right) \left( \frac{\lambda^{-2}}{\sigma_e^2 + \lambda^{-2}} \right).$$

The CRB is the inverse of the Fisher information, and a lower bound on the estimation variance can be expressed as

$$\text{Var}[\hat{N}] \geq N^2 (\sigma_e^2 \lambda^2 + 1).$$

### Average Consensus with Noise

#### Theorem

Assume the initial values at nodes  $x_i$  are i.i.d. with mean  $\mu$  and variance  $\sigma^2$ , the final error at nodes is Gaussian distributed  $e \sim \mathcal{N}(0, \sigma_e^2)$ . Also assume that  $N$  is large. When average consensus is used, the Fisher information for estimate of system size  $N$  is

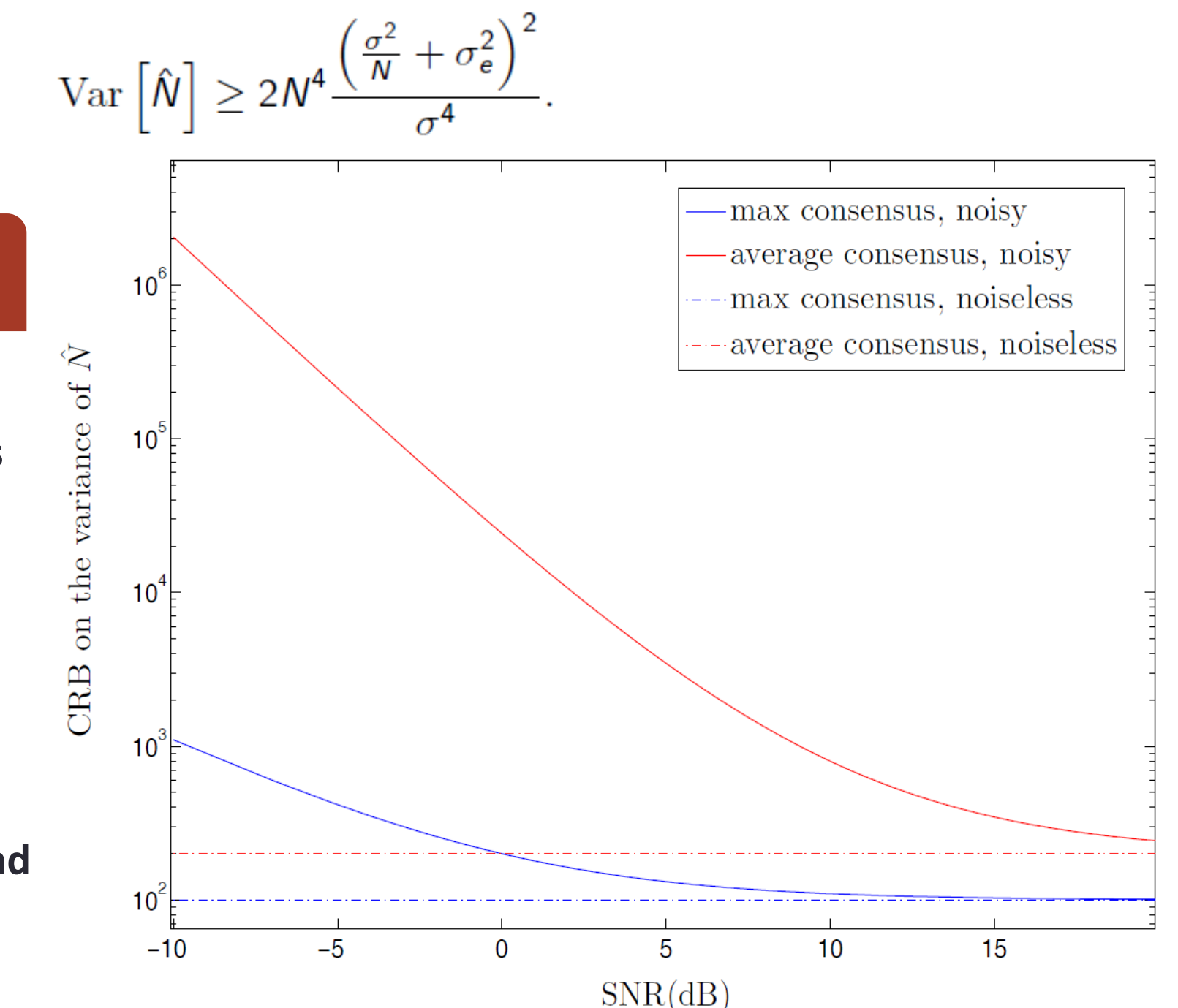
$$\mathcal{I}_{\text{avg}} = \frac{1}{2N^4} \left( \frac{\sigma^4}{\left( \frac{\sigma^2}{N} + \sigma_e^2 \right)^2} \right).$$

When  $N$  is large,  $\mathcal{I}_{\text{avg}} \approx \frac{1}{2N^4} \left( \frac{\sigma^2}{\sigma_e^2} \right)^2 = \frac{1}{2N^4} (\text{SNR})^2$ , where SNR is defined as  $\text{SNR} = \frac{\sigma^2}{\sigma_e^2}$ . The CRB is the inverse of the Fisher information, and a lower bound on the estimation variance can be expressed as

$$\text{Var}[\hat{N}] \geq 2N^4 \frac{\left( \frac{\sigma^2}{N} + \sigma_e^2 \right)^2}{\sigma^4}.$$

## CONCLUSIONS

- For max consensus without noise,  $x_i$  does not affect Fisher information and Cramer-Rao Bound
- Max consensus has lower CRB (noiseless case)
- How noise affect FI and CRB is presented



## REFERENCES

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## ACKNOWLEDGMENT

This work is funded in part NSF award ECCS – 13079282 and the SenSIP Center, School of ECEE, Arizona State University

