SAIC Analysis of Data Acquired at Camp Butner, NC

Dean Keiswetter
The Large Scale Classification Project at Camp Butner provides an excellent opportunity to compare and contrast classification performances for static and reconnaissance EMI data and for a variety of analysis approaches. SAIC analyzed EM61 data acquired in reconnaissance mode as well as Metal Mapper and TEMTADS data acquired while stationary. Our analysis included single- and multi-source solvers. Our classification utilizes a decision tree targeting the intrinsic polarizabilities. The decision tree incorporates uncertainty in unanticipated targets-of-interest and has hasn’t changed dramatically since being developed using data acquired at Aberdeen Proving Ground, Camp Sibert, and Camp San Luis Obispo. We also experimented in the number of training labels (starting with no on-site labels) used to fine tune the classifier. Finally, we utilized two different analysis environments; Oasis montaj and IDL. Two commercial firms, NAEVA and Parsons, also utilized the UX-Analyze module in Oasis montaj to classify Metal Mapper stationary data. During our presentation, we will discuss performances of the various combinations and present lessons learned.
SAIC DATA ANALYSIS OF DATA ACQUIRED AT CAMP BUTNER

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Outline

Background
- Datasets analyzed
- Analysis environment
- Inversion schemes
- Classification approach

EM61 data as pre-screen

Classification performance

Failure Analysis

Stop by Poster #61 for more details
Science Applications International Corporation (SAIC)

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Tom Furuya data analyst
Jim Kingdon data analyst & analysis algorithms
Nagi Khadr data analyst
Jonathan Miller analysis algorithms
Bruce Barrow failure analysis
Tom Bell technical advisor

Supported by ESTCP Project’s MM-0910 & MM-0134
Sensor Data

Dynamic

EM61

Cued

MetalMapper

TEM-TADS
Analysis Environment

UX-Analyze

Stop by Poster #60 for more details

Oasis montaj
• High performance database
• Advanced data processing
• Dynamic linking (maps, data, profiles, etc.)
• Professional map production
• Audit trail
Single target solvers

Standard dipole model

- Location (X,Y,Z), orientation (Ψ, Θ, Φ), & intrinsic polarizabilities

Utilized two single source, but multi-stage solvers – each designed to avoid local minima

- Generally produce the same answers
- Subtle difference in recovered polarizabilities are sometimes observed
- Excellent data for establishing best practices
Multi-source Solver

Multi-source solver for handling multiple objects within the sensors’ field of view (MM-1662)

- Seed the area with sources
- Predict signals with forward model
- Find a linear combination that best match observed signal using sparse solution solver
- Add new seeds
- Iterate

Perform multi-dipole inversion on derived target locations
Classification Approach

- Compare unconstrained polarizabilities for the target under investigation to a signature library

- “Library match” metric
  1. Primary polarizability \((\beta_1)\)
  2. Ratio secondary to primary \((\beta_2 / \beta_1)\)
  3. Ratio tertiary to primary \((\beta_3 / \beta_1)\)

- Decision boundary chosen to accommodate training data
Axial Symmetry

- Targets with axially symmetric response that do not match expected munitions included in “can’t decide”
  - Hedge against unexpected munitions (e.g. 3” Stokes mortar)
EM61 as pre-screener

- Lower coil only, four gates
- Unconstrained 3-polarization
- Identified high confidence
  - UXO → dig
  - Clutter → leave
- All others request cued data
- Classification based on
  - Size ($\sum \beta$ 1st time gate)
  - Measured decay
  - Screen on fit quality
  - Generalized likelihood ratio test to assign probabilities
## EM61 as pre-screener

<table>
<thead>
<tr>
<th></th>
<th>UXO</th>
<th>CLUTTER</th>
</tr>
</thead>
<tbody>
<tr>
<td>Declared</td>
<td>68</td>
<td>251</td>
</tr>
<tr>
<td>Actual</td>
<td>59</td>
<td>249</td>
</tr>
</tbody>
</table>

![Decay constant (Ch4/Ch1) vs Fit size](image)
Classification Performance

2,290 anomalies
- 0 training
- 0 can’t analyze

1,021 classified
- 139/142 munitions correctly classified (97.9%)
- 877/879 clutter correctly classified (99.8%)

1,269 can’t decide
- 29 UXO, 1,240 clutter
**Signature Variability**

- Munitions in each class (37mm, M48, 105mm) are not identical
- Response curves can vary due to target condition: different model, fuze & tail boom present/absent, etc.

<table>
<thead>
<tr>
<th>Correctly Classified as UXO</th>
</tr>
</thead>
<tbody>
<tr>
<td>37mm</td>
</tr>
<tr>
<td>M48 fuze</td>
</tr>
<tr>
<td>105mm</td>
</tr>
</tbody>
</table>
Signature Comparison:
ID 1201 versus library signatures
Misclassified Munitions (1 of 3)

1201

Principal polarizability crosses the other two

Not in our library

Symmetry metric based on polarizations 1 & 2 instead of 2 & 3
Misclassified Munitions (2 of 3)

Signature Comparison:
ID 2504 versus library signatures
Misclassified Munitions (2 of 3)

Classified as clutter based on size

Inverted depth and polarizabilities too small
Signature Comparison:
ID 429 versus library signatures
Misclassified Munitions (3 of 3)

Decision metric of 0.80, just below our threshold of 0.81.

Decent signal strength put it in the high confidence clutter category.
"Can’t Decide" Category

<table>
<thead>
<tr>
<th>Cannot Decide sub-categories</th>
<th>Total Count</th>
<th>No. of UXO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low SNR</td>
<td>141</td>
<td>1</td>
</tr>
<tr>
<td>No source within 0.8m</td>
<td>25</td>
<td>0</td>
</tr>
<tr>
<td>Axial symmetry</td>
<td>1059</td>
<td>8*</td>
</tr>
<tr>
<td>Buffer</td>
<td>44</td>
<td>20</td>
</tr>
<tr>
<td><strong>TOTAL</strong></td>
<td><strong>1269</strong></td>
<td><strong>29</strong></td>
</tr>
</tbody>
</table>

*modifying our UXO/clutter threshold and not hedging for unexpected munitions types (viz., axial symmetry) would have reduced the unnecessary digs by 951.
## Summary/Conclusions

Our attempt to conservatively pre-screen using EM61 data (inverted size & measured decay) resulted in two false negatives.

Classification based on intrinsic polarizabilities is effective.

The vast majority of UXO were readily classified.

- 37mm showed the most variability and were the most difficult for us.

### Areas for classification performance improvement

- Low SNR targets – Longer stacks, more robust classifier
- Multiple targets – Adaptive array positioning, improved multi-target solvers
- Misclassified munitions – Consolidate and adopt program-wide best practices for recognizing and dealing with outliers
Analysis Interface
NRL TEM array
Number of targets: 2

Archive Documentation for each anomaly processed