CS649
Sensor Networks
IP Track Lecture 4-5: Distributed Target Tracking in Sensor Networks

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

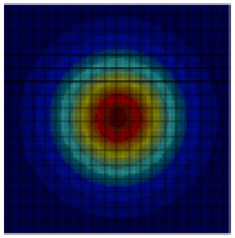
Prediction $$p(\mathbf{x}_k|\mathbf{z}_{1:k-1}) = \int p(\mathbf{x}_k|\mathbf{x}_{k-1})p(\mathbf{x}_{k-1}|\mathbf{z}_{1:k-1})\,d\mathbf{x}_{k-1}$$

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

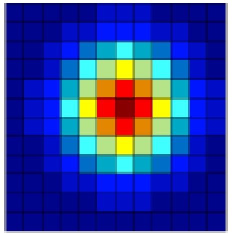
*M.S. Arulampalam, S. Maskell, N. Gordon, and T. Clapp, "A Tutorial on particle filters for online nonlinear/non-gaussian Bayesian tracking," IEEE Transactions on Signal Processing, vol. 50, no. 2, 2002.

Specific Bayesian Tracking Algorithms

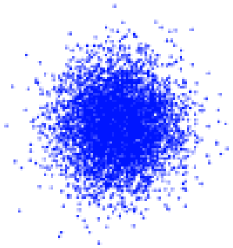
- Kalman Filter
  - Linear state transition and measurement models
  - Gaussian process and measurement noises
  - Bayesian filter reduces to sequential updates of mean and covariance matrix of the state
  - Extended Kalman filter for nonlinear cases via linearization
- Grid-Based Methods
  - Discrete 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

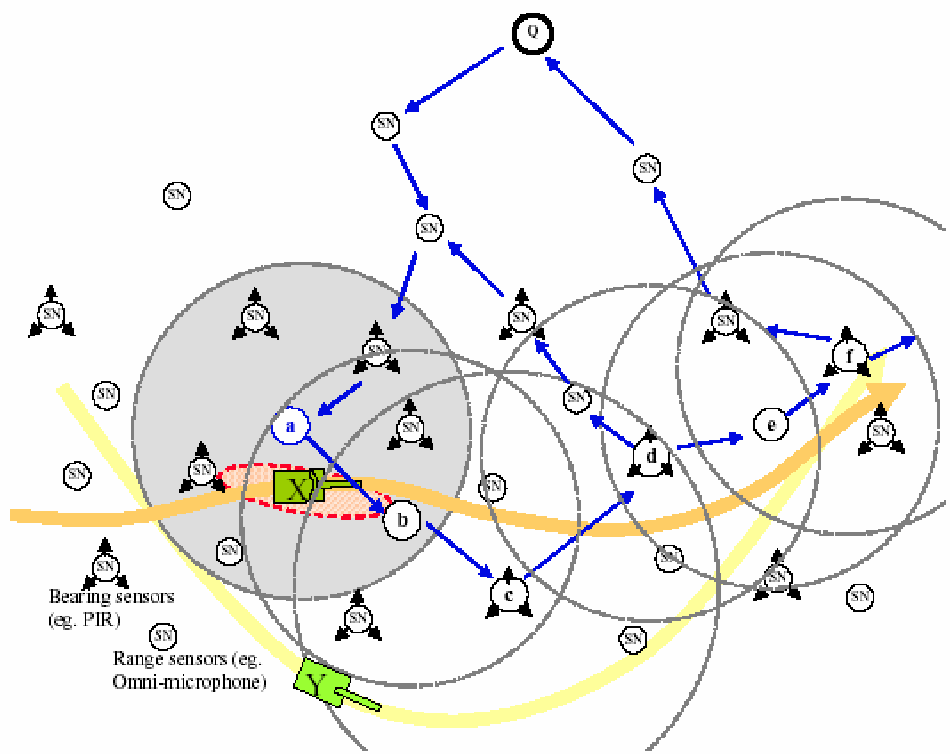
Traditional Data Association Approaches for MTT

- 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

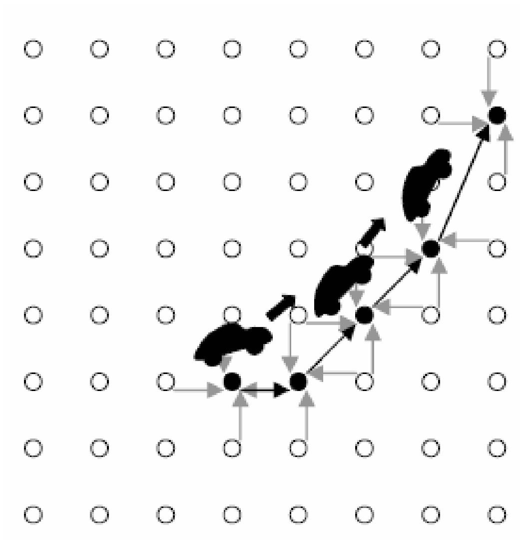


- *Discovery*: Node *a* detects *X* and initializes tracking
- *Query Processing*: A query is routed toward region of interest (around *a*)
- *Collaborative Processing*: Node *a* collaborate with other nodes to estimate the target states
- *Communication*: *a* hands off estimate to *b*, *b* to *c*, etc.
- *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)

$$\underbrace{\boxed{p(\mathbf{x}^{(t+1)} \mid \overline{\mathbf{z}^{(t+1)}})}}_{\text{updated belief}} \propto p(\underbrace{\boxed{\mathbf{z}^{(t+1)}}}_{\text{new data}} \mid \mathbf{x}^{(t+1)}) \cdot \int p(\mathbf{x}^{(t+1)} \mid \mathbf{x}^{(t)}) \cdot \underbrace{\boxed{p(\mathbf{x}^{(t)} \mid \overline{\mathbf{z}^{(t)}})}}_{\text{current belief}} \, d\mathbf{x}^{(t)}$$

- 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

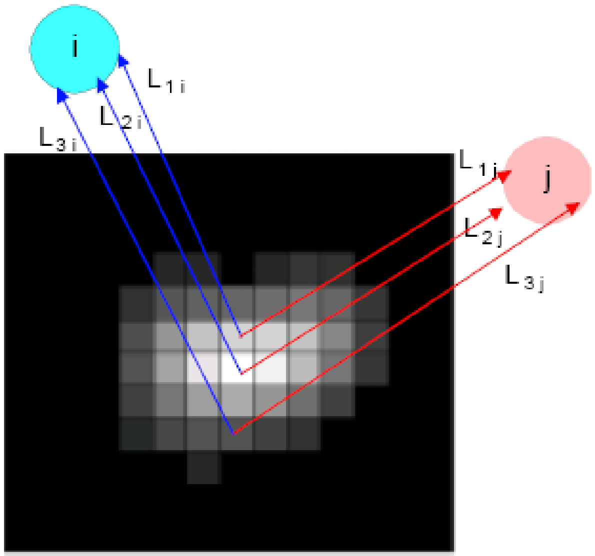
$$\varphi(\mathbf{x}_j, \hat{\mathbf{x}}, \hat{\Sigma}) = -(\mathbf{x}_j - \hat{\mathbf{x}})^T \hat{\Sigma}^{-1} (\mathbf{x}_j - \hat{\mathbf{x}})$$

- 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

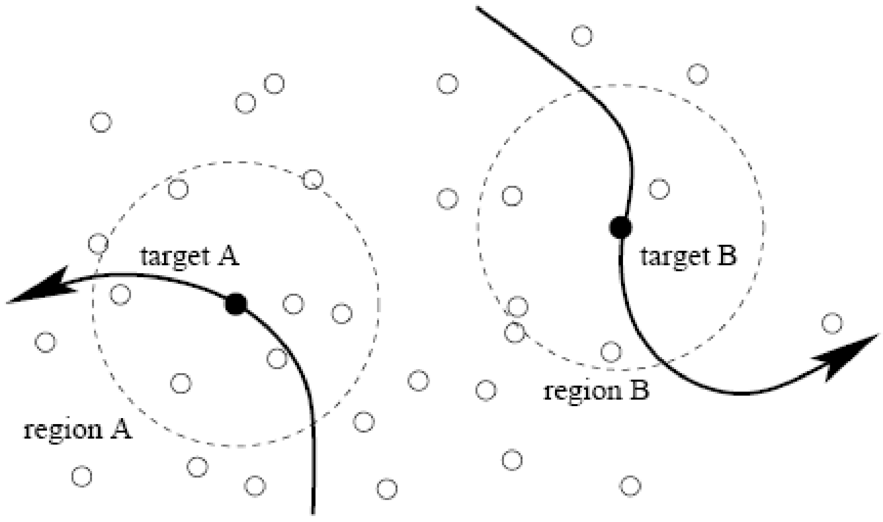
- Pros:
  - Minimizes communications of measurements
  - Good scalability with number of targets (only one active node for each target) if targets are well separated
  - Appropriate for network of low-power devices
- Cons:
  - Potential issue with many redundant tracks without proper track initiation 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

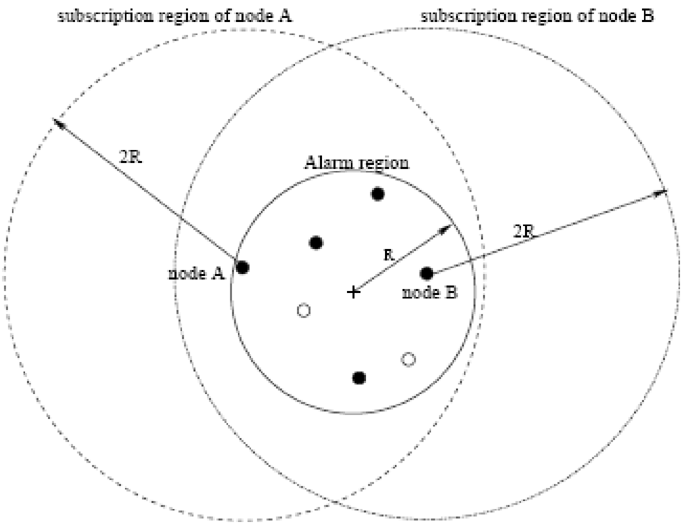
Geographically Based Group Management

- 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



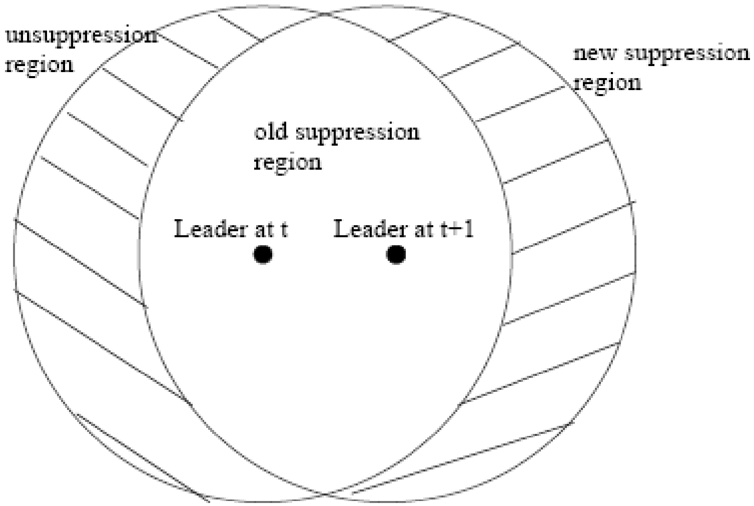
Distributed Detection and Track Initiation

- 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



Dynamic Clustering for Acoustic Target Tracking in Wireless Sensor Networks

Wei-Peng Chen
Jennifer C. Hou
Lui Sha

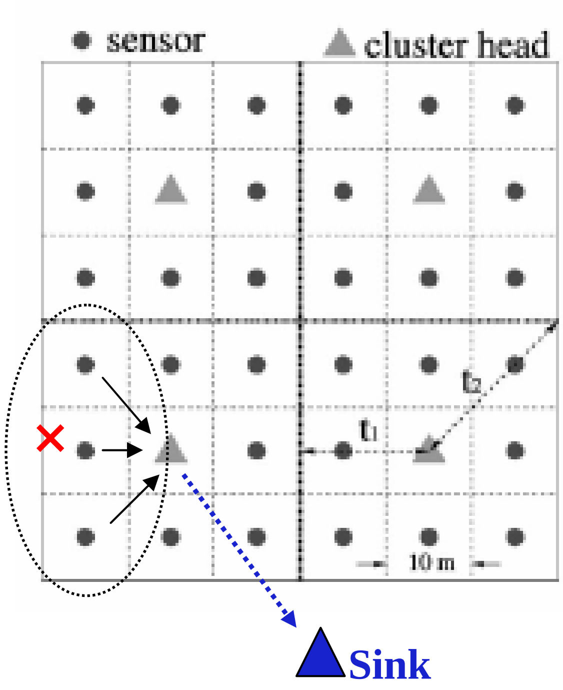
IEEE Transactions on Mobile Computing, vol.3, no.3, July-September, 2004, pp. 258-271

Overview

- Objective: A dynamic clustering architecture and algorithms to facilitate collaborative signal/information processing for acoustic target tracking
- Basic approach:
  - Assume a hierarchical sensor network with
    - Sparsely placed high-capability nodes as candidate cluster heads (CH)
    - More densely distributed low-end sensors
  - Formation of a cluster is driven by detection events
    - Decentralized CH election algorithm/protocol triggered by detection
    - The CH invites sensor nodes in the vicinity of the target to join the cluster
  - Using pre-calibrated Voronoi diagram based on static node locations to structure the clustering

Basic Set-up and Specific Issues to Address

- Roles of the Two-Tiered Nodes
  - **CH**: Detects and classifies the target, forms a cluster to solicit sensor information from sensor nodes, localizes the target, reports the target information to a sink
  - **Sensors**: detect and classify the target, respond to requests from CH to provide sensor information
- Issues Addressed
  - (**I1**) How upper tiered nodes cooperate to ensure that only one CH closest to the target is active (for a single target) with high probability (CH election)
  - (**I2**) How to ensure only sufficient number sensors reply to an active CH's request for necessary but not redundant sensor information (cluster size)
  - (**I3**) How to minimize the collision of packets (at the application layer)

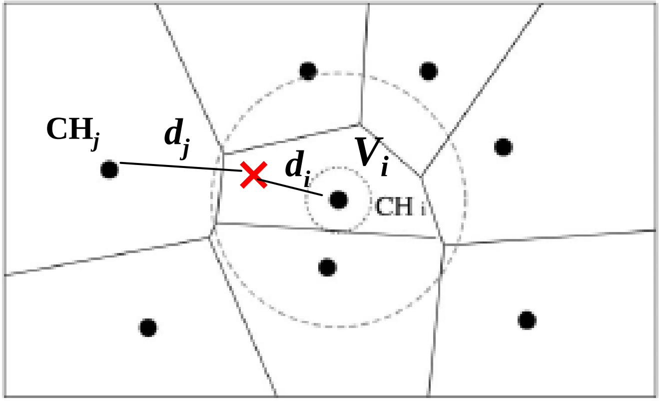


Energy-Based Localization and Voronoi Diagram

- Energy-based detection using received signal strength r_i

$$r_i = a \cdot \|x - x_i\|^{-\alpha} + n_i,$$

- Assume a low noise and homogeneous propagation models, the target lies within the Voronoi cell of node i with highest r_i
- A nonlinear lease square approach can be used to localized the target



$$r_i > r_j \Leftrightarrow d_i < d_j \Leftrightarrow X \in V_i$$

$$(x, y) = \arg\min_{(x,y)} \sum_{i=1}^{m} \frac{(x - o_{x_i})^2 + (y - o_{y_i})^2 - \rho_i^2}{\rho_i^2},$$

Dynamic Clustering Algorithm

- Calibration and Tabulation
  - Construction of the Voronoi diagrams
  - Derivation of parameters for the clustering algorithm based on the Voronoi diagram
- Cluster Head Volunteering
  - Decentralized election of a cluster close to the detected target
  - Broadcast the detected energy strength and extracted signature to sensors for soliciting sensor information
- Sensor Replying
  - Match the buffered data with the broadcast signature from the active CH
  - Reply with its local signal strength if there is a match and it is *close* to the sensor
- Reporting Tracking Results
  - CH sends the location and target information to a sink

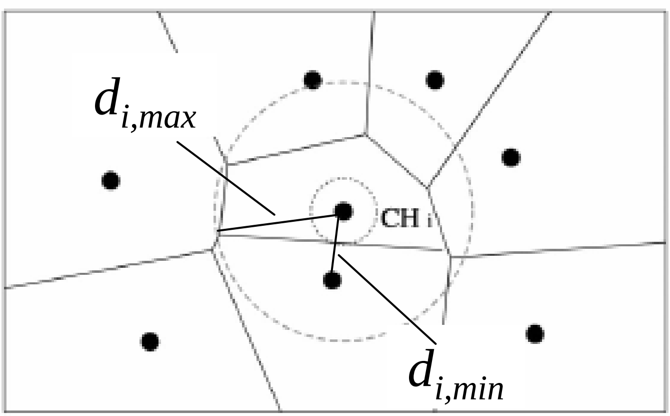
Calibration and Tabulation

- Construction of Voronoi Diagrams
  - Two diagrams: one among CHs and one for the entire network
  - Each node only needs information on neighboring cells in the Voronoi diagram structures
- Response tables to determine *back-off* timer values for CH volunteering and sensor replying
  - Response table at the CHs: The conditional probability that a target is inside the CH's Voronoi cell given the distance to the target
  - Response table at the sensors: The conditional probability that a target is inside the sensor's Voronoi cell given the ratio of the signal strengths at the CH and at the sensor, $r_{i \to j}$

Calibration and Tabulation: Algorithm for Derivation of the CH Response Table

- The probability that the target is in $V(\mathrm{CH}_i)$ given the distance to the target d
  - $d < ½\, d_{i,min}$: $\Pr(i|d) = 1.0$
  - $d > d_{i,max}$: $\Pr(i|d) = 0.0$
  - $½\, d_{i,min} < d < d_{i,max}$: $0.0 \le \Pr(i|d) \le 1.0$

```
CALCPr(i|d)(d)
gain ← 0; loss ← 0
for j ← 1 to resolution
    θ ← 2π · j/resolution
    x ← CH_i.x + d · cos(θ); y ← CH_i.y + d · sin(θ)
    if (x, y) is within Voronoi cell V(CH_i)
        gain++
    else if (x, y) is within V(CH_k) and dist((x, y), CH_k) > 1/2 ·d_{k,min}
        loss++
return gain/(gain+loss)
```



Voronoi diagram among CHs

- d can be estimated as $d = (r/a)^{-1/\alpha}$

Calibration and Tabulation: Algorithm for Derivation of the Sensor Response Table

- Probability that the target is in $V(S_j)$ given the signal strength ratio between the strength at CH_i, r_i, and r_j
  - From the ratio and the locations of CH_i and S_j, we can estimate $\Pr(j \mid r_{i \to j})$ based on the algorithm used for the CH probability
  - Based on the calculated probabilities, the sensor also derive the probability that the target is located neither in its nor its neighbors' cells $\Pr(\overline{N_j} \mid r_{i \to j})$

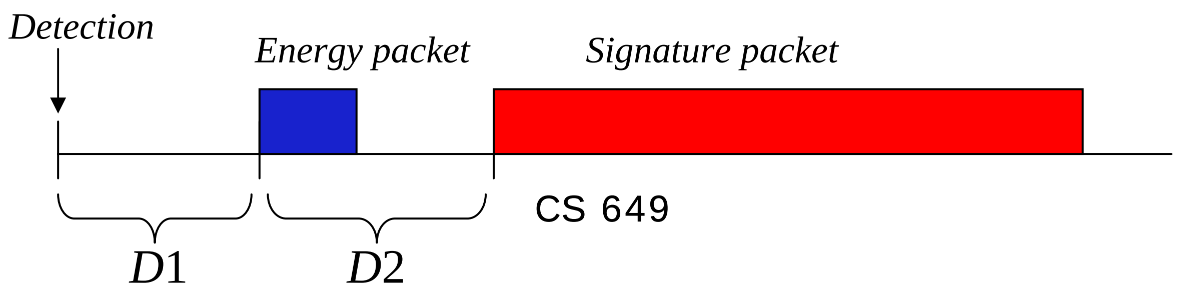
- The computation of probabilities for sensors can be done at the nearest CHs if sensor nodes do not have sufficient computational capabilities

Cluster Head Volunteering

- Basic idea: Each CH with detection volunteers itself with random back-off inversely proportional (approximately) to the probability that it is the closest CH to the target (estimated from the response table)

$$D = W_{min} + (W_{max} - W_{min}) \cdot (1 - \Pr(i|d)) + U(W_{ran}),$$

- A Two-Phase Broadcast Scheme: separate the broadcasts of energy (short) and signature (long) packets
  - **R1**: A CH sets its back-off timer to $D1$ for the energy packet
  - **R2**: Broadcast its energy packet when the timer expires and set the timer to $D2$; If overheard a packet with stronger signal strength, cancel its participation
  - **R3**: Broadcast the signature packet when the timer expires



Sensor Replying

- Each sensor receiving the signature packet searches the local buffered data for a match with an appropriate time lag
- The sensor will not reply if $\Pr(j \mid r_{i\to j}) = 0$ or $\Pr(\overline{N_j} \mid r_{i\to j}) = 1$
- the sensor reply after a random back-off

$$D' = W'_{min} + (W'_{max} - W'_{min}) \cdot (1 - \Pr(j|r_{i\to j})) + U(W'_{ran})$$

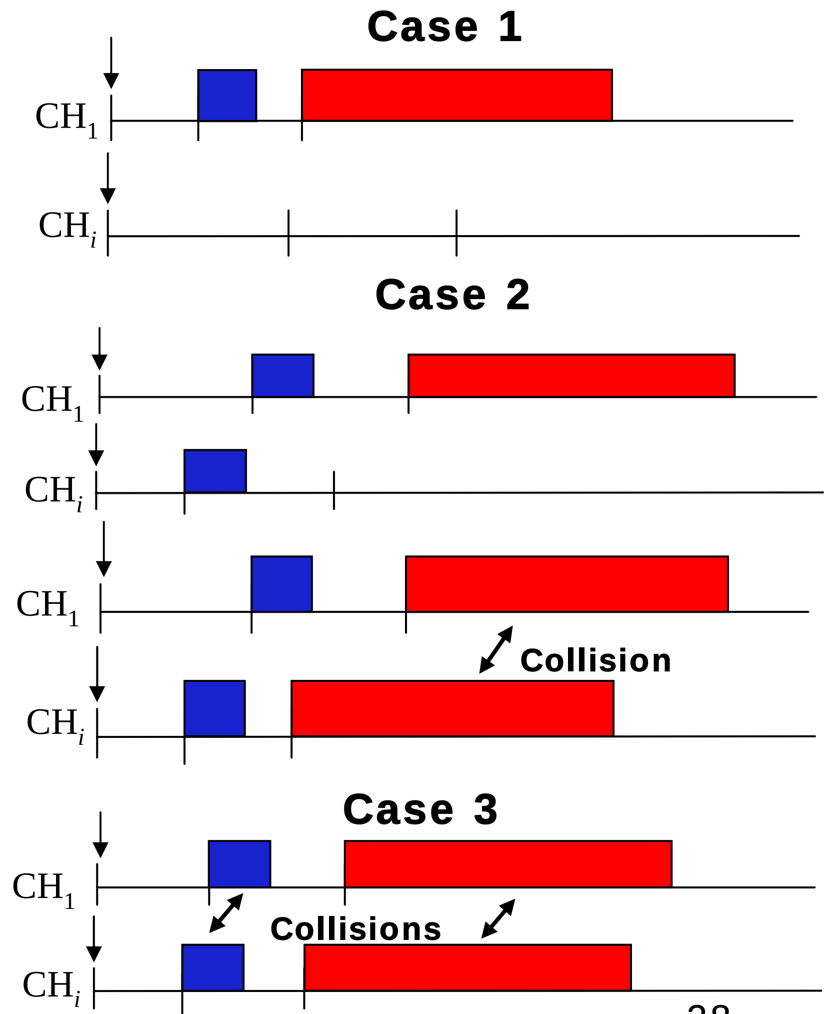
- When the timer expires, the sensor sends a reply packet with signal strength only if
  - The detected signal strength is higher than that of any overheard reply packet; or
  - It is a neighbor of the sensor who replied with the highest signal strength

Reporting Localization Results

- Once the CH broadcast its signature packet, it sets a timer to wait for replies from sensors
- The CH localizes the target based on received information when
  - The timer expires; or
  - It receives sufficient sensor information (sensor information from a sensor with the highest signal strength and its neighboring sensors)
- The CH report the result of the localization to the sink(s)

Analysis of the Dynamic Clustering Algorithm

- Consider the three cases: Assume CH_1 is the cluster head closest to the target
  - Case 1: CH_1 transmits its energy packet earlier than any other CHs without collision
  - Case 2: Another CH, CH_i, transmits it energy packet earlier than CH_1 without collision
  - Case 3: The energy packet of CH_1 collides with the energy packet of another CH
- With proper choice of parameters, we can ensure
  - Cases 2 and 3 have small probability
  - For case 2, CH_1 is able to broadcast its energy packet before any signature packet transmission to prevent other CHs from further volunteering
  - Case 3 occurs with a very small and bounded probability



Performance of the Dynamic Clustering Algorithm

- Performance metrics
  - Location error
  - Latency
  - Number of event detected and reported
  - Number of collisions
  - Control message overhead
- Issue regarding the ratio of communication to detection range
  - The paper assumes the communication range is twice of the detection range
  - Performance degrades as the ratio decreases

Addressing Issues with Multiple Targets?

- The proposed scheme can be extended to multiple target scenarios if the classification can be performed reliably:
  - Might not work with unreliable classification
  - Need enhancements to address false alarm
  - Bayesian tracking and data association could be performed at the sink if the latencies of the reports are small enough
- Data Association for Multiple Target Tracking in Sensor Networks:
  - S. Oh, S. Sastry, and L. Schenato, "A hierarchical multiple-target tracking algorithm for sensor networks," *IEEE ICRA 2005*.
    - Static clusters, MCMC for efficient and scalable data association.
  - L. Chen, M. Cetin, and A. S. Willsky, "Distributed data association for multi-target tracking in sensor networks," *FUSION 2005*.
    - Flat architecture: no supernodes or cluster heads
    - Distributed algorithm via message passing algorithms for graphical model