Multi-Modal Inverse Scattering for Detection and Classification Of General Concealed Targets:

Landmines, Targets Under Trees, Underground Facilities

Research Team:

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Research Overview

• Sensing of landmines, targets under trees and underground structures are very distinct missions, although they fall under the general problem of sensing concealed targets in the presence of a complex, stochastic environment

• Rather than focusing on one of these areas, we exploit their inter-relationships to investigate the general concealed-target problem

• Particular examples will be investigated by connecting members of the MURI to appropriate members of the user community (e.g. landmines: Army Countermine Office, Ft. Belvoir, VA)

• Undertake a multi-modal (multi-sensor) approach to effect inversion, with insights from the evolving inversion used to refine/optimize the inter- and intra-sensor parameters

• Will exploit the fact that future (and current) DoD systems will rely increasingly on autonomous vehicles (e.g. *multiple* robots, UAVs and UUVs that can be positioned to optimize the sensor platform as the inversion is undertaken)
Multi-Modal Inversion of General Targets Embedded In Arbitrary Stochastic Layered Media

General Adaptive Algorithms and Phenomenological Insights

Landmines

Underground Structures

Concealed Ground Structures

Application-Specific Questions/Issues
Multiple UAV Sensor Platforms
Flight Paths and Sensor Parameters Refined as Inversion Undertaken

Multiple Robotic Sensor Platforms
Robot Positions & Sensor Parameters Refined as Inversion Undertaken

Concealed
Ground Target

Landmines

Conduit/
Tunnel

Underground Facility
Multiple Sensors

Multi-Sensor Physics-Based Constrained RDOF

Direct Inversion

Reverse-Time Migration

General Nonlinear Inversion

Inversion Confidence

High

Inversion complete

Optimize Intra-Sensor Parameters Optimize Inter-Sensor Parameters

Phenomenology from Forward Models

Statistical Inversion

Adaptive HMM Multi-sensor mutual information Multi-sensor, adaptive Bayesian

Adaptive Coarse-to-Fine Pruning

Phenomenology from Forward Models
## Initial Phase: Wide-Area Surveillance

<table>
<thead>
<tr>
<th>Modality</th>
<th>Land Mines</th>
<th>Targets Under Trees</th>
<th>Underground Facilities</th>
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<tr>
<td>Radar, SAR</td>
<td>X</td>
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<td>X (conduits, entry points)</td>
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## Second Phase: Near-In Sensing

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<td>X (moving vehicles)</td>
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<td>Magnetic EMI, Magnetometer</td>
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Multiple Sensors

Multi-Sensor Physics-Based Constrained RDOF

Direct Inversion

- Reverse-Time Migration
- General Nonlinear Inversion

Statistical Inversion

- Adaptive HMM
- Multi-sensor mutual information
- Multi-sensor, adaptive Bayesian

Adaptive Coarse-to-Fine Pruning

Optimize Intra-Sensor Parameters
Optimize Inter-Sensor Parameters

Inversion Confidence

Inversion complete

Phenomenology from Forward Models
JCFO, Cont.

Associate each training sample with parameter $Beta$, and each feature with parameter $Theta$

example: training data of 128 samples, 17 features for each sample

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```

Object1: feature1 feature2 feature3 feature4...... feature17  $\rightarrow$ Beta[1]

Object2: feature1 feature2 feature3 feature4...... feature17  $\rightarrow$ Beta[2]

... ... ...

Object128: feature1 feature2 feature3 feature4...... feature17  $\rightarrow$ Beta[128]

---

Training Objective: Estimating parameters of $Theta$ and $Beta$

Feature Selection: Sparsity in $Theta$ implies that it finds only a few features highly relevant for classification. (making some Theta[i]=0)

Kernel function selection: Sparsity in $Beta$ implies that it finds a small subset of data highly representative of the different classes (making some Beta[i]=0)

Find the maximum a posterior (MAP) estimate of $Theta$ and $Beta$ using EM algorithm.
Physics-Based versus JCFO for EMI and MAG (Area 2)

JCFO picks 4 features and used 5 of 128 training vectors!
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Phenomenology from Forward Models
Three Sensor Experiment

- Experimental Scenario #1
  - 6 Mines
  - > 20 Clutter objects
  - Relatively uniform distribution

- Experimental Scenario #2
  - 7 Mines
  - > 25 Clutter objects
  - Non-uniform distribution
Burial Scenario #1

1.8m by 1.8m Scan Region

Seismic Sources

Mines
VS-2.2 (7cm deep)

TS-50 (1.5cm deep)
w/ Nail

M-14 (0.5cm deep)

VS-50 (1cm deep)

PFM-1 (1.5 cm deep)

VS-1.6 (6.5cm deep)

Assorted Metal Clutter (2 to 4 cm deep)

Shells (4cm deep)

Threaded Rod (3.5cm deep)

Dry Sand (5cm deep)

Penny (5.5cm deep)

Rocks (3 and 4 cm deep)

Nails (4cm deep)

Cans (3 and 2.5 cm deep)

Ball Bearing (3.5cm deep)

Shells (5.5cm deep)
EMI Sensor
Image (90 dB scale)

“Energy” in Imaginary part of the response 1 KHz to 60 KHz
GPR Sensor
Raw Data-Air Data

\[ x = 68 \text{ cm} \]

\[ x = 110 \text{ cm} \]
Seismic Sensor

Radar: R.F. Source, Demodulator, and Signal Processing

Signal Generator

Elastic Wave Transducer

Signal Generator

Radar: R.F. Source, Demodulator, and Signal Processing

Waveguide

E.M. Waves

Elastic Surface Wave

Mine

Displacements
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AMMP Bayesian Processing

\[ \Lambda(r) = \frac{\int f(r/\Theta, H_1) f(\Theta/H_1) d\Theta}{\int f(r/\Omega, H_0) f(\Omega/H_0) d\Omega} \]

- Two modes of adaptation
  - Statistical parameters tracked and updated (e.g. covariance matrix)
  - Priors on uncertain parameters modified based on context (e.g. size, depth of radar response indicates an anti-tank mine, EMI library modified accordingly)
\[ f(r_x / H_1) = \sum_{i=1}^{2} p(\theta_i^1) \left[ \sum_{j=1}^{N_i(\theta_i)} f(r_x / t_{\theta_i,j}, H_1) p(t_{\theta_i,j}) \right] \]

\[ \theta_1^1 = \text{AP}, \quad \theta_2^1 = \text{AT} \]
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- **12 Mine types (2-5 of each AT, AP, LM, HM)**
- **4 types metallic clutter:**
  - CL1: < 3g
  - CL2: 3 to 10g
  - CL3: 11 to 40g
  - CL4: > 40g
- **Non-metallic clutter:**
  - Wood
  - Plastic
  - Stone
- **Blank Ground**
Performance with Bayesian AMMP

Energy Detector
• 100% Detection
• 73% False Alarm

Feature-Based Detector
• 100% Detection
• 76% False Alarm

Feature-Based Detector w/ Region Processing
• 100% Detection
• 24% False Alarm

Feature-Based Detector w/ Bayesian AMMP
• 100% Detection
• 17% False Alarm
Multiple Sensors

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Inversion Confidence

High

Inversion complete
Computational domain $100\lambda_0 \times 100\lambda_0$ ($= 3m$ at $f_0 = 1KHz$, the central frequency) with $c_0 = 3km/sec$, surrounded by a perfectly matched layer (pink).

The array has 185 receiving elements $\lambda_0/2$ apart for an aperture of $92\lambda_0$. 
Kirchhoff migration imaging results

Down: Homogeneous, 1%, 2%, 3% STD. Across: different realizations.
Across: Homogeneous, 1%, 3%STD, for an array of size $10\lambda_0$. The focusing strength is normalized to have peak equal to one.
Coherent interferometric imaging results II

Down: 0%, 1%, 3% STD. Across: $\Omega_d = 0, 10, 20\%$. All: $\Delta_d = 40\%$
IV. 2D Multi-Frequency EM and Seismic Imaging

Figure 7: Configuration for seismic imaging of underground structures.

- 16 × 16 sources/receivers in the soil.
- The 3-layer medium models the presence of top soil.
- Shear Waves are neglected for such deep imaging cases for the seismic case.
Multi-Frequency EM Imaging of an Underground Room

Figure 10: Imaging with 4 frequencies between 10–70 MHz. Left: Reconstructed Image from multi-frequency EM data. Right: The ground truth.

- The wall is well reconstructed because of its large EM contrast with background ($\chi = 1.5$).
Multi-Frequency Seismic Imaging of an Underground Room

Figure 11: Imaging with 4 frequencies between 100–1000 KHz.
Left: Reconstructed Image from multi-frequency seismic data.
Right: The ground truth.

- The air inside is well reconstructed because of its large acoustic contrast with background.
The Joint EM/Seismic Image versus Single-Modality Images

Joint Image $\alpha A + B$.  Seismic Image $A$. EM Image $B$.

- The joint image is significantly better than single-modality images.
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Quadtree BackProjection

- Space-Time Domain Decomposition
  - Image Patch Dividing and Sub-Aperture Formation (Virtual Sensor)
  - Divide and Conquer Strategy
- Computational Complexity $O(N^2 \log_2 N)$
Quadtree Pruning

- Multiresolution Imaging
  - Intermediate Data with Energy Function
    - $d(u,t) \Rightarrow di(u,t,1,1) \Rightarrow \ldots \Rightarrow di(u',t',\xi,\eta) \Rightarrow \ldots \Rightarrow di(1,1,\xi,\eta) \Rightarrow f(x,y)$
  - Intermediate Stage Data Pruning $\Rightarrow$ Early Detection
Overall Multi-Sensor Problem

Airborne Primary Sensor

Ground-Based Primary Sensor, Over-Pass Capable

ROI & Desired Sensor

Estimated labels

Multi-Sensor Auxiliary Sensors
Issue: Performance vs. Cost
Test Case: PSI Forward-Looking Radar Data

Build a classifier using trainin data from all of lane 51.

Proceed down the lanes in 20m increments, query informative points with an imperfect labeler and adjust (re-train) classifier accordingly. Classify remaining unlabeled points in (20m) section of lane before moving on to next (20m) section of lane.
Operating point of auxiliary sensor

Performance on same unlabeled testing data (Lanes 52, 54, and 56 run consecutively)

- (AL) All mines
- (AL) Metal mines only
- (AL) Plastic mines only
- All mines
- Metal mines only
- Plastic mines only

Probability of Detection vs. False Alarm Rate (m^2)

Pd vs. Pfa
Schedule

8:30-9:00 Overview
9:00-9:30 Waymond Scott
9:30-10:00 Jim McClellan
10:00-10:30 Leslie Collins

10:30-10:45 Break

10:45-11:15 George Papanicolaou
11:15-11:45 Qing Liu
11:45-12:15 Lawrence Carin
IMA "Hot Topics" Workshop:
Adaptive Sensing and Multimode Data Inversion
June 27-30, 2004
With partial funding from DARPA and Army Research Office

Organizers:

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