TECHNICAL REPORT

Use of Target Shape and Size in Classification of UXO in Survey Data

SERDP Project MR-1455

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1.0 INTRODUCTION

AETC, working with our subcontractor and partner, Visual Learning Systems, Inc. (VLS) has completed Year 1 of our development of a UXO target picker and probabilistic classifier based primarily on shape metrics within an inductive learning software environment for detecting and discriminating UXO. This effort builds upon our prior research effort in the Seed Project, SERDP UX-1354. In the Seed Project, working with vehicular towed-array data from the 2001 Badlands Bombing Range (BBR) UXO survey, we showed that:

- Little or no further performance gain can likely be achieved using machine-learning techniques that focus only on the physics-based fitting parameters to make decisions about ordnance classification;
- There is substantial value in the use of shape and size information derived from target images created from high-density mapped sensor data to make ordnance classification decisions;
- Pattern recognition techniques that incorporate size and shape information can dramatically reduce the number of non-UXO targets while maintaining most of the sensitivity of traditional physics-based approaches for finding true UXO.

As a result of the progress made in the Seed Project, we proposed and were approved to undertake an additional two year effort. The primary focus of the new project is to develop an automated target selection and analysis approach for UXO that uses size and shape metrics from two-dimensional magnetic anomaly signature images to increase the accuracy of subsurface UXO detection while reducing the number of false positives UXO declarations. As we did in the Seed Project, we are using an existing commercial automated feature extraction (AFE) software utility, Feature Analyst ® as the base inductive learning system for UXO detection and classification. This software utility was developed and is owned by VLS, Inc. It is designed and interfaced to operate as a feature extraction software extension for leading commercial geographic information systems (GIS) and remote sensing and photogrammetry applications including ESRI ArcGIS, Leica Geosystems ERDAS IMAGINE, Intergraph GeoMedia and BAE Systems SOCET SET. To use Feature Analyst one must have one of these applications to access the various tools, algorithms and workflows used for feature extraction and target recognition. In this project Feature Analyst operates in conjunction with ArcGIS. Geosoft OASIS Montaj has also developed an extension for ESRI ArcGIS, which allows Analysts to access VLS and Geosoft tools within the same host GIS application. The shape functions (Regions of Interest, ROIs) created by Feature Analyst operating in an ArcGIS environment can be imported directly into Montaj.

In the 2004 Seed Project, we worked only with the Vehicular Multi-sensor Towed Array Detection Systems (MTADS) magnetometry survey data collected in 2001over 110 acres of the Badlands Bombing Range (BBR). Ten acres of this area was set aside for training; it contained 25 known UXO and about 150 items of ordnance scrap. The latter items were left over from prior use of the range.

During Year 1 of this project, we began development of the enhanced target picker and probabilistic target classifier using the same dataset. Once the preliminary development work was completed, we extended the effort to evaluate MTADS Airborne survey data from this same

110 acre area. Following adaptations of the input parameters for the target picker and the target ranker for the airborne survey data analysis, the entire 1,685 acre airborne survey dataset was analyzed using the automated approaches developed for the 110 acre area. The 1,685 acre Airborne dataset was prepared by AETC and provided as mapped data files (without prior knowledge of the ground truth) to VLS for analysis. AETC prepared all vehicular and airborne survey datasets in both the standard dipole presentation format and as Analytic Signal presentations using Oasis Montaj routines to make the conversions. These are described in detail in later sections of this report. **Figure 1** shows an adaptation of our Program Plan for this

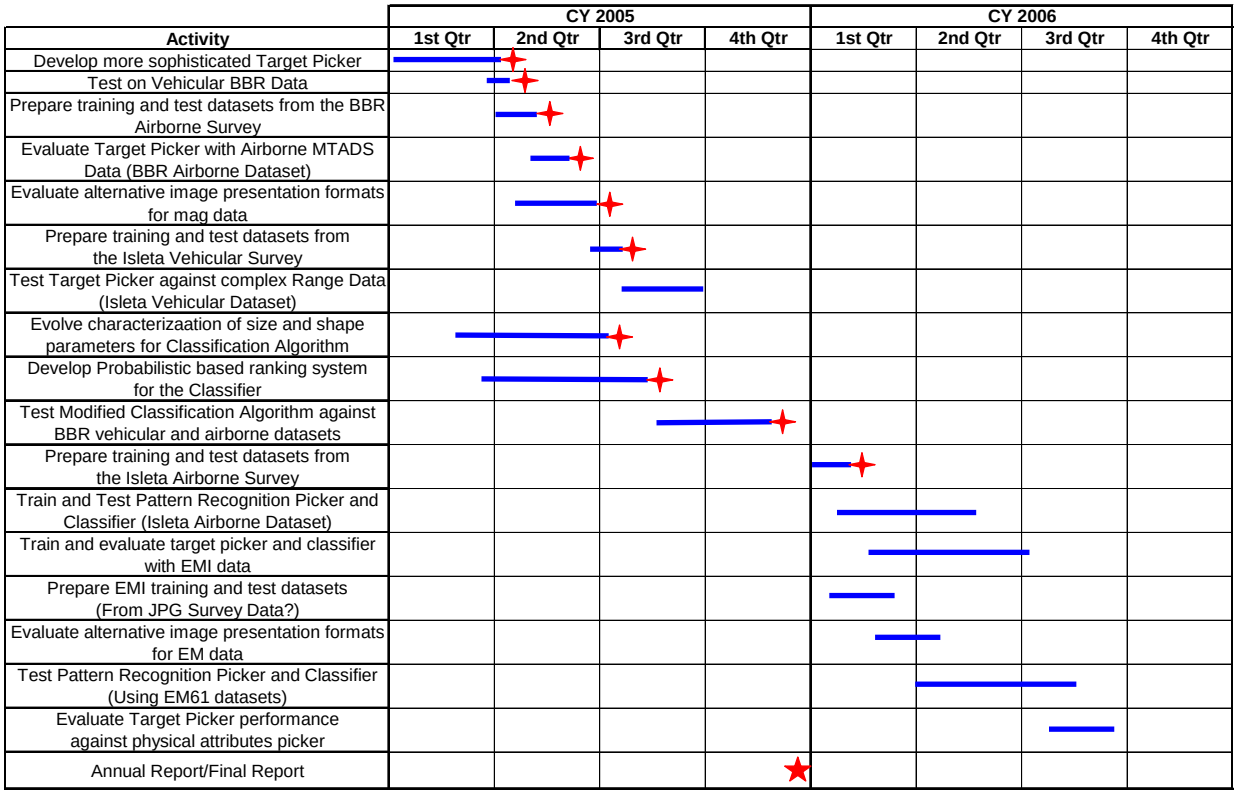


Figure 1. Progress during year one from the UX1455 Program Plan.

project. Funding arrived in March 2005 and work began at a slow pace. The effort has been ramped up as we progressed with the preliminary developments. The red crosses in Figure 1 signify efforts on tasks or subtasks that have been completed. We deferred beginning analysis of Isleta data until the second year of the project. All datasets have been developed for this effort, which will begin in January 2006.

1.1 Year 1 Project Goals

During Year 1, we have:

- Developed a probabilistic evaluator for the Target Picker and Classifier, which we now call the Target Ranker. The resulting probabilistic based ranking system can be adjusted to either maximize UXO detections or minimize the size of the total dig list;

- Evolved the characterization of size and shape parameters and developed a more sophisticated Target Picker to improve classification of UXO and minimize false positives;
- Tested the new probabilistic classifier approach on the original vehicular MTADS magnetometry data to validate the results of the probabilistic ranking system with the original results obtained in the Seed Program. All development work and testing has been carried out using both dipole and Analytic Signal image presentations;
- Adapted the target picker and target ranker for airborne MTADS data and evaluated its performance using alternative image presentation formats; and
- Classified the entire Airborne MTADS dataset using a UXO target model that was created from limited ground truth data collected over the seeded site. We used the UXO target model to automatically create ROIs and calculate probabilities using shape metrics.

1.2 Year 1 Results

During Year 1 research we have:

- Developed a prototype UXO classification tool and workflow approach that incorporates the machine learning approaches in Feature Analyst. The first learning pass uses the Target Picker to automatically select all candidate ROIs that are potentially UXO. The second pass, referred to as the Target Ranker, classifies each ROI primarily using shape parameters and then assigns each ROI a probability.
- During the Target Ranker phase, this shape classifier was trained to output a probability associated with each shape (ROI) – a numerical value (0.0-1.0) based upon how closely the shape in question matches the positive training examples. The analyst then determines the threshold probability at which to assume all values greater are likely associated with UXO, and should be dug.
- Using the vehicular data this technique proved to reduce the number of false positives by over 50% (compared to the human analyst approach) while correctly classifying 100% of the known UXO. The result of this two-step approach, using the seeded site containing ground truth, is a Target Model for UXO that can be run in batch mode on additional data without the need for additional ground truth data.
- The value of the system is that it provides the human-in-the-loop with a simple software tool capable of (a) automated target selection and UXO classification (b) updating the UXO classification approach in the field through a simple interface that allows the Analyst to provide additional positive and negative examples of UXO targets and (c) the ability to create Target Models that can be run in batch mode for a site where there is minimal information on UXO locations.

1.3 Year 2 Project Goals

In Year 2 of the project we will work on testing the UXO classification tool in a more complex geologic setting with more diverse UXO challenges (using the Isleta Pueblo vehicular and airborne datasets). The project goals for Year 2 include:

- Refinement of the Target Picker and Target Ranker approaches for UXO detection and discrimination;
- Testing on the more complex Isleta dataset using both the vehicular and airborne MTADS survey data;
- Developing improvements to the VLS commercial Feature Analyst software for use in UXO mapping; and
- Working with EMI-array survey data.

2.0 SUMMARY OF THE APPROACH DEVELOPED FOR UXO DETECTION

This section provides a summary of the approach we developed for detecting UXO using the two-pass process of Target Picker and Target Ranker (see **Figure 2**). Finding UXO in a survey image is analogous to the well-studied problem of automatically extracting features from remotely sensed imagery. VLS has developed a range of new machine-learning techniques and other technologies associated with feature identification in optical, multi-band, monoscopic and stereo imagery. These capabilities for Automated Feature Extraction (AFE) are all incorporated into the commercial software product Feature Analyst, which is owned by VLS.

This approach addresses the AFE problem by creating a system built around machine learning, in particular, inductive learning. A human analyst employs six visual attributes to classify objects in images. These attributes are *color*, *texture*, *pattern*, *spatial association* (context), *shape*, and *size*. Feature Analyst uses machine-learning techniques to incorporate each of these characteristics during object-recognition and image classification. Using this approach provides a powerful classification capability for objects depicted in images. Several published studies by the National Geospatial-Intelligence Agency,[4] the US Forest Service,[5] and others have evaluated the accuracy, speed, and labor savings of the Feature Analyst approach for object-recognition and feature extraction from imagery.

In this project we are adapting and extending the capabilities of Feature Analyst for the identification and classification of UXO in geophysical magnetometry survey data. Feature Analyst provides the inductive learning framework for specific development of the Target Picker and Target Ranker algorithms. In Section 3 we provide a more detailed discussion of the Target Picker parameters, as well as a discussion of the development of the Target Ranker algorithm.

2.1 Creating a Training Set

The development of the target picker relies on inductive learning, which in turn requires the use of a training set. For this problem domain, training examples are selected by a human analyst by digitizing a small (5 to 10) set of sample UXO in the survey data image (e.g., from the MTADS magnetometry data). Ideally the training set examples should be spatially distributed and representative of the diversity of the UXO targets at the site (**Figure 3**).

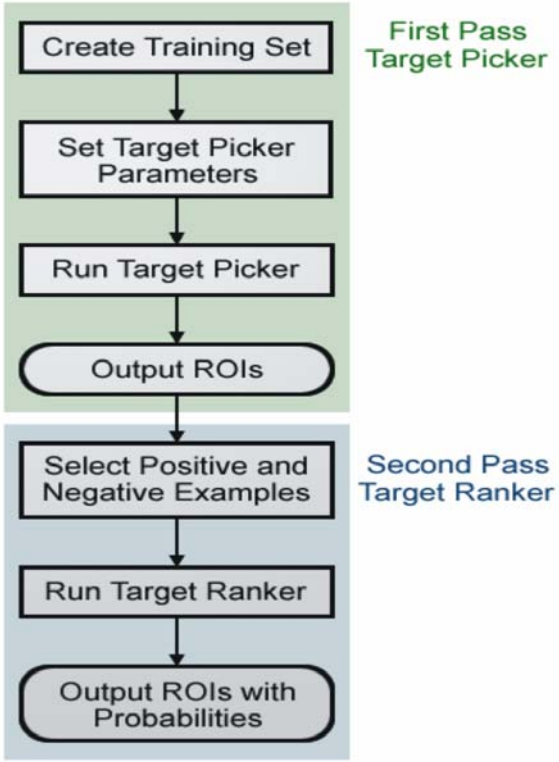


Figure 2. The two-pass workflow approach for automatic classification of UXO. The Target Picker provides a semi-automated method for generating ROIs and the Target Ranker classifies the ROI and assigns a confidence interval.

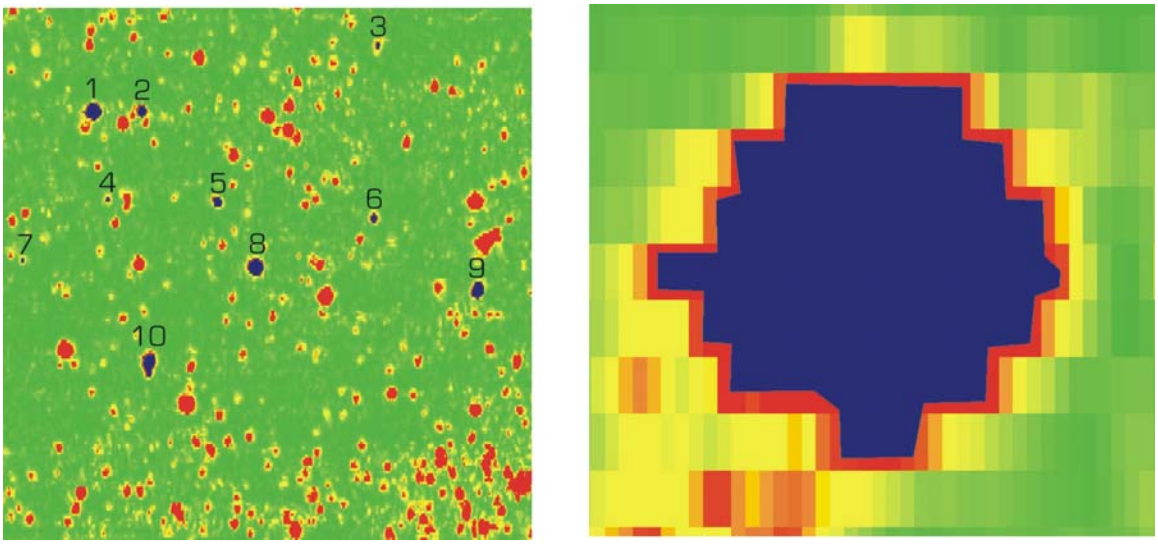


Figure 3. The left image shows ten training set examples from the airborne survey of the seeded site. The right image is a close-up of a digitized polygon (example 1) showing how the analyst has drawn the outline around the center of the UXO target.

After the creation of the training set, the Analyst then sets the Target Picker learning and post-processing parameters from pull-down menus in Feature Analyst. The Target Picke r

incorporates the tools in the inductive learning interface of the Feature Analyst extension here operating within the master utility ArcGIS. The setup screen is shown in **Figure 4**. The available parameters (including the modifications described in Section 3) include:

- **Selection of Input Bands** – For the types of color-mapped raster images used in this project, the analyst selects the default of all bands in the magnetometer image. Feature Analyst can accept multiple types of inputs including thematic grids, airborne and satellite images and digital elevation models (DEMs). If all pertinent information exists in a few bands, the analyst has the ability to select only the relevant bands.
- **Histogram Stretch** – The analyst can apply a histogram equalization stretch to the raster image.
- **Spatial Input Representation** – The analyst can apply various pixel patterns to be used as spatial inputs to a learning algorithm. This is described in more detail and illustrated in Section 3.
- **Aggregation** – Aggregation is the name of an algorithm that eliminates output polygons below a certain size and fills in holes in a polygon below a certain size. The size is selected by the analyst and usually corresponds with a minimum mapping unit threshold.

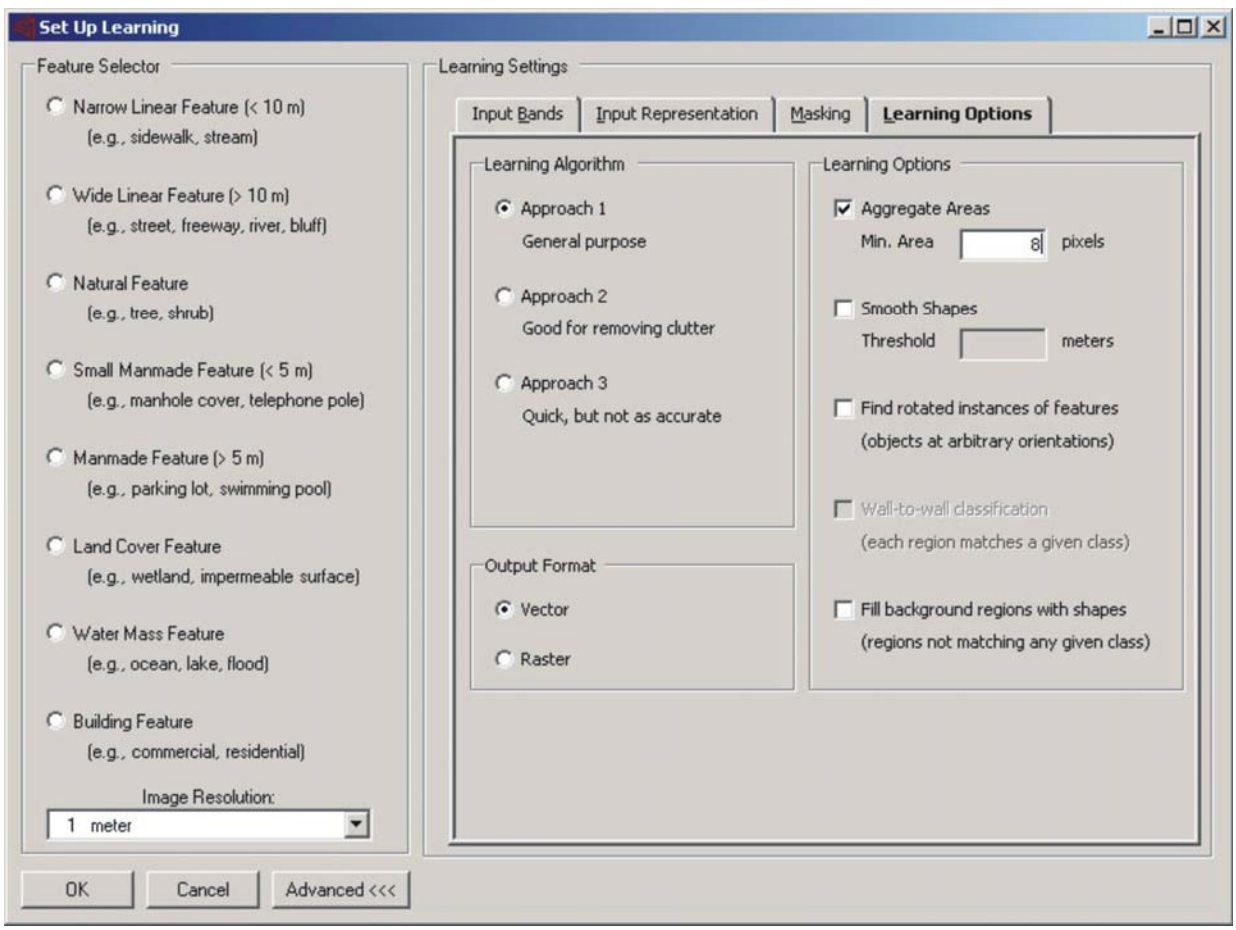


Figure 4. Screen clip showing the Feature Analyst user interface setup, which provides options for the user to define the parameters for the learning algorithm used as the Target Picker.

- **Smoothing** – The analyst has the option to use various algorithms for smoothing the output polygon shapes to reduce the number of vertices in the output polygon.
- **Rotation** – Rotation is used in conjunction with the pattern mask and learning algorithm. This parameter eliminates the need for the analyst to provide training set examples of targets with similar signatures at different orientations.

2.2 Run the Target Ranker

The Target Ranker returns for each ROI an estimated probability (between 0 and 1) of the ROI being UXO. Setting up the Target Ranker requires the analyst to select a few ROI examples as UXO (positive) and non-UXO (negative). It then uses size and shape parameters of the ROIs to estimate a probability via an inductive learning algorithm. In addition to assigning a probability to each ROI, the process generates a Target Model (file) that can be run in a fully-automated fashion on additional sites. With this approach, the Target Model is run in batch mode; there is no requirement for the human-in-the-loop to provide any additional training examples or to set additional parameters.

2.3 Application of the Approach to the Common Vehicular and Airborne Data

The Feature Analyst two-pass approach for detecting and classifying UXO was applied to the 110 acre common survey area:

- **Accuracy** – Based on test results from the seed target area and the 100 acre common survey areas (measured against known ground truth) the Target Picker captured 100% of the UXO with minimal human intervention and fewer clutter (false alarms) than appeared in the human analyst physics-based dipole fitting analysis. These observations held using images derived either from the dipole data or from Analytic Signal presentations. See the details of these processes below.
- **Adaptiveness** – The Feature Analyst inductive learning approach to UXO detection and discrimination is adaptive. Once the training examples have been learned by both the target picker and the ranker, analysis of additional data can take place without further intervention by the human analyst. Alternatively, UXO and non-UXO discovered during field remediation can be provided back to the learning algorithm as new training set examples, which will allow for update and improvement of the prediction process as remediation progress is underway.
- **Efficiency** – The Target Ranker outputs a probability value for each classified ROI. This allows the UXO site manager to prioritize the dig list. Most projects do not provide either enough time or money to dig all suspected UXO; hence, the ability to set a confidence interval for UXO allows the team to be more efficient in recovery of the most potentially dangerous items.
- **Automation** – Feature Analyst provides a methodology for the Analyst to create a Target Model that can be run in a 100% automated batch mode. The human-in-the-loop can create a model using a small portion of the site, such as we will show in detail below for the seeded site, and then use that model to classify the entire site. This approach was used to develop a UXO Target Model for the entire airborne BBR dataset.

- **Software Tools** – Feature Analyst is commercial software utility used for feature extraction throughout the geospatial community. Incorporating the Target Picker and Target Ranker workflow and algorithms into Feature Analyst provides the UXO community with a promising new tool that works within leading GIS and remote sensing software utilities. The purchasing or licensing of Feature Analyst does represent a significant investment. Most UXO service providers have one of the required GIS utilities resident in their operations. The costs of the Feature Analyst utility is not significantly different than acquiring IDL (for use with the MTADS DAS) or acquiring Geosoft utilities for UXO data processing.

3. METHODS

3.1 Task 1: Develop a Probabilistic Evaluator

The first task in this project was to develop a probabilistic evaluator for use with both the Target Picker and Target Ranker. In the Seed Project, the Feature Analyst predictions were developed as a two-class problem; targets were declared as UXO or not-UXO using only the dipole image data. The first step in developing a probabilistic evaluator required us to convert the "hard-class" predictions into "soft" probabilistic predictions. This was done by changing the activation function for the Artificial Neural Network (ANN) to match appropriate assumptions, which would allow it to give predictions between 0 and 1.

The next challenge was to generate an algorithm to combine the probabilities from an ensemble (group) of predictions, weighted by the perceived confidence of each ANN's fidelity. Finally, individual predictions for each pixel were required to be grouped and then the grouped pixels given one probability (for the Target Picker stage). Grouping two-dimensional sets of probabilities to create Regions of Interest (ROIs) was done by thresholding the probabilities at 0.5 and keeping connected groups of 1's whose groupings are greater than a minimum size.

The grouped pixels were then passed as input to the Target Ranking step where it used size and shape parameters to generate a new probability. We explored several ways of generating probabilities and combining the Target Picker predictions with the Target Ranker predictions. To date, it works best to have the Target Ranker generate predictions independent of the Target Picker probability predictions. This is an area where additional research is required because smoothing some ROIs generated by the Target Picker can alter their shape parameters in a manner that negatively impacts the performance of the Target Ranker.

As described in the proposal, the refined Target Picker and Target Ranker use the two-step process; incorporating shape metrics primarily in the classification (ranking) process. The resulting probabilistic ranking of all targets in the dig list can be adjusted to either maximize UXO detections (i.e., reduce the number of false negatives) or minimize the size of the total dig list at the risk of misclassifying a few UXO. This approach provides flexibility for the human-in-the-loop analyst, who we envision acting as a reviewer of this automated process. The probabilistic ranking process uses the probabilities carried forward by the multi-step learning process (ROIs from the first pass and probabilities from the second pass). We envision the

human analyst attention as being concentrated on the targets appearing below the dig threshold in the final ranking. The objective of this intervention is to eliminate false negatives by providing additional insight from either visual analysis or physics-based evaluation of borderline targets. With this approach, the human-in-the-loop can account for site complexities, such as geology, interferences from overlapping anomalies, glitches in the data, etc.

3.2 Task 2: Evolve Size and Shape Characterizations

Our approach for UXO detection involves the use of multiple spatial attributes including size, shape, texture, pattern, and spatial association (contextual classification). In the first pass of learning (Target Picker) we investigated the use of shape attributes to enhance the detection of UXO targets and removal of clutter; however, we found that shape and size were more effectively used during the second stage of ranking after candidate regions of interest were defined. This is consistent with our previous experience developing successful approaches to deal with similar problems. In general, in this field it is poor practice to expect a learning algorithm to usefully incorporate all attributes in a single pass. Experiments that we ran during the development for the seed project confirmed that it is better to capture all candidate ROIs for UXO during an initial pass, without emphasizing discrimination between UXO and scrap, then to concentrate on recognizing non-UXO targets using probabilistic ranking during a second pass.

The shape classifier used in the previous UXO project created shape patterns based on the entire list of Feature Analyst options. These include the following attributes: *number of vertices*, *number of holes*, *perimeter length*, *area of the shape*, *area of the bounding rectangle*, *compactness*, *second order moments*, *rotational invariant measure*, and *scale invariant measure*. Each of these was used with the probability classifier. We tested various subsets of these attributes to determine which were the most effective; however, in the end, using all attributes and allowing the learning algorithm to discriminate among them was found to be the most effective approach.

3.3 Task 3: Develop An Enhanced Target Picker and Target Ranker

In Task 3 we developed a more sophisticated automated screening approach (pass one) to increase the inclusion of all viable UXO candidates, while continuing to the extent possible to reject non-UXO. In the seed project, UX-1354, we focused on an inductive learning approach to maximize the accuracy of *both* classes (i.e., yield the most correctly classified UXO with the fewest false positives). With that approach, however, some UXO were missed.

In this project, our goal is to force *all* UXO through the target picker step, even at the expense of significantly expanding the number of non-UXO ROIs. This was accomplished by creating an appropriate training set, as described in more detail below. During the second pass, the intent was to predict the probability of ROIs being UXO versus non-UXO. Having the second pass of learning provide a probability ranking allows the Analyst to focus on selecting a probability threshold for specifying a dig list with an acceptable amount of UXO (e.g., high confidence of 100%) with as few digs as possible. If during the digging process the lowest true UXO probabilities are too small, little scrap is removed from the dig list.

Incorporating an accurate and inclusive training set is of the utmost importance for a learning algorithm to create accurate predictions. During our development work in this project,

we tested several alternative training sets incorporating various learning parameters. The training set examples were always digitized shapes of known UXO; however, we tried altering the number of examples used, the spatial distribution of examples, and the types of shape polygons (large, small, compact, etc). Parameters that were varied included histogram stretching of the image, rotation of the pattern mask, and spatial representation of the pattern mask. Our intent was to determine the dependence of the quality of the output results on the training set choice and the parameters, as described in later sections.

A machine learning algorithm can be confused by a target feature that is not also easily discernable by visual inspection (see **Figure 5**). In field data real UXO anomaly signatures have variability, which can cause difficulty in classification and discrimination of UXO from clutter. In the seeded site for instance, we found there were four (of the 25) ROIs from the vehicular dipole dataset that tended to confuse the learner (see **Figure 6**). These ROIs, when classified during the first pass, invariably returned a majority of the false positives. It is interesting to note that three of these problem ROIs in the vehicular data did not create the same difficulty in the airborne dataset. This is likely because the overlying small clutter above the UXO was not detectible in the airborne survey.

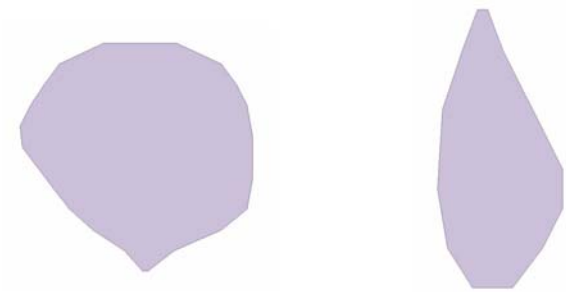


Figure 5. Sample ROI shapes for a UXO target on the left and a non-UXO target on the right.

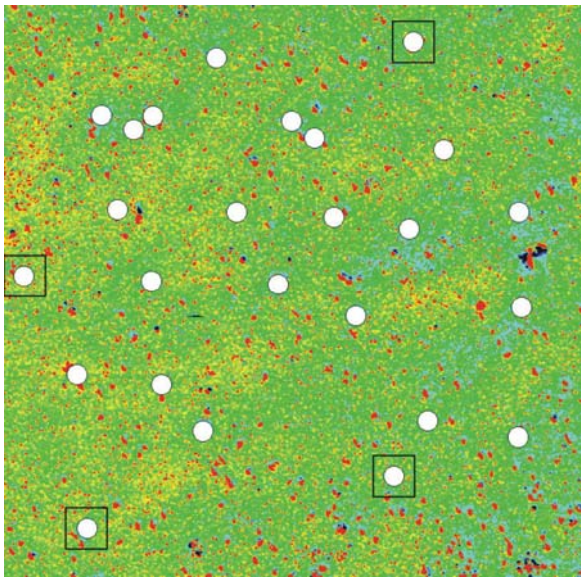


Figure 6. For the vehicular dipole data, the four UXO locations, shown in the black outline boxes, caused inclusion of most of the false positives in during classification. The white circles are map symbols showing the location of the seeded UXO.

3.4 Task 4: Evaluate The Target Picker and Target Ranker

We began our development work in this project focusing on the Seeded Site from the 2001 BBR survey. This site contained 25 known UXO and 114 known scrap items. This dataset provides a satisfactory set of positive and negative examples to develop a UXO identification workflow using Feature Analyst. We conducted hundreds of experiments using this data, which are summarized in Section 4.

4. RESULTS

This section provides the results on discriminating UXO versus non-UXO for both the vehicular and airborne MTADS datasets collected over the BBR site. AETC provided VLS with both the dipole processed and analytic signal processed versions of the MTADS survey data. Results of our studies are presented primarily in the form of ROC curves for those datasets where ground-truth for UXO and non-UXO have been established. The statistics used to build the ROC

curves are the true positive (UXO) and false positive (non-UXO) pr edictions. Previous reports on the BBR site describe the types of UXO and non-UXO that were planted on or dug[2,3] from the BBR site.

VLS had the ground truth for the 110 acre vehicu lar survey area from our studies during the Seed Project. These sam e ground truth apply, of course, to the parts of the airborne dataset that fall within this 110 acre are a. The dipol e and Analytic Signal m apped data files for the entire 1,685 acres of the Airborne Survey were provided to VLS. The ground truth (derived from the 1,000 digs on the Airborne site) was w ithheld, however until after the analysis was complete and submitted to AETC. AETC graded the VLS declarations against the known target dig results and returned the re sults to VLS in the form of a ROC curve reported later in this report. Appendix A includes a set of tables th at provide the x-coordi nate, y-coordinate, and probability value for each prospective target from the various analyses.

4.1 Methodology

The UXO identification methodology for the results presented was as follows:

1. First pass – Target Picker:
    a. Hand digitize five known UXO;
    b. Set learning parameters as input for Feature Analyst;
    c. The Target Picker g ives training examples to learner and returns ROIs (shapefile polygons).

2. Second pass – Target Ranker:
    a. The analyst locates and se lects positive and negative exam ples (known UXO and known non-UXO from the ROIs selected by the Target Picker) as input to Feature Analyst Target Ranker.
    b. Feature Analyst returns a UXO classif ication probability f or each shape (ROI returned by the Target P icker) based primarily on the shape characteristics of the ROI.

3. Evaluation of Experiments
    a. Perform leave-one-out cross validation on the dataset to genera te the predic ted probability for each ROI. These probabiliti es are generated for an individual ROI when it was its turn to be left out of the training stage.
    b. Develop receiver op erating characteristics (ROC) curves generated b y establishing the probabi lity threshold for predicting UXO versus non-U XO and plotting the cum ulative fraction of true positives versus the num ber of false positives.

4. Batch Processing
    a. Run the trained and automated two-pass algorithms on new data.
    b. Set the threshold at a leve l that provides a high c onfidence that all UXO will be retrieved, while at the sam e time, as a secondary goal, reducing the num ber of digs.

4.2 Datasets

The datasets used in this project during 2005 were from the 2001 survey of the Impact Area of the Badlands Bombing Range. The Impact Area consists of about 2,000 acres on Bouquet Table (a high mesa) about 10 miles west of Interior South Dakota. This area was used for many years as a ground artillery training range by the South Dakota National Guard. The projectiles fired from many directions from various firing points up to 10 miles from the center of the range. The primary aiming point was a structure near the center of the range, which consisted of as many as 50 automobile bodies that were stacked in a pile. Therefore, the range, in addition to being cluttered with shrapnel from exploded projectiles, is cluttered with automobile parts (particularly near the area of the bull's eye). **Figure 7** shows a USGS topo map of the area. The Impact Area border is shown in orange. The superimposed magnetic anomaly image is from a prior MTADS vehicular survey conducted in 1999. Ordnance from the 1999 survey areas was cleared following the survey. The vehicular survey areas used in this project are shaded in blue in this figure. With the exception of the plot labeled as the Seed Target Area, none of the blue shaded areas were surveyed or cleaned during the 1999 survey. Prior to the 2001 survey, 25 inert seed targets were installed in the 10-acre Seed target area. They were buried, consistent with the live ordnance that was recovered following the 1999 survey. All the areas shaded in blue were surveyed both with the MTADS vehicular towed array and the Airborne MTADS.

In addition, the Airborne MTADS surveyed 1,685 acres of the Impact Area, which included virtually all the areas lying on top of Bouquet Table. **Figure 8** shows a magnetic anomaly image map of the 1,685 acre survey, presented in dipole image format.

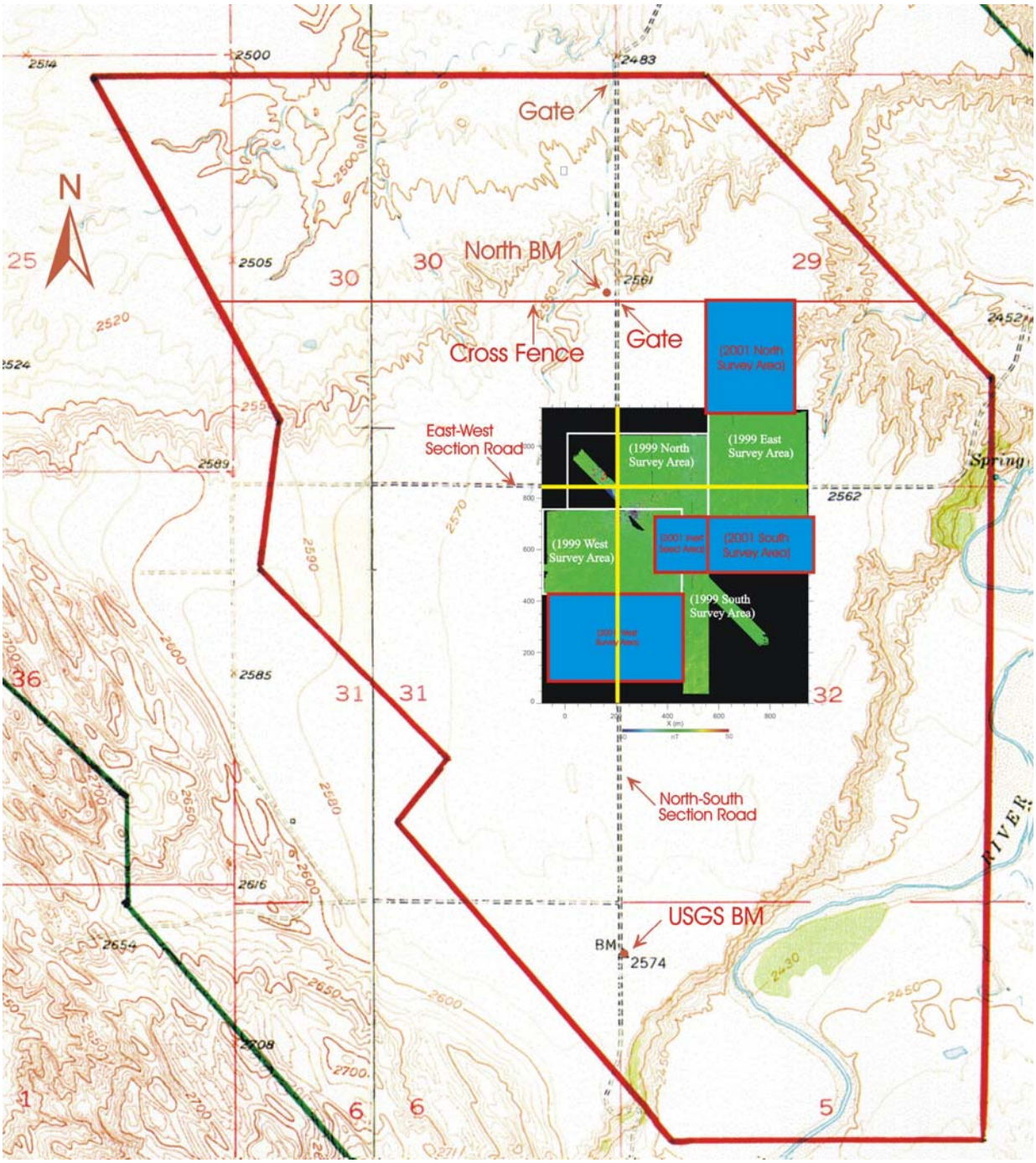


Figure 7. Portion of a USGS 7.5 minute topo map of Bouquet Table. The border of the Impact Range is outlined in orange. The areas shaded in blue were surveyed in 2001 with the vehicular and Airborne MTADS. These data were used in this project.

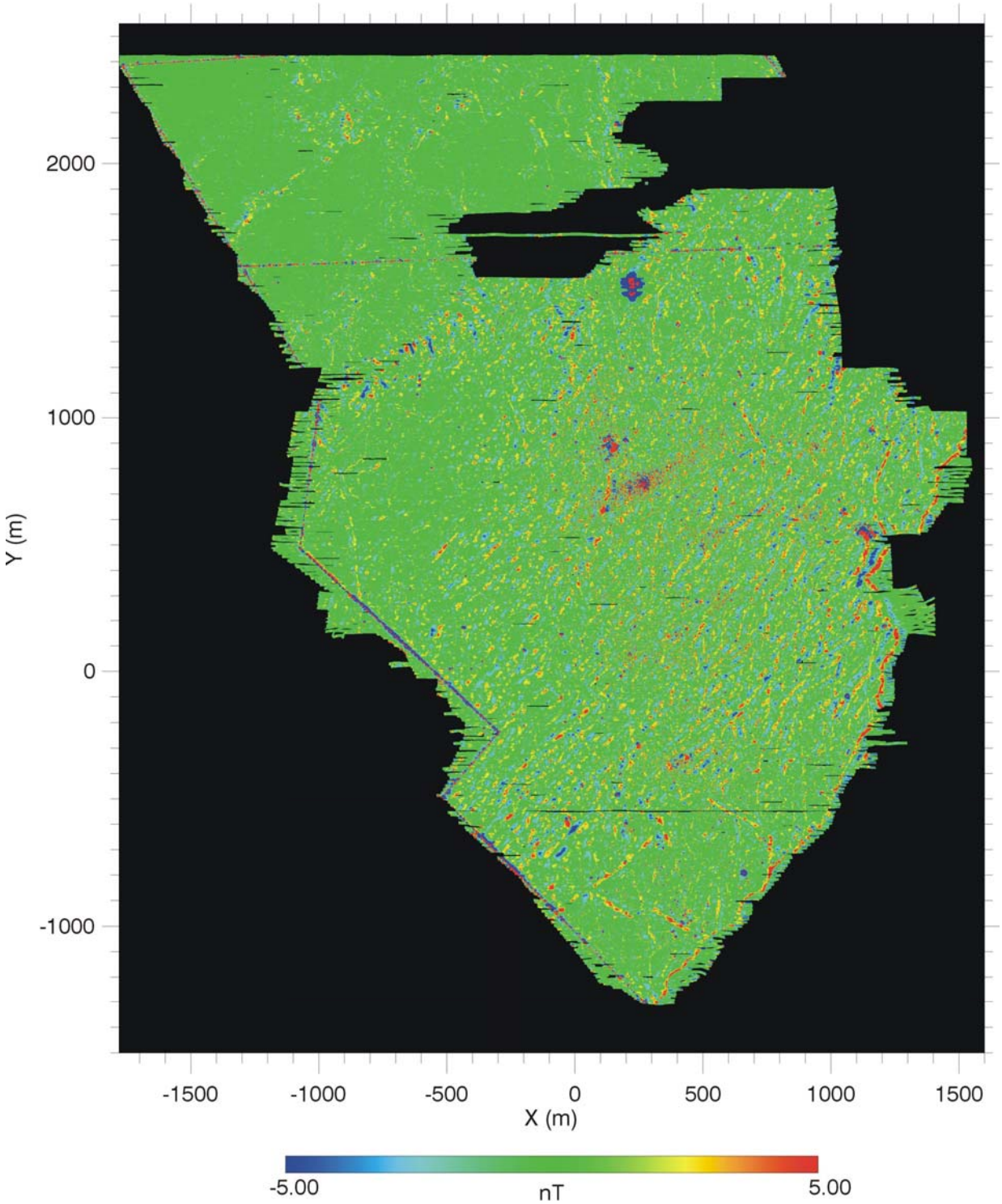


Figure 8. Magnetic anomaly image map in dipole format for the Airborne MTADS survey of the Impact Range on Bouquet Table.

AETC provided dipole and Analytical Signal mapped data files for both the vehicular and airborne MTADS datasets collected over the 110 acre BBR site. Two complementary 24-bit GeoTIFF images of the data were presented for analysis – the first displays the 2-D magnetic dipole anomaly image map based upon the magnetometry survey data; the second displays the analytic signal which is approximately the vertical gradient of the magnetic signal (see **Figure 9**). The common starting point for both images is a regular Easting/Northing grid of the magnetometer data which, in this case, were generated via the built-in MTADS DAS function based on a nearest neighbor technique. Since the data collected using the airborne system shows a minimum four-fold increase in sampling density along the East/West flight direction compared to the orthogonal (North/South) cross-track direction, the grid Easting resolution was chosen to be 0.25-m while the grid Northing resolution was chosen to be 1.0-m. For data collected using the vehicular system, the directional sampling density preference is less pronounced and so a 0.25-m x 0.25-m grid resolution was chosen.

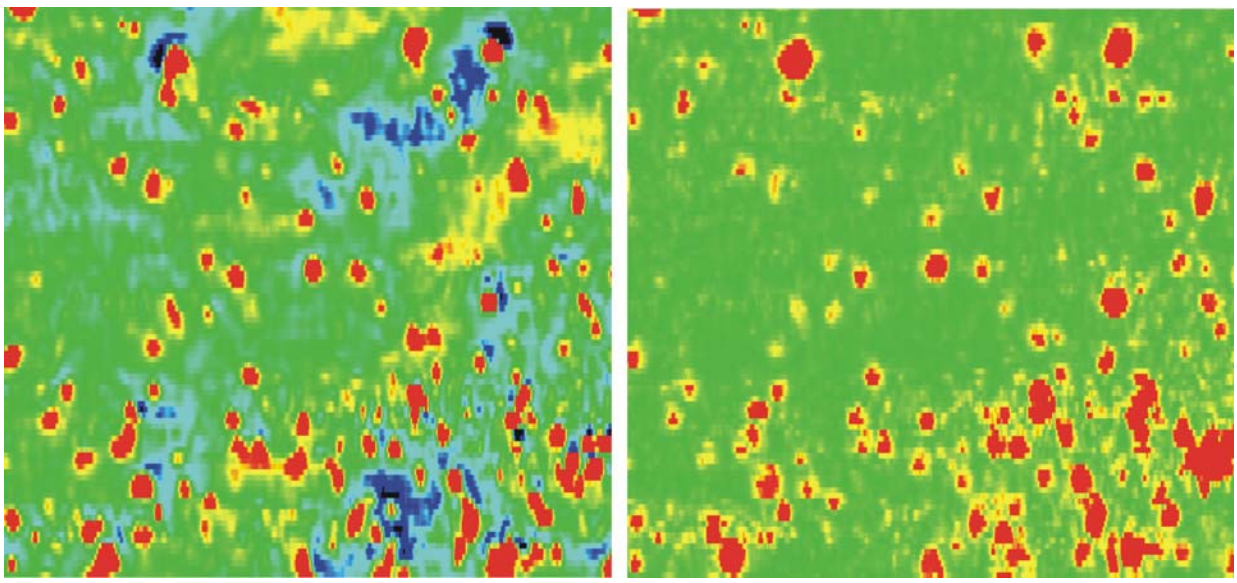


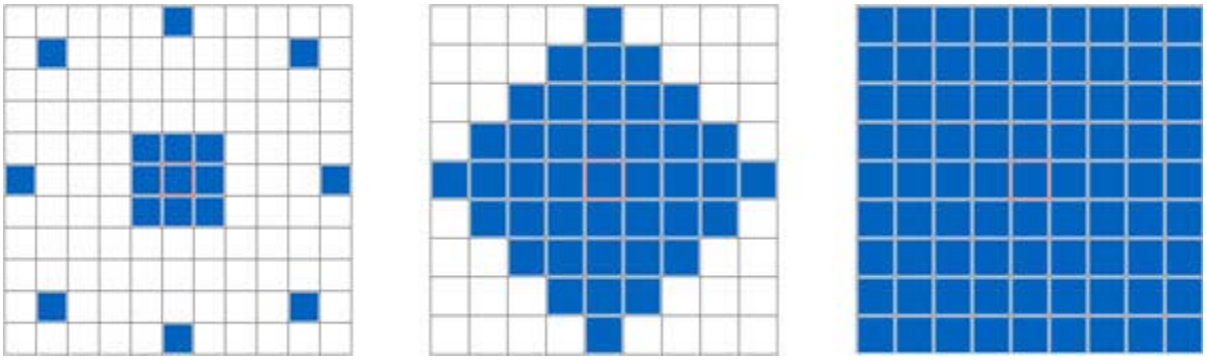
Figure 9. Image clips (dipole presentation on the left, analytic signal on the right) of the two complementary 24-bit GeoTIFF images from the vehicular survey data.

The analytic signal was computed from the grid data using the built-in Oasis Montaj GRIDASIG utility, with the z-derivative (vertical signal derivative) being determined via the "FFT method" setting. The resulting analytic signal grid was then sampled at the original grid coordinates. In order to convert both the magnetometer and analytic signal grid data to 24-bit geo-tif images, the data were scaled to bytes ranging from 0 to 255 and formatted into three interleaved 2-D byte arrays based on the Red, Green and Blue arrays described in the MTADS primary color palette. The palette ranges were chosen as ±30 nT (vehicular) and ±6 nT (airborne) for the magnetometer data images and ±300 nT/m (vehicular) and ±12 nT/m (airborne) for the magnetometer data images. As the final step, the relevant geo-referencing information was transferred to an embedded standard structure.

4.3 Learning Parameters

We investigated the affects of using various available parameter choices, as described in Section 2. We found the following for each parameter during our experiments:

- **Selection of Input Bands** – For these images, it is important to include all bands in the GeoTIFF image.
- **Histogram Stretch** – The analyst can apply a histogram equalization stretch to the raster image. The experiments show that sometimes a histogram stretch can improve results; these cases are indicated below.
- **Aggregation** – Aggregation is an algorithm that eliminates output polygons below a certain size and fills in holes in a polygon below a certain size. The size of the appropriate value for each experiment is described below.
- **Smoothing** – Smoothing the polygons was found to improve accuracy and was done for each result presented below.
- **Rotation** – We found in all cases it was better to turn rotation off.
- **Spatial Input Representation** – The analyst can apply various pixel patterns to be used as spatial inputs to a learning algorithm. For the experiments, we tested what we felt were the most likely candidates for appropriate input representations. Various Bull's eye patterns were tested (including #1 width 11; #2 width 11 and 13; #4 width 9 and 11), Manhattan patterns with widths 5 and 9; and Square patterns with widths 5 and 9. **Figure 10** shows examples of each of these types of input patterns. We also tested various non-standard input representations that seemed to best fit observed UXO, as discussed below.



(a) Bull's Eye (b) Manhattan 9x9 pattern (c) Square 9x9 pattern

Figure 10. Spatial input pattern in Feature Analyst showing a sample Bull's Eye pattern (#1, width 11), Square Pattern (width 9), and Manhattan pattern (width 9). The blue boxes represent pixels used by the learning algorithm and the red squared box in the center is the pixel at which the prediction is being made. The different arrangements provide alternative mechanisms for which to include spatial context in the learning process.

4.4 Vehicular MTADS Survey of the 10-Acre Seeded Site: Dipole Processing

Figure 11 shows the ROC curve for the Vehicular MTADS dipole processed dataset for the 10 acre seeded site. 96% of the ordnance (24 of 25 seed targets) is included in the top half of the dig list. However, as shown, 100% UXO detection (25 UXO) is not achieved until nearly 100% of the non-UXO are picked up as well. The human-in-the-loop physics-based analysis contained 134 selected candidate UXOs. The machine learning Target Picker selected only 74 ROIs, which is a reduction of 60 digs for UXO candidates (with a total of 49 false positives). The training set for the first pass in the Seed Target dataset was created by first selecting a small set of examples, running the process, and then returning to the training set and adding additional

examples, as needed. The parameter settings used in Feature Analyst for the dipole dataset are listed below.

- **Input representation**
  - The most effective was a Square pattern of width 9.

- **Aggregation**
  - The smallest known UXO was just over 20 pixels in area; therefore, the aggregation was set to below 20. If the resultant set returned results with the smallest known UXO polygon larger than 20 pixels, aggregation could be run at the new minimum as a post process to further reduce clutter.

- **Histogram Stretch**
  - The results were better without the histogram stretch.

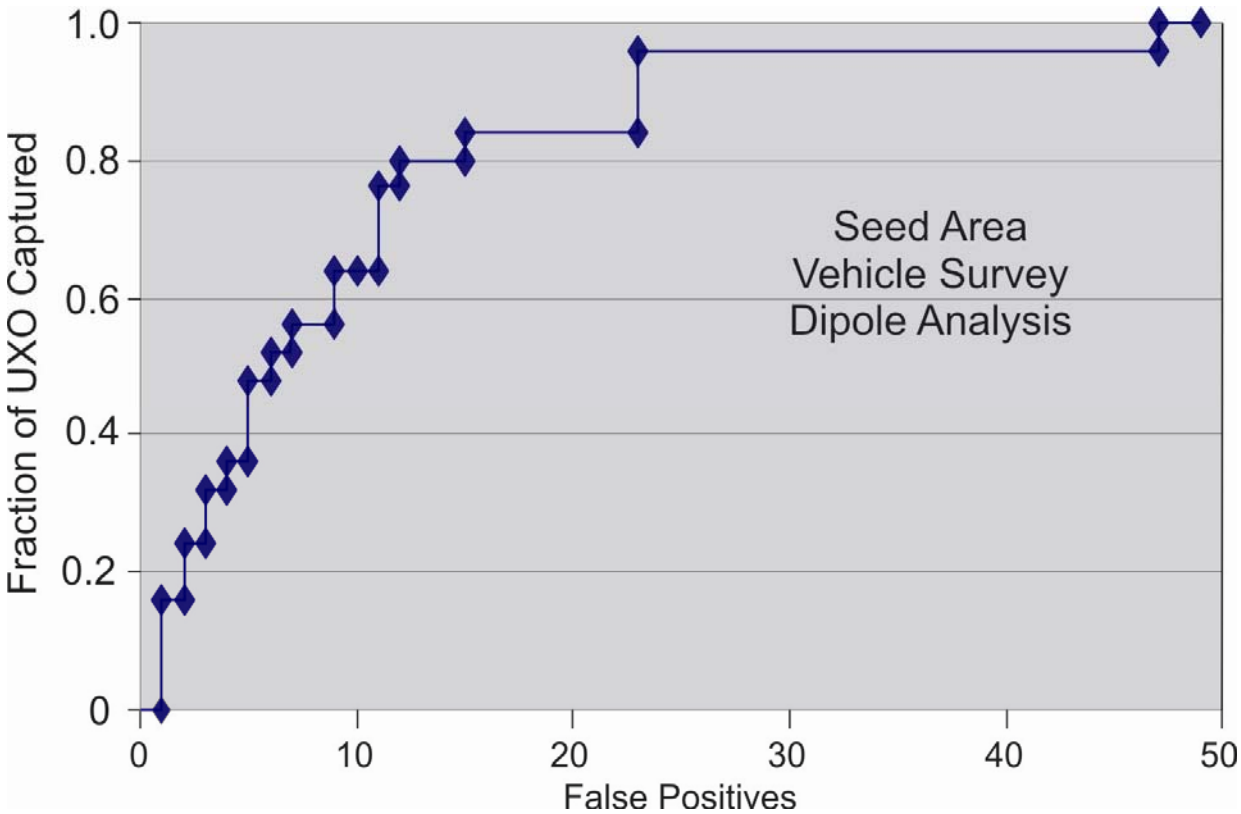
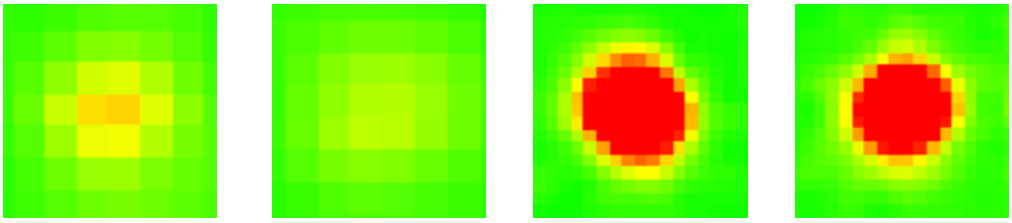


Figure 11. ROC Curve for the dipole analysis of the vehicular survey of the Seed Target Area. The Target Picker returned 74 ROIs including the 25 UXO seed targets.

4.5 Vehicular MTADS Survey of the 10-Acre Seeded Site: Analytic Signal Processing

Two known UXO in this dataset did not contain the pixel characteristics typical of those displayed by the rest of the ground truth set (**Figure 12**). When these two examples were not given to the learner as part of the training set, the resulting shapefile contained between 69-119 ROIs – but did not include these two known UXO. When either one of these UXO were

included in the training set, the resulting shapefile ballooned to between 393-871 ROIs. Since the dipole presentation first pass provided substantially fewer targets while retaining all known UXO, the Analytic Signal processed data were not further pursued.



(a) (b) (c) (d)

Figure 12. Analytic Signal processing proved to reduce the amount of clutter overall with the exception of two important ground truth UXO outlier points (a) and (b) (at coordinates (722786, 4838120) and (722819, 4838143) respectively). Two typical analytic signal ground truth points are shown in (c) and (d).

The Feature Analyst parameter settings are listed below for the analytic signal vehicular data.

- **Input representation**
  - The optimal pattern was Bull's Eye 1, width 11
- **Aggregation**
  - The aggregation was set to 8 since the ROIs were smaller with this data.
- **Histogram Stretch**
  - The histogram stretch improved results mildly.

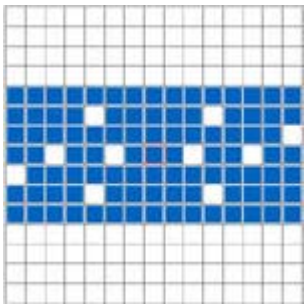
As described in Section 4.2, the MTADS DAS presentations were used to scale the pallets for the dipole images, Oasis Montaj was used to scale the pallets for the Analytic Signal images. Pallets with only a single vertical scale were provided to VLS for each presentation. Selections were made which provided a reasonable representation for the known UXO (±30 nT for the vehicle dipole data and ±300 nT/m for the vehicle Analytic Signal data). The representation, as shown in the two examples on the left of Figure 10 was too course for the Analytic Signal data. It is likely that a narrower pallet presentation (120 nT/m or 150 nT/m) would have worked better for this particular analysis.

4.6 Airborne MTADS Survey of the 10-Acre Seeded Site: Dipole Processing

Figure 11 shows the ROC curve for the airborne MTADS dataset with dipole processing. A total of 73 ROIs were selected by the Target Picker. 100% of the UXO are classified correctly when the threshold is reduced to 0.05. At this threshold value, a total of 96% of the non-UXO were incorrectly classified as UXO, totaling 46 false positives. The input parameter settings are given below.

- **Input representation**
  - User defined rectangular pattern as follows. The width of each pixel comprising the airborne dataset is 1/4 th the height of the pixel (as described

previously); therefore, in order to compensate for this irregularity, the input representation was stretched horizontally.



- **Aggregation**
  - The appropriate aggregation setting for this dataset was 15.

- **Histogram Stretch**
  - The results were better without the histogram stretch.

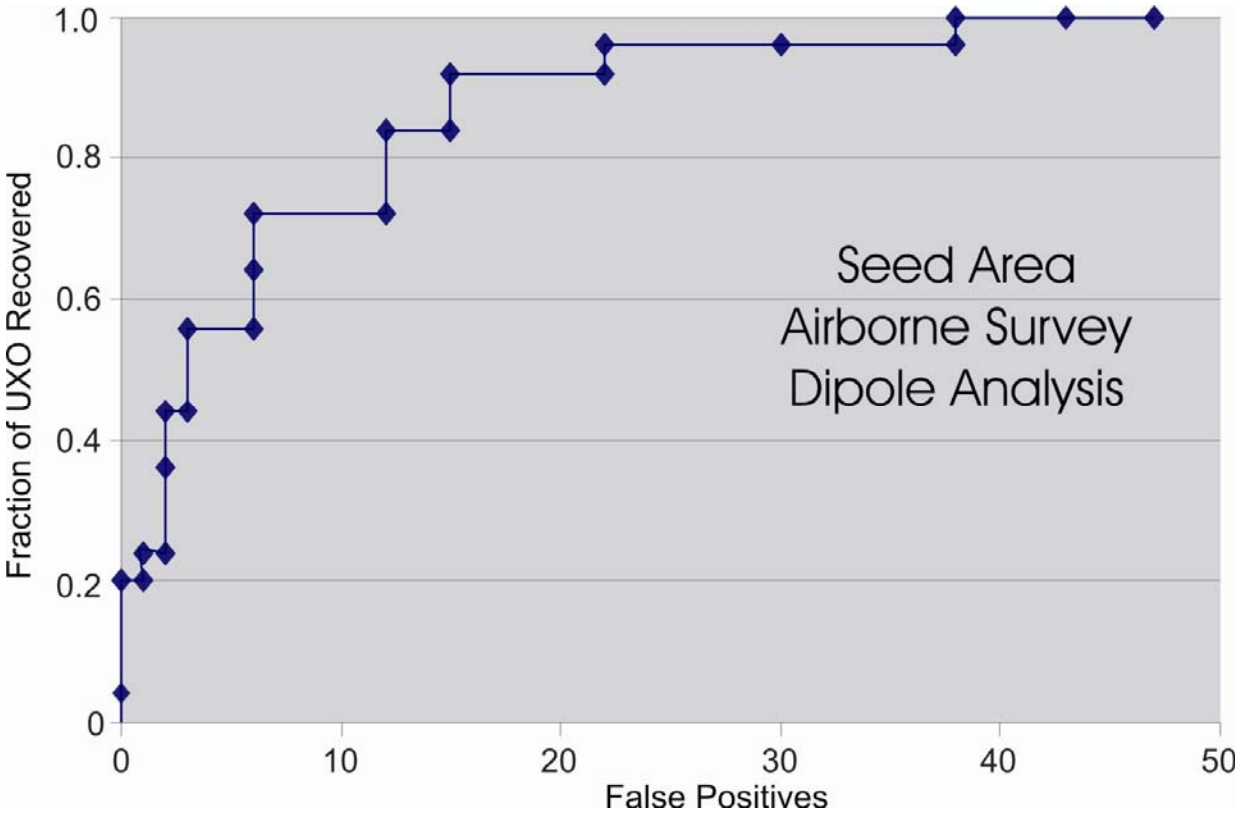


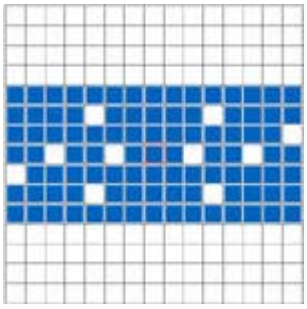
Figure 13. ROC curve for the dipole analysis of the airborne survey of the Seed Target Area. The Target Picker returned 73 ROIs including the 25 seed UXO targets.

4.7. Airborne MTADS Survey of the 10-Acre Seeded Site: Analytic Signal Processing

Figure 14 shows the ROC curve for the Airborne MTADS collected over the seeded site where the data was processed with the analytic signal approach. A total of 97 ROIs were

selected by the Target Picker. All of the UXO were classified correctly with 57% of the non-UXO returned by the Target Ranker as false positives (41). The parameter settings for the Target Picker are listed below:

- **Input representation**
  - User defined rectangular pattern as follows . The airborne datasets pixel dimensions are vertically oblong; therefore, in order to compensate for this irregularity, the input representation was stretched horizontally.



- **Aggregation**
  - The aggregation was set to 8 to match the size of the ROIs for this dataset.

- **Histogram Stretch**
  - Experiments were run with and without applying a histogram stretch, and it is best to not have a histogram stretch.

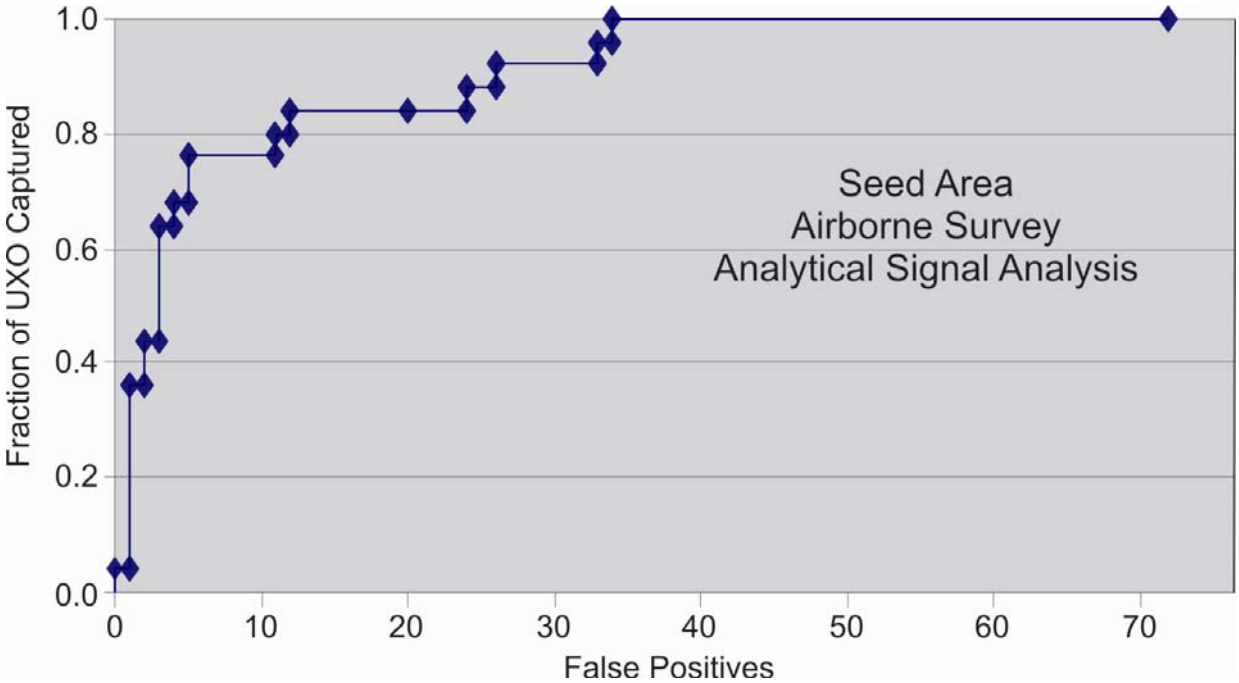


Figure 14. ROC curve for the airborne survey of the Seed Target Area with Analytic Signal Analysis. The Target Picker returned 97 ROIs.

4.8 South and West Survey Area Datasets

The design of Feature Analyst allows the analyst to develop a target recognition or feature extraction model and then apply the model in an automated mode. This provides (a) an automated approach for treating multiple similar datasets; (b) a methodology for sharing workflows, and (c) a framework for developing a library of feature extraction models. As described above, we developed target recognition models using vehicular and airborne survey data from the Seed Target Area for both dipole and analytic signal image presentations. The results from the analytic signal and dipole airborne datasets were similar. The palate that was chosen for the vehicular analytic signal image of the Seed Target Area was likely too course, leaving two of the known UXO as uncharacterized.

Because of their work with these datasets during the Seed Project (UX-1322) VLS had the ground truth (based on the dig results) for the South and West vehicular survey areas. Therefore, as a logical next step the target recognition models developed from the Seed Target Area were tested on these limited survey areas. The target recognition models, generated from the Seed Site, were applied to the South and West analytic signal and dipole airborne survey datasets, and the vehicular dipole datasets. Feature Analyst provides a menu option called Batch Processing for applying target models to new data. The South and West locations each contained 3 known UXO; thus the ratio between correctly classified UXO and incorrectly classified non-UXO is very dissimilar to that of the seeded site. Results for these areas are presented below.

The probabilities returned by the Target Ranker for the known UXO in the South and West survey areas were high compared to most of the non-UXO. The seeded site appears to contain more obscure and borderline UXO than the South and West locations; for this reason the threshold could potentially be increased for the South and West data sets. It is likely that the signals of the inert UXO in the Seed Target Area were more varied and difficult to characterize because some of them were poorly degaussed and because they were physically located close to the bull's eye and were therefore buried in the midst of relatively high levels of metallic clutter from exploded ordnance and from car body parts scattered about from projectile explosions. Perhaps the target recognition models prepared from the seed target area are more robust for these reasons.

4.9 Vehicular Survey of the South Area: Dipole Signal Processing

The ROC curve for the vehicular survey of the South Area is shown in **Figure 15**. All the UXO were identified in the top 30% of the dig list. In the vehicular survey of the Seeded Area effectively 100% of the dig list had to be excavated to recover all UXO.

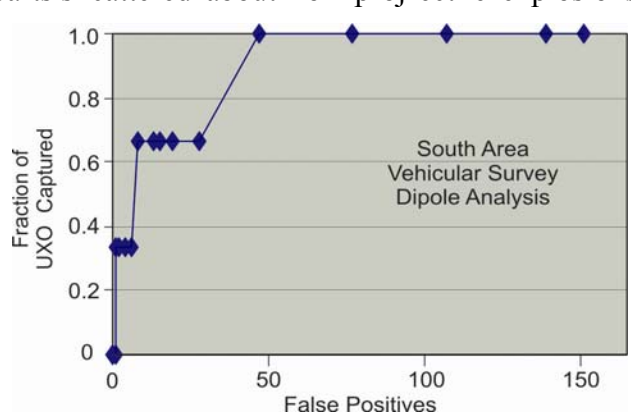


Figure 15. ROC curve for the vehicular survey of the South Area with dipole analysis. The Target Picker returned 151 ROCs.

4.10 Airborne Survey of the South Area: Dipole Signal Processing

Figure 16 shows the ROC curve for the dipole analysis of the airborne survey of the South Area. The total number of ROIs returned by the target picker was similar to the dipole analysis of the vehicular survey of the same area. Less than half of the dig list would have to be dug to recover all the ordnance.

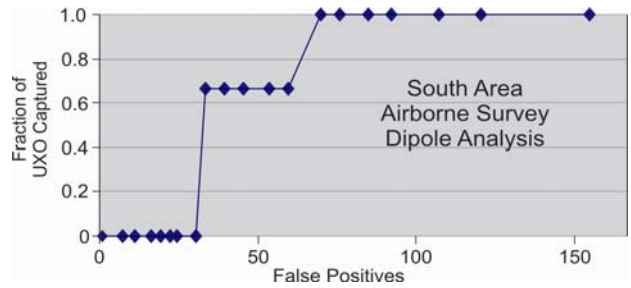


Figure 16. ROC curve for the dipole analysis of the airborne survey of the South Area. The Target Picker returned 155 ROIs.

4.11 Airborne Survey of the South Area: Analytic Signal Processing

Figure 17 shows the ROC curve for the same survey shown in Figure 16. In this case the analysis was based upon the analytic signal image. The target picker returned more ROIs than the dipole analysis, however the UXO were recovered at the very top of the dig list. The South Area, at 20 acres is twice as large as the Seed Target Area.

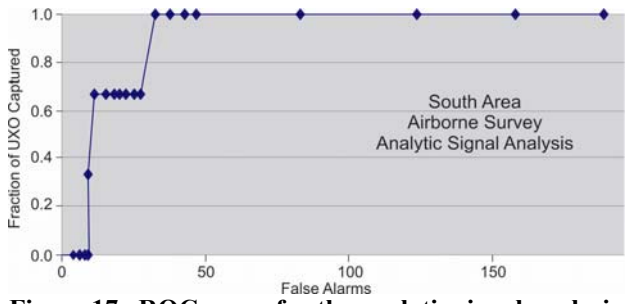


Figure 17. ROC curve for the analytic signal analysis of the airborne survey of the South Area. The Target Picker returned 189 ROIs.

4.12 Vehicular Survey of the West Area: Dipole Signal Processing

The West Survey Area, at slightly over 40 acres, lies well south of the bull's eye. **Figure 18** shows the ROC curve for the dipole processing of the vehicular survey. The target picker returned only 127 ROIs for the area, which is twice as large as the number returned for the vehicular survey of the South Area. Based upon digging in 2001, three UXO were recovered from the area.

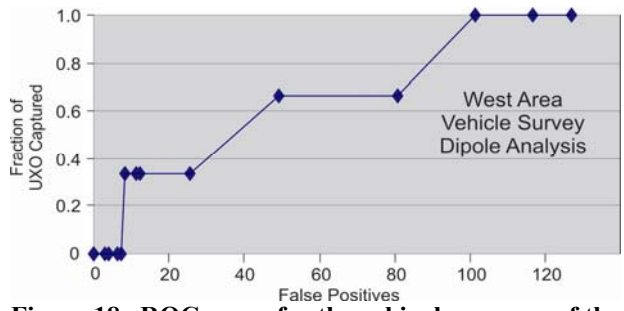


Figure 18. ROC curve for the vehicular survey of the West Area with dipole presentation analysis. The Target Picker returned 127 ROIs.

4.13 Airborne Survey of the West Area: Dipole Signal Processing

Figure 19 shows the ROC curve for the airborne survey of the West Area with dipole image processing. Although the Target Picker returned a relatively large number of ROIs (232), the Target Ranker recovered all 3 of the UXO in the first 15% of the dig list.

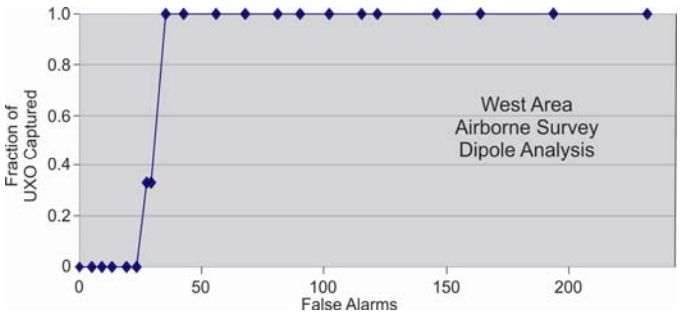


Figure 19. ROC curve for the airborne survey of the West Area with dipole image analysis.

4.14 Airborne Survey of the West Area: Analytic Signal Processing

Figure 20 shows the ROC curve for the airborne survey of the West Area with analytic signal image processing. The Target Picker returned 427 ROIs, more than 3 times the number returned in the analysis of the vehicular survey of the same area. The target ranker recovered the 3 UXO targets in the top 25% of the dig list.

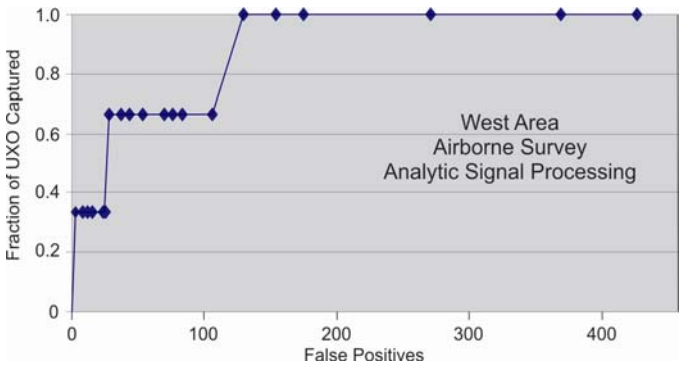


Figure 20. ROC curve for the airborne survey of the West Area with analytic signal image analysis.

4.15 Airborne Survey of the Entire 1,685-Acre Site: Analytic Signal Processing

The UXO target model created from the seeded site using the airborne MTADS datasets and used to batch process the data from the South and West Areas was also used to batch process the entire airborne survey. Only the data from the Seed Target Area were deleted from the airborne dataset; data from the South, West, and North survey areas were included. VLS knew the ground truth for the 6 known targets in the South and West Areas, but did not have ground truth from the remainder of the airborne survey area.

For completeness, we review below the development of the Airborne Analytic Signal target model:

- A total of five positive UXO ground truth examples (from planted inert ordnance) were provided to the Target Picker using the MTADS airborne analytical signal processed dataset;

- Target Picker parameter settings were identical to those described earlier for the spatial input representation, aggregation and learning approach. The total resulting output of ROIs from the Target Picker for the seeded site was 97;

- The Target Ranker was then used to assign probabilities to each of the 97 shapes using shape metrics. The 25 positive UXO examples were specified from these 97 shapes and the remainder was specified as negatives (non-UXO). **Figure 21** is a clipped image of probabilities returned from the Target Ranker from an analytic signal image showing how they relate to the size and shape of various ROIs.

- This defined the target model; it was then written to a file for use with other datasets.

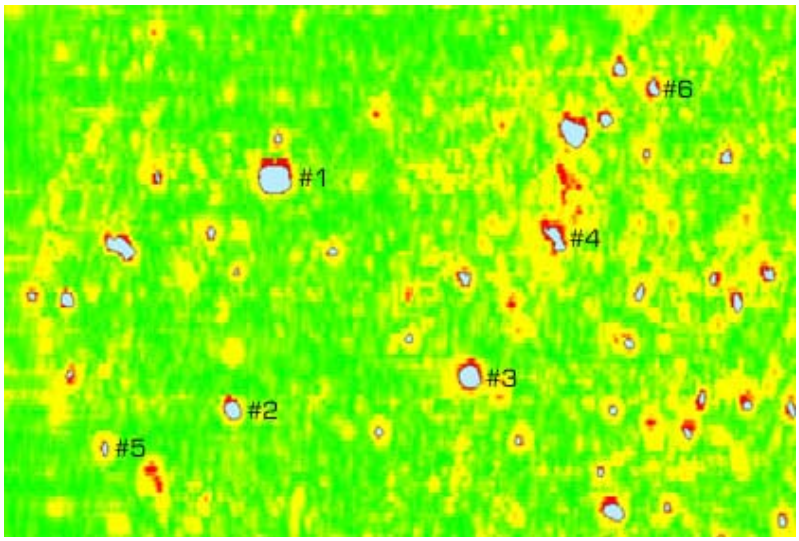


Figure 21. Shown is a 100 X 200 m clip from the Airborne Analytic Signal image map generated from the target ranker. ROI shapes are superimposed on the image. Shape numbers 1, 2, and 3 closely resemble UXO; the target ranker assigned them probabilities 0.97, 0.84, and 0.95. Shape numbers 4, 5, and 6 do not resemble UXO, their evaluated probabilities were 0.03, 0.04, and 0.03.

The target model was then applied to the entire MTADS airborne analytical signal processed dataset for batch processing. The total number of ROIs returned by the Target Picker (5,985 polygons), were submitted to the Target Ranker. Each ROI polygon was assigned a feature ID, X and Y coordinates, and a probability value by the Target Ranker.

The target list had 5,985 entries. VLS, based upon the performance results described above for the Seed Target Area and the South and West Areas, assigned a probability threshold of 0.2 for the ordnance declaration cutoff. Therefore, VLS declared 1,293 targets as UXO and the remaining 4,692 ROIs returned by the target picker as Not-UXO. The output table was provided to AETC for scoring. **Figure 22** is the ROC curve from the grading of the ranked and classified target list provided by VLS. The entire spreadsheet with provided ground truth is included in the appendix.

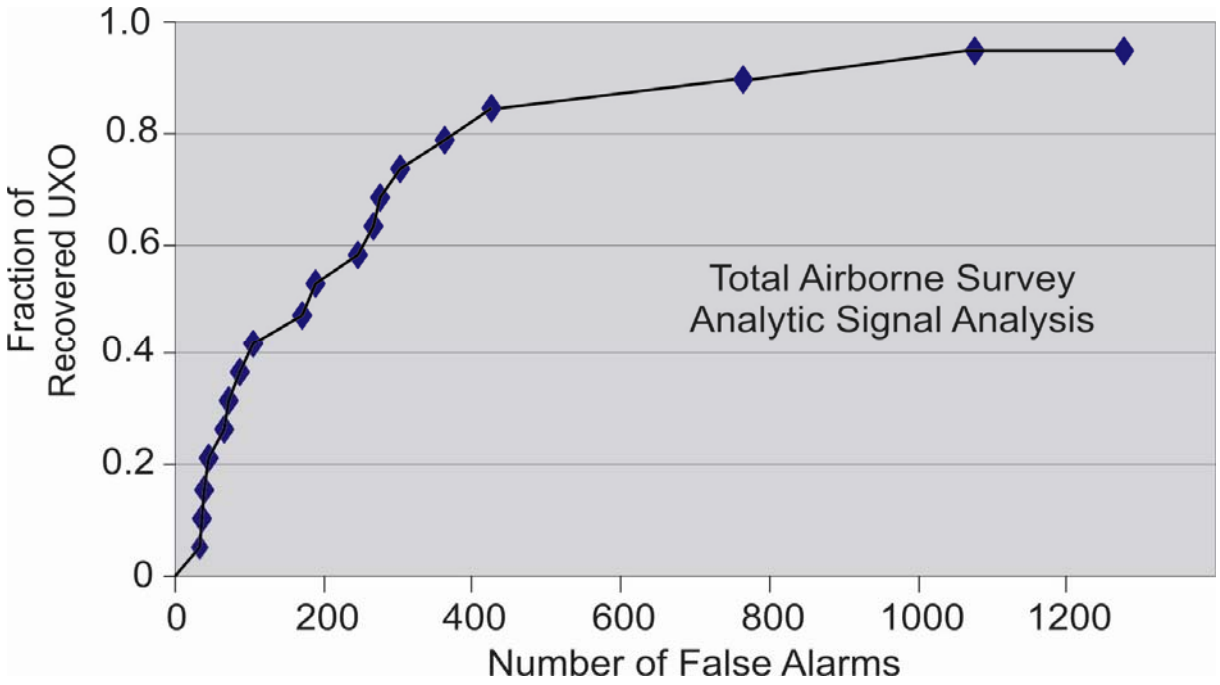


Figure 22. ROC curve for the entire Airborne Survey. The Target Picker returned 5,985 ROIs. 1,293 anomalies were declared as UXO. The analyst correctly identified 18 of 19 UXO projectiles.

The first 16 UXO were captured in less than 10% of the target list returned by the Target Picker. UXOs number 17 and 18 were captured at anomaly numbers of about 800 and 1000 of the declared list of UXO. The remaining UXO, a false negative, did not appear until target number 5,462, which was assigned a UXO probability of ~3% by the Target Ranker.

We have investigated possible reasons why the Target Ranker evaluated the false negative projectile so far down the probability list. **Figure 23** shows a screen clip of the MTADS DAS analysis of the target. In this analysis it is a high value target characterized by 5 sensor tracks over the anomaly. The fit quality is relatively high at 0.94. A clutter target overlaps the northwest part of the larger signature but is small compared to the larger signal. The analytic signal image clip for a 60 X 60 m area around the target is shown in **Figure 24**. The analytic signal image for this anomaly is significantly expanded over the dipole image counterpart. It also includes an additional target about 5 m NW of the primary target (see Figure 23) as part of the image. The Target Picker drew an ROI around this whole area as a single anomaly rather than breaking it up into multiple anomalies. As such, the generated ROI had the general crescent shape typical of many non-UXO shrapnel patterns that resulted from projectiles impacting before they exploded. This ROI was then incorrectly ranked and became a false negative. We feel that it is likely that a QA review of the predictions of the Target Ranker based upon the anomaly images and the ROIs would likely flag this anomaly for further review.

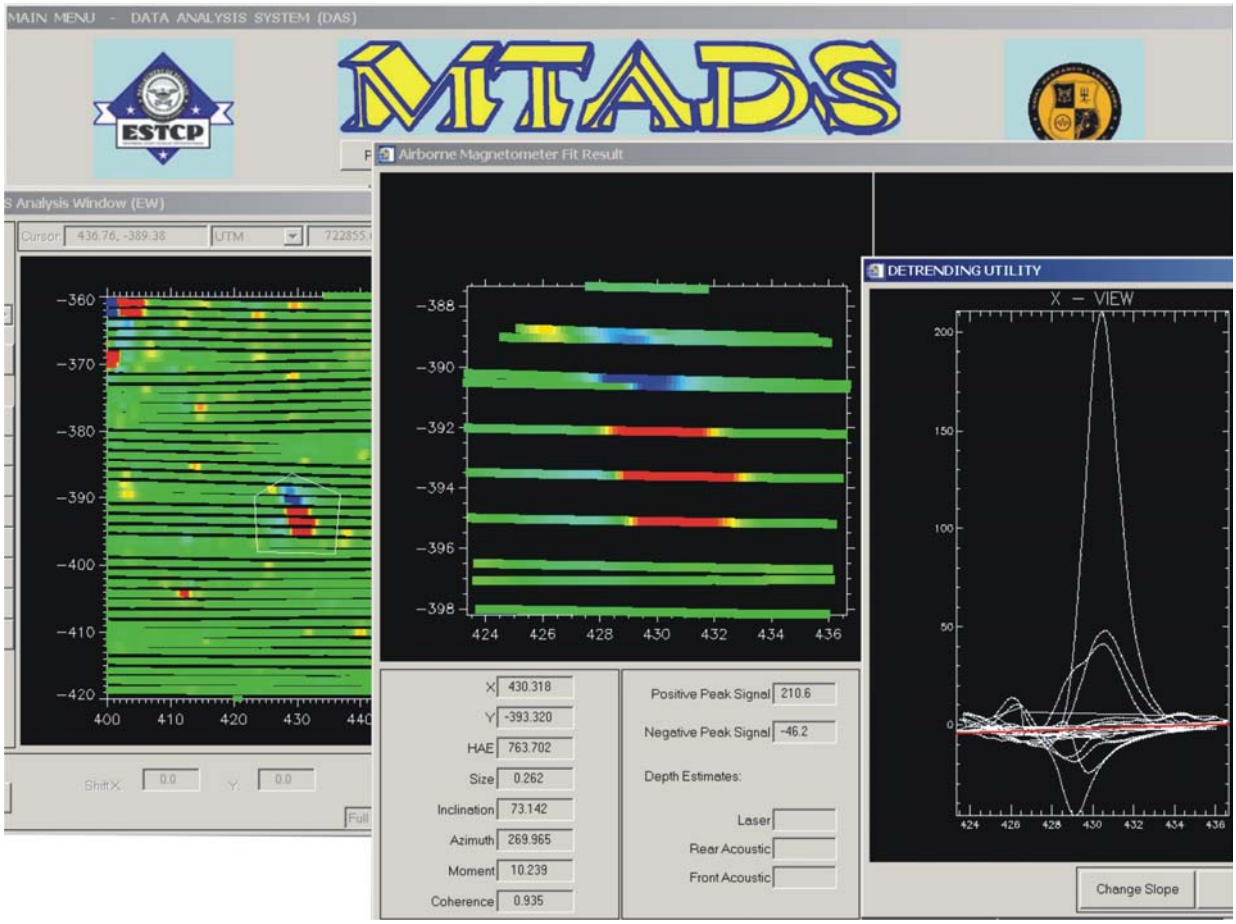


Figure 23. Screen clip from the MTADS DAS analysis of the projectile appearing as a false negative above in the airborne analysis. On the left, the anomaly as it appears in the dipole data is boxed by the analyst. The center image shows the data selected for fitting. The right image shows the individual sensor tracks over the anomaly.

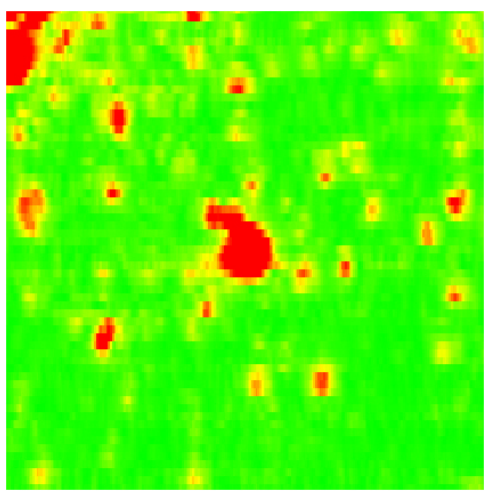


Figure 24. 60 X 60 m clip from the Analytic Signal presentation showing the false negative target at the center of the image.

5. CONCLUSIONS AND FUTURE WORK

- During the first year of this project we developed a prototype classification tool using the Feature Analyst framework to differentiate UXO from non-UXO. As part of this task, the shape classifier was adapted to output a certainty probability for each shape – a numerical value between 0.0 and 1.0. This probability evaluates how closely the shape matches the positive examples that were used to form the target model. The analyst or site manager must then determine the probability threshold at which to assume that all targets with higher values should be classified as UXO, and should therefore become priority dig targets. We note again that the classifier can be updated at any time during the digging process by providing the dig results (positive and negative) to updating the target model.

- We have shown that it is possible to correctly identify with high confidence all of the UXO among the ROIs selected by the target picker. The two-pass workflow in Feature Analyst with the Target Picker and Target Ranker modules operating separately successfully separates the ROIs into likely UXO and targets unlikely to be UXO. The target ranker routinely batch processed the entire (massive) airborne dataset and ranked all ROIs. Using a conservative threshold of 0.20 provided a UXO dig list with about 1,300 entries. This number of entries is similar to the dig list generated by the MTADS DAS analyst using physics-based algorithms and hands-on analysis of each individual target. The latter process required ~35 hours of analyst time. Eighteen of nineteen known UXO were correctly identified by the automated target ranker.

  As an aside, the ground truth for this exercise is based upon the 1,000 targets dug behind the MTADS DAS analysis. There is no proof that the MTADS DAS analysis identified all the intact projectiles from the airborne survey dataset.

- The analytical signal processing of the magnetometer data was important, particularly for the airborne datasets. Using the analytical signal data also has the advantage that it locates the coordinates correctly for the individual targets. When working with the dipole presentations, only the positive lobes of the dipole signatures are used for training because various orientations of the individual targets creates such a variable dipole image when the negative part of the signature is included that it is not practical to try to train on the full dipole signature.

- What results from this two-step approach, using the seeded site containing ground truth, is a Target Model for UXO that can be run in batch mode. Further benefits include:

  - The UXO dig list is automatically prioritized based on the probability values from the target ranker. The probabilities generated by the target ranker are based upon mathematically and statistically sound principles. The binning probabilities generated by the human analyst from the MTADS DAS, and by others using other physics-based fitting algorithms are basically intuitive (gut-feel) assignments that vary from analyst to analyst.

- Digging the high-probability UXO targets based upon the target ranker optimizes both budget and schedule constraints. We assume that the approach developed in this project is unlikely to ever be used without review by a human analyst. The most experienced available analyst should focus on mid-range probability values, particularly those immediately below the UXO cutoff threshold. A human analyst can also likely make significant contributions by reviewing the targets on the dig list above the cutoff threshold. VLS was instructed that a fence line surrounded the range, that a group of trailers was parked in the north central part of the site, and that a destroyed homestead (with a reinforced concrete basement) was located northwest of the crossroads. These areas were censored from their data analysis, however many other areas such as ground water sampling wells, geological benchmarks, trash collecting barrels, remnants of past internal fences, and geological interferences were not disclosed. Many of these features can be identified by visual inspection of the data by an analyst and targets associated with them deleted from the dig list.
- The two-pass workflow and assignment of probabilities to UXO targets allows the analyst or the site manager to export mid-range probability UXO targets to a traditional physics-based classifier. This workflow approach has the potential to integrate the best tools of both inductive learning approaches and established geophysical techniques such as dipole fitting.

- In a wide area search of a new area such as that carried out using the MTADS airborne dataset, Feature Analyst, used with the prototype UXO Toolkit developed in this project, can be used to quickly and automatically classify all candidate ROIs returned by the Target Picker. Even without any prior existing ground truth, the parameters for the target picker can be opened up to pass target sizes consistent with the known site usage. Subsequently, the target ranker can be programmed with a target model from other sites that contain ordnance known to be present at the current site. The target picker and ranker can be run with these parameters in a batch mode to generate a preliminary dig list. As targets are dug, the target model can be updated based upon the ground truth resulting from preliminary target digs. This process could be iteratively (and automatically) repeated at the end of each day of digging until it was felt that an optimum target model had been constructed.

- The inductive learning approaches in Feature Analyst with the UXO Toolkit are adaptive, robust, simple to use, and can be potentially deployed in many different geologic settings for UXO classification. However, the accuracy of the UXO classification will always be based on several key factors including:
  - **The quality of the magnetometer data**. The vehicular and airborne MTADS system produced excellent data for UXO target detection and discrimination. Careful planning and execution of the UXO survey is the necessary first step in producing a high-quality classification.
  - **Pre-processing the MTADS data to enhance signal-to-noise ratios and reduce clutter**. We found the analytical signal processing approach to produce excellent

results for the BBR site. Obviously each UXO site is unique because of geology, historic use, cultural noise, etc. but careful preprocessing of the survey data was important.

- **Cultural features.** Knowledge of the characteristics of the site, including the identity and location of manmade and cultural features can greatly aid the analyst in preprocessing the data and also during the analysis process.
- **The experience and training of the analyst.** These factors are also very important especially when selecting training set examples. In order to generalize, Feature Analyst requires diversity and spatial distribution in the selection of both positive and negative UXO training set examples.
- **Workflow is important**. The analyst should consider the Feature Analyst and UXO Toolkit as a semi-automated application for classifying and ranking UXO targets. Based on the probability threshold selected by the analyst, there will be a subset of ROIs that should be passed to physics-based algorithms for additional classification as well as for quality control purposes.

Future Work

During the second year of the project we will continue to develop and refine the target picker and the target ranker. This will be done by addressing other challenging sites and data sets. We will continue the project by working with the vehicular and airborne datasets from the wide area survey at the Isleta (Kirtland Precision Bombing) Range. This site contains a wider range of ordnance types, than BBR. Additionally, the terrain at Isleta is somewhat more rugged than the BBR, and there is considerably more active geological interference than on the BBR. We have prepared the datasets for the vehicular and airborne surveys for analysis and have tentatively prepared training sets of UXO and non-UXO targets based upon both seed targets and dug targets.

In addition, we plan to evaluate the approach using data from EM array surveys. Currently, we are considering data from the Jefferson Proving Ground. If we can identify better, newer, or more extensive EM datasets, we can switch to these.

6.0 REFERENCES

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