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Practical Strategies for UXO Discrimination

Leonard Pasion
Black Tusk Geophysics

Nicolas Lhomme
Sky Research, Inc.

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The cleanup of UXO-contaminated lands has been hampered by labour, cost, and time intensive site remediation methods. The two main impediments to site remediation are the lack of an effective method of UXO characterization and the time and labour-intensive methods required to excavate each suspect UXO. At some sites the ratio of non-ordnance to ordnance items exceeds 100:1. Developing the ability to discriminate between ordnance and non-ordnance items is essential in reducing the costs of cleanup.

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ACRONYMS AND ABBREVIATIONS

AGC	Advanced Geophysical Classification
CCR	combined classifier ranking
CSM	conceptual site model
DAGCAP	Defense Advanced Geophysical Classification Accreditation Program
DGM	digital geophysical mapping
EMI	Electromagnetic induction
ESTCP	Environmental Security Technology Certification Program
GPS	Global Positioning System
IMU	Inertial Measurement Unit
ISO	Industry Standard Object
ISS	Informed Source Selection
IVS	Instrument Verification Strip
MQO	measurement quality objectives
QA	Quality Assurance
QC	Quality Control
SERDP	Strategic Environmental Research and Development Program
SNR	Signal-to-Noise ratio
TEM	Time domain Electromagnetic
TEMTADS	Time-Domain Electromagnetic Multi-Sensor Towed Array Detection System
TOI	Targets of Interest
UXO	unexploded ordnance

1.0 DETECTION AND CLASSIFICATION OF UNEXPLODED ORDNANCE USING EMI DATA

The cleanup of UXO-contaminated lands has been hampered by labour, cost, and time intensive site remediation methods. The two main impediments to site remediation are the lack of an effective method of UXO characterization and the time and labour-intensive methods required to excavate each suspect UXO. At some sites the ratio of non-ordnance to ordnance items exceeds 100:1. Developing the ability to discriminate between ordnance and non-ordnance items is essential in reducing the costs of cleanup.

The remediation of UXO contaminated sites can, approximately, be described as a three-step process: (1) detection, (2) classification, and (3) excavation. In the context of the UXO remediation problem, detection is the process of determining the location of subsurface metallic targets that are potentially UXO. Since many UXO contaminated sites can be in the order of thousands of acres, a preliminary site assessment is generally carried out to delineate boundaries of UXO contamination such that ground based geophysical detection surveys can be more efficiently fielded. This process of “Footprint Reduction” is achieved through the examination of historical records and airborne surveys.

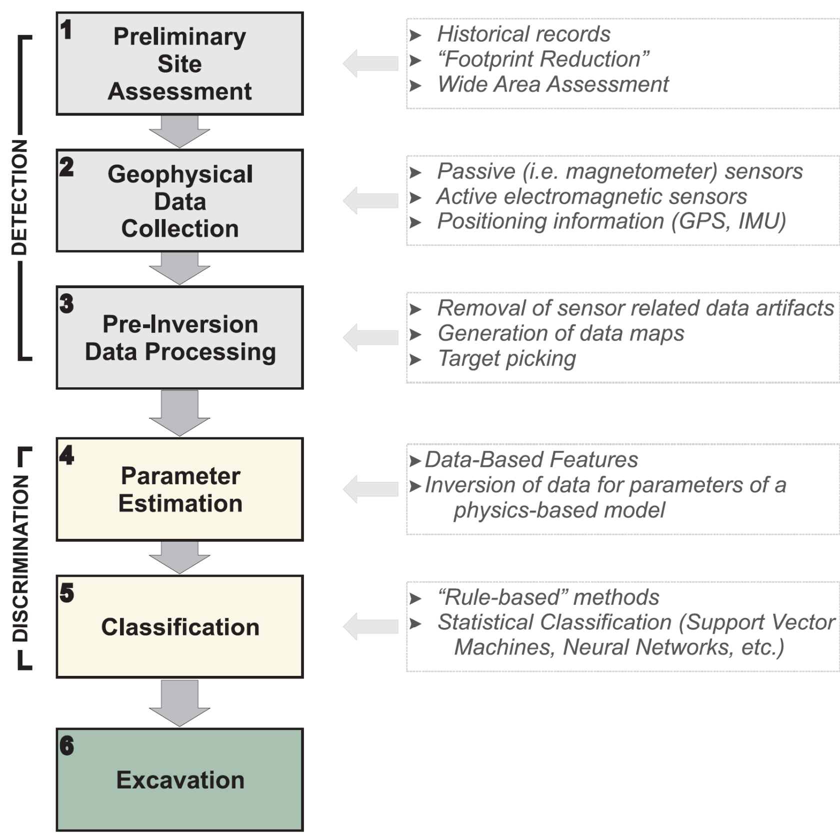

Figure 1. UXO Site Remediation with Geophysical Surveys

While airborne systems can delineate regions of high UXO contamination (such as bombing targets), ground based geophysical surveys are required to detect isolated, smaller and deeper targets.

“Mag and Flag” is the traditional method of UXO detection. This technique uses analog, handheld metal detectors to sweep UXO-contaminated land. The term "Mag” is used because the traditional metal detectors for this purpose were magnetometers. Locations where the detector has signalled the presence of a metallic item are flagged for excavation. Therefore “Mag and Flag" is strictly a detection technique, and has no ability to discriminate between UXO and non-UXO items. Additional factors make “Mag and Flag” an inefficient technique for UXO remediation. Detection performance is limited by the ability of the operator. Human factors, such as fatigue, heat, motivation and hunger, can negatively impact the quality of collected data and the ability to recognize the presence of buried targets. There is also limited quality control of the “Mag and Flag” procedure since a data maps of the survey area are not produced and, therefore, it is not possible to confidently assess the UXO contamination at site.

Figure 2. Detections from a “Mag and Flag” Survey Carried Out with a Schonstedt Passive Magnetometer.

Photo from Report of the Defense Science Board Task Force on Unexploded Ordnance, Nov 2003, page 12.

For these reasons, UXO detection transitioned from analog “Mag and Flag” operations to digital geophysical mapping (DGM). Digital geophysical mapping involves deploying geophysical instrumentation that collects data that are stored and geolocated using Global Positioning System (GPS) to map sites. By switching to DGM, quality control of detection operations improved since a historical record of data and coverage could be established. In addition, objective, physics-based methods could be used to identify locations of potential UXO and to establish the maximum depth for which ordnance could detected.

Magnetic and electromagnetic surveys have long been the standard geophysical techniques used for DGM, and they have proven to be successful in detecting UXO in remediation projects and UXO technology demonstrations. Magnetometry is a passive detection system. The high magnetic susceptibility of a ferrous target causes distortions to the Earth's field which are measured by a magnetometer (Figure 1.3). In general, the magnetometer is far enough away from the target such that the secondary field can be approximated well by a dipole. Magnetometry is a valuable geophysical tool for UXO detection due to the ease of data acquisition and its ability to detect relatively deep targets.

However, magnetic data can have large false alarm rates due to geological noise, and there is an inherent non-uniqueness when trying to determine the orientation, size and shape of a target (Billings, 2004).

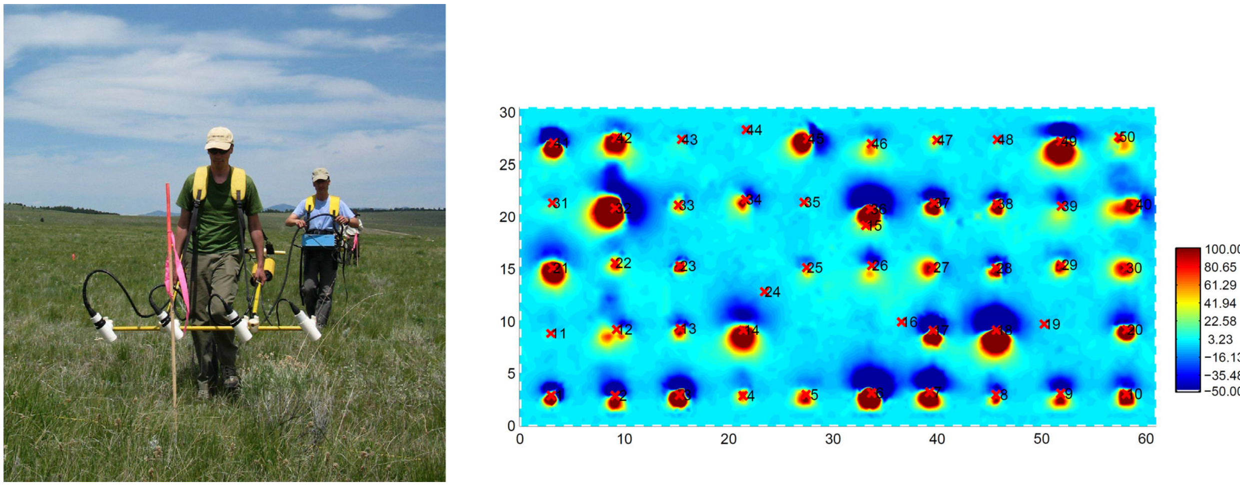

Figure 3. Left: An Array of Magnetometers. Right: A Magnetometer DGM Acquired Over a Test Site.

Electromagnetic induction (EMI) sensors detect a buried target by illuminating the subsurface with a time varying primary field. If the buried target is conductive, eddy currents will be induced in the target, and subsequently decay. These currents produce a secondary magnetic field which is then sensed by a receiver coil. In contrast to magnetometry, electromagnetic induction surveys are relatively immune to geologic noise and are more diagnostic for target shape and size.

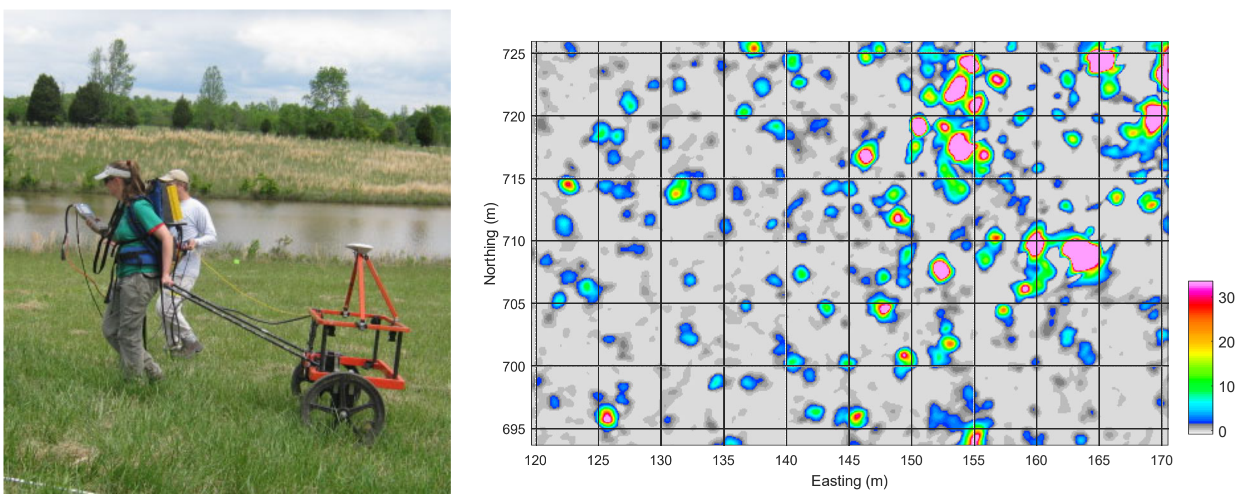

Figure 4. The Geonics EM61-MK2 Metal Detector.

Left: single cart mode. Right: example of EM61 DGM using the second time gate.

For many years the Geonics EM61 Time domain Electromagnetic (TEM) instrument was the DGM workhorse for UXO projects. The EM61 consists of a single transmitter coil and a pair of receivers: a main receiver coil coincident with the transmitter, and a second "focusing" receiver that is 30 cm above the main receiver and transmitter. The transmitters and receivers are 1 x 0.5m rectangular coils. The main coils can measure the TEM response at 4 times centered at 0.216, 0.366, 0.660 and 1.266 ms. The EM61 is referred to as a mono-static sensor, since the transmitter and receiver are co-located (note: the "focusing" receiver is only used in gradient mode, and measures a single channel). Once an EM61 survey is completed, the data is then processed to remove sensor related data artifacts such as instrument drift and spikes, as well as background geologic signal through a high pass filter. From this map, an initial target list is generated by identifying anomalies whose maximum amplitude or energy exceeds a threshold level chosen by the interpreter. The threshold level is chosen to meet a pre-defined clearance depth requirement, or it can be selected with the objective of maximizing the detection of buried ordnance expected at a site without including an excessive number of anomalies from sensor noise (e.g., selecting the threshold to be some multiple of the noise floor).

Classification is the process of determining, for each anomaly in the target list, the likelihood of it being a UXO. The objective is to minimize the number of false positives and, therefore, unnecessary excavations. UXO discrimination is achieved by extracting parameters from geophysical data that reflect characteristics of the target that generated the measured signal. These parameters come in two forms: (1) data-based parameters that are directly inferred from the data, such as amplitude and energy and (2) model-based parameters that are variables of a mathematical forward model that can reproduce the data.

In UXO detection and classification applications, the point dipole source model is the most common method for representing the electromagnetic response of a compact metallic target. The parameters of the dipole model are the dipole location and the dipole polarizability tensor. From the polarizability tensor we derive the orientation of the target, and the principal polarizabilities, which are intrinsic properties of the target. The size, shape, wall-thickness, electromagnetic material properties (i.e., magnetic permeability and electrical conductivity) determine the amplitude and decay characteristics of the dipole polarizabilities. Library based classification involves comparing a set of dipole polarizabilities, and comparing them to a library of polarizabilities for known target types.

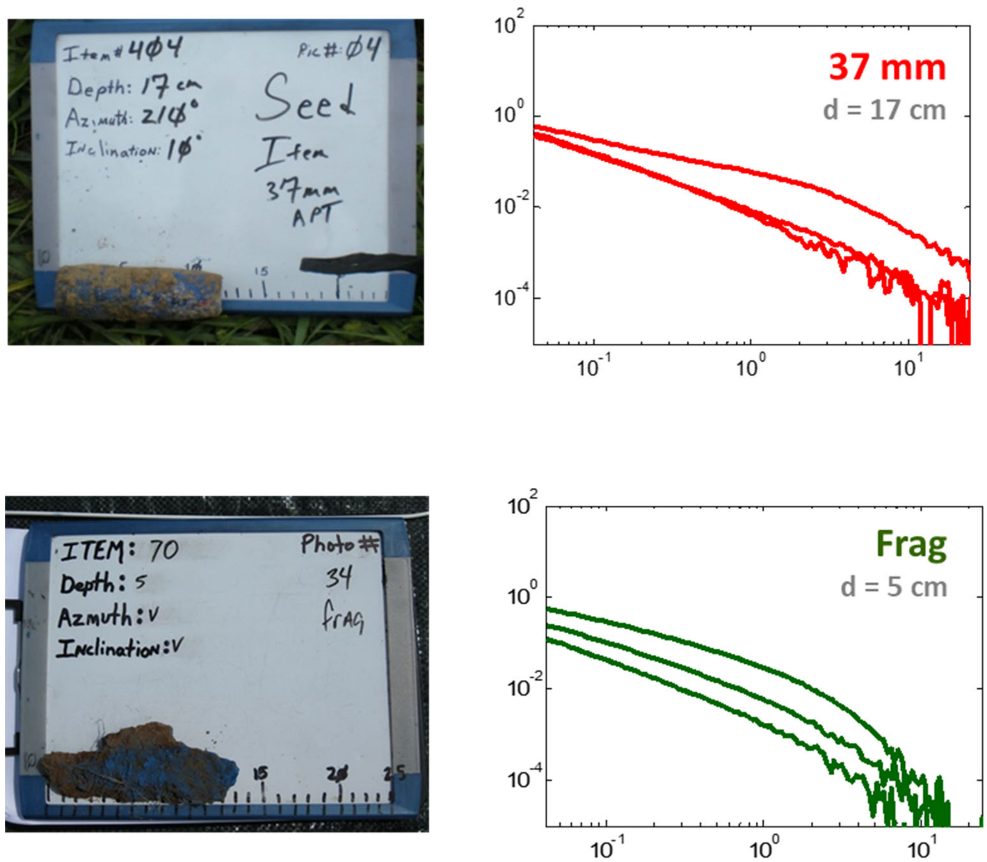

Figure 5. Examples of the Dipole Polarizabilities.

The relative size of the 3 polarizabilities provides an indication of the shape of the target. An axial-symmetric target will have 1 large "principal" polarizability (L1) and equal "secondary" (L2) and "tertiary" (L3) polarizabilities (i.e., L2=L3). A target without symmetry will have 3 polarizabilities of different sizes.

Early on during the Environmental Security Technology Certification Program (ESTCP) Live-Site study, it became clear that ability to classify with the Geonics EM61is limited. During the Camp Butner Live Site demonstration, Geonics EM61 MK2 cart data were acquired, and inverted for dipole parameters. Comparison of recovered polarizabilities to ground truth revealed that the Geonics EM61 MK2 data did a poor job of recovering the shape of targets. The ability to accurately recover shape requires that the target is illuminated in multiple directions by the primary field produced by the transmitter. For the Geonics EM61, this can only be achieved by acquiring data at larger offsets with sufficiently high Signal-to-Noise ratio (SNR). In addition, dynamic data acquired with a mono-static sensor requires centimeter level accuracy in positioning to accurately estimate dipole parameters. The amplitude of the recovered polarizabilities was a more robust feature for discriminating from scrap. However, this limits the classification scenarios for the EM61 to sites with large Targets of Interest (TOI) and small scrap. At Camp Butner, this was not the case, with the EM61 data being unable to distinguish between the smaller TOI (e.g., 37mm and fuzes) and many similar sized scrap targets. As a result, the classification performance was poor with the majority of anomalies requiring to be dug before all TOI were recovered.

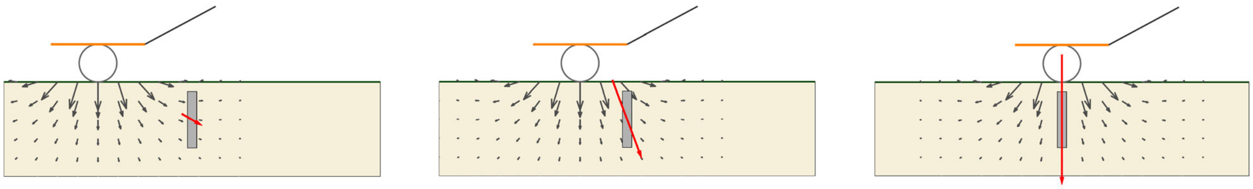

Figure 6. Illumination of a Target with the Geonics EM61.

In order to resolve each of the principal directions of a target, the Geonics EM61 must be able to acquire data at larger offsets with sufficient SNR.

At the Camp Butner Live-Site demonstration, the Metal Mapper (Classic) and TEMTADS 5x5 data were also acquired. These instruments represent early examples of advanced classification sensors. Advanced classification sensors are designed to produce data from which dipole parameters can be more reliably estimated. Multiple transmitters are able to illuminate a buried target with a primary magnetic field at multiple angles, thereby improving the ability to resolve the 3 principal polarizabilities that characterize a target. Advanced Geophysical Classification (AGC) sensors are multi-static, featuring multiple 3-component, "vector" receivers simultaneously sampling the secondary field over multiple time channels. Multiple receivers improve the accuracy with which target location can be estimated.

The combination of improved electronics increasing the SNR of the data and the improved integration of Inertial Measurement Unit (IMU) and GPS streams with EMI sensor data, has led to the feasibility of reliable classification with "one-pass" systems, i.e., where a full-coverage EMI dataset acquired in a dynamic mode is suitable for classification. Of course, "one-pass" classification might not be suitable at some sites depending on site conditions and classification problem. A further increase in SNR is achieved by acquiring a "cued" measurement. In the "cued" or "static" mode, a digital geophysical map is first used to identify data anomalies at a site, and an EMI system is placed over each anomaly pick, and data are stacked and averaged to reduce the noise in the measured data. A DGM survey for identifying potential anomalies followed by a cued survey to interrogate each anomaly is called "two-pass" classification.

Figure 7. Examples of Validated AGC Sensors. Left: MPV (Shown in Cued Mode). Right: MetalMapper 2x2.

Photos from "AGC Sensor Status" by Jeffrey Leberfinger, SAGEEP 2021.

With the development of advanced sensors, it is possible to extract reliable dipole model parameters from both dynamic and cued data at many sites. If the dynamic data and site conditions allow for “one-pass” classification, the resulting parameters can be immediately input to a library-based classification system to determine the likelihood that the target is a UXO. If a two-pass system is being utilized, the dipole parameters from the dynamic data inversion will be (1) used to more accurately position the cued instrument and (2) to reduce the number of required cued locations by eliminating anomalies that are unlikely to have a target. Screening out anomalies is a process called Informed Source Selection.

The following sections outline some of the key components of the data processing: Parameter Estimation, Informed Source Selection (for two-pass surveys), Classification, and Software implementation.

Figure 8. AGC Sensors Validated for One-pass Classification. Left: The APEX Sensor. Right: The UltraTEM Towed Array.

Photos from “AGC Sensor Status” by Jeffrey Leberfinger, SAGEEP 2021.

2.0 IMPLEMENTATION OF PARAMETER ESTIMATION

Dipole parameters are recovered from inversion of the geophysical data. The optimal parameter set minimizes a data misfit function (such as a least squares measure) and satisfies any prior information we have of the target. The inversion is carried out by:

1. Estimating target location. This problem is solved at a subset of early time channels. Because recovery of dipole polarizabilities (step 2) depends on the initial location estimate, care must be taken at this step to ensure a good solution. In particular, we must be careful to avoid convergence of the iterative nonlinear inversion to a suboptimal local minimum. This is accomplished with an initial search for good starting models: a constrained linear inversion of fixed locations identifies candidate starting models. A predefined number (usually 5) of the best candidate models is then fed to a nonlinear inversion for location.

2. Estimating target orientation and polarizabilities. Given a location estimate we can recover estimates of polarizability tensors at each time channel by solving a linear inverse problem at each channel. Constraints may be imposed here to ensure that the recovered tensor is physical (i.e., has positive eigenvalues). Principal polarizabilities can then be determined using joint diagonalization, which aims to find a common set of eigenvectors across all time channels.

This two-step approach to inversion also forms the basis of the N-dipole approach to multi-object inversion. Because local minima are exacerbated in multi-object cases, a key component of a multi-object inversion algorithm is a thorough search for candidate target locations (Song, 2011).

Uniquely identifying the number of dipole sources that contribute to the observed data has proven to be a difficult problem. A multi-object inversion has more degrees of freedom than a single-object inversion and so should provide a better fit to the data. This improved fit can be balanced with a preference for a parsimonious model using information theoretic criteria. However, in practice these criteria are not particularly robust in the presence of noise and so have had limited utility.

Similarly, decomposition of the multi-static response matrix promised to be diagnostic of the number of sources in the data (Shubitidze et al., 2012). However, simulations of multi-object scenarios indicated that the number of significant eigenvalues (corresponding to scaled polarizabilities) was also highly sensitive to noise and this diagnostic had limited practical application.

Our preferred approach to identifying multi-object scenarios is to carry out 1, 2, and 3 object inversions on all targets, and then use library matching to determine if any of the recovered polarizability models correspond to a target of interest. While this approach has successfully identified multi-object cases in demonstration data sets, it does add significant computation time to the inversion and complicates quality control by introducing spurious models. For example, multi-object inversion can often produce deep sources with large amplitude polarizabilities that may appear similar to TOI. These sources are the consequence of an overly complex model (i.e., too many assumed sources) and have little contribution to the predicted data. Automated criteria for identifying these models have been developed and will be further discussed in section 5.

Advanced forward models that capture non-dipolar effects in the observed data have also been developed and applied to processing of EMI data (Shubitidze et al., 2011). While these models are more physically complete, ESTCP demonstrations have shown that, in practice, the dipole model is adequate in almost all cases. For example, if non-dipolar effects become significant in the near field of a large target, the dipole model can likely still be used to recover large amplitude, slow decaying polarizabilities that are diagnostic of a target of interest. Furthermore, in some cases, multi-object inversion can be used to resolve the polarizabilities for the body and tail of responses of large targets.

Time domain EMI sensors are sensitive to the response of viscous magnetic soils: the relaxation of the induced magnetization in ferromagnetic grains produces a characteristic decay that is superimposed on the response of a conductive target. Modelling studies in Strategic Environmental Research and Development Program (SERDP) project MR-1573 showed that the combined response, within the sensitivity of EMI sensors, is linear. At the majority of sites, the background magnetic soil response can be sufficiently removed from dynamic data using a de-median filter, and can be removed from cued data using background measurements that are subtracted from data.

At sites with high levels of magnetic soil response (e.g. Kaho-olawe, HI), noise due to variable sensor clearance height and spatial variability in magnetic susceptibility can lead to errors in conventional background subtraction methods. For vertical component sensors such as the Geonics EM-61, these effects were mitigated by fitting the soil response and subtracting it from the observed data. For data acquired with multi-static, multi-component EMI sensors, we have found that inverting cued data multiple times with varying levels of background response (via scaling the amplitude of background measurements or using background measurements from across the site) can improve inversion results.

3.0 INFORMED SOURCE SELECTION

Beginning with the Former Camp San Luis Obispo ESTCP demonstration, advanced EMI sensors have been deployed for dynamic detection surveys. Advanced sensors have obvious advantages for target detection, including higher resolution and longer off-times than conventional EM-61 arrays. However, detection with advanced sensors is not always preferable as their lower production rates may be too expensive at sites with low target densities. The UltraTEM and APEX systems, designed for a single pass for detection and classification, may offset these increased survey costs by avoiding the cued interrogation step altogether.

Target detection with advanced sensors has motivated the development of Informed Source Selection (ISS) techniques that use modelling and inversion to pick and screen detected targets. For example, the dipole filter developed under SERDP MR-1711 fits observed detection data with a layer of dipole sources and then identifies possible targets based on the quality of the fit between observed and predicted data. The initial filter picks must be followed with a full multi-object inversion to resolve closely-spaced targets and screen out likely clutter on the basis of fast-decaying polarizabilities.

Another inversion-based ISS approach, developed under SERDP MR-2225, inverts dynamic soundings for single sources, and then identifies possible targets based on source locations that cluster. This approach, which we term dipole clustering, must also be followed with full multi-object inversions of the dynamic data for subsequent source selection (i.e. screening).

ISS can also be implemented by generating initial picks with straightforward bump picking on the data, followed by the full inversion step employed by both dipole filtering and dipole clustering. This is a somewhat more conservative approach – there is no inversion or screening at the initial picking stage. Direct comparison of the relative merits of the ISS methods is an ongoing topic of research.

Prediction of a detection threshold is a necessary step in ISS using data-based target picks, and decision support tools have been developed under SERDP MR-2226 to carry out this analysis for advanced sensors. Typically, the detection threshold corresponds to the minimum amplitude z-component response in a receiver as the sensor traverses over the target. As with the EM-61, the worst-case detection scenario occurs for a target in a horizontal orientation, but the target azimuth in this worst case depends on sensor geometry.

Regardless of our approach to generating initial picks, screening out anomalies on the basis of estimated polarizabilities is a key step for all ISS methods. At this step we aim to eliminate fast decaying clutter from our target list. This decision requires an analysis of the expected variability of polarizabilities at the site, in order to ensure that no potential TOI are screened out. For this analysis we have used synthetic seeding - which emplaces simulated targets into the observed detection data – to estimate site-specific polarizability variance. Inversion of synthetically seeded TOI allows us to determine conservative thresholds for target screening that account for the effects of site-specific noise on recovered polarizabilities.

4.0 CLASSIFICATION

Early efforts to classify with dipole model parameters used simplified size and decay features derived from estimated polarizabilities (e.g., Beran and Oldenburg, 2008). These parameters were often poorly constrained in EM-61 data, but large ordnance items (e.g., 4.2" mortars at Camp Sibert, AL) did cluster in size-decay space. However, with the deployment of the Time-Domain Electromagnetic Multi-Sensor Towed Array Detection System (TEMTADS), Berkeley Unexploded Ordnance Discriminator (BUD), and MetalMapper at Former Camp San Luis Obispo, CA in 2009, it was apparent that polarizabilities estimated using these advanced sensors could be directly used for classification.

However, size-decay parameters are still useful in the training stage: unidentified clusters in this feature space may correspond to novel TOI not yet in the polarizability library. This step remains an important part of the classification analysis, as unexpected munitions are often encountered.

Alternatively, novel TOI can be identified by comparison with a comprehensive polarizability library. In practice, library matching to find TOI can produce many false positives if small items that tend to match clutter (e.g., 20 mm projectiles or fuzes) are included in the comprehensive library. If these items can be removed from the analysis, then comprehensive library matching becomes practicable.

Metrics derived from the estimated model can be used to identify potential TOI. In this analysis we do not match the estimated polarizabilities against a library, but instead use features of the polarizabilities that were diagnostic of TOI at previous sites. For example, TOI are typically characterized by large amplitude, slow decaying polarizabilities relative to non-TOI. In addition, the rotational symmetry of most ordnance is manifested as a small deviation between transverse polarizabilities. These individual metrics can be combined into a single, library-independent metric for identification of novel TOI. Retrospective analyses indicate that classification diglists generated with this approach perform quite well, with false alarm rates only ~10% larger than library-based methods. This suggests that model metrics provide a robust method for identification of any TOI that may be absent from the polarizability library.

Many flavours of statistical classifier have been applied to advanced classification for munitions response, including: Support Vector Machines (Zhang et al., 2008) Relevance Vector Machines, Neural Networks (Hart et al., 2001, Zhang et al., 2008), and Semi-Supervised learning (Liu et al., 2008). While good performance has been achieved in many cases, machine-learning algorithms have not consistently outperformed library matching, and most groups doing advanced classification now employ this latter approach. In addition, no particular machine learning expertise is required to use library matching, making advanced classification more readily accessible to users in industry.

Library matching computes a decision statistic that is a mismatch between library and estimated polarizabilities, and then ranks targets for digging by increasing mismatch. Though straightforward in principle, there is some art to the calculation of the decision statistic. Due to the dynamic range of the data and polarizabilities, time channels should be scaled to provide a more equal weighting between early and late time channels. An additional consideration is the range of time channels over which to calculate the mismatch with respect to each polarizability.

The lower amplitude secondary polarizabilities are often more strongly affected by noise and so we often truncate the range of the mismatch for these parameters. Automated criteria to determine site-specific channel ranges for the polarizability mismatch have been developed to assist with these decisions.

Multi-stage classification approaches can be used to first identify well-constrained TOI using all polarizabilities, followed by a conservative mismatch that employs only the primary polarizability or size/decay features to identify more difficult cases that are affected by noise. Alternatively, a combined classifier ranking (CCR) automatically merges diglist rankings from aggressive (all polarizabilities) and conservative (primary polarizabilities and size/decay features) classifiers to obtain a single diglist. The result is a conservative diglist that minimizes the analyst-specified decision points required in a multi-stage classification approach.

Regardless of the classification strategy, the analyst must specify a stop dig point in the dig list. While statistical methods can be used to model the probabilities that remaining targets are TOI, these predicted probabilities are sensitive to the underlying assumptions (e.g., normal distributions for TOI and non-TOI with respect to the decision statistic) and so may not provide a realistic representation of a posteriori probabilities. A graphical approach to selecting the stop dig point plots the decision statistic (or its inverse) as a function of dig number to produce a monotonically-decreasing L-shaped curve. An inflection point on this curve can be diagnostic of the point where all TOI are found. However, this criterion is not particularly robust in cases where there TOI and non-TOI are similar and there is no sharp inflection point on the L-curve. Finally, visual inspection of the polarizabilities in diglist order can be used to set the stop dig point. While this subjective decision will depend on the judgement and experience of the analyst, it can be verified with objective methods (e.g., digging past the stop dig point, and random sampling).

To ensure AGC performance is maintained at a site, a blind seed program is implemented. Quality Control (QC) seeds are emplaced by the contractor, and the seed details (location and type) are "firewalled" from analysts and data collection teams. Quality Assurance (QA) seeds are emplaced by the government and the QA seed information is blind to contractors. To ensure that classification decisions will correctly classify all QA and QC seeds, it is useful to use synthetic seeding where seed targets (usually Industry Standard Objects (ISOs) are emplaced at depth ranges as defined by the seeding plan.

5.0 SOFTWARE

While inversion and classification algorithms are essential to the success of advanced classification, flexible and user-friendly software tools are equally important to the process. At the time of writing this document, there were 3 software packages validated under the U.S. Department of Defense Advanced Geophysical Classification Accreditation Program (DAGCAP) program for advanced Geophysical classification: UX-Analyze, UXOLab, and EMCLASS.

Some important software features that make advanced classification feasible and efficient:

1. *Background correction tools*. Processing of cued data requires removal of background response from the measured data. Tools for visualization and querying of background measurements can help to eliminate bad backgrounds (e.g., with significant response from metallic targets) from the processing workflow.
2. *Data Quality and Validation*. Processing of both cued and dynamic data requires workflows enabling the completion of several tasks.
   a. Daily verification that all measurement quality objectives (MQOs) pass for the Instrument Verification Strip (IVS) and calibration/function tests.
   b. Validation of production data. Verifying all MQOs pass and generating recollect/gap data for the field team.
3. *Data processing and Inversion*. Software should allow the analyst to build flexible workflows for background correction and inversion. Optimized processing is required for modern projects where the number of targets can be upwards of several hundred thousand
4. *Quality control of inversion results.* The QC display should visualize all information required for an analyst to make a decision, including: estimated polarizabilities, observed and predicted data (in both spatial and time displays), and extrinsic parameters (location, depth, and orientation). Capability to quickly toggle between inversion results or individual models allows the analyst to identify problems with individual inversions and to fail spurious models.
5. *Searching target or model subsets.* Visual inspection of every inversion result is tedious and prohibitively slow for most realistic data sets, and an analyst should focus QC efforts on problematic inversions. This can be accomplished with data and model metrics that are diagnostic of fit quality and model reliability, together with software functionality for taking the union, intersection or difference between sets identified using different metrics. Data misfit (equivalent to fit coherence) is the most obvious metric for identifying poor fits. Additionally, model offset (the deviation of the recovered target location from the center of the cued sounding) can be used to identify poorly constrained inversion results that do not meet MQOs.
6. *Quality control of classification results.* QC of inversion results will, ideally, ensure that estimated polarizabilities can be reliably used for classification. In practice, a visual review of the classification diglist is also required so that the analyst can check that diglist order is sensible. We visualize the diglist by plotting estimated polarizabilities and best-matching polarizabilities in diglist order, together with the decision statistic. This display can be queried to view the QC window so that the analyst can further investigate any questionable decisions.

7. *Threshold detection modelling and synthetic seeding.* A modelling module is required to calculate the detection thresholds and clearance depths of items in the conceptual site model (CSM). The ability to detect and classify targets is dependent on site noise. By synthetic seeding directly into data collected at the site, analysts attain a better sense of the detection and classification potential at the site. With a seeded data set, the analysts can more confidently define or verify detection, ISS, and/or classification parameters.

8. *Audit trail.* It is important to have a detailed log of every processing step applied to the data.

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