Dynamic Sensor Resource Management for ATE

MURI Kickoff Meeting

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

David A. Castañón

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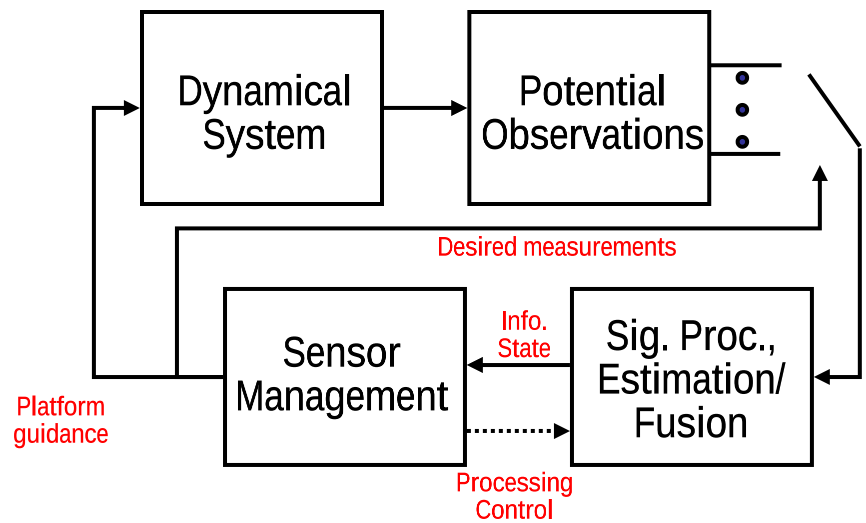
Critical ATE Challenges

- 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

What is needed: 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
- Providing the "active" control of distributed sensor resources to support missions of interest

Adaptive Sensor Management for ATE



- Dynamics include objects of interest and sensors
- Hierarchy of control: where sensors are and what information they collect
- Key: actions selected based on information state

Our Approach: Model-Based Approach

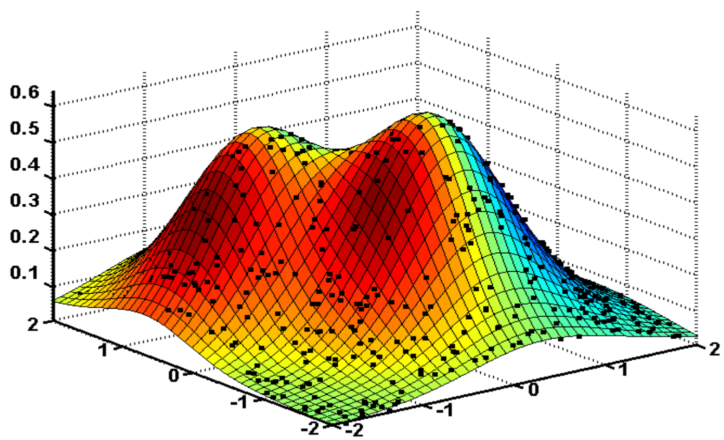
- View sensor management as a control/ optimization problem
- However, this requires models to …
  - Represent information state
  - Predict how information state will change as a consequence of actions
  - Evaluate potential changes with respect to mission objectives
  - Select observations/actions adaptively in real time

Representation

- Key ATE information: location and type of objects of interest and uncertainties
  - Standard representations (JMPs, Particles, ...)
- Problem: Many objects → very high dimensional space of possible *information states*
  - Hard to precompute or learn policies
- Problem: need type information representation compatible with multi-sensor, multi-modal fusion
  - Observe features, not types
  - Incorporate hierarchical inferencing with graphical models

Prediction

- Statistical models of how information changes in response to sensing actions
  - May have insufficient domain information to specify
  - Insufficient data for empirical estimation of nsities



•Not adequate sampling for estimation of density
•May be adequate for support of density?

Evaluation

- Ideally, would relate information state to mission objectives
  - Tracking accuracy, classification costs, ...
  - Hard to integrate objectives, specify time horizon
- Alternative: use information theoretic metrics
  - Entropy variations, information rates

Selection

- Combinatorial explosion in possible actions as number of objects increases
- Various types of policies
  - Static (Myopic): Current actions selected to optimize immediate improvement in information
  - Dynamic: Current actions selected to optimize information over a sequence of times
    - Open-loop policies: sequences of actions
    - Closed-loop policies: sequences of contingent actions based on information

Promising Results - 1

- Aggregation of information state: evolving on simpler lower dimensional space
  - Identifiable from physics and experimental data
- Learn intrinsic dimensions of prior (shape) spaces, and posterior (likelihood) spaces (Costa-Hero '05)

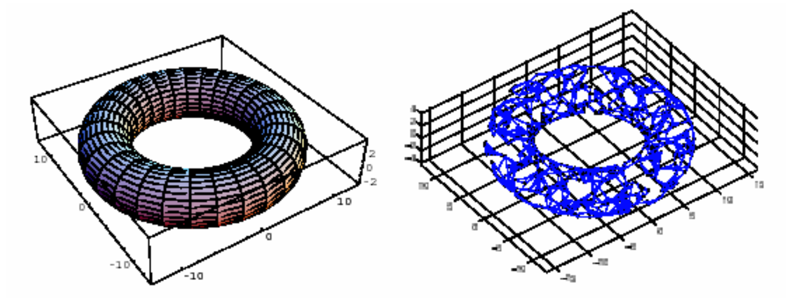


Fig. 2. Samples from digits 0 through 9 in the MNIST database.

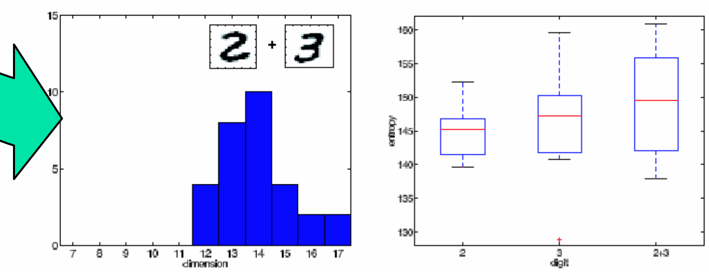
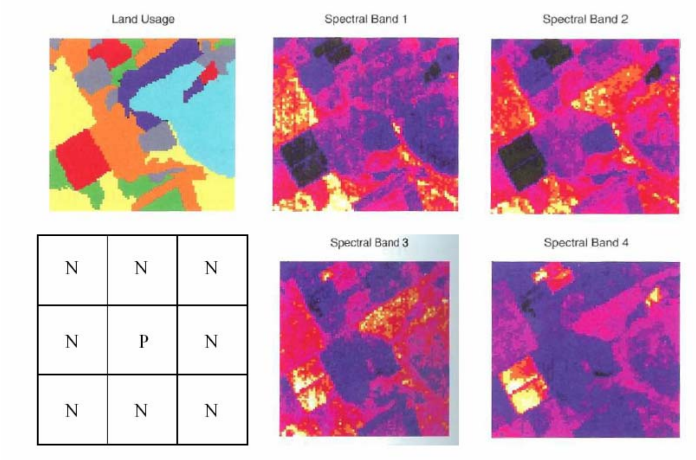


Fig. 6. Histogram of intrinsic dimensionality estimates and boxplot of entropy estimates for digits 2+3 in the MNIST database using a 5-NN graph ($N = 10$, $Q = 15$).

Promising Results - 2

- Task-driven dimensionality reduction
  - Develop low-dimensional feature spaces that come close to intrinsic information space
  - Generate predictive statistical models for feature evolution



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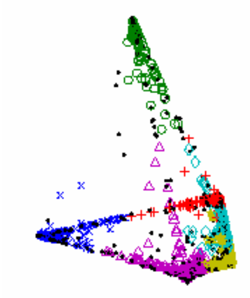
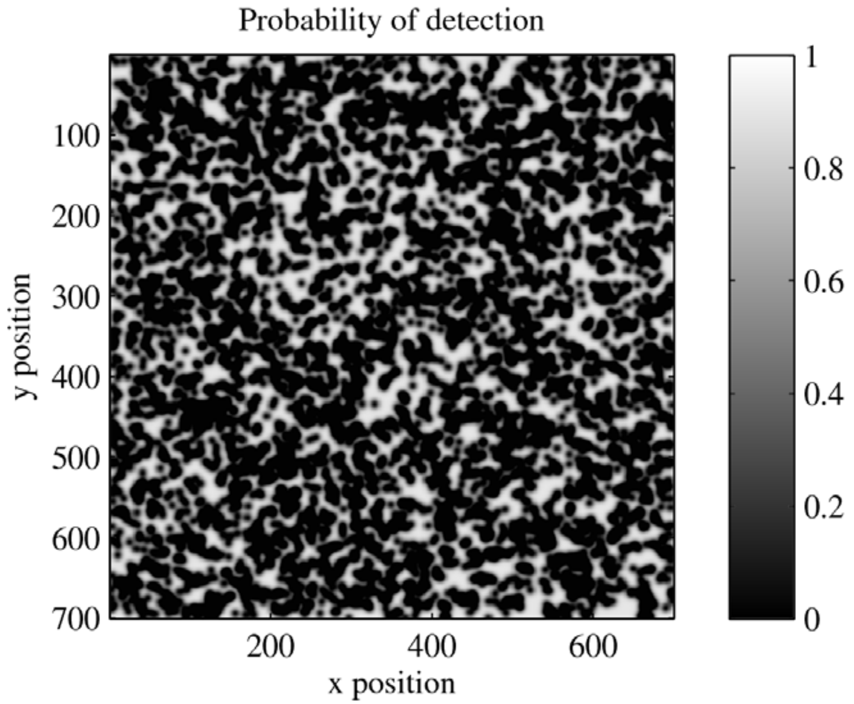


(b) CCDR

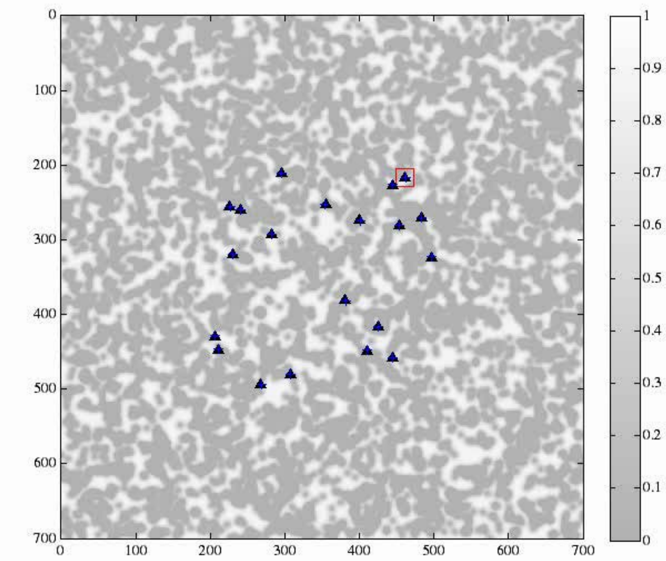
Promising Results - 3

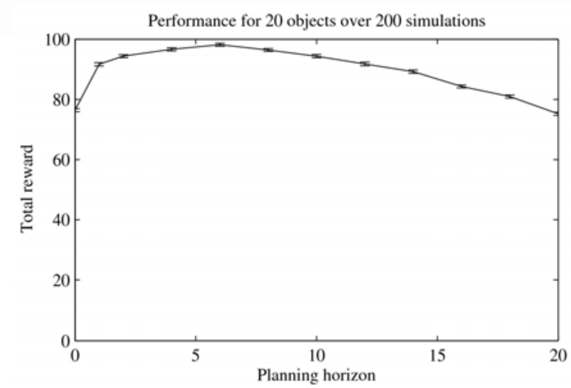
- Information-based Sensor Management for tracking in complex clutter
  - Given collection of sensors, select set of measurements to maximize information collected over period of time to track multiple objects
  - Combinatorial optimization
  - Receding horizon policy



Simulation Results

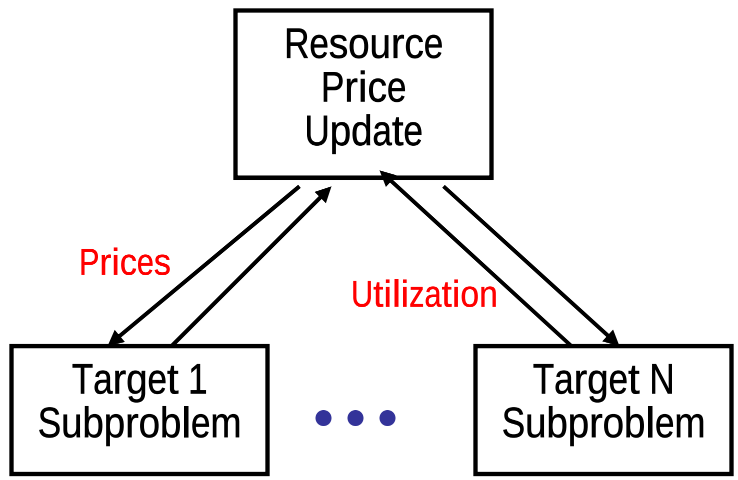
- 20-40 objects moving independently
- Probability of detection dependent on position (e.g. due to obscuration)
- Observation consists of detection flag and, if detected, a linear Gaussian measurement of position
- Information state propagated using unscented Kalman filter





Promising Results - 4

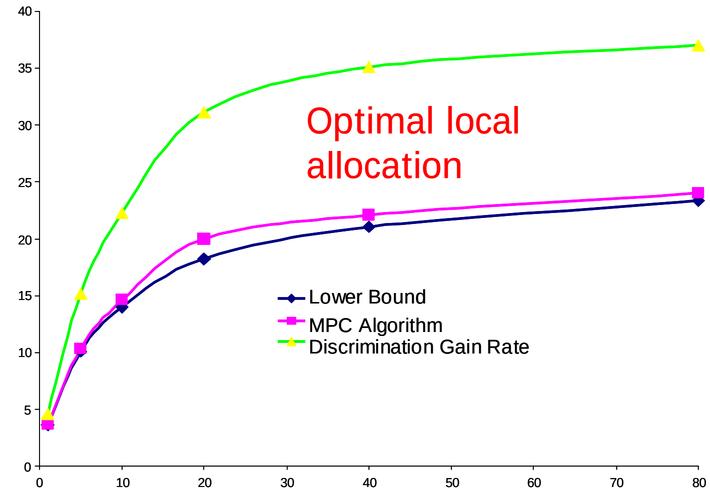
- Scalable multi-object sensor management through hierarchical pricing
  - Distributes heterogeneous sensor resources across targets
  - Provides performance lower bound for classification problems (simple inference)
  - Prices: used to satisfy utilization constraints

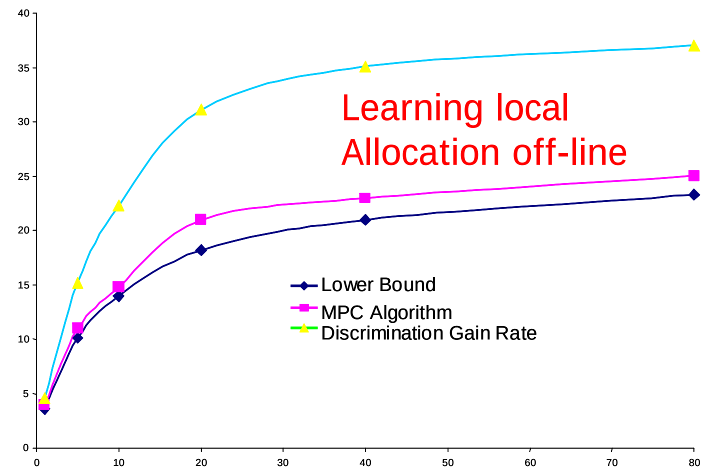


Feedback strategy for target subproblems used to estimate utilization for price updates

Simulation Results

- Two radars, one low- and one high-resolution imaging
  - Different durations/mode
  - 250 seconds of observation time
  - 100 objects, 3 types
- Comparison of myopic information-based algorithm, dynamic pricing algorithm and bound
  - Weighted classification error cost





What we'll be doing
I: Topics where we're up and running - 1

- Apply general Dimensionality Reduction framework to radar sensing context (shape, measurement...)
  - Develop predictive sensor models based on aggregate features
  - Evaluate accuracy of framework by simulating simple imaging, tracking, or detection task
- Extend information-based sensor management approach
  - Kinematic + ID
  - Heterogeneous sensors/modes

What we'll be doing
I: Topics where we're up and running - 2

- Extension of hierarchical sensor management (SM) using pricing to search/track/ID
  - Multi-mode scheduling, passive/active sensing
- Learning sequential decision strategies with limited data
  - Finite state machine representation
- Performance bounds on SM strategies
  - Information-theoretic and optimization bounds
  - Depending on resource constraints, network

What we'll be doing
II: Topics on the Horizon - 1

- Integration of SM algorithms with Fusion graphical models for information state evolution
- Learning approaches for density representation, performance prediction and optimization
  - Dimensionality reduction for side information and likelihood function spaces
  - Approximations to optimal performance prediction
  - Approximations to optimal sensing/mobility actions
- Extensions of SM algorithms to incorporate trajectory and signal processing control
  - Multiple time scale control
  - Aggregate models for trajectory control

What we'll be doing
II: Topics on the Horizon - 2

- Robust SM algorithms with unknown models
  - Integrated parametric/non-parametric models
  - Adaptive real-time learning/refinement
- Hybrid SM algorithms using learning and real-time resource allocation
  - Focus on multi-modal, multi-sensor missions
  - 3D classification, search and track
- Extensions of SM to broad area sensors
  - Act on areas instead of objects
  - Different paradigms
- Performance bounds for general SM systems
  - Extensions of earlier results