Sequential Adaptive Sensor Management

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Adaptive Sensor Scheduling

Sensor Scheduling Space

Multimodality ground target tracking

UAV target tracking with geo-obscuration

Multimodality mine detection in clutter
Progress (since Jan 04)

- Theory of information gain (IG) scheduling developed and applied to tracking and mine detection
  - Result: IG sandwich bound on risk
  - Implication: Information-driven strategy can be made to approximate any risk-optimal strategy

- Theory of classification reduction for POMDP and RL algorithms
  - Result: Action labels are equivalent to class labels in a related weighted classification problem
  - Implication: Optimal strategy can be implemented by optimal classifier

- Theory of active waveform design
  - Result: Optimal sequential energy allocation strategy derived
  - Implication: 90% improvement in MSE achievable in Rayleigh scattering environments
Progress Highlighted Today

1. Classification reduction of multistage policy search [Blatt&Hero:NIPS05]

2. Sequential design for imaging Rayleigh scattering media [Rangarajan&Raich&Hero:SSP05]
Progress 1: Multistage policy search

Binary action tree of the decision process

Nodes are information states: $s_k = f(S_k|Y_{k-1}, a_{k-1})$
Exact Classification Reduction of Optimal Multistage Policy Search

• Proved that solution to optimal sensor scheduling problem is equivalent to an optimal (weighted) classification problem (Blatt&etal:NIPS05)

• Implications:
  – Robust adaptive sensor scheduling can be accomplished with robust adaptive classification algorithms (SVMs, Radial Basis Nets, Ensemble learners, etc).
  – Can approximate optimal policy (classifier) directly instead of through approximations of the value function (Q learning)
  – Can use state of art methods of training optimal classifier (RL, boosting, bagging, random forests, etc)
Landmine Detection Application

• Sensors under development at Georgia Tech (Waymond Scott)
• Data set used is the GATech “Three Sensor Dataset” (Feb.2004)
  • Includes metal detector, radar, and seismic vibrameter.
  • Collection performed on three scenarios of mine/clutter arrangements.
  • Data used to guide sensor statistical simulations at U.Mich.
# Landmine Types

<table>
<thead>
<tr>
<th>Metal Anti-tank*</th>
<th>Metal Anti-personnel*</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1" alt="VS-1.6" /></td>
<td><img src="image2" alt="VS-2.2" /></td>
</tr>
<tr>
<td><img src="image3" alt="TS-50" /></td>
<td><img src="image4" alt="Others:" /></td>
</tr>
<tr>
<td>VS-1.6</td>
<td>VS-2.2</td>
</tr>
<tr>
<td>Others:</td>
<td>TS-50</td>
</tr>
<tr>
<td>M-14, Butterfly, VS-50</td>
<td></td>
</tr>
</tbody>
</table>

Low-metal Anti-tank  

Low-metal Anti-personnel

* This type is not in the three sensor dataset.
Clutter Types

<table>
<thead>
<tr>
<th>Hollow Metal</th>
<th>Non-hollow Metal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shell</td>
<td>Others: Ballbearing</td>
</tr>
<tr>
<td>Popcan-Crushed</td>
<td>Threaded rod</td>
</tr>
<tr>
<td>Popcan-Uncrushed</td>
<td>Screw</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Hollow Non-metal*</th>
<th>Non-hollow Non-metal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shell</td>
<td>Big Rock</td>
</tr>
<tr>
<td>Shells</td>
<td>Medium Rock</td>
</tr>
<tr>
<td>Popcan-Uncrushed</td>
<td>Non-hollow</td>
</tr>
</tbody>
</table>

* This type is not in the three sensor dataset.
Observed Landmine Signatures

<table>
<thead>
<tr>
<th>EMI</th>
<th>GPR</th>
<th>Seismic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rock</td>
<td>Nail</td>
<td>Plastic Anti-personnel Mine</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Plastic Anti-tank Mine</td>
</tr>
</tbody>
</table>
Observed Clutter Signatures

<table>
<thead>
<tr>
<th></th>
<th>EMI</th>
<th>GPR</th>
<th>Seismic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Popcan (Crushed)</td>
<td>![EMI Image]</td>
<td>![GPR Image]</td>
<td>![Seismic Image]</td>
</tr>
<tr>
<td>Popcan (Uncrushed)</td>
<td>![EMI Image]</td>
<td>![GPR Image]</td>
<td>![Seismic Image]</td>
</tr>
<tr>
<td>Shell</td>
<td>![EMI Image]</td>
<td>![GPR Image]</td>
<td>![Seismic Image]</td>
</tr>
<tr>
<td>Penny</td>
<td>![EMI Image]</td>
<td>![GPR Image]</td>
<td>![Seismic Image]</td>
</tr>
</tbody>
</table>
Multistage Landmine Detection Experiment

- Single spatial location to be sequentially probed with three possible sensors
- Reward is probability of correct decision minus time to make decision
- Each sensor responds differently to clutter and landmine types.
- Landmines and clutter are characterized in general sub-classes.
- Sub-classes are:
  1. Metal Anti-tank
  2. Low-metal Anti-tank
  3. Metal Anti-personnel
  4. Low-metal Anti-personnel
  5. Hollow Metal Clutter
  6. Non-hollow Metal Clutter
  7. Non-hollow Non-metal Clutter
  8. Background

- Observed statistics from the Three Sensor Dataset were used to generate vectors with appropriate means for the 8 classes.
Feature Definitions

- 5 Total features were considered in this experiment.
- The features reflect the phenomenology of the sensors used in the experiment.
- Features are:
  - EMI 1 - Conductivity
  - EMI 2 - Size (signature extent)
  - GPR 1 - Depth
  - GPR 2 - Radar Cross Section (RCS)
  - Seismic – Resonance
- Features are not calibrated. They are a measure of physical quantities of interest.
## Sensor Performance Matrix

- Using the Three Sensor Dataset, the following Response Table was qualitatively derived.
- This table was used as a guide for setting sensor statistics in statistical simulation.

<table>
<thead>
<tr>
<th>Object Type</th>
<th>Feature</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>M-AT</td>
<td>M-AP</td>
<td>P-AT</td>
</tr>
<tr>
<td>Sensor</td>
<td>EMI</td>
<td>High</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Conductivity</td>
</tr>
<tr>
<td></td>
<td>GPR</td>
<td>High</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Depth</td>
</tr>
<tr>
<td>Seismic</td>
<td>High</td>
<td>Medium</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Description</th>
<th>Feature</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Signal Detectable</td>
<td>P-AT</td>
</tr>
<tr>
<td>Medium Signal Detectable</td>
<td>M-AT</td>
</tr>
<tr>
<td>High Signal Detectable</td>
<td>P-AP</td>
</tr>
<tr>
<td></td>
<td>M-AP</td>
</tr>
<tr>
<td></td>
<td>Cltr-1</td>
</tr>
<tr>
<td></td>
<td>Cltr-2</td>
</tr>
<tr>
<td></td>
<td>Cltr-3</td>
</tr>
<tr>
<td></td>
<td>Cltr-4</td>
</tr>
<tr>
<td>Plastic Anti-tank Landmine</td>
<td>Plastic Anti-Personnel Landmine</td>
</tr>
<tr>
<td>Metal Anti-tank Landmine</td>
<td>Metal Anti-Personnel Landmine</td>
</tr>
<tr>
<td>Hallow, Metal Clutter</td>
<td>Hallow, Non-metal Clutter</td>
</tr>
<tr>
<td>Non-hallow, Non-metal Clutter</td>
<td>Background</td>
</tr>
</tbody>
</table>
The Sensor Scheduling and Decision tree

New location

EMI

EMI data

Seismic data

Final detection

GPR

GPR data

Final detection

Seismic

Seismic data

Final detection
Simulation Details

- State at time t: all the available information.
- Expected reward:
  
  \[(\text{Prob. of correct decision}) - (\text{cost of sensor deployment}) \times (\text{number of dwells})\]

- Scheduler:
  - Weighted classification building block:
    - Weights sensitive combination of $[7,2]$ and $[7,3]$ \text{[tansig, logsig]} NN.
- Mine Detector:
  - Unweighted classification building block:
    - $[7,2]$ \text{[tansig, logsig]} feed forward NN.
- Training used 1000 trajectories
  - Equiprobable mine/clutter scenarios
  - Adaptive length gradient learning with momentum term
  - Reseeding applied to avoid local minima
- Performance evaluation using 10,000 trajectories.
Performance Comparison

Optimal sensor scheduling improves detection performance while reducing average dwell time.
## Optimal Policy for Mean States

### Policy for specific scenarios:

<table>
<thead>
<tr>
<th>Sensor</th>
<th>EMI (1)</th>
<th>GPR (2)</th>
<th>Seismic (3)</th>
<th>Feature</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>M-AT</td>
<td>M-AP</td>
<td>P-AT</td>
<td>P-AP</td>
<td>Cltr-1</td>
<td>Cltr-2</td>
</tr>
<tr>
<td>High</td>
<td>High</td>
<td>Medium</td>
<td>High</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>High</td>
<td>High</td>
<td>High</td>
<td>Medium</td>
<td>Medium</td>
<td>Low</td>
</tr>
<tr>
<td>High</td>
<td>Medium</td>
<td>High</td>
<td>Medium</td>
<td>Low</td>
<td>Low</td>
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<tr>
<td>High</td>
<td>Medium</td>
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<td>High</td>
<td>Low</td>
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<tr>
<td>High</td>
<td>Medium</td>
<td>High</td>
<td>Medium</td>
<td>Medium</td>
<td>Low</td>
</tr>
<tr>
<td>High</td>
<td>Medium</td>
<td>High</td>
<td>High</td>
<td>High</td>
<td>Low</td>
</tr>
</tbody>
</table>

Optimal sequence for mean state:

- 2 2 2 2 2 2 2 2
- 3 1 3 1 3 3 3 3
- D D D 3 D D D D
Progress 2: Optimal Waveform Design

- **Upper left box** - Beam scheduling, waveform selection, beam steering operator, and transmission into the medium, denoted by channel function $H_{ch}$.
- **Right side box** - Processes received signals and retransmits.
- **Lower left box** - Processes output after reinsertion.

3rd Year ARO MURI Review
Aug 3, 2005
Recall Motivation

- Sequentially illuminate a medium and measure backscatter using an array of sensors.

- Applications to in mine detection, ultrasonic medical imaging, foliage penetrating radar, nondestructive testing, and active audio.

- **GOAL**: Optimally design a sequence of waveforms using an array of transducers
  - To image a scatter medium (Estimation).
  - To discover strong scatterers (Detection).
Why Sequential Design?

• Application: unattended sensors with limited battery life:

=> Total available energy is constrained.

• Energy management

=> Is there an optimal sequential energy allocation strategy”

• Benefit of spatial adaptivity with optimal energy management?

NB: Generalizes Time Reversal approach:

• Full waveform design strategy
• Sensor noise taken into account
• Optimal energy management is used
Mathematical Formulation: 2 Stage Design, Linear Medium

- Channel between transmitted field and received backscattered field,

\[
H_{ch} = HDH^T
\]
\[
H = [h_1, h_2, \ldots, h_V]
\]
\[
D = \text{diag}(d); \quad d = [d_1, \ldots, d_V]^T.
\]

- Four signal processing steps

\[
x_1 = v
\]
\[
y_1 = H_{ch}x_1 + n_1 = HDH^Tv + n_1 = Ld + n_1
\]
\[
x_2 = s(y_1)
\]
\[
y_2 = H_{ch}x_2 + n_2 = Ls(y_1) + n_2,
\]

where receiver noises \( n_1, n_2 \) are i.i.d \( \mathcal{CN}(0, \sigma^2 I) \).

- Design objective: minimize MSE under transmitted energy constraint

\[
\phi(u, \text{MSE}) = u^H \text{MSE} u.
\]
Analytical Results: Optimal 2 Stage Design

- Constraint: \( E = E_1 + E_2 \leq E_{\text{max}}, \ E \left[ \| s(y_1) \|^2 \right] = E \left[ \tilde{E}_2(y_1) \right] = E_2. \)

\[
s(y_1) = v^* g \left( \frac{\left\| u^H L^\dagger (y_1 - \hat{y}_1) \right\|}{\| u^H L^\dagger \| \| \sigma \|} \right)^2 \geq \tilde{\rho}(y_1) \]

\[
v^* = \arg\min_{\nu} u^H (L^H L)^{-1} u
\]

- MSE improvement factor: \( \phi_2(u, \text{MSE}_2) \approx 0.68 \phi_1(u, \text{MSE}_1) \)
Nearly optimal design

\[ s(y_1) = v^* A I \left( \frac{u^H L^\dagger(y_1 - \hat{y}_1)}{||u^H L^\dagger||\sigma} \right)^2 \geq \tilde{\rho}(y_1) \]

- Performance gain: \( \phi_2(u, \text{MSE}_2) \approx 0.72 \phi_1(u, \text{MSE}_1) \)
- Compare to optimal: \( \phi_2(u, \text{MSE}_2) \approx 0.68 \phi_1(u, \text{MSE}_1) \)
Gains Maintained for Detection

- Detection Problem for the Linear Medium under energy constraint.
- Sequential energy allocation for two-stage detection.
- Criteria: ROC curves
- Assumptions
  - Linear Medium
  - AWGN
  - Single scatterer vs nse alone
Progress: Rayleigh scattering extensions

- Assume that $d$ is complex normal zero mean unknown variance.
- Imaging area divided into $V$ cells and $\{\gamma_i\}_{i=1}^V$ is the average scatterer reflection power in the cells.
Design of two-step strategy

- Sequence of received signals for Rayleigh scattering medium are
  \[ y_j | x_j \sim \mathcal{CN}(0, R_{y_j}), \quad j = 1, 2, \ldots, n, \]
  \[ R_{y_j} = \sum_{i=1}^{V} \gamma_i R_i \left( x_j\{y_k\}_{k=1}^{j-1} \right) + \sigma^2 I. \]

- Multiplicative Model (parameters appears in variance).
- Use analogous nearly optimal design for energy allocation
  \[ E_2(y_1) = A \mathbf{I} \left( \left[ \frac{\hat{\gamma}_1(y_1) - \gamma}{\sqrt{\text{MSE}_1(x_1)}} \right]^2 > \rho \right) \]

- Two-step estimate:
  \[ \hat{\gamma}_2 = \frac{w_1 \hat{\gamma}_1(y_1) + w_2 \hat{\gamma}_1(y_2)}{w_1 + w_2} \]

- weights \( w_1 \) and \( w_2 \) are chosen to minimize MSE
Results for Rayleigh Scattering

• Optimal design parameters and MSE improvement factor are

\[ \rho_{\text{opt}} \approx 0.8885, \quad \alpha_{\text{opt}} = \frac{E_{1\text{opt}}}{E_0} \approx 0.66, \]

\[ \text{MSE}_2(\gamma) \approx 0.6821 \text{ MSE}_1(\gamma). \]

• MSE gain for constrained optimization (\( \gamma \geq 0 \))

\[ \text{MSE}_{2c}(\gamma) \approx 0.1263 \text{ MSE}_{1c}(\gamma). \]
Future Directions

• **Optimal scheduling**
  – Include more realistic physics-based features for mines and clutter
  – Include more actions: multi-modality wide area search
  – Unattended groups of sensors: multisensor scheduling

• **Sequential waveform design for estimation and detection.**
  – Go beyond optimal energy allocation between various steps.
  – Adapt the waveform to obtain further improvement.
    • Multi Armed Bandit Problems
    • Reinforcement Learning
    • POMDP
Pubs Since Jan 2004

- Thesis

- Journal

- Conference
Pubs Since Jan 2004

- Conference (ctd)
Synergistic Activities and Awards

• IEEE ICASSP-05, IEEE SSP-05, A. Hero plenary speaker
• General Dynamics, Inc
  – K. Kastella: collaboration with A. Hero in sensor management, July 2002-
  – M. Moreland Melbourne: collaborator
  – Ben Shapo: MS student collaborator
• ARL
  – NRC ARLTAB: A Hero is member of NAS oversight/review committee
  – ARLTAB SEDD: A. Hero participated in yearly review
• Georgia Tech: Jay Marble spent 1 month last spring with Weyman Scott
• Night Vision Lab: Jay Marble participated in meeting at Duke
• Foundations and Applications of Sensor Management (Springer - 2006)
  – A. Hero is Chief Editor (with Castenon, Cochran and Kastella) of book
Synergistic Activities (ctd)

• UM Student Jay Marble spent May at Georgia Tech (working with Waymond Scott)
  • Goals:
    • Identify existing data sets for algorithm validation: “Three Sensor Dataset” (Feb 2004)
    • Study sensors to determine if (first order) sensor physics can be useful. ??
    • Investigate seismic sensor as a deployable confirmation sensor.
    • A MATLAB module was produced that adaptively reduced surface clutter from GPR data. The same module was shown to be useful in partially calibrating EMI data. This module was shared with the MURI partners.

• Jay Marble will spend August at Night Vision Lab (working with Steve Bishop)
  • Goals:
    • Indirectly support the Autonomous Mine Detection System (AMDS)
    • Identify new data sets for algorithm validation: “Check Test 1” (April 2005)
    • Apply multi-stage reinforcement learning algorithms to Army problems.
    • Further develop demonstration software for illustrating algorithm performance.
Theory and Application of Sensor Management (Springer)

Co-authors
- Al Hero - UM
- Chris Kreucher - GDAIS
- Keith Kastella - GDAIS
- Doug Cochran - ASU
- Edwin Chong - CSU
- Bill Moran - UMelbourne
- David Castenon - BU
- Larry Carin – Duke
- Bob Washburn – AlphaTech
- Demos Teneketzis – UMichigan
- Venu Veeravali – UIUC/NSF
- Bob Boneau – AFRL
- Stan Musick - AFRL

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2 Decision Theory and Stochastic Control theory (Dave, BM)
3 Statistical inference bounds and asymptotics (RN, LC, BM)
4 Multi-Armed Bandits in Sensor Management(Teneketzis & Washburn)
5 Information Theoretic Approaches (AH, Dave, LC)
6 Sensor management for multi object tracking (KK, CK, AH)
7 Analysis based non-myopic strategies (BW, Dave, Mike S.)
8 Simulation based non-myopic strategies (EC, AH, CK)
9 Active Learning and Sampling (Rui, LC, RN)
10 Waveform libraries & selection (BM, DC, BB)
11 Sensor modeling, sensor physics and waveform design (BB, BM, DC)
12 Distributed and decentralized approaches to SM (Venu/Demos)
13 Open questions and future applications
Transitions

- Effort underway to integrate classification reduction into pruning of waveform libraries under ISP Phase II (Schmidt and Moran, Raytheon)
- SM approaches are being integrated into human in the loop data mining for bioinformatics applications (Woolf, UM Dept of Chem Eng)
- Collaboration with GD on Willow Run experiment for multi-modal tracking of dismounts and vehicles
- Transition of SM to control of sensor swarms (GD) – resulted in DARPA RUM Proposal.
Personnel on A. Hero’s sub-Project (2004-2005)

- Chris Kreucher, 4th year grad student (Graduated Feb 2005)
  - MS UM-Dearborn
  - General Dynamics Sponsorship

- Neal Patwari, 3rd year doctoral student
  - BS Virginia tech
  - NSF Graduate Fellowship/MURI GSRA

- Doron Blatt, 3rd year doctoral student
  - BS Univ. Tel Aviv
  - Dept. Fellowship/MURI GSRA

- Raghuram Rangarajan, 3rd year doctoral student
  - BS IIT Madras
  - Dept. Fellowship/MURI GSRA

- Raviv Raich, PostDoc
  - PhD Georgia Tech (Tong Zhou advisor)