EE 6886: Topics in Signal Processing
-- Multimedia Security System

Lecture 12: Media Sensor Network

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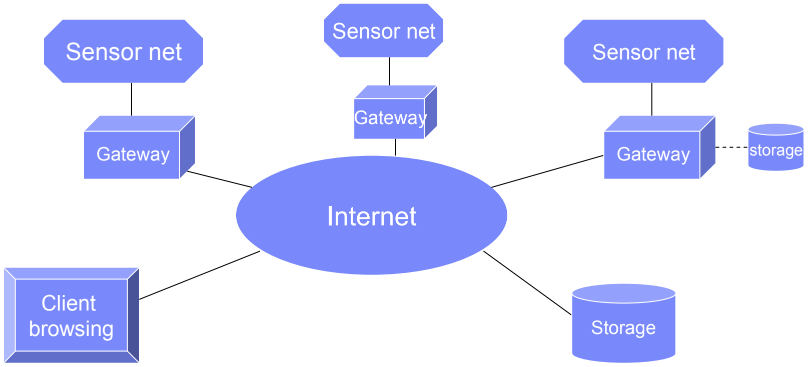
Course Outline

- ☐ Multimedia Security :
  - Multimedia Standards – Ubiquitous MM
  - Encryption and Key Management – Confidential MM
  - Watermarking – Uninfringible MM
  - Authentication – Trustworthy MM
- ☐ Security Applications of Multimedia:
  - Audio-Visual Person Identification – Access Control, Identifying Suspects
  - Media Sensor Networks
  - VoIP Security
  - Key Managements

Sensor Networks

- ❑ Sensor networks significantly expand the existing Internet into physical spaces.
- ❑ The data processing, storage, transport, querying, as well as the internetworking between the TCIP/IP and sensor networks present a number of interesting research challenges



Existing Wireless Sensor Hardware

- ❑ WING NG Sensors
- ❑ iPAQ with 802.11 and A/D Cards
- ❑ Berkeley MICA Mote
- ❑ Smart Dust
- ❑ Characteristics of these hardware:
  - Part cost
  - Size
  - Weight
  - Battery capacity
  - Sensors
  - Memory
  - CUP
  - Operating system
  - Processing capability
  - Radio range

Challenges in designing sensor network systems and applications

- Limited hardware:
  - Limited processing,
  - Limited storage
  - Limited communication capabilities
  - Limited energy supply
  - Limited bandwidth
- Limited support for networking:
  - Peer-to-peer network
  - Mesh topology and dynamic, mobile, and unreliable connectivity.
  - No universal routing protocols or central registry services.
  - Each node acts both as a router and as an application host.
- Limited support for software development:
  - Tasks are typically real-time.
  - Tasks are massively distributed
  - Involves dynamic collaboration among nodes
  - Must handle competing events.
  - Software architecture must be codesigned with the information processing architecture.

Advantages of Sensor Networks

- Dense networks of distribued communicating sensors can improve signal-to-noise ratio (SNR) by reducing average distances from sensor to source of signal, or target.
- Increased energy efficiency in communications is enabled by the multihop topology of the network.
- The greatest advantages of networked sensing are in improved robustness and scalability.
- A decentralized sensing system is inherently more robust against individual sensor node or link failures.
- Decentralized algorithms are also more scalable in practical deployment and may be the only way to achieve the large scales needed for some applications.

Sensor Network Applications

- A sensor network is designed to perform a set of high-level information processing tasks such as:
  - Detection
  - Tracking
  - Classification.
- Measures of performance of these tasks are well defined:
  - False alarms / Miss
  - Classification errors
  - Track quality
- Applications of sensor networks are wide ranging in application requirements, modes of deployment, sensing modality, or means of power supply. Sample commercial and military applications include:
  - Environmental monitoring (e.g., traffic, habitat, security)
  - Industrial sensing and diagnostics (e.g., appliances, factory, supply chains)
  - Infrastructure protection (e.g., power grids, water distribution)
  - Battlefield awareness (e.g., multitarget tracking)
  - Context-aware computing (e.g., intelligent home, responsive environment)

Example of Application: Smart Transportation (I)

- Objectives: Networked Sensors Making Roads Safer and Less Congested
- Existing Infrastructure:
  - Plenty of sensors are already in use for traffic monitoring purposes.
  - Sensors embedded in roadbeds or alongside highways measure traffic flow.
  - Cameras at street intersections look for traffic violations.
  - Sensors in vehicles monitor speed and other conditions.
  - ➔ But, these sensors do not talk to each other as often as we would like them to.
- In the near future:
  - Cars and trucks equipped with wireless sensors can warn each other of imminent collision or other road hazards ahead.
  - Continuously monitor their own conditions and transmit emission data to a service station to enable just-in-time maintenance.
  - Use wireless connection to download music and movies while waiting at a gas station.
  - The crucial difference lies in:
    - Real-Time Flow of Information.
    - Real-Time Processing of Information.

Example of Application: Smart Transportation (II)

- ❑ When sensors are used to guard critical infrastructure such as power plans or airports, they can provide a virtual enclosure around the facilties to guard against unauthorized intrusion.
  - Existing security systems require human personnel to watch video feeds around the clock and pick out "unusual" events.
  - Smart sensor networks will have to rely on in-network intelligence to
    - Focus on interesting events
    - Filter out detractors
    - Extract meaning from raw sensor readings or video streams
    - Transmit only relevant scene features to human user.

Collaborative Processing

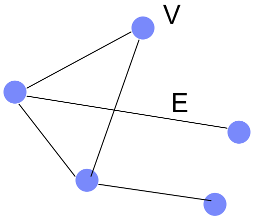
- ❑ Many sensing tasks require a sensor network system to process data cooperatively and to combine information from multiple sources.
- ❑ Traditional centralized sensing and signal processing systems:
  - Raw data collected by sensors are relayed to the edges of a network.
  - From the scalability point of view, the nonlocal processing at the edges depletes precious bandwidth.
  - If every sensor has some data that it needs to send to another node in a network, then a well-known wireless capacity result by Gupta and Kumar states that the per node throughput scales as $\frac{1}{\sqrt{N}}$
  - This states ➔ as the number of nodes increases, every node spends almost all of its time forwarding packets of other nodes.
- ❑ In a sensor network, data from multiple sensors with overlapping sensing regions is almost always correlated.
- ❑ Redundant information can be removed in the data, through in-network aggregation and compression local to the nodes that generate the data.
- ❑ For energy-constrained and multiuser decentralized systems, it becomes critical to:
  - selecting the sensor nodes that participate in a sensor collaboration
  - balancing the information contribution of each against its resource consumption or potential utility for other user.

Issues on Localization and Tracking

- ❑ Localizing and tracking moving objects stimuli or objects is an essential capability for a sensor network in many practical applications.
- ❑ Tracking exposes the most important issues surrounding:
  - Collaborative processing
  - Information sharing
  - Group management including which nodes should sense, which have useful information and should communicate, which should receive the information and how often.

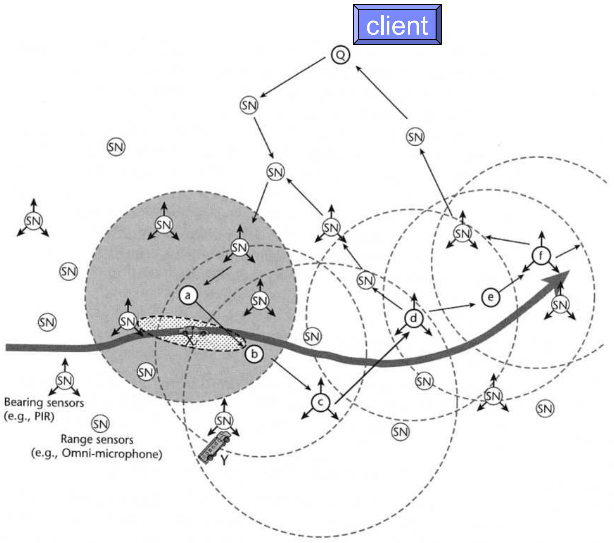
Sensor Network as an Abstract Tuple

- ❑ Sensor Network: $G = <V, E, P_V, P_E>$:
  - V and E specify a network graph.
  - P_V is a set of functions that characterizes the properties of each node in V, such as:
    - Location
    - Computational capability
    - Sensing modality (e.g., acoustic, seismic, magnetic, IR, temperature, light, video).
    - Sensor output type (e.g., signal amplitude, source direction-of-arrival, target range, target classification label).
    - Energy reserve
  - P_E specifies properties for each link, such as:
    - Link capacity
    - Link Transmission quality.



A Tracking Scenario

- ❑ Tasks:
  1. Discovery
  2. Query processing
  3. Collaborative processin
  4. Communications
  5. Reporting



The fundamental information issues

- ❑ In collaborative processing, the issues of target detection, localization, tracking and sensor tasking and control.
- ❑ In networking, the issues of data naming, aggregation, and routing
- ❑ In databases, the issues of data abstraction and query optimization.
- ❑ In human-computer interface, the issues of data browsing, search and visualization
- ❑ In infrastructure services, the issues of network initialization and discovery, time and location services, fault management, and security

Sensing Model

- We will formulate our estimation problem using standard estimation theory.
- The time-dependent measurement, $z_{i,t}$ of sensor i with characteristics $\lambda_{i,\ t}$ is related to the parameters, x_t, that we wish to estimate through the following observation model:

$$z_{i,t} = h\ (x_t, \lambda_{i,t}).$$

where h is a function depending on target state x_t and sensor characteristics $\lambda_{i,\ t}$

- A special case would be:

$$h\ (x_t, \lambda_{i,t}) = fi\ (x_t, \lambda_{i,t}) + w_{i,t}$$

Example for sensing model

- Assume that all sensors are acoustic sensors measuring only the amplitude of the sound signal so that the state vector $x= [\ x, y]^T$ is an unknown target position, and

$$\lambda_i = [\zeta_i, \sigma_i^2]^T.$$

- Where ζ_i is the known sensor position and σ_i^2 is the known additive noise variance.
- Then the parameters are related to the measurements by

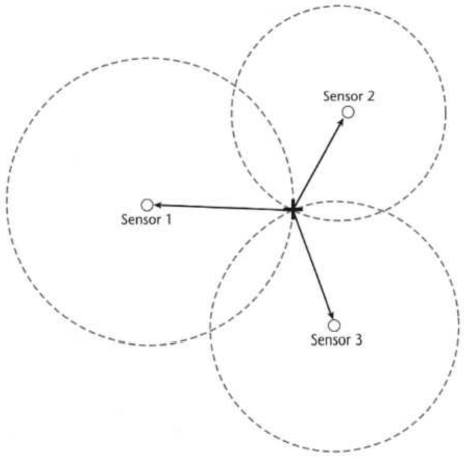
$$z_i = a_i\ /\ ||x - \zeta_i||^{\alpha/2} + w_i.$$

- Where a_i is a given random variable representing the amplitude of the signal at the target, α is a known attenuation coefficient. The term w_i is a zero mean Gaussian random variable with variance σ_i^2.

Collaborative Localization

- If the signal attenuation model is known one can recover one range constraint per amplitude measurement.
- One needs at least three independent distance measurements.
- One may use time difference of arrival of signals at the sensors to estimate the range or bearing information.
- Assume x = 2 in the signal propagation model, omitting the noise term, we can rewrite the signal model as

  $||x||^2 + ||z_i||^2 – 2X^Tz = a_i / z_i.$



Bayesian State Estimation for Tracking

- The relationship between the *a posteriori* distribution p(x|z), the *a priori* distribution p(x) and the likelihood function p(z|x) is given by Bayes Theorem:

$$p(x \mid z) = \frac{p(z \mid x)p(x)}{\int p(z \mid x)p(x)dx} = \frac{p(z \mid x)p(x)}{p(z)}$$

- We only need to compute the numerator and normalize it as necessary. This Bayes rule can be written as:

$$p(x \mid z) \propto p(z \mid x)p(x)$$

- Given a set of distributed measurements in K sensors, z_1, …z_K, the Minimum-Mean-Squared Error (MMSE) estimate is the expected value of the distribution p(x|z_1, …, z_K):

$$\overline{x} = \int xp(x \mid z_1,...z_K)dx$$

An important concern in sensor network

- The standard estimation theory does not consider but which is of great importance to distributed sensor networks:
  - Fact ➔ the knowledge of the measurement value z_i and sensor characteristics λ_i normally reside only in sensor i.
- In order to compute the belief based on measurements from several sensors, we must pay a cost for communicating that piece of information.
- Determining what information each sensor node needs to receive from other sensor nodes is an important decision.

Centralized Estimation

- At any time instant t, each sensor I informs a central processing unit about its measurement.
- “Jointly” use the measurement collection $z_t = \{z_{1,t}, z_{2,t}, \ldots, z_{K,t}\}$.
- The centralized tracking algorithm utilizes all K measurements at every time step.
- If the communication between the sensors and the central unit is through radio, the power needed to communicate reliably is proportional to the communication distance raised to a constant power α, where $\alpha > 2$.
- From the energy point of view, it is inefficient.
- From the processing point of view, the complexity of the centralized algorithm scales linearly with K.

Sequential Estimation

- Measurements may be acquired over time.
- Assumptions:
  - Conditioned on $x^{(t)}$, the new measurement $z^{(t)}$ is independent of the past measurement history $z^{(t-1)}$.
  - Conditioned on $x^{(t-1)}$, the new position $x^{(t)}$ is independent of $z^{(t-1)}$.
- Under these assumptions, based on the new measurement, the sensor node computes the new belief using the Bayes rule:

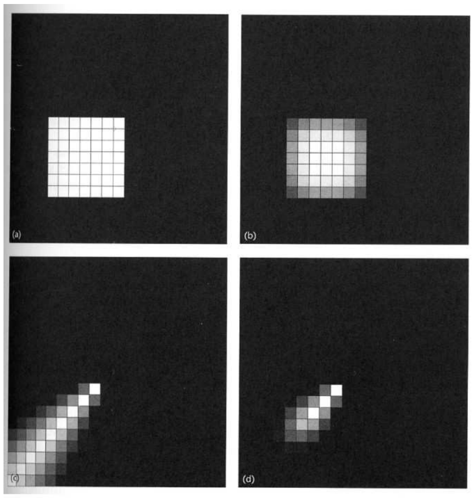
$$p(x^{(t)} \mid z^{(t)}) \propto p(z^{(t)} \mid x^{(t)}) p(x^{(t)} \mid z^{(t-1)})$$
$$= p(z^{(t)} \mid x^{(t)}) \int p(x^{(t)} \mid x^{(t-1)}) p(x^{(t-1)} \mid z^{(t-1)}) dx^{(t-1)}$$

Example of Sequential Estimation

- Computation of a posteriori distribution about a target position using sequential Bayesian estimation.

(a) A posteriori distribution $p(x^{(t-1)} \mid z^{(t-1)})$
(b) The predicted belief $p(x^{(t)} \mid z^{(t-1)})$ is obtained by convolving the a posteriori distribution with the target dynamics $p(x^{(t)} \mid x^{(t-1)})$.
(c) $P(z^{(t)} \mid x^{(t)})$ is the likelihood of observation at time t.
(d) The a posteriori distribution $p(x^{(t)} \mid z^{(t)})$ at time t is computed by combining the likelihood function and predicted belief.

- Kalman filter: a special case where the belief distributions and error models are Gaussians and the system dynamics model is linear.



Representation: Parametric and Nonparametric approaches

❑ Parametric Representation (e.g., Gaussian Approximation):

- Allows only a small number of bits to be transmitted.
- We may approximate the belief by a Gaussian.
- Only mean and covariance need to be transmitted.
- The Kalman filter equations are recursive update equations of the mean and covariance of the Gaussian distribution.

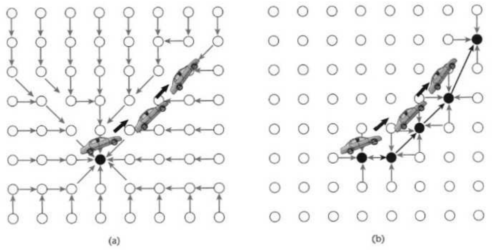
❑ Nonparametric Representation:

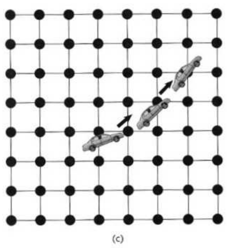
- Approximate the belief by weighted point samples.
  - Initially, the belief is parameterized by a history of measurements.
  - Once the belief begins to look unimodal, we will approximate the belief by a Gaussain.

Design Consideration in Distributed Tracking

❑ Storage and communication of target state information in a sensor network.

- narrow, gray arrows denote communication paths.
- narrow, black arrows denote sensor hand-offs.





(a) A fixed node stores the target state.
(b) Leader nodes are selected in succession according to information such as vehicle movement.
(c) Every node in the network stores and updates target state information.

Tracking Multiple Objects

- Tracking multiple interacting targets distributed over a geographical region is significantly more challenging for two reasons:

1. Curse of dimensionality: The joint state space of multiple targets is a product space of individual state spaces for the targets. Estimating the phenomenon states jointly suffers from the state-space explosion. This is inherent in any high-dimensional estimation problem, regardless of whether the sensing system is centralized or distributed.

2. Mapping to distributed platforms: An estimation algorithm for tracking multiple targets will have to be mapped to a set of distributed sensors, as will the state-space model for the estimation problem. To ensure the responsiveness and scalability of the system, the communication and computation should be localized to relevant sensors only.

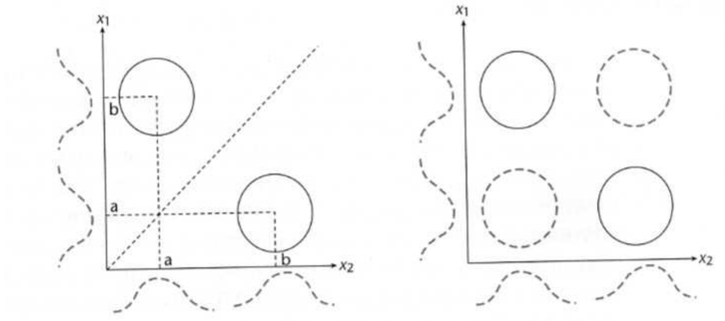
State-Space Decomposition

- Objectives: Systematically decomposes a high-dimensional estimation problem into more manageable lower-dimensional sub-problems.
- Allows the tracking problem to be solved separately by location estimation and identity management.
  - Location estimation requires frequent local communication
  - Identity management requires less frequent, longer range communication.

Optimization Issues

❑ A tracking task can be formulated as a constrained optimization problem <G, T, W, Q, J, C>:
  - G: the sensor network
  - T: a set of targets (location, shape, signal source type).
  - W: signal model for how target signals propagate and attenuate in the physical medium.
  - Q: a set of user queries, specifying query instances and query entry points.
  - J: Objective function, defined by task requirements. (E.g., localization accuracy).
  - C: Constraints (e.g., the amount of time, withing energy range..)

Example: switching between joint density and marginal densities



(a) (b)

Data Association in Multiple Target Tracking

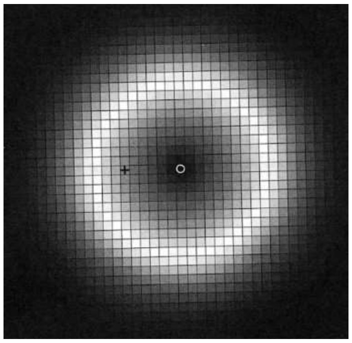
- The state space X of N targets can be understood as a product of individual target state spaces Xn.
- The distributed Kalman filter is a global method, requiring each sensor node to communicate its measurement to a central node.
- Recently, other distributed approaches that exploit peer-to-peer networking in sensor networks were proposed.
- Replicated information is another serious problem in distributed tracking.
- One source of information double counting is due ot loopy propagation of evidence in a network.
- Another source of information double counting is due to multiple sensor nodes observing a single target and reporting multiple detections.

Sensor Models

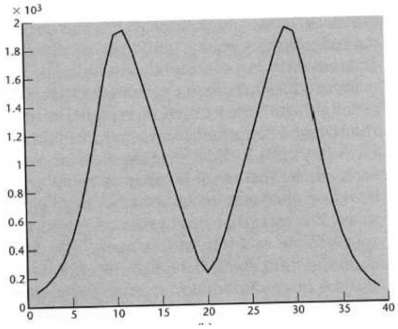
- Two common types of sensors for tracking: acoustic amplitude sensors and direction-of-arrival (DOA) sensors.
- An acoustic amplitude sensor node measures sound amplitude a the microphone and estimates the distance to the target based on the physics of sound attenuation.
- An acoustic DOA sensor is a small microphone array. Using beam-forming techniques, a DOA sensor can determine the direction from which the sound comes, that is, the bearing of the target.
- Range sensors measure distance based on received signal strength or time difference of arrival (TDOA), while DOA sensors estimate signal bearing based on TDOA.
- Acoustic sensors are most popular. Other sensors include imaging, motion, infrared or magnetic sensors..

Acoustic Amplitude Sensor

- ❑ Sensor amplitude attenuates.



Likelihood function p(z|x) for acoustic amplitude sensors. The circle denotes the sensor location, and the cross the true target location.



Likelihood along the horizontal line past the sensor location

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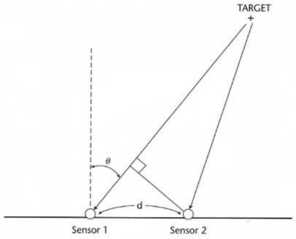
DOA Sensor

- ❑ Beam-forming algorithms are commonly used in radar, speech processing and wireless communications to enhance signals received at an array of sensors.
- ❑ Assume we have a microphone array composed of M identical omnidirectional microphones.
- ❑ The data collected at the m-th microphone at time t is:

$$g_m(t) = s_0(t - t_m) + w_m(t)$$

- ❑ Where s_0 is the source signal, w_m is the noise and t_m is the time delay, which is a function of the direction of arrival θ .
- ❑ The relative time delay between two sensors with a spacing d can be expressed as a function of the bearing angle θ.

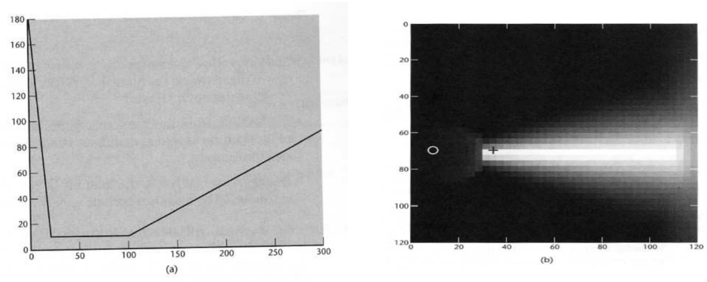
$$t_m = \frac{d}{c}\sin\theta$$



Likelihood function for the DOA sensor

(a) Standard deviation in bearing estimation versus range.

(b) Likelihood function p(z|x)



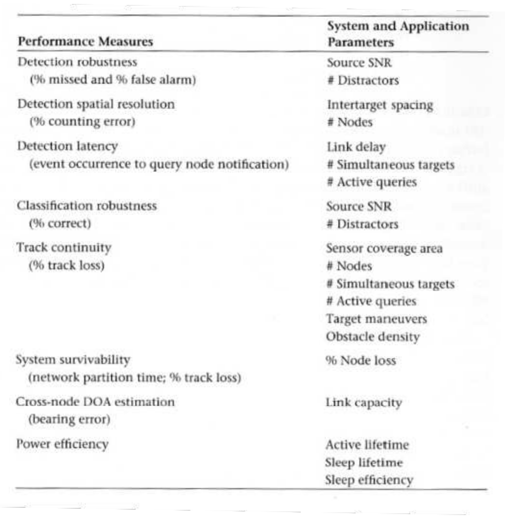
Performance Comparison and Metrics

- ❑ Detectability
- ❑ Accuracy
- ❑ Scalability
- ❑ Survivability
- ❑ Resource usage

Measures

- ❑ Source SNR
- ❑ Obstacle density
- ❑ Network sleep efficiency

Sample performance measures and parameters for tracking and localization problems.



Performance Measures	System and Application Parameters
Detection robustness (% missed and % false alarm)	Source SNR # Distractors
Detection spatial resolution (% counting error)	Intertarget spacing # Nodes
Detection latency (event occurrence to query node notification)	Link delay # Simultaneous targets # Active queries
Classification robustness (% correct)	Source SNR # Distractors
Track continuity (% track loss)	Sensor coverage area # Nodes # Simultaneous targets # Active queries Target maneuvers Obstacle density
System survivability (network partition time; % track loss)	% Node loss
Cross-node DOA estimation (bearing error)	Link capacity
Power efficiency	Active lifetime Sleep lifetime Sleep efficiency

Summary and Other Issues

- Tracking problem is a representative problem for studying a number of information processing issues for sensor networks.
- Focused on the probabilistic formulation of the tracking problem using Bayesian estimation theory.
- The distributed representation of state information plays a key role in designing sensor network processing algorithms.
- Other issues:
  - Networking sensors: Medium Access Control and Routing
  - Infrastructure: Topology control, time synchronization, etc.
  - Sensor tasking and control
  - Sensor network databases: querying, interfaces, storage, aggregation
  - Sensor network platforms and tools: hardware, programming challenges, simulations
  - Applications and future directions: Secure embedded systems, programming models and OS, management of groups, lightweight signal processing, etc.

References

- Feng Zhag and L. Guibas, “Wireless Sensor Networks: An Information Processing Approach”, Chapter 1 and Chapter 2, Elsevier 2004.
- Ching-Yung Lin, Deepa Kundur and Chun-Shien Lu (eds.), “Visual Sensor Network,” EURASIP Journal of Applied Signal Processing, Fall 2006.