CS649
Sensor Networks
IP Track Lecture 3: Distributed Target Tracking in Sensor Networks

I-Jeng Wang

http://hinrg.cs.jhu.edu/wsn06/

Multiple Target Tracking in Wireless Sensor Networks

- Problem: Based on distributed sensor measurements, senor nodes collaborate to detect presence of targets of interests, estimate and update (track) states (position, velocity, etc.) of targets over time.
- Key Challenges:
  - Data/information dissemination, management, and storage
  - Dynamic resource allocation and control
  - Combining measurements from multiple and potentially multimodal sensors (data fusion problem)
  - Multiple target disambiguation
  - Operating under uncertainty
  - Real-time constraints

Traditional (Centralized) Multiple Target Tracking (MTT) Problem

- Measurements (radar returns, acoustic detections, etc.) arrives over time and are typically processed at a centralized location
- Two Key Sub-Problems
  - Data association: find a partition of observations such that each element of a partition is a collection of observations generated by a single target or clutter
  - State estimation: incrementally estimate and update the state (position) of each target over time
  - Two problems are intertwined
- Other Important Issues
  - Track initiation and management
  - Target identification and classification

Basic Formulation of Bayesian Tracking for a Single Target*

- State transition model

$$\mathbf{x}_k = \mathbf{f}_k(\mathbf{x}_{k-1}, \mathbf{v}_{k-1})$$

i.i.d. process noise

- Measurement model

$$\mathbf{z}_k = \mathbf{h}_k(\mathbf{x}_k, \mathbf{n}_k)$$

i.i.d. measurement noise

- Bayesian filter (tracker)

Belief update $$p(\mathbf{x}_k|\mathbf{z}_{1:k}) = \frac{p(\mathbf{z}_k|\mathbf{x}_k)p(\mathbf{x}_k|\mathbf{z}_{1:k-1})}{p(\mathbf{z}_k|\mathbf{z}_{1:k-1})}$$

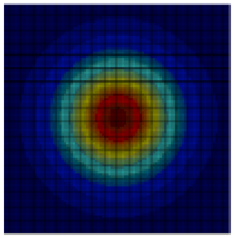
Prediction $$p(\mathbf{x}_k|\mathbf{z}_{1:k-1}) = \int p(\mathbf{x}_k|\mathbf{x}_{k-1})p(\mathbf{x}_{k-1}|\mathbf{z}_{1:k-1})\,d\mathbf{x}_{k-1}$$

Normalization $$p(\mathbf{z}_k|\mathbf{z}_{1:k-1}) = \int p(\mathbf{z}_k|\mathbf{x}_k)p(\mathbf{x}_k|\mathbf{z}_{1:k-1})\,d\mathbf{x}_k$$

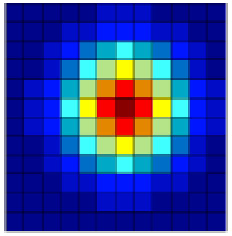
*M.S. Arulampalam, S. Maskell, N. Gordon, and T. Clapp, "A Tutorial on particle filters for online nonlinear/non-gaussian Bayesian tracking," IEEE Transactions on Signal Processing, vol. 50, no. 2, 2002.

Specific Bayesian Tracking Algorithms

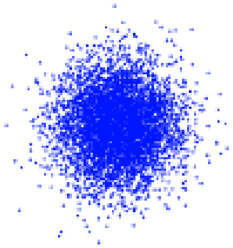
- Kalman Filter
  - Linear state transition and measurement models
  - Gaussian process and measurement noises
  - Bayesian filter reduces to sequential updates of mean and covariance matrix of the state
  - Extended Kalman filter for nonlinear cases via linearization
- Grid-Based Methods
  - Discrete state space (or discretize the state space as an approximation)
  - Update posterior probability at the discrete states
- Particle Filtering Methods
  - Approximate the brief function by randomly sample the state space using sequential Monte Carlo techniques



Gaussian (Parametric)



Grid



Particles

Traditional Data Association Approaches for MTT

- Nearest neighbor (possibly with assignment algorithms)
  - Associate with each track the measurement closest to its prediction (either Euclidean or Mahalanobis distance)
- Multiple Hypothesis Tracker (MHT)
  - Simultaneously maintain multiple hypotheses of association that has high scores
  - Dynamically prune or discard hypotheses to avoid explosion of number of hypotheses
- Joint Probability Data Association (JPDA)
  - Associate all measurements with high prediction scores to each track
  - Update the belief with all measurements
- Comparisons and Implementation Issues for Sensor Networks

Information-Driven Dynamic Sensor Collaboration for Tracking Applications

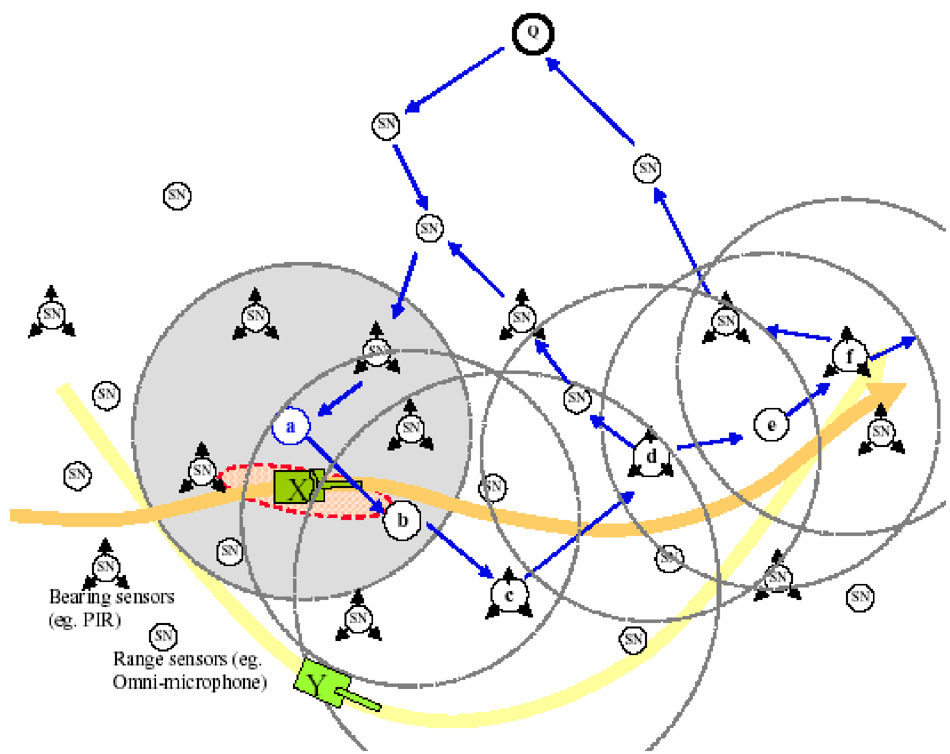
Feng Zhao

Jaewon Shin

James Reich

IEEE Signal Processing Magazine, 2002

A Tracking Scenario



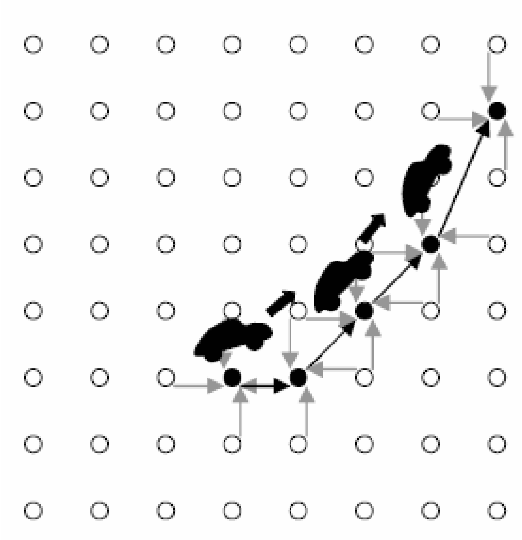
- *Discovery*: Node *a* detects *X* and initializes tracking
- *Query Processing*: A query is routed toward region of interest (around *a*)
- *Collaborative Processing*: Node *a* collaborate with other nodes to estimate the target states
- *Communication*: *a* hands off estimate to *b*, *b* to *c*, etc.
- *Reporting*: Node *d* or *f* reports tracking information back to the querying node
- *Data Association* if multiple targets

Basic Setting and the Leader-Based Approach (Single Target)

$$\boxed{p(\mathbf{x}^{(t+1)} | \overline{\mathbf{z}^{(t+1)}})} \propto p(\boxed{\mathbf{z}^{(t+1)}} | \mathbf{x}^{(t+1)}) \cdot \int p(\mathbf{x}^{(t+1)} | \mathbf{x}^{(t)}) \cdot \boxed{p(\mathbf{x}^{(t)} | \overline{\mathbf{z}^{(t)}})} \, d\mathbf{x}^{(t)}$$

updated belief — new data — current belief

- At any time instant, there is only one leader where
  - A new measurement is taken
  - Belief is updated based on Bayesian filtering
- The leader selects the new leader node from its neighborhood to handoff the tracking responsibility
  - Communicate the current belief to the new leader
- Minimize communication of measurements across nodes



Information-Directed Approach for Leader Selection

- Basic idea: Select sensors to collaborate (and the leader node for handoff) based on information utility measures and appropriate cost function (e.g. communications, energy)

measurements including data from node *j*

measurement from node *j*

$$O(p(\mathbf{x}|\boxed{\overline{\mathbf{z}_j^{(t)}}})) = \alpha\phi(p(\mathbf{x}|\overline{\mathbf{z}_{j-1}^{(t)}}, \boxed{\mathbf{z}_j^{(t)}})) - (1-\alpha)\psi(\mathbf{z}_j^{(t)})$$

Overall value by incorporating measurement from node *j*

Information utility of measurement from node *j* (e.g. mutual information)

Cost of incorporating measurement from node *j*

$$\hat{j} = \arg\max_{j \in A} O\left(p\left(\mathbf{x} \mid \{\mathbf{z}_i\}_{i \in U} \cup \{\mathbf{z}_j\}\right)\right)$$

Metrics for Information Utility

- Information-theoretic measure: Entropy

$$\varphi(p(\mathbf{x} \mid \{\mathbf{z}_i\}_{i\in U} \cup \{\mathbf{z}_j\})) \triangleq -H_p(x). \quad H_p(x) = -\int_S p(x)\log p(x)dx$$

- Mahalanobis distance measure

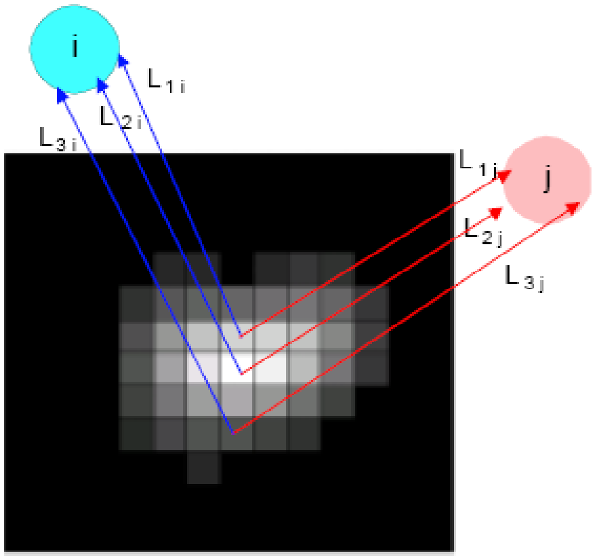
$$\varphi(\mathbf{x}_j, \hat{\mathbf{x}}, \hat{\Sigma}) = -(\mathbf{x}_j - \hat{\mathbf{x}})^T \hat{\Sigma}^{-1} (\mathbf{x}_j - \hat{\mathbf{x}})$$

- Expected posterior distribution

$$\hat{p}(\mathbf{x}^{(t+1)} \mid \overline{\mathbf{z}^{(t+1)}}) = C \cdot \hat{p}(\mathbf{z}_i^{(t+1)} \mid \mathbf{x}^{(t+1)}) \cdot p(\mathbf{x}^{(t+1)} \mid \overline{\mathbf{z}^{(t)}})$$

$$\hat{p}(\mathbf{z}_i^{(t+1)} \mid \mathbf{x}^{(t+1)}) = \sum_{v_k \in S(\mathbf{x}^{(t+1)})} L_{ki}(\mathbf{x}^{(t+1)}, v_k) \cdot \left[p(\mathbf{x}^{(t+1)} \mid \overline{\mathbf{z}^{(t)}}) \right|_{\mathbf{x}^{(t+1)} = v_k}$$

$$L_{ki}(\mathbf{x}^{(t+1)}, v_k) \triangleq \hat{p}(\mathbf{z}_i^{(t+1)}(\mathbf{x}^{(t+1)} = v_k) \mid \mathbf{x}^{(t+1)})$$



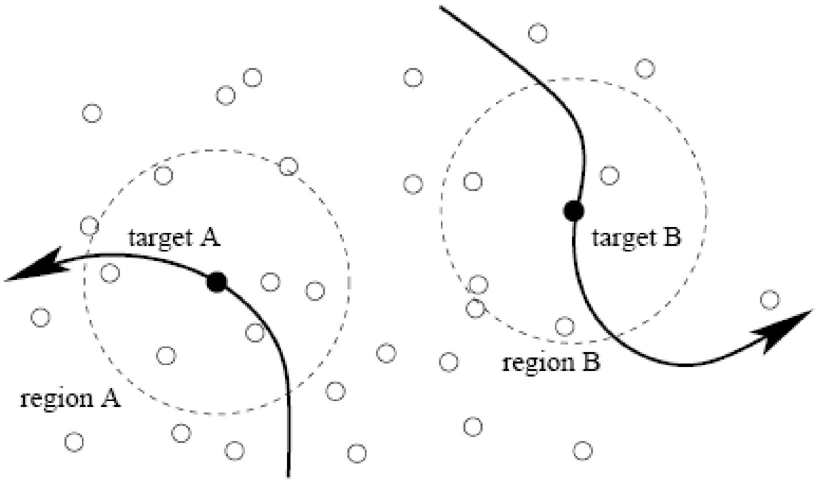
Pros and Cons of the Simple Leader-Based Approach

- Pros:
  - Minimizes communications of measurements
  - Good scalability with number of targets (only one active node for each target) if targets are well separated
  - Appropriate for network of low-power devices
- Cons:
  - Potential issue with many redundant tracks without proper track initiation and management
  - Difficulties in handling ambiguity with track collisions resulting from redundant tracks or target crossovers
  - Minimum use of collaborative signal processing to improve localization and tracking performance

Distributed Group Management for Track Initiation and Maintenance in Target Localization Applications

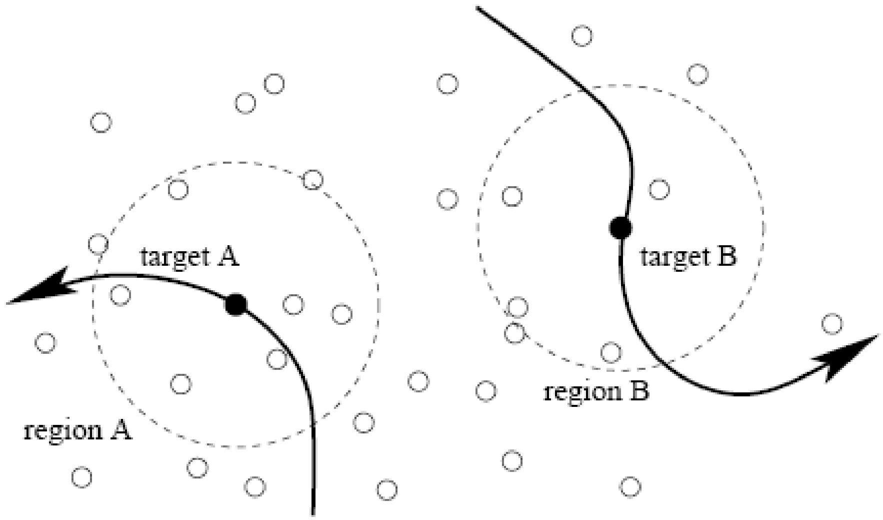
Juan Liu
Jie Liu
James Reich
Patrick Cheung
Feng Zhao
IPSN, 2003

Geographically Based Group Management



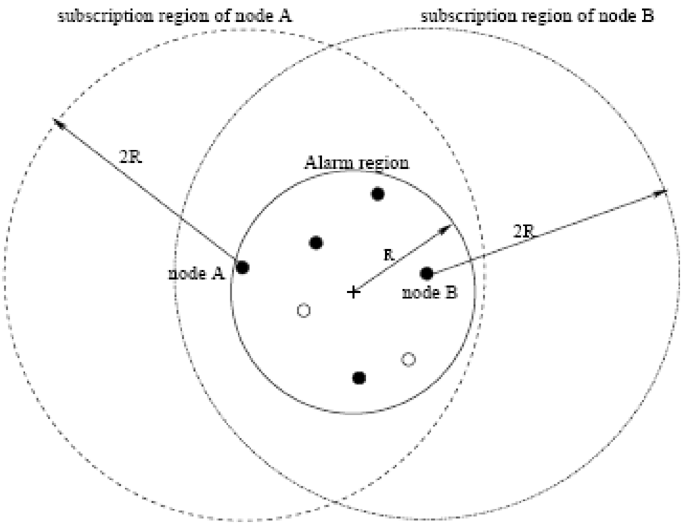
Geographically Based Group Management

- Dynamically form and maintain collaborative groups based on proximity
- At any point of time, each group has a unique leader and focuses on tracking a target using the leader-based tracking technique
- Information dissemination is constrained to each group using geographical-based routing protocols



Distributed Detection and Track Initiation

- Each node runs a stand-alone detection using the likelihood ratio detector
- Nodes with detection form a collaborative group and elect an leader by
  - Broadcast its detection (with detection time and score) to neighbors within 2*R* radius
  - Among all detect received within t_{comm} select an leader with earliest timestamp (or highest likelihood ratio if tied)
- The leader suppresses all nodes within radius 2*R* from further detection to prevent creation of redundant track
- The leader initializes the belief state and starts the tracking algorithm



Dynamic Group Maintenance Via Suppression and Unsuppression

- As the leader handoffs its responsibility to a new leader based on the information-based method, the leader use SUPPRESSION and UNSUPRESSION messages to update the group membership and prevent new detections of the same target from initiating redundant track
- The suppression region is determined based on the current belief state