Algorithms and Bounds for Networked Sensor Resource Management

MURI Year 1 Review

Integrated Fusion, Performance Prediction, and Sensor Management for Automatic Target Exploitation

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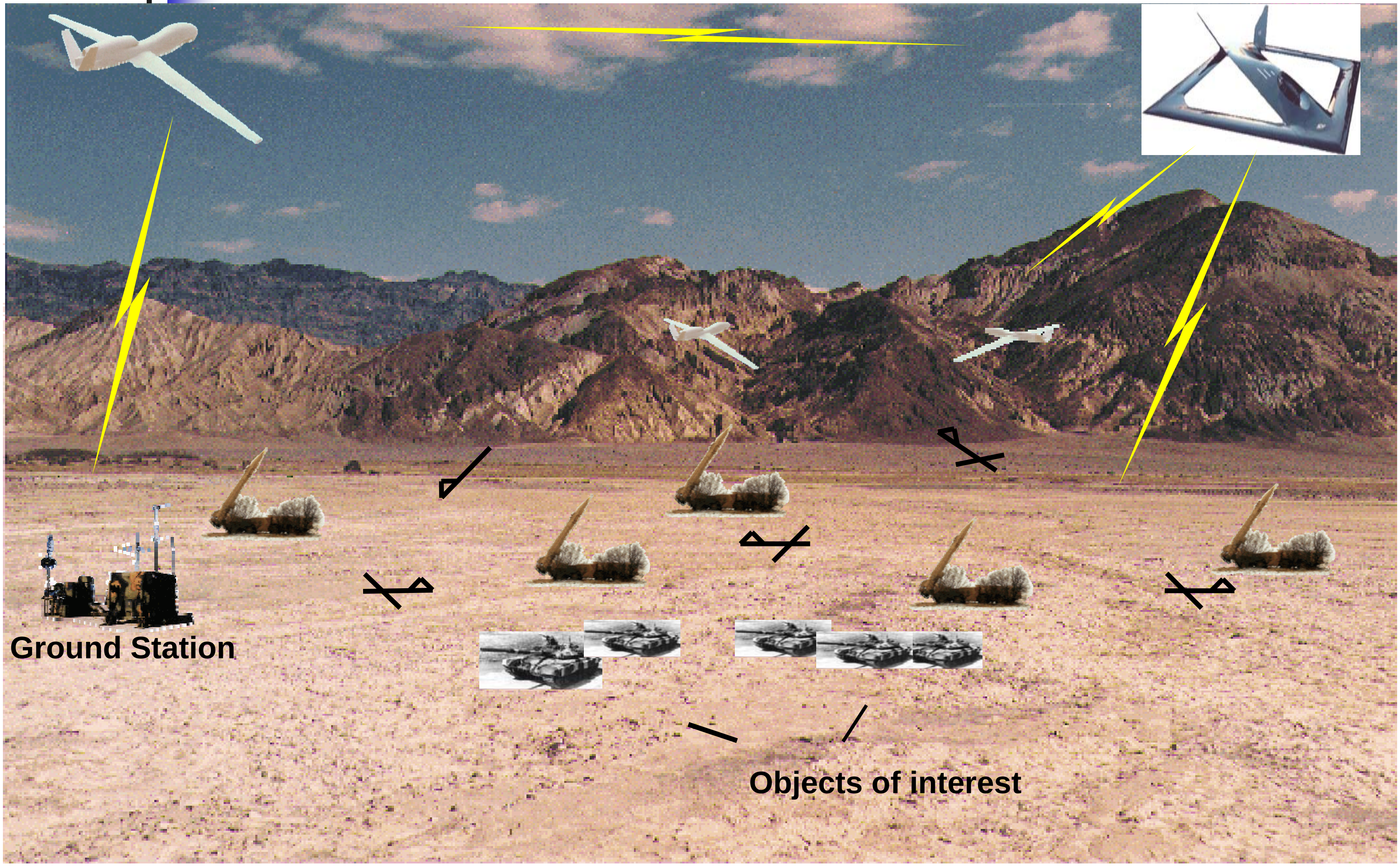
Critical ATE Challenges

- Detect/classify reactive agile targets
  - Low RCS, inhomogeneous clutter, complex environments, short exposure times, ...
- Exploit new sensing capabilities
  - Multiple heterogeneous platforms
  - Multi-modal sensing
  - Dynamic, steerable platform trajectories, sensing modes, focus of attention
- In support of ATE mission objectives
  - Generate appropriate actionable information in a timely manner with limited resources
  - Select actions based on performance models of sensing, signal and information processing

Activities this year

- Asynchronous Hierarchical Estimation with Unreliable Communications
    - Data fusion protocols for networked sensors with message losses
- Dynamic Model Identification for Unknown Shapes
    - Track LADAR features to infer 3-D ball-and-spokes model with 6 DOF motion
- Adaptive Data Fusion in Sensor Networks
    - Sensor management for tracking objects, detecting and identifying maneuvers
- Performance Bounds and Real-Time Algorithms for Sensor Management
    - Focus of this talk

Problem: Heterogeneous sensors, Multiple Objects of Interest

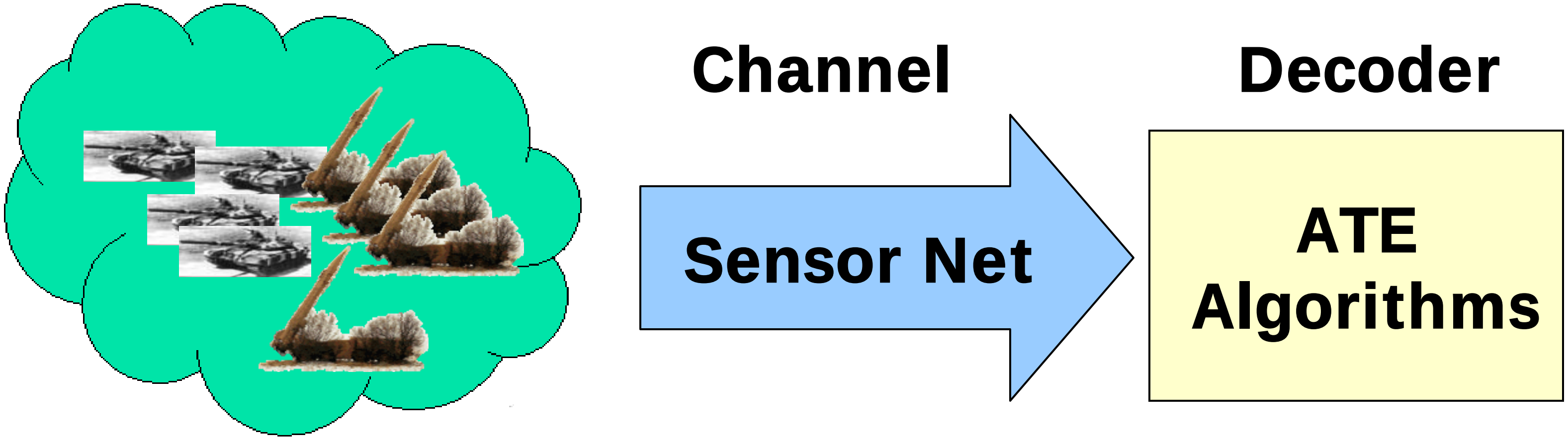


Objective: A scalable theory of active sensor control for ATE

- Addressing heterogeneous, distributed, multi-modal sensor platforms
- Incorporating complex ATE performance models and real time information
- Integrating multiple ATE objectives from search to classification
- Scalable to theater-level scenarios with multiple platforms, large numbers of objects
- Robust to model errors and adaptive to new information and models

Simplified Information View of Problem

- View sensors as “channels” with “capacity”



Signal sources

Channel

Decoder

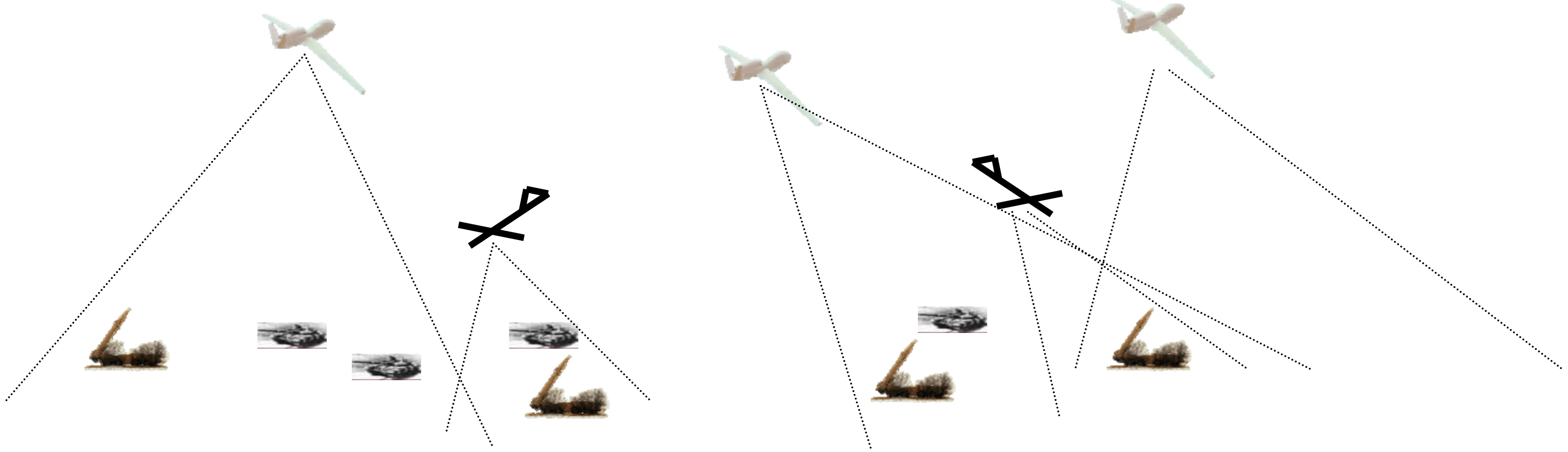
Sensor Net

ATE Algorithms

- But that is an incomplete picture!
  - You have a choice of what to sense and how to sense it
  - The targets are often part of the channel (active sensors)

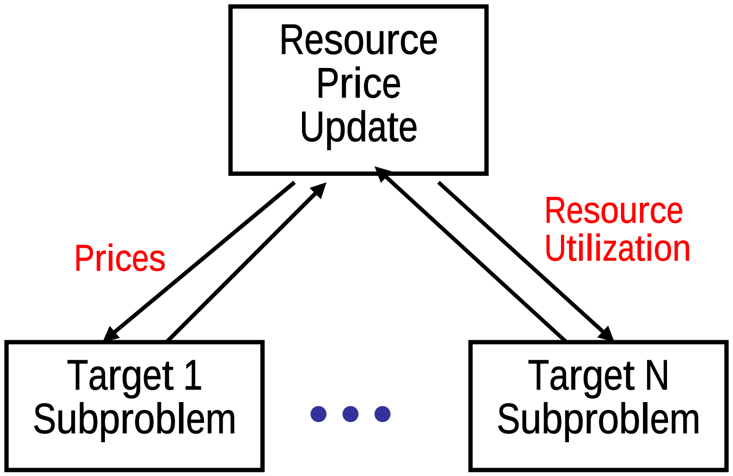
Different Paradigm: Multi-server Systems

- Sensors as network providers of service, targets as jobs
  - Overlapping fields of regard, limited capacity
  - Optimize allocation of bundles of resources to jobs subject to capacity and reachability
- Characterize achievable network performance



Approach: Pricing Algorithms for Scalable Sensor Management

- Goal: sensor management algorithms and bounds that scale to objects and sensors
- Principal difficulty: exponential explosion in:
  - Scenario states
  - Potential sensor actions➔ Not suitable for real-time
- Our approach: *price sensor utility* based on scenario information



Resource Price Update

Prices

Resource Utilization

Target 1 Subproblem

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Target N Subproblem

Strategy for target subproblems used to estimate utilization for price updates

Assumptions

- Available information state of each object
- Can evaluate expected performance metrics for each object given allocated sensor resources
  - Achieved track accuracy, classification accuracy, information gain, ...
  - E.g. using performance bounds for inferencing models, reinforcement learning, single object optimization, information theory, ... (Hero, Fisher-Willsky-Williams, Castañón, ...)
- Steerable sensors (ESAs, gimballed EO/IR or ladar, with limited resources (duty, field of view, ...)

Model Problem

- Sensors j = 1, ..., M, with resource levels R_j
- Targets i= 1, ..., N, with information states π_i
- Objective: partition sensor resources over targets
- Strategies for sensor use on target i: γ_{ik}
  - Results in performance J_{ik}, resource use from each sensor j: R_{ijk}
- Set of strategies across targets: $\gamma_k = \{\gamma_{1k}, \ldots, \gamma_{Nk}\}$

Example: Classification with Multimode Radar

- R_j : Duty for radar j over plan interval
- γ_{ik} : Strategy for using radar duty from multiple radars for target i
- R_{ijk} = expected duty from radar j used by strategy γ_{ik} on target i
- J_{ik} = expected classification error for target i when using strategy γ_{ik}
- Key issue: selection of strategies for each target that use available duty

Example: Multi-target Tracking in Variable Terrain

- Extension of Fisher-Williams-Willsky idea
- M sensors with given resources R_j
- N objects under track
- Maximum of one action per object
  - Action k from sensor j on object i takes R_{ijk} resources
  - Information-theoretic criteria gives value of action
- Objective: select actions on objects given available resources

Integer optimization

- Find best strategy across all targets to maximize cumulative performance given resources

$$\max_{\underline{\gamma}_k} \sum_{i=1}^{N} J_{ik}$$

$$\text{subject to constraints}$$

$$\sum_{i=1}^{N} R_{ijk} \leq R_j \text{ for all } j = 1, \ldots, M$$

- Integer program when set of strategies allowed for each target is finite
  - Large number of possible strategies indexed by k

Pricing Algorithms

- Key idea: Exploit the fact that there are many more targets than sensors
  - Use “prices” for sensors to identify relative utilization
  - Standard idea in optimization: exact penalty

$$\max_{\underline{\gamma}_k} \sum_{i=1}^{N} J_{ik}$$

subject to constraints

$$\sum_{i=1}^{N} R_{ijk} \leq R_j \text{ for all } j = 1, \ldots, M$$

⟺

$$\max_{\underline{\gamma}_k} \min_{\lambda_j \geq 0} \sum_{i=1}^{N} J_{ik} + \sum_{j=1}^{M} \lambda_j \Big(R_j - \sum_{i} R_{ijk}\Big)$$

Weak Duality Performance Bounds

- A simple interchange: Lagrangian relaxation

$$\max_{\underline{\gamma}_k} \min_{\lambda_j \geq 0} \sum_{i=1}^{N} J_{ik} + \sum_{j=1}^{M} \lambda_j \Big(R_j - \sum_{i} R_{ijk}\Big)$$

$$\Longrightarrow$$

$$\min_{\lambda_j \geq 0} \max_{\underline{\gamma}_k} \sum_{i=1}^{N} J_{ik} + \sum_{j=1}^{M} \lambda_j \Big(R_j - \sum_{i} R_{ijk}\Big)$$

  - Right side problem is optimistic (**upper bound on performance** of sensor system with existing resources)
  - **Convex** over prices (maximum of linear functions)
  - Inner maximization in right side problem ***decouples over targets*** given prices
    - No combinatorial explosion of strategies

Pricing Algorithms

- Prices will implicitly trade desired sensor utilization on each target with available resources
- Finding “best” prices: non-differentiable optimization
- Algorithms
  - Subgradient descent
  - Bundle techniques
  - Column generation

Subgradients

- Given a guess at set of prices λ_j, can find a direction where prices can be improved
  - Requires finding best strategy k* for each target given the prices
  - Subgradient direction:

$$[-(R_1 - \sum_i R_{i1k^*}), \ldots, -(R_M - \sum_i R_{iMk^*})]$$

    - Drop price if sensor is underutilized, raise price if overutilized

Subgradient Algorithms

- Direct subgradient search:
  - Modify prices in direction of subgradient using step size
  - Different step size rules (Polyak, Bertsekas, ...)
  - Slower version of gradient descent: many iterations
- Alternative approach: Bundle techniques
  - Aggregate subgradient information across iterations
  - Use subgradients and function values to obtain piecewise linear convex approximation near current price guess
  - Penalize step size to limit error due to approximation (proximal point)
  - Iteration: solve quadratic programming problem with linear constraints
  - Few iterations, complex

Column Generation

- Alternative approach to computing bound

$$\min_{\lambda_j \geq 0} \max_{\gamma_k} \sum_{i=1}^{N} J_{ik} + \sum_{j=1}^{M} \lambda_j \Big(R_j - \sum_i R_{ijk}\Big)$$

⟺

$$\max_{q_k \geq 0} \sum_k \sum_{i=1}^{N} q_k J_{ik}$$

subject to

$$\sum_k \sum_i q_k R_{ijk} \leq R_j, j = 1, \ldots, M$$

$$\sum_k q_k = 1$$

  - Linear program, corresponds to using random mixtures of strategies
  - Requires knowing J_{ik}, R_{ijk} for each strategy k
    - Enumeration? Many k...
- Key result: *Sparsity*
  - At most M+1 q_k will be nonzero!

Exploiting Sparsity

- Restrict admissible strategies k to a subset k ∈ A
- Solve small linear program
  - Get prices for sensors

$$\max_{q_k \geq 0} \sum_{k \in A} \sum_{i=1}^{N} q_k J_{ik}$$

subject to

$$\sum_{k \in A} \sum_{i} q_k R_{ijk} \leq R_j, j = 1, \ldots, M$$

$$\sum_{k \in A} q_k = 1$$

- Use prices to find new strategy
  - k* obtained by target-by-target optimization
  - Select strategy that maximally improves bound
- If k* already in A, stop; else, add k* to A and repeat iteration

Experiments

- Classification mission: 100 objects, 3 types, with Bayesian costs for misclassification
- Two electronically steered array radars, one low- and one high-resolution
  - Different pulse widths → different duty required per measurement
  - Different confusion matrices per radar
  - 4 minutes of observation time per sensor
- Target strategies: conditional sequences of at most five sensor actions per object
  - Computed given sensor “prices” using stochastic dynamic programming algorithms target-by-target
  - Could use any other performance bound or metric

Comparison of Pricing Algorithms

- Note: cost of iteration dominated by computation of target strategies for current price guess
  - Each iteration costs approximately same for all three algorithms
  - Would change if table estimates of single target performance were available
    - Subgradient iterations would be much simpler
    - Column generation, bundle comparable
- Number of iterations required for price convergence:
  - Subgradient: 360
  - Bundle: 25
  - Column Generation: 11

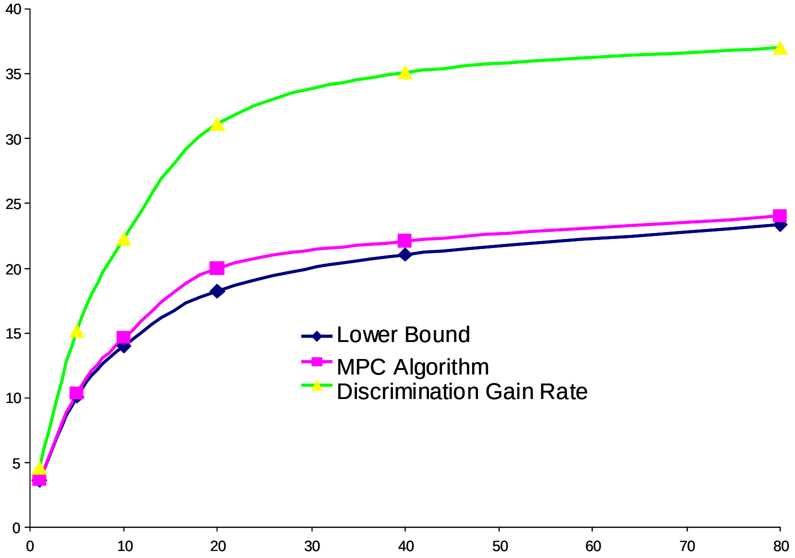
Prices to Actions: A Complex Story

- Prices don't guarantee feasibility of allocations
  - Randomized allocations of strategies by multiple sensors
  - No detailed scheduling of activities for sensors among targets
- Real time sensor management approach: Model-predictive control (MPC) with receding horizon planning window
  - Given current target and sensor information, plan next batch of sensor actions using approach above (1-5 minutes)
  - Solution is random mixture of strategies per target
  - Sample mixture of policies across targets, independently per object
  - Schedule initial actions by sensors conforming to policy
  - Process information, update object information states and resolve
- Main Result: MPC algorithms guarantee feasibility of sensor allocation
  - But performance guarantees missing...evaluate in simulation

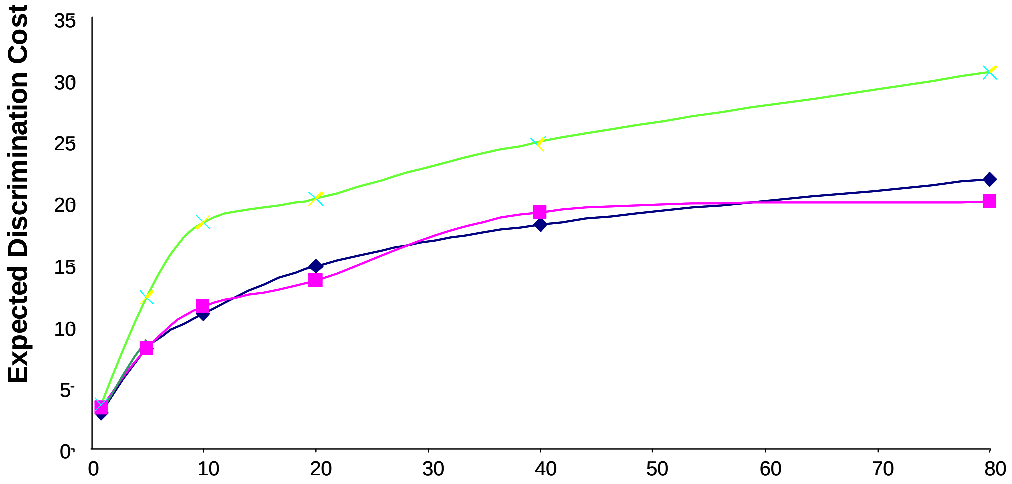
Simulation Results

- Comparison of myopic information-based algorithm, dynamic pricing algorithm and bound
  - Weighted classification error cost

200 secs/sensor



250 secs/sensor



Future Directions - 1

- Extension of hierarchical sensor management (SM) using pricing to search/track/ID
  - Multi-mode scheduling, passive/active sensing
  - Integrate graphical inferencing models
  - Incorporate performance bounds at individual target levels
- Distributed algorithms for pricing negotiation among sensors
- Extensions of SM algorithms to incorporate trajectory control

Future Directions - 2

- Robust SM algorithms using learning and real-time resource allocation
  - Deal with unknown objects
- SM for area sensors
  - Act on areas instead of objects
  - Different paradigm: not jobs, but batches of jobs...
- Performance bounds for general SM systems