UXO DISCRIMINATION AT CAMP SAN LUIS OBISPO WITH THE METALMAPPER

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Abstract

The MetalMapper is an electromagnetic metal detector that is being commercialized by Geometrics, Inc with support from the Environmental Security Technology Certification Program (ESTCP). Together with several other systems, the MetalMapper participated in an ESTCP-sponsored classification study at the former Camp San Luis Obispo (SLO) located a few miles northwest of San Luis Obispo, CA. Operating independently, the MetalMapper conducted two surveys: a dynamic mapping survey for target detection; a precision (“Cued ID”) static measurement over detected targets for use in discrimination. The SLO study involved a number of different organizations deploying both commercially available EM and magnetic sensors and advanced EM systems such as the MetalMapper. Following the completion of the field work by these organizations, nearly 2000 targets identified from the detection surveys were then dug. Using a common set of targets, demonstrators prepared a dig list prioritized according to the probability that a particular target was a target of interest (TOI). The dig lists were scored by the Institute for Defense Analyses (IDA).

The primary objective of this paper is to describe MetalMapper system, the data processing, and the methodology employed for assembling the prioritized dig list. We also present the scoring results for the MetalMapper as provided to us by the IDA.

Introduction

Over a period of 10 years or more, the UXO community has relied on so-called “seeded” sites to test and validate commercially available technology as well as new technology for the detection and classification of UXO. Two such sites are the Standardized UXO Technology Demonstration Sites (USAEC 2009) located at Aberdeen Proving Ground (APG) and Yuma Proving Ground (YPG). Demonstrators who access these sites submit prioritized dig lists and are scored by the Aberdeen Test Center (ATC) for performance as detectors and for discrimination. Constructed at considerable expense, the ground truth for the sites at APG and YPG is not provided to demonstrators and hence there is no opportunity for retrospective study. The ESTCP discrimination studies are designed to provide
the opportunity to demonstrate technology on live sites that have been carefully selected to provide tractable operational and discrimination challenges. The site at Camp SLO is the second site to be selected by ESTCP. It was selected to be more challenging from both the operational and interpretational viewpoint than the first such demonstration area, which was located at the former Camp Siebert in Alabama. The SLO site is located approximately 7 mi NW of the town of San Luis Obispo, CA (Figure 1). Covering an area of approximately 12 acres (4.77 ha), the site was formerly used as a mortar (4.2 in, 81mm, and 60mm) and rocket (2.36 in anti-tank) range.

**The MetalMapper: An Advanced EMI System**

With support from ESTCP, Geometrics, Inc (San Jose, CA) is commercializing an advanced time-domain electromagnetic induction (EMI) sensor for the detection and classification of UXO. The MetalMapper system is based on concepts and technology for an Advanced Ordnance Locator (AOL) developed and implemented to the proof-of-concept stage with support from the Naval Explosive Ordnance Demolition Technology Division (NAVEDTECHDIV, Indian Head, MD)(Snyder 2005; George 2006; George 2007).

Figure 2 shows the MetalMapper being deployed at SLO. The antenna array is mounted to a wooden skid attached to the front-loader of a Kubota tractor. The antenna array consists of 3 mutually orthogonal 1m x 1m transmitter loops (red/green/blue squares in Figure 2) and an array of 7 triaxial receiver cubes with side dimension 10cm. Each cube has 3 identical and mutually orthogonal induction coils. The receiver therefore approximates a point measurement of the time rate of change of the vector secondary magnetic field \( \frac{\partial B}{\partial t} \). A battery-powered man-portable instrument package weighing approximately 45 lbs operates the system in the time-domain mode.

**Modes of Operation**

The instrument package contains a transmitter and a 24-ch 16-bit data acquisition system. The base frequency of operation is under operator control. There are two acquisition modes: a) Continuous Mode; b) Static Mode.

**Continuous Mode Acquisition:** The continuous operating mode is used for mapping. In this mode, only the Z (horizontal) transmitter loop is activated, and after activation the data sampling continues until the operator halts data acquisition. All data samples are stored in a single binary data file. Typically, data from a single survey profile are stored in the same data file. The operator selects a base frequency \( f_0 \), and a sample period \( T \). Sampling at a rate of 250 KHz (4 \( \mu \)s), the DAQ acquires data for each of the 22 channels over the prescribed sample period \( T \), and rectifies and stacks the transient (off-time) intervals Then, each of the transients are decimated into a sequence of logarithmically spaced time gates controlled by a decimation factor set by the operator. The parameters for both continuous and static mode acquisition used at SLO are shown in Table 1.
Static Mode Acquisition: The static operating mode is used for acquiring precision data while the system is not moving (static). In this mode, the three transmitters are activated sequentially during which time 22 transients (21 receiver coil plus a current sensor) for each transmitter polarization are acquired. These data are assembled into a single data sample, decimated as explained above, and stored to a binary data file. Only a single data sample is stored in each data file. Similar to continuous-mode acquisition, the operator can control the base frequency, and the acquisition sample time. In addition, he can set a stack count that permits stacking successive acquisition cycles. Acquisition is halted at the end of the stack count, and the average data sample is stored into a binary file. The acquisition parameters for static acquisition (Table 1) were set so that we acquired 8 ms time-bandwidth transients sampled over 42 logarithmically spaced time gates.

### Table 1: Acquisition parameters for continuous (Cont) and static mode MetalMapper data acquisition at SLO.

<table>
<thead>
<tr>
<th>Mode</th>
<th>Tx</th>
<th>f₀ (Hz)</th>
<th>T (s)</th>
<th>N₁</th>
<th>N₂</th>
<th>Δt (s)</th>
<th>tmin</th>
<th>tmax</th>
<th>Ngates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cont.</td>
<td>Z</td>
<td>270</td>
<td>0.1</td>
<td>27</td>
<td>1</td>
<td>0.1</td>
<td>114</td>
<td>900</td>
<td>44</td>
</tr>
<tr>
<td>Static</td>
<td>Z/Y/X</td>
<td>30</td>
<td>0.9</td>
<td>27</td>
<td>10</td>
<td>27</td>
<td>106</td>
<td>7912</td>
<td>42</td>
</tr>
</tbody>
</table>

Tx = Z transmitter only; 'Z/Y/X' = All 3 Tx loops (sequential)

f₀ (Hz) = Base frequency of Tx waveform
T (s) = Sample Period
N₁ = Tx period per sample period (T)
N₂ = Number of sample periods to stack
Δt (s) = Effective sample period
tmin = delay time at minimum time gate (μs)
tmax = Delay time at maximum time gate (μs)
Ngates = Number of time gates per transient

MetalMapper Surveys at SLO

Of the three advanced EMI systems demonstrated at SLO, the MetalMapper was the only system that was operated in the mapping mode as well as in the static mode. We surveyed the entire study area in the mapping (continuous) mode with a lane spacing of 0.75m. Using a detection map compiled from the continuous-mode detection survey, we picked targets that we used in a static-mode (Cued ID) survey.

**The Detection Survey**

The target map (Figure 3) is a base map for the SLO study area. The area consists of 53 30x30m blocks. We have over-plotted as green or blue dots the locations of 1561 MetalMapper targets that were...
dug after geophysical field work was completed at the site. The dig results for the 154 targets marked with green symbols were supplied to demonstrators to use as training data. The remaining 1407 targets marked with blue symbols represent the test set that was used for scoring. The ground truth for those targets was withheld from the demonstrators until after the target list was scored by the Institute for Defense Analyses (IDA). Although the detection map covered all 53 blocks, targets falling within the 8-block area (K6-N7) and the narrow NW-SE trending strip immediately below it were excluded from the test set for budgetary reasons. The inset in Figure 3 is a segment of the target detection map covering survey block M13. Targets are marked with yellow circles. The map also shows the survey line coverage for block M13. It took approximately 10 field days to acquire the data for the detection map giving us an average production rate of 1.2 acre/day.

**The Static-Mode Survey**

During the static-mode survey, the MetalMapper returned to the site of the target anomaly and acquired a static-mode data point using the acquisition parameters listed in Table 1. In many cases, two or more data sets were acquired for a single target. In some cases, this was due to the fact that both peaks from a double-peak anomaly were picked. In other cases, the target was one we selected for a second reacquisition during our repeat static survey. We picked a total of 2179 targets for the static survey. At the end of the survey, we selected 314 targets to repeat based on the horizontal offset between the estimated target positions from the antenna platform. Targets with good signal-to-noise (SNR) and other data quality measures (e.g., model fit) that had a horizontal offset of 40cm or more from the antenna platform were measured again at the estimated site of the target rather than the original target pick. Over a period 7 field days, we acquired a total of 2492 static data points for an average production rate of 360 pts/day (40 pts/hr). On our best day, we measured 494 data points.

**Static Data Processing and Discrimination**

**Static Data Processing**

Static data sets are processed by approximating the observed secondary fields with a single point dipole as a model. The dipole-model has been widely used for interpretation of EM data from UXO surveys (MacInnes 2002; Grimm 2003; Smith 2004; Pasion 2007; Snyder 2008). We refer the interested reader to our reference citations for details on the theory for the modeling. A flow diagram for the processing is shown in Figure 4. A static data point from SLO consists of a set of 21 transients from each of 3 transmitter polarizations (Z,Y, and X). After subtracting a background transient, these transient data are input into a modeling program (MM/RMP). The modeling program estimates the target position and its three attitude angles and, from knowledge of those values, it estimates a set of 3 principal polarizability rate transients.

Figure 4: Flow diagram illustrating target parameter extraction with a dipole model. Observed transient data are reduced to a set of 3 principal polarizability rate transients.
The input data and the resulting polarizability transients for a 60mm target are illustrated in Figure 4. Principal polarizability transients such as those in Figure 4 are the electromagnetic characterization of the target. For the purpose of discrimination, we reduce the polarizability transients to a set of scalar “features” by computing the 0th and 1st order moments of each of the three principal polarizability curves as illustrated in Figure 5 (Smith 2002). Using ratios of the moments, we obtain a parameter \( \tau \) with units of time that is indicative of the persistence of a particular principal transient in time. We also compute parameters relating to shape. For discrimination with neural nets, we selected 9 of the scalar parameters listed in Figure 5 as the feature vector to use as the input to our neural networks.

**Discrimination with an Automated Neural Network**

Our training set consisted of MetalMapper static data sets acquired in proximity to the 154 targets for which ground truth was provided to demonstrators plus 58 additional data sets acquired from targets seeded in a test strip and a test pit located at SLO. Altogether there were 269 static data sets with ground truth that could be used as training. Graphical analysis with these data shows that the targets of interest separate and cluster together in distinct regions. Typical of such scatter plots is the “beta” plot shown in Figure 6. The plot indicates that the targets of interest separate into clusters and that much of the clutter can be discriminated simply on the basis of a feature such as \( P_{0x} \) that indicates relative target size.

Using the scalar features (Figure 5) extracted from training data, we trained a multi-layer perceptron neural network (ANN) with a single output value \( p \) in the range \( 0 \leq p \leq 1 \) (Figure 7 - inset). Targets with ANN output values \( p > 0.5 \) are more likely to be UXO and conversely those with values...
p<0.5 are more likely to be non-UXO.

The performance of the ANN when applied to the whole training set\textsuperscript{2} is shown by the ROC curve in Figure 7. These results show the ANN is able to correctly discriminate 95% of the UXO with a false positive rate (clutter targets incorrectly identified as UXO) of less than 5%. However, there is one outlying target that would require us to dig approximately 80% of the clutter before we finally dig the target.

**Target ID Using Library Matching**

As we indicated earlier, historical records and limited reconnaissance digging indicated that there were only 4 munitions targets of primary interest (TOI): mortars (4.2 in, 81mm, and 60mm), and 2.36 in “bazooka” rockets. Each of these target types are easily distinguished by visually examining the shape of their principal polarizability curves. Average polarizability curves for the 4 TOI at SLO are shown in Figure 8. The averaged curves (red/green/blue lines) are derived from 12-15 static measurements of the targets placed at different depths and orientations. Using a library of 5 “type” curves\textsuperscript{3}, we ran a mathematical curve matching algorithm on the unknown polarizability curve sets resulting from the processing of the target data sets. It is beyond the scope of this paper to explain in detail the matching algorithm. Suffice it to say here that we matched the major (largest) polarizability (\(P_x\)) curve for amplitude and shape to each of the library curves. Secondly, we matched the ratio of the average of the two minor curves (\(P_T = \sqrt{\frac{P_y P_z}{P_x}}\)) for shape only. We combined the 3 matching scores (major curve-size and shape, aspect ratio-shape) to provide a final matching score. For each target, we reported the best (maximum) of the 5 possible scores together with target type that produced it.

**Assembling the Dig List**

The final product of any effort to discriminate is a “dig list” that establishes the priority for digging each target. A flow diagram of the process we used to assemble the dig list is shown in Figure 9. The dig list is divided into 4 target categories as follows:

\textsuperscript{2} During training, the training set is randomly divided into 3 groups: a training group (~50%), a selection group (25%), and a test group(25%).

\textsuperscript{3} There were in fact 2 variations of 60mm mortars encountered at SLO. One variation was an intact mortar round complete with fins and a fuse. The other type consisted of the mortar body alone. The 60mm mortar body has a distinctly different electromagnetic size and its largest polarizability transient decays more rapidly than its full-bodied counterpart. As such, we found it necessary to add a 5\textsuperscript{th} type (60mm body) to our library for matching.
1. **Category 1**: High confidence non-munitions targets. These targets can be safely left in the ground.

2. **Category 2**: Targets for which the discrimination decision is ambivalent. **Dig!**

3. **Category 3**: High confidence munitions targets. **Dig!**

4. **Category 4**: Targets wherein the data are either too poor or too confusing to analyze. **Dig!**

An important element of the dig list is the boundary or threshold (marked $T_d$ in Figure 9) established by the interpreter between category 1 and category 2 targets. Ideally, all target lying above $T_d$ are clutter that can be safely left in the ground. Figure 9 also suggests how we integrated 2 different discrimination methods (ANN and Library Curve Matching) together with a set of rules to generate the target list. Briefly the rules go as follows:

1. **Data Quality** – If data quality (represented by the model Fit statistic) falls below an established threshold (75%), the target is designated as Category 4.

2. **Target Size** – Small targets (P0x < 500 cm³) are designated as Category 1 targets and ranked in that category according to their Fit statistic. Thus, small targets with a poor fit statistic will fall closer to $T_d$ than a similar target with a better fit statistic.

3. **ANN vs. Library Match** – This is basically a “winner-take-all” decision where we accept the result that gives the highest dig priority. If, for example, the ANN decision suggests “clutter” but the library match suggests “TOI”, then we accept the library matching.

The effect of the rule-based decisions, primarily the ANN vs. Library Match decision, can be seen in the training ROC curve (Figure 7 – Red curve). The library matching tends to catch some TOI targets that are erroneously classified as clutter. In particular, note on the red curve that the hard false negative seen at $P_{fp} = 0.8$ is now gone. As a result, the modified ROC curve rises to $P_d = 1.0$ at the point where $P_{fp} = 0.1$. That means that 90% of the clutter objects can be safely left in the ground (i.e., there are no more TOI targets in the remaining items to dig).
An alternative way of viewing the results of the rule-based decision is to overlay a contour plot of the decision surface (i.e., a contour plot of the decision statistic $0 \leq p_d \leq 1$) over a scatter plot of 2 scalar features. In Figure 10, we show such a plot using the ($\log_{10} \tau_x$, $\log_{10} P_{0x}$) plane of the 9-dimensional feature space. The underlying scatter plot is based on the ground-truth for all the targets in the test dig at SLO. The ground truth was provided by IDA to those involved in interpretation only after the target lists had been scored. By comparing the 2 panels in Figure 10 (left to right), one can see that the effect of the decision rules is to slightly modify the position of the 0.5 contour ($T_{0.5}$) in order to capture some of the false negative points on the left hand panel (i.e., magenta colored symbols falling on the dark side of the red contour) so that in the right-hand they are correctly classified as TOI.

Scoring Results

We were scored by IDA on a target set consisting of 1063 targets blind targets (all MetalMapper targets that were not training targets where a priori ground truth was provided). Of those targets, there were 206 that were designated TOI. The remaining 857 targets (clutter) mostly consisted of munitions debris (MD). Figure 11 shows the MetalMapper performance in the form of the ROC curve provided to us by the IDA. We have enhanced the graphics in order to highlight various important details.
The abscissa on the graph is labeled (Number of) “Unnecessary Digs”. Another term for this is number of false positives (targets designated as TOI but found to be clutter). Note that the ROC curve starts at 15 digs, corresponding to the number of targets we placed in the “Cannot Analyze” category (4). Three points on the curve are marked with colored dots. The dark blue dot indicates the designated threshold point (Tcl) defining the boundary between category 1 and category 2 on the dig list. The line colors match the color scheme shown for the dig list in Figure 9. The cyan dot marks the point in the list at which the last TOI would have been dug. On our list, this point occurs at 310 unnecessary digs.

On the expanded inset to the plot, we have labeled the 4 TOI that were improperly classified. It is beyond the scope of this paper to elaborate in detail on each of these “misses”. Suffice it to say here that with regard to the 2 targets labeled “2.36” there are persuasive reasons for suggesting that the ground-truth for those 2 targets (1782/1541 and 1718/1475) were incorrectly labeled. But the 37mm (292/1502) and the 60mm (1177/775) represent real misclassifications. In retrospect analyses, we have established that we would definitely identify the 37mm as a TOI had we known that it was among the munitions of interest. The 60mm target (1177/775) on the other hand represents a deep 60mm that was overlain by two much smaller 60mm tail booms (Figure 12C). In this case, the magnitude of the 2 shallow 60mm tail booms shown on the white board (Figure 12C) overpowered a weaker field arising from the deep 60mm TOI. Our modeling program is based on a single point dipole. That program estimated the principal polarizability curve set shown in Figure 12A. More advanced modeling software is currently under development that permits modeling a target with 2 or more dipoles (Song 2009; Song 2010). Using a multiple dipole model on this particular target (again in retrospect), Song has successfully modeled the data from the 1177/775 target to show that there is a deeper target with a polarizability characteristics much like a 60mm.

Figure 11: The ROC curve indicating the performance of the MetalMapper for 1063 blind targets at SLO.

Figure 12: Figure showing how a multiple dipole inversion program (Song 2009; Song 2010) helps interpretation in the case of multiple interfering targets. The TOI is a deep 60mm mortar overlain by shallow 60mm tail booms. Panel A shows the polarizability curves for 1-tgt inversion. Panel B shows the resulting 2 sets of curves when analyzed with Song’s program. Panel D shows the geometric mean curves for static measurements over 10-15 60mm mortar bodies.
mortar. For comparison, Figure 12D shows the average polarizability curves for a 60mm body from an ensemble of MetalMapper static data sets for 60mm targets at different depths, and attitudes.

Summary and Conclusions

At the former Camp San Luis Obispo we demonstrated the MetalMapper, one of the advanced EMI systems for UXO detection and classification. The MetalMapper was operated in its dynamic acquisition mode to generate a detection map over the 12 acre site. When used in this mode, our average production was approximately 1.2 acres/day with a profile spacing of 0.75m. Using targets picked from the detection map, the MetalMapper was deployed in its static “cued ID” acquisition mode. Each target site was reacquired using GPS navigation to position the MetalMapper antenna over the target. A single static measurement consisting of 21 8ms receiver transients for each of 3 transmitter loops is acquired. When operating in the static mode, the average production rate was approximately 40pts/hr. The performance of the system during field operations met or exceeded our expectations.

Target parameters were extracted from each of the static data sets and used to compile a prioritized dig list. Targets were classified and prioritized for digging based on a combination of classification with a neural network, target identification using a library matching method based on target library consisting of 5 types, and rule-based decisions that helped to integrate everything into a final list. The neural network was trained with parameters derived from free-air static measurements from target specimens provided at the site together with ground-truth from 154 targets from a “training dig”. All other dig results were withheld from the demonstrators until the dig lists were submitted and scored by the IDA. The MetalMapper scoring was based on a total of 1063 targets comprising all targets that had been dug excluding targets used for training. The discrimination scores were excellent. They show that using simple scalar features we were able to achieve a 95% probability of detection (Pd) with a very low rate of false positives (Pfp~5%). Our specified operating point was at Pd (98%). At that point our false positive rate doubles to 10%. At our operating point, we ended up leaving misclassifying 4 targets of interest. After retrospective target analyses, two of the misclassification are explainable and should probably be removed. The other two misclassifications were due to 1) a new target type (37mm projectile) that we did not train for, and 2) a deep mortar that was screened by overlying clutter.

The performance of the MetalMapper at SLO demonstrates that this new generation of advanced EMI sensors can be deployed at live sites having significant operational challenges. Discrimination performance using target parameters extracted from static-mode MetalMapper data was excellent. The performance we have shown here in this paper is confirmed and reinforced by similar performance scores returned by the IDA for three other (data processing only) demonstrators using the same MetalMapper data set. The performance scores suggest that advanced EMI systems like the MetalMapper can be used to generate dig lists that can significantly reduce the number of unnecessary digs.

Our retrospective analyses show that there is room for incremental improvement in discrimination performance. On the operational level, feed-back into the interpretation process in which new UXO types such as the 37mm projectiles are made known as soon as they are identified during digging can eliminate one source of miss-classification. Improvements in modeling software that automatically tag a target anomaly as possibly resulting from 2 or more interfering targets will also help to reduce false negatives. It is likely, however, that there will always be a few mis-classified targets no matter how sophisticated our modeling and classification methods become.
Acknowledgement

We would like to acknowledge help from Dr. Lin-Ping Song (University of British Columbia/Sky Research, Inc) for providing us with the polarizability curve estimates shown in Figure 12B. These estimates are based on his multiple target inversion program. The case history of the MM-1177 target is discussed in more detail in (Song 2010).

References


