SENSOR MANAGEMENT FOR ESTIMATION IN WIRELESS SENSOR NETWORKS

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OUTLINE

- Introduction
  - Sensor management: Motivation and problem formulation
  - State of the art
- Sensor management approaches
  - Sensor management in WSNs
    - Multi-objective optimization (MOP) based sensor management for target tracking with uncertainty
  - Sensor management in crowdsourcing based WSNs
    - Cloud sensing enabled target localization
- Concluding remarks
**Sensor Management in WSNs**

- Power consumption profile of sensor nodes

![Graph showing power consumption profile]

- Limited resources (energy, bandwidth, etc.)
- Proper management
  - Energy: conserve to prolong lifetime of the WSN
  - Bandwidth: more efficient transmission

http://www.intechopen.com/books/small-scale-energy-harvesting/electrostatic-conversion-for-vibration-energy-harvesting
Sensor networks for estimation: Environment/health monitoring, target localization and tracking

Limited network resources: Sensor battery power, communication bandwidth, storage and computing capacity

Resource management: Optimal sensor selection/scheduling, optimal inter-sensor collaboration
Sensor Management for Estimation in WSNs

- **Resource management:** Optimal sensor selection/scheduling, optimal inter-sensor collaboration
  
  a) **Sensor selection/scheduling:** Find optimal tradeoff between estimation accuracy and sensor activations over space and/or time
  
  b) **Sensor collaboration:** Find optimal inter-sensor communication topology and power allocation scheme
SENSOR SELECTION

- **Sensor selection (myopic/one-time ahead):** Select optimal subset of sensors in space to minimize estimation error (or other performance measure) subject to energy constraints (or other constraints)
- **Example:** sensor selection for field estimation

*Figure:* sensor network for field estimation (left); 14 selected sensors (right)
Sensor Scheduling

- Sensor scheduling (multiple-time ahead/non-myopic): Seek optimal sensor schedules in both space and time
- For example, sensor scheduling for target tracking

Figure: sensor schedule at $t = 10$ (left); sensor schedule at $t = 24$ (right)
Sensor selection/scheduling: several variations of the problems have been addressed according to types of measurement models, cost/utility functions, energy and topology constraints, and length of time horizon (one-time ahead, finite time, infinite time)
STATE OF THE ART: SENSOR SELECTION

Sensor selection for different types of measurement models:

a) Linear measurement model (commonly studied): *closed form* of estimation distortion (namely, mean squared error) w.r.t. sensor selection variables [JoshiBoyd'09] (and many others)

b) Non-linear measurement model: *No closed form* of estimation distortion w.r.t. selection variables; alternative performance measure of sensor selection: entropy, mutual information, Fisher information (inverse of Cramér-Rao lower bound on estimation error) [JWFisher'03, WangEstrin’04, ZuoPKV’07, ShenLiuPKV'14, ChepuriLeus’15]

c) Quantized measurement: *No closed form* of estimation distortion w.r.t. selection variables; alternative performance measure used while incorporating the effect of quantization [ZuoPKV’08, MasazadePKV'10]
STATE OF THE ART: SENSOR SELECTION

Sensor selection Under Noise/Signal correlation:

a) Uncorrelated measurement noise (commonly studied): observations are *conditionally independent* given the underlying parameter; each sensor contributes to Fisher information in an *additive* manner [JoshiBoyd'09, ChepuriLeus’15] (and many others)

b) Weakly correlated measurement noise: noise covariance matrix has small off-diagonal entries; assumption of weak noise correlation facilitates problem formulation and has computational merits [Jamali-Rad’14, ShenPKV’14]

c) Arbitrary noise correlation: involved formulation but efficient solution has been found recently [LiuPKV’16]
STATE OF THE ART: SENSOR SELECTION

Sensor selection for different cost/utility functions and constraints:

a) Choice of cost/utility function relies on types of measurement models:
   - Mean squared error: linear measurement model
   - Information measures including Shannon and Fisher: non-linear measurement model [Zhao’02, JWFisher’03]

b) Constraints on sensor selection:
   - Number of selected sensors (commonly used)
   - Sensor Coverage: geographically distributed sensor nodes to ensure network-wide sensing coverage [Wang’11]
   - Energy harvesting constraints: sensors with energy harvester subject to causality constraints of power flow [LiuWangPKV’16, Calvo-Fullana’16]
STATE OF THE ART: SENSOR SCHEDULING

a) Sensor scheduling for linear dynamical systems (finite time horizon)
   - Scheduling continuous/discrete-time Kalman filters [MoSinopoli'11]
   - Sensor scheduling via design of sparse Kalman filter gain matrices [MasazadePKV'12]
   - Compressive sensing based probabilistic sensor scheduling for target tracking [CaoPKV’15]

b) Sensor scheduling for non-linear dynamical systems (finite time horizon)
   - Recursive Fisher information or Posterior Cramér-Rao lower bound as surrogate performance measure for nonlinear systems [ZuoPKV’07, ShenPKV’14, ChepuriLeus’15]
STATE OF THE ART: SENSOR SCHEDULING

c) Sensor scheduling for linear dynamical systems (infinite time horizon)

• Optimal sensor schedule for an infinite horizon problem can be approximated arbitrarily well by a periodic schedule with a finite period [Shi’11, Tomlin’12]

• Periodic switching policy using lower bound on the performance of scheduling sensors over an infinite time [Ny’11]

• Determine optimal periodic sensor schedules by designing optimal sparse Kalman filter gain matrices under periodicity conditions [LiuPKV’14]
**State of the art: Distributed Algorithms**

- **Distributed sensor selection**: In the absence of the fusion center, sensor selection is carried out in a distributed way and by the sensors themselves.

- **Why is this important?** Robust to failure of FC, low communication burden between sensors and FC.

- **Why is this difficult?** Each sensor has access only to the information in its neighborhood; Make a global decision based on local data & local communications.
STATE OF THE ART: DISTRIBUTED ALGORITHMS

- Distributed algorithms
  - Greedy algorithm based on submodular utility function (with diminishing return property) [Krause’10]
  - Distributed sensor selection for parameter estimation under linear Gaussian model with weakly correlated measurement noise [Jamali-Rad’15]
  - Distributed sensor selection for estimation of spatially-correlated random field [LiuHero’16]
Sensor Collaboration: Determine optimal inter-sensor communication strategies (namely, collaboration links) in order to enhance the estimation performance under limited network resources.
STATE OF THE ART: SENSOR COLLABORATION

Approaches for sensor collaboration
- Power allocation for communication systems with fully-connected collaboration network [Fang’09, Fanaei’14]
- Sensor selection and power allocation under given network topologies: tree, branch, linear [Mitra’06, Mitra’08]
- Linear coherent estimation with spatial collaboration under arbitrary known network topologies [KarPKV’13]
- Sensor collaboration with unknown network topologies: jointly optimize sensor-to-sensor (collaboration) and sensor-to-FC (selection) schemes [LiuPKV’15]
- Sensor collaboration in the presence of temporal dynamics: determine inter-sensor communication strategy while tracking a random process rather than estimating a static parameter [KarPKV’12, LiuPKV’16]
Almost everyone has devices with built-in sensors.
CROWDSOURCING BASED WSNs
Crowdsourcing based WSNs

The users may not participate in sensing and inference tasks unless suitable incentives are provided to them.

Sensor management

STATE OF THE ART: CROWDSOURCING BASED WSNs

Sensor management in crowdsourcing based WSNs

- Concept [Mullen’06]
- Walrasian equilibrium based sensor management [Chavali, Nehorai’12], [Masazade, Varshney’13]
- Auction design for resource management [Yang’16], [Chen’16]
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TARGET TRACKING IN WIRELESS SENSOR NETWORKS
TARGET TRACKING
TARGET DYNAMICS

- Target motion dynamics: \( x_{t+1} = Fx_t + w_t \)
  
  \[ x_t = \begin{bmatrix} x_t & y_t & \dot{x}_t & \dot{y}_t \end{bmatrix}^T \]
  
  i.i.d Gaussian noise

  Target location  Target velocity

- Isotropic power attenuation model of target:

  \[ P_{i,t}(x_t) = \frac{P_0}{1 + \alpha d_{i,t}^n} \]
  
  Power at distance 0  Distance between target and sensor \( i \)

- Signal amplitude received by sensor \( i \) at time step \( t \):
  
  \[ h_{i,t}(x_t) = \sqrt{P_{i,t}(x_t)} \]
TARGET TRACKING
SENSOR MEASUREMENTS

- **Uncertainty** in wireless sensor networks
  - Random interruptions in the channel
  - Sensor failures
  - Jamming or interference
  - Obstacles

- Unreliable analog sensor measurements
  
  \[ z_{i,t} = \begin{cases} 
  h_{i,t}(x_t) + v_{i,t}, & \text{with probability } p_s^{(i)} \\
  v_{i,t}, & \text{with probability } 1 - p_s^{(i)}
  \end{cases} \]

- Probabilistic model:
  
  \[ p(z_{i,t}|x_t) = p_s^{(i)} \mathcal{N}(h_{i,t}(x_t), \sigma^2) + (1 - p_s^{(i)}) \mathcal{N}(0, \sigma^2) \]
Target Tracking
Sensor Measurements

- Quantized sensor measurements:
  
  \[ D_{i,t} = \begin{cases} 
  0 & -\infty < z_{i,t} < \eta_1 \\
  1 & \eta_1 < z_{i,t} < \eta_2 \\
  \vdots \\
  L - 1 & \eta_{(L-1)} < z_{i,t} < \infty 
  \end{cases} \]

- Probabilistic model

  \[
  p(D_{i,t} = l | \mathbf{x}_t) = \Pr(\eta_l \leq z_{i,t} \leq \eta_{l+1} | \mathbf{x}_t) \\
  = p_s^{(i)} \Pr(\eta_l \leq z_{i,t} \leq \eta_{l+1} | z_{i,t} \sim \mathcal{N}(h_{i,t}(\mathbf{x}_t), \sigma^2)) \\
  + (1 - p_s^{(i)}) \Pr(\eta_l \leq z_{i,t} \leq \eta_{l+1} | z_{i,t} \sim \mathcal{N}(0, \sigma^2))
  \]
TARGET TRACKING FILTER

Estimation of the target location is based on the posterior probability density function (pdf)

Recursive filter for estimation:
- **Predict** the target location with posterior pdf
- **Update** the estimate using the sensor measurements
**Particle Filtering**

- Particle filter: \( f(x_t | D_{1:t}) \approx \sum_{s=1}^{N_s} w^s_t \delta(x_t - x^s_t) \)

\[ w^s_{t+1} \propto f(D_{t+1} | x^s_{t+1}) \text{ (Updating weights)} \]

\[ w^s_{t+1} = \frac{w^s_{t+1}}{\sum_{s=1}^{N_s} w^s_{t+1}} \text{ (Normalizing weights)} \]

\[ \hat{x}_{t+1} = \sum_{s=1}^{N_s} w^s_{t+1} x^s_{t+1} \]

\( \{ x^s_{t+1}, N_s^{-1} \} = \text{Resampling}(x^s_{t+1}, w^s_{t+1}) \)
SENSOR MANAGEMENT

- Weights in particle filtering are updated through measurements from selected sensors

- Sensor management criteria: estimation lower bound, Fisher information, mutual information...
Fisher Information

- Cramer-Rao lower bound (CRLB): lower bound for estimation performance

- Fisher information (FI): inverse of CRLB

\[
E \left\{ [\hat{x}_t - x_t] [\hat{x}_t - x_t]^T \right\} \geq J_t^{-1}
\]

\[
J_t = E[-\Delta x_t^T \log p(D_t, x_t)]
\]
\[
= E[-\Delta x_t^T \log p(D_t|x_t)] + E[-\Delta x_t^T \log p(x_t)]
\]
\[
= J_t^D + J_t^P
\]

- FI for analog sensor measurement model
- FI for quantized sensor measurement model
**Mutual Information**

- Mutual information (MI) for analog sensor measurement model
  \[ I(z_t; x_t) = H(z_t) - H(z_t|x_t) \]

- Mutual information for quantized sensor measurement model
  \[ I(D_t; x_t) = H(D_t) - H(D_t|x_t) \]

- Mutual information upper bound (MIUB)

\[
I(z_t; x_t) = \sum_{i=1}^{N} I(z_{i,t}; x_t | z_{i-1,t}, \cdots, z_{1,t}) \\
\leq I(z_{i,t}; x_t | z_{i-1,t}, \cdots, z_{2,t}) \\
\leq I(z_{i,t}; x_t).
\]
SIMULATION: WSN
**Simulation:** Analog data, 5-bit quantized data, and 2-bit quantized data

Target tracking performance with analog data, 5-bit quantized data, and 2-bit quantized data, (a) MSE performance; (b) average percentage of reliable sensors selected.

MI selects more reliable sensors – better MSE
SIMULATION: MI AND MIUB

Target tracking performance for MI and MIUB, $A=2$. 

![Graph showing target tracking performance for MI and MIUB with time step $t$ on the x-axis and percentage of reliable sensors on the y-axis.](image-url)
**MOP based Sensor Management**

- Number of sensors to be selected not predetermined

- **Multiple** objectives:
  
  - Lifetime (max)
  - Detection capability (max)
  - Information gain (max)
  - Estimation error (min)
  
  - Energy costs (min)
  - Communication costs (min)
  - Deployment costs (min)

  Conflicting
MOP based Sensor Management

Sensor management in existing literature:
- Maximize information gain (or minimize error metric), subject to a constraint on the number of sensors

\[
\begin{align*}
\text{maximize} & \quad \alpha \log \det \left( \sum_{i=1}^{N} \alpha_{i,t} J_{i,t}^D + J_{t}^P \right) \\
\text{subject to} & \quad \sum_{i=1}^{N} \alpha_{i,t} \leq A
\end{align*}
\]

- Selection state of sensor \( i \) at time step \( t \)

MOP based sensor management
- Determines the optimal sensor set (the number of sensors and which sensors)
- Saves resources: use more or less sensors as needed
MOP based Sensor Management

Objective functions

- FI based objective function

\[
f_1(\alpha_t) = \frac{\log \det \left( \sum_{i=1}^{N} J_{i,t}^D + J_{i,t}^P \right) - \log \det \left( \sum_{i=1}^{N} \alpha_{i,t} J_{i,t}^D + J_{i,t}^P \right)}{\log \det \left( \sum_{i=1}^{N} J_{i,t}^D + J_{i,t}^P \right)}
\]

- MIUB based objective function

\[
f_1(\alpha_t) = \frac{\sum_{i=1}^{N} I^{(i)} - \sum_{i=1}^{N} \alpha_{i,t} I^{(i)}}{\sum_{i=1}^{N} I^{(i)}}
\]

Information gap between all sensors and selected sensors

- Sensor cardinality based objective function

\[
f_2(\alpha_t) = \frac{1}{N} \sum_{i=1}^{N} \alpha_{i,t}
\]
**MULTIOBJECTIVE OPTIMIZATION PROBLEM (MOP)**

- *n* objective optimization problem:

\[
\min_{\alpha} \{f_1(\alpha), f_2(\alpha), \ldots, f_n(\alpha)\}
\]

subject to \(a \leq \alpha_i \leq b, h(\alpha) = 0, g(\alpha) \leq 0\)

- Feasible solutions: those that satisfy constraints
- Solution \(\alpha^1\) dominates \(\alpha^2\) (\(\alpha^1 \succ \alpha^2\)) if and only if

\[
\begin{align*}
  f_u(\alpha^1) &\leq f_u(\alpha^2) \quad \forall u \in \{1, 2, \ldots, n\} \\
  f_v(\alpha^1) &< f_v(\alpha^2) \quad \exists v \in \{1, 2, \ldots, n\}
\end{align*}
\]

- \(\alpha^*\) is called a Pareto optimal solution if and only if there is no \(\alpha\) that dominates \(\alpha^*\)
- Utopia point: at which all objectives are minimized

1. [http://www.noesissolutions.com/Noesis/sites/default/files/Pareto_Front.png](http://www.noesissolutions.com/Noesis/sites/default/files/Pareto_Front.png)
Solving MOP

- Weighted sum: \( w_1f_1(\alpha_t) + (1 - w_1)f_2(\alpha_t) \)
  - Uniform spread of Pareto solutions not guaranteed
  - Reduce design alternatives

- Nondominating sorting genetic algorithm-II (NSGA-II)
  - Sort individuals according to level of nondomination
  - Store nondominated solutions
  - Guarantee diversity

1. R. T. Marler et al., 2004
2. K. Deb et al., 2002
**Solution Selection**

- **Knee point solution**
  - Small sacrifice in one objective results in a large gain in another

  \[
  \alpha_t = \arg\max_{\alpha^2, \ldots, \alpha^P} \text{slope} \{\alpha^\rho\}
  \]

  \[
  \text{slope} \{\alpha^b\} = 180 - \left[\arctan \left( \frac{f_1(\alpha^a) - f_1(\alpha^b)}{f_2(\alpha^a) - f_2(\alpha^b)} \right) \frac{180}{\pi}\right]
  \]

- **Compromise solution (CS)**
  - Closest to Utopia point

  \[
  \alpha_t = \arg\min_{\alpha^1, \ldots, \alpha^P} \sqrt{\sum_{j=1}^{n} (f^*_j - f_j(\alpha^\rho))^2}
  \]
**Simulation: WSN**

![Simulation Diagram]

- Sensor
- Target Track

Sensor positions at different times:
- $t=1$: Sensor positions 1, 2, 3, 4, 5
- $t=3$: Sensor positions 6, 7, 8, 9, 10
- $t=8$: Sensor positions 11, 12, 13, 14, 15

Target Track positions at different times:
- $t=3$: Target at position 16
- $t=8$: Target at position 17
SIMULATION: Pareto Front

Pareto optimal front obtained by using NSGA-II at time step $t=3$ and $t=6$, (a) FI; (b) MIUB

(a)

(b)
SIMULATION: SOLUTION SELECTION

Tracking performance at each time step with different solution selection methods.
**SIMULATION: NSGA-II, CVX, WS**

Tracking performance for MOP with NSGA-II, convex relaxation, and weighted sum methods (a) MSE for MIUB; (b) MSE for FI.

WS rarely produces a uniform spread of points on the Pareto front with a uniform spread of weights.
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CLOUD SENSING

Users → Request → Cloud platform → Data → Permission → Sensors
A Few Cloud Sensing Examples

- Find lost/stolen items
- Spectrum Sensing in Cognitive Radio nets.
- Customer need assessment using embedded sensors
- Smart Cities
Cloud Sensing Example

**BILATERAL MECHANISM FRAMEWORK**

**FC**: provides the service of finding the target in the WSN

**User**: wants to find the target by paying the FC for the service

Problem encompasses Signal Processing and Economics.
BILATERAL MECHANISM FRAMEWORK

When to trade?
How much to pay?

How to define the utilities?
How to manage the sensors in the WSN?
MECHANISM DESIGN FACTORS

i. Individual rationality (IR)
   - Non-negative utilities.
   - Guarantees the participation of the users.

ii. Incentive compatibility (IC)
   - Utility of telling truth \( \geq \) Utility of lying.
   - Ensures honest reporting.
MECHANISM DESIGN FACTORS

iii. **Ex post** efficiency

- Buyer gets the service whenever his/her total gain is greater than the cost of service provisioning.
- Seller does not provide the service whenever the cost of service provisioning is greater than the buyer’s gain.
MECHANISM DESIGN FACTORS

- **Maximize** the social welfare – the total expected utilities of the FC and the user
  - Need to define utility functions
- **Investigate** the IR, IC and ex post efficiency properties of the mechanism
  - Need to define IR, IC and ex post efficiency
- Formulate the **optimization problem**
Utility Definition

Sensor selection state
\[ z = [z_1, z_2, \ldots, z_N] \]

Cost \( C(z) \)

Gain \( G(z) \)

Probability of trade
\[ p(v_f, v_c) \]

Payment
\[ x(v_f, v_c) \]

Private valuations
\[ U_C(v_c) \text{ (Per unit gain)} \]
\[ v_c \sim f_c : [a_c, b_c] \rightarrow \mathbb{R}_+ \]

\[ U_f(v_f) \text{ (Per unit cost)} \]
\[ v_f \sim f_f : [a_f, b_f] \rightarrow \mathbb{R}_+ \]

Expected utility
\[ U_C(v_c) = \bar{p}_c(v_c) [v_c G(z)] - \bar{x}_c(v_c) \]

\[ U_f(v_f) = \bar{x}_f(v_f) - \bar{p}_f(v_f) [v_f C(z)] \]

Value of gain
Payment
Payment
Value of cost
**Definition of IR and IC**

**IR condition**

**User:**\[ U_c(v_c) \geq 0 \]

**FC:** \[ U_f(v_f) \geq 0 \]  
Utility if lying

**IC condition**

**User:**  
\[ U_c(v_c) \geq \bar{p}_c(w_c) [v_c G(z)] - \bar{x}_c(w_c) \]

Utility if honest

**FC:**  
\[ U_f(v_f) \geq \bar{x}_f(w_f) - \bar{p}_f(w_f) [v_f C(z)] \]  
Gain

Cost

Utility if lying

**Private valuation**

**User:** \( v_c \)  
**FC:** \( v_f \)

**Untruthful valuation**

**User:** \( w_c \)  
**FC:** \( w_f \)

**Utility**

**User:** \( U_c(v_c) \)  
**FC:** \( U_f(v_f) \)
DEFINITION OF EX POST EFFICIENCY

For an ex post efficient bilateral mechanism, the trading *probability* is

\[ p(v_f, v_c) = \begin{cases} 
1 & \text{if } v_f C(z) < v_c G(z) \\
0 & \text{if } v_f C(z) > v_c G(z) 
\end{cases} \]

Private valuation **User**: \( v_c \in [a_c, b_c] \)  
**FC**: \( v_f \in [a_f, b_f] \)
OPTIMIZATION PROBLEM

Total social welfare

\[
\begin{align*}
\text{maximize} & \quad \int_{a_f}^{b_f} U_f(v_f) f_f(v_f) dv_f + \int_{a_c}^{b_c} U_c(v_c) f_c(v_c) dv_c \\
\text{subject to} & \quad U_f(b_f) + U_c(a_c) \geq 0 \\
& \quad \bar{p}_f \text{ is decreasing, } \bar{p}_c \text{ is increasing}
\end{align*}
\]

IR and IC

Objective

Design trading probability and payment function using KKT conditions

Impossibility of ex post efficiency has been proved

\[ p(v_f, v_c) \]
\[ x(v_f, v_c) \]

Private valuation

User: \( v_c \in [a_c, b_c] \)
FC: \( v_f \in [a_f, b_f] \)

Utility

User: \( U_c(v_c) \)
FC: \( U_f(v_f) \)
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    - Optimal auction design for sensor management in target localization and tracking problems

- Concluding remarks
INTRODUCTION

- Crowdsourcing
- Energy consumption – incentive is needed
- Fusion center designs optimal auction mechanism to buy data from users – gets the optimal solution of from whom to buy data and how much to pay to the winning user
INTRODUCTION

REVERSE AUCTION

From whom to buy??

Auctioneer

Fusion center

Users

Bidder 1

Bidder 2

Information about target

I will ask for $30

I will ask for $50

Value estimate per unit energy cost

I will ask for $30

I will ask for $50
**INTRODUCTION**

**REVERSE AUCTION**

Sensor

Value estimate per unit energy cost

Fusion center

Decide *from whom to buy* & *how much to pay*
Mechanism Design

- Optimization
  - Maximize expected utility of FC \(\rightarrow\) Profit
  - Subject to IR, IC, and resource constraints
- Analyze the constraints
- Find an equivalent optimization problem
- Solve the optimization problem through dynamic programming method or convex optimization method
A UCTION D ESIGN WITH OTHER CONSIDERATIONS

- Sensors send quantized bids to the FC (Because of limited resources or privacy issues)

Bidder

Value estimate per unit energy cost

• Bandwidth/resource constraint
• Privacy issues

Fusion center

Quantized value estimate

State of Charge (SOC)
SUMMARY

- Overview of sensor management problems including state-of-the-art discussion
- Multi-objective optimization problem based sensor management
  - Dynamic sensor selection
- Optimal auction design for sensor management problems
  - Crowdsourcing
  - Optimization
Open research problems

- Joint distributed sensor management and parameter estimation
- Non-parametric sensor selection based on online streaming data
- Scalable methods for large-scale networks
- Other inference problems: detection and classification
- Graph signal processing problems such as topology design/inference for suitable objective functions
- Privacy issues need to be considered in crowdsourcing based WSNs
- Sensor management in fully autonomous sensor networks
Thank You!