Scalable Information-Driven Sensor Querying and Routing for ad-hoc Heterogeneous Sensor Networks

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Introduction

- Focus: sensor networks that are applicable to tracking and identification problems
- Necessities:
  - Novel routing and
  - Collaborative signal processing algorithms
- Key for scalability, low latency and energy awareness in large sensor networks

Introduction

- The paper presents 2 techniques:
  - IDSQ
  - CADR
- Information utility measure to select sensors
- Dynamically guide data routing
  - Maximize information gain
  - Minimize detection latency and BW consumption
  - Minimize power consumption
- Generalization of directed diffusion

Sensing Model

- General form:

$$z_i(t) = \mathbf{h}(x(t), \lambda_i(t))$$

- Linear measurements:

$$\mathbf{h}(x(t), \lambda_i(t)) = \mathbf{H}_i(t)x(t) + w_i(t)$$

- Acoustic sensors:

$$z_i = \frac{a}{||x_i - x||^{\alpha/2}} + w_i, \lambda_i = [x_i, \sigma_i^2]$$

Estimation

- Blief:

$$p(x|z_1, \ldots, z_N)$$

- Estimate:

$$\widehat{x} = \mathbf{E}[x|z_1, \ldots, z_N]$$

- Uncertainty:

$$\Sigma_{\widehat{x}} = \mathbf{E}[(x - \bar{x})(x - \bar{x})^T|z_1, \ldots, z_N]$$

Problem Formulation

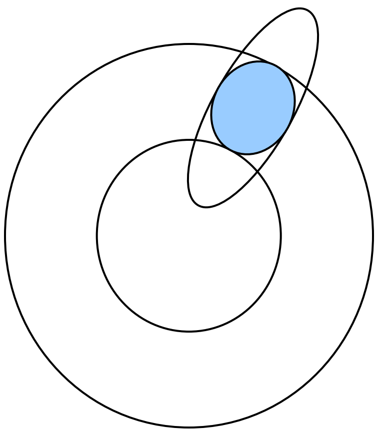
- Querying a sensor is costly
- Thus sensor characteristics and measurements reside in the individual sensors
- Goal:
  - Select good subset of sensors
  - While reducing communication costs

Information Utility Measures

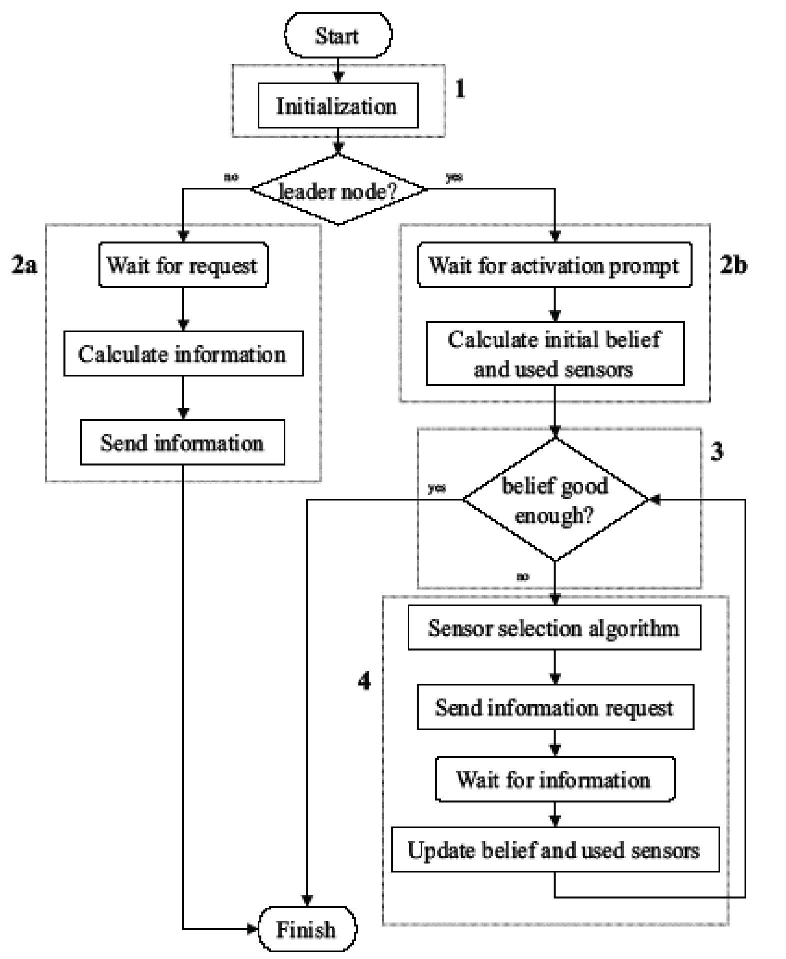
- $\psi(p_x) = -\mathbf{det}(\Sigma)$
- $\psi(p_x) = -\mathbf{Tr}(\Sigma)$
- $\psi(p_x) = -h(p_x)$
- $\psi(p_x) = -\mathbf{vol}(\Gamma_\beta)$

$\Gamma_\beta = \{x \in S : p(x) \geq \beta\}$

- $\psi(p_x) = (x_j - \widehat{x})^T \Sigma^{-1} (x_j - \widehat{x})$



Information Driven Sensor Querying



Composite Objective Function

- Up till now, ignored communication cost
- Composite Objective Function:

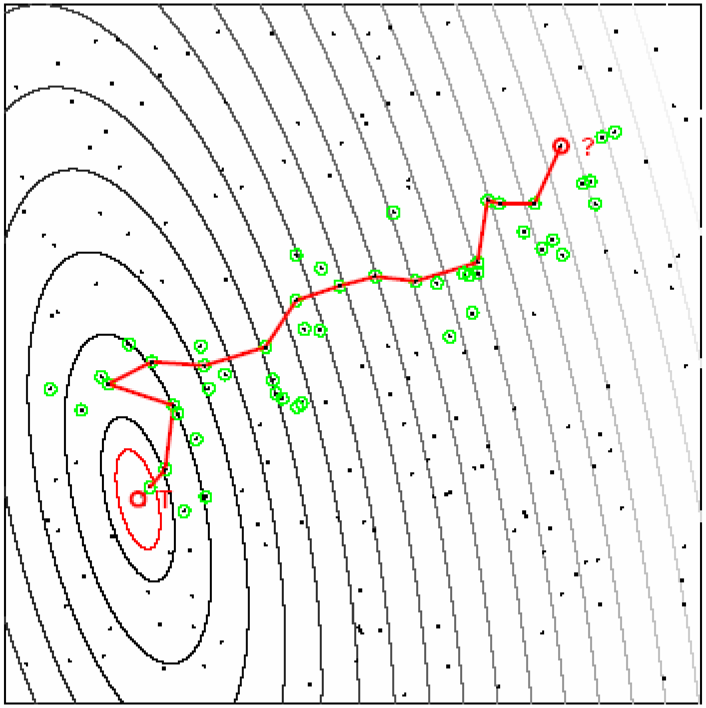
$$M_c(\lambda_l, \lambda_j, p(x|\{z_i\}_{i \in U})) =$$
$$\gamma M_u(p(x|\{z_i\}_{i \in U}), \lambda_j) - (1-\gamma) M_a(\lambda_l, \lambda_j)$$

- *Eg.*

$$\begin{aligned} M_u(x_j, \widehat{x}, \Sigma) &= -(x_j - \widehat{x})^T \Sigma^{-1} (x_j - \widehat{x}) \\ M_a(x_j, x_l) &= (x_j - x_l)^T (x_j - x_l) \end{aligned}$$

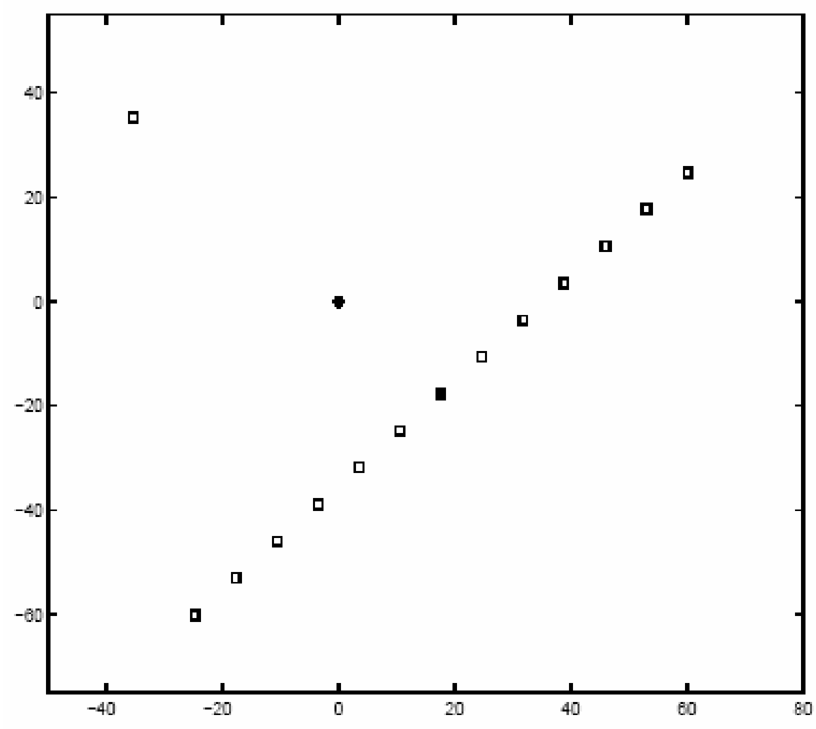
Constrained Anisotropic Diffusion Routing

- Global knowledge of sensor properties:
  $x_o = \arg_x[M_c = 0]$
- w/o global knowledge
  - The node that locally maximizes M_c
  - Steepest gradient
  - Composite
- Incremental updates
- Local computations

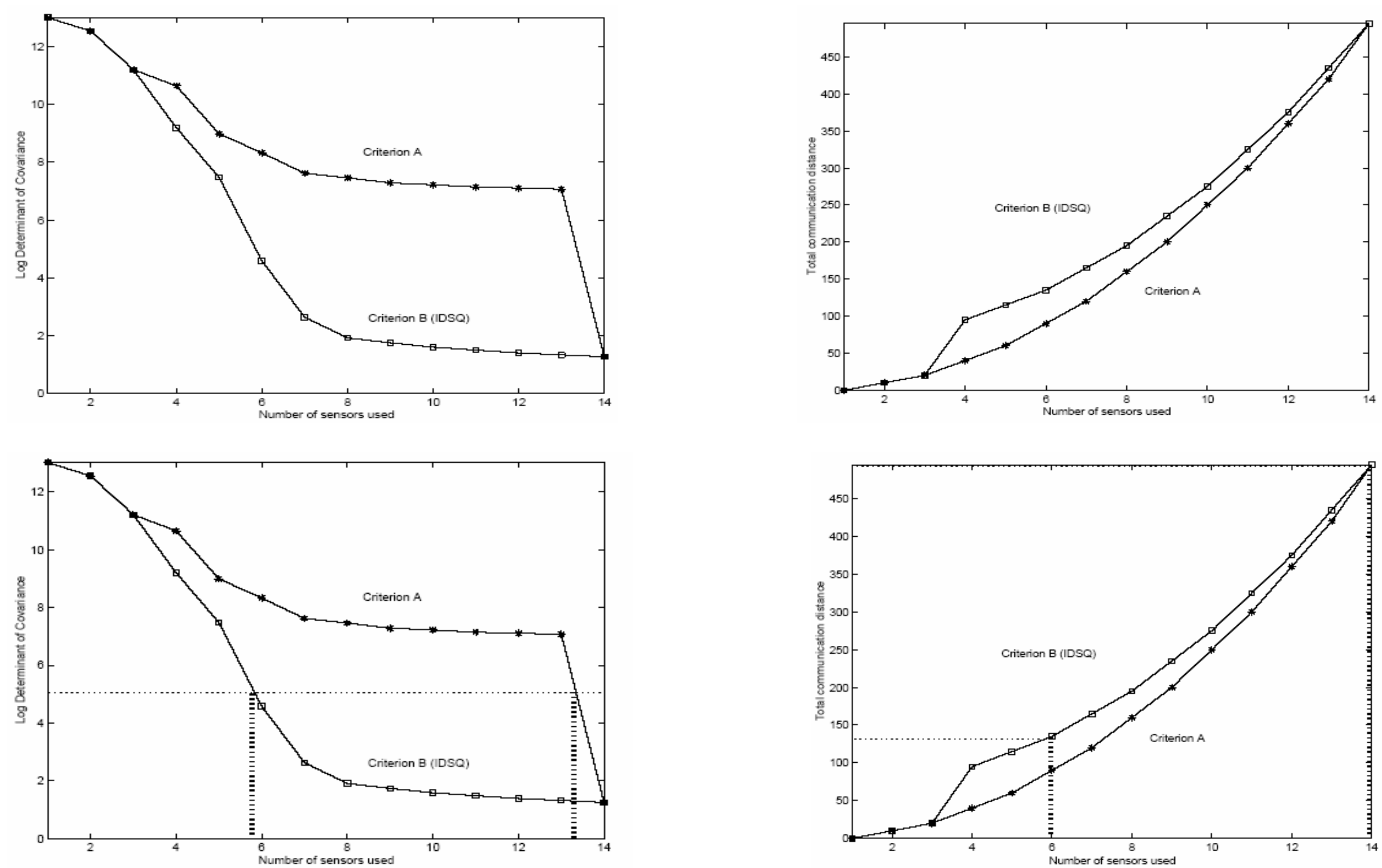


Experimental Results - IDSQ

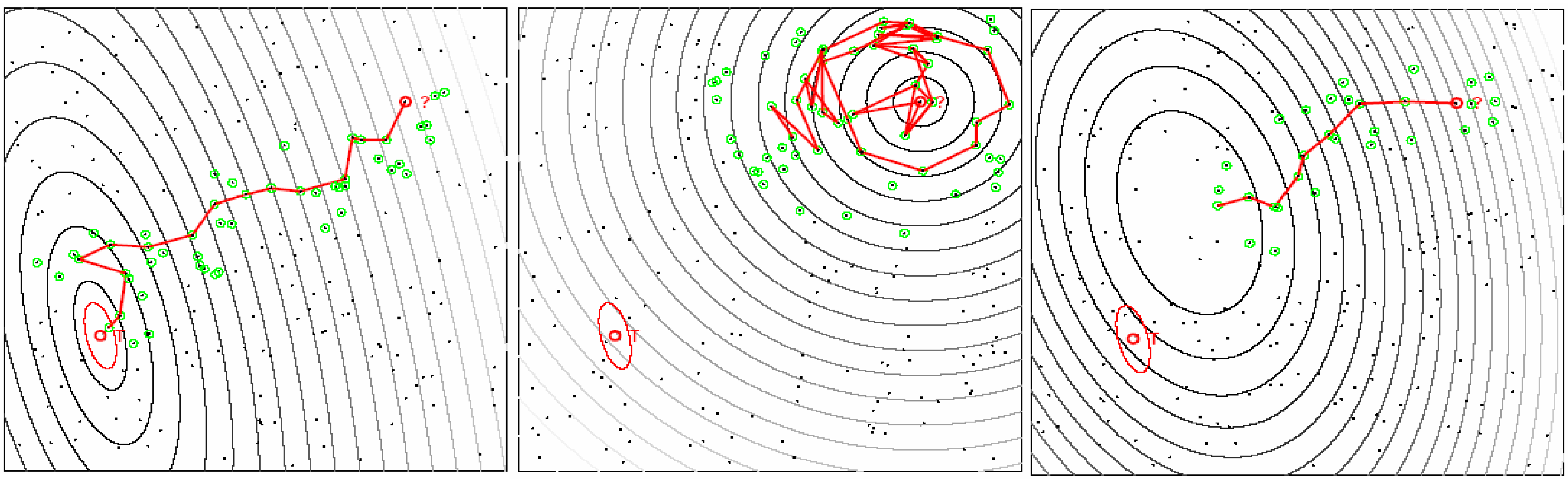
- Sensor model: $z_i = \frac{a}{||x_i - x||^{\alpha/2}} + w_i,$
- Leader is the centroid sensor
- Others selected one at a time by leader
- Sensor selection is performed:
  A. Nearest Neighbor
  B. Mahalanobis Dist.



Experimental Results - IDSQ



Experimental Results - CADR



$\gamma = 1$ $\gamma = 0$ $\gamma = 0.2$

Discussion

- Belief Representation
  - Parametric – Gaussian
  - Particle filters
- Updates:
  - Kalman filter
  - EKF
  - Particle re-sampling

Conclusion

- A new approach to distributed, collaborative signal processing in sensor networks is presented
- Two key ideas outlined:
  - IDSQ – Based on information gain
  - CADR – Additional constraints (energy, communication)
- Incremental update of the belief
- Local computations
- Presented experimental results