UXO Classification Procedures Applied to Advanced EMI Sensors and Models

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Abstract—Unexploded Ordnances (UXO) classification procedure consists of the following: background subtractions, data inversions and targets feature parameters estimations, and separating UXO from non-hazardous anomalies. First, each dataset is normalized by a corresponding Tx-current; then, all data files are background subtracted; third, the background corrected data are inverted and targets intrinsic (effective polarizabilities) and extrinsic (locations) are extracted; next, the extracted intrinsic and extrinsic parameters are used for generating prioritized and training targets lists; finally, once the ground truth for training targets are provided, then prioritized targets are reclassified and final dig list is created. In this paper, the detailed steps of UXO classification procedure using the advanced EMI sensors and models are presented along with the processing and analysis approaches that are used to generate a prioritized dig list.

Index Terms—UXO; EMI; Sensors; Detection; Classification; Forward and Inverse models; Soils.

I. INTRODUCTION

UXO cleanup cost at former and active USA DoD training sites is estimated in the tens of billions of dollars. Munitions response actions, which is a very time consuming process, on many sites are forecast to take several decades \cite{1}. To reduce the cost per site and accelerate the pace of cleanup, recently advanced EMI sensors and models were developed for distinguishing buried UXO from the vast quantity of harmless pieces of metal found on any site. These advanced classification technologies allow resources to be directed to removing only the UXO.

The UXO cleanup problem has three main stages: detection, inversion, and classification \cite{2}. Detection of UXO can be considered a binary-hypothesis problem in which one must determine whether there are objects present or not. Great developments have been made on this first stage by the introduction of a series of sophisticated ultra-wideband sensors designed to increase detection probability. These devices work in the electromagnetic induction (EMI) range of frequencies, which extends from tens of Hz to just under 100 kHz, and can collect time-domain \cite{3}-\cite{5} or frequency-domain \cite{6}-\cite{8} geophysical data of remarkable richness and diversity. State-of-the-art EMI sensors are capable of recording target responses, whether in scalar \cite{3}, \cite{6}, \cite{9} or vector form \cite{7}, \cite{10}-\cite{12}, with unprecedented spatial resolution and a spectral range that allows a rather complete characterization of buried objects. The collected data are normalized with respect to the appropriate Tx currents and are background corrected, which are typically collected once every two hours during data collection.

During the second step of the process, the background corrected data are inverted and targets intrinsic (classification features) and extrinsic (locations and orientations) are determined simultaneously. The inversion approach used here is based on the physically complete, fast, accurate, robust, and clutter-tolerant forward model, called the ortho-normalized volume magnetic source method. The method starts from the assumption that the measurable secondary field is radiated by a set of elementary dipole sources infused throughout a volume at a set of singular points \cite{13}. The Green functions that connect these sources with the measured field are turned into an orthonormal basis to streamline the calculations. The spatial distribution of the responding dipoles (their amplitudes scaled by the primary field) traces a map of “response activity” that reveals the targets below. This orthonormalized volume magnetic source (ONVMS) model \cite{13} is a generalization of the dipole model that simultaneously allows for the presence of several targets in the field of view of the sensor and for the possibility that one or more of the targets is of such complexity—by being large or heterogeneous, for example—that it needs more than one dipole to account for the spatial or temporal nuances of its response. The need to determine the locations of the sources as well as their intrinsic features results in a computationally costly nonlinear inversion in which one defines an objective function, that provides a measure of the misfit between predictions and measurements and performs a least-squares minimization. These objective functions tend to have many local minima, resulting in incorrect predictions. There is a procedure that uses elementary sources to locate a singularity directly but its generalization to multi-target scenarios is not straightforward. To avoid this difficulty, our group has employed a two-step inversion approach that combines the ONVMS technique with...
differential evolution (DE), a continuous genetic algorithm [15], [16]. The procedure alternates between linear ONVMS time-dependent-amplitude determinations and DE location searches, iterating until it reaches convergence.

At the final stage of the process it is necessary to classify the detected objects as UXO or clutter and, if the former, to determine the type of ordnance to which they belong. This classification step uses data derived training anomalies ground truth and statistical classification tools.

II. EMI DATA PRE-PROCESSING, BACKGROUND CORRECTION AND QUALITY CHECK

All advanced EMI data are delivered in TEM file formats; The TEM files are converted to csv files; To illustrate in detail EMI data preprocessing, background correction and data quality check procedures let us consider Metal Mapper System, which is an advanced EMI instrument for UXO detection and discrimination. The MM has three orthogonal square transmitter coils of side 1 m and seven cubic receiver coils of side 10 cm. The transmitters fire one by one, inducing magnetic response and eddy currents in the metallic objects nearby, and in each instance the 21 receivers simultaneously measure the time-dependent secondary flux that originates from the targets, for a total of 63 measurements at each sensor location. Each of these measurements consists of a complete transient response over a range of time from approximately 100 μs to 8 ms and distributed over \( N_p = 42 \) approximately logarithmically-spaced time gates. The sensor is equipped with a GPS system that records the locations of possible targets of interest; it does not require a local positioning system, owing to its rigid structure. First, the measured transient signals \( S^n_{kp}(t_p) \) are normalized to the corresponding transmitter currents maximum \( \max(I^k(t)) \) as

\[
D^n_{kp}(t_p) = \frac{S^n_{kp}(t_p)}{\max(I^k(t))}
\]

The background files, which are typically collected once every two hours, are pre-processed in the same manner as targets files in equation 1. All background data are compared to each other over the period of the project to estimate the background fluctuation statistics. The background data are analyzed via the Joint Diagonalization technique described in [14]. Figure 1 shows the eigenvalues versus time for Fort Ord, CA and Waikoloa, HI background MM data. The results show that Waikoloa site, which consists magnetic soils, has strong background response than the Fort Ord, CA soil.

Following analysis of the background data collected each day, all target files for that day were background corrected as:

\[
Data^n_{kp}(t_p) = D^n_{kp}(t_p) - 0.5 \cdot (B^n_1(t_p) + B^n_2(t_p))
\]

where \( B^n_\alpha(t_p), \alpha = 1,2 \) are normalized background data collected before and after \( D^n_{kp}(t_p) \) signal, i.e. each target data is corrected using the respective background data collected closest in time.

III. EXTRACTING TARGET INTRINSIC PARAMETERS

The combined ONVMS-DE algorithm is used to extract targets intrinsic and extrinsic parameters. The algorithm yields the targets’ total ONVMS (effective polarizabilities), which then are used for classification. The total ONVMS contains three moments, \( M_{xx}(t), M_{yy}(t), \) and \( M_{zz}(t), \) along the primary axes in the target’s own reference frame. These moments are similar to simple dipole moment components but carry more information, accounting for the targets’ inherent heterogeneities. The ONVMS-DE algorithm outputs the time-decay curves of the target’s total ONVMS tensor \( M^k_{ij}(t_k) \).
The next step is to determine the time decay of the primary components of the total ONVMS in the target’s reference frame. While this can be done by standard diagonalization—i.e., finding \( M(t_k) = V(t_k) D(t_k) V^T(t_k) \), where \( V(t_k) \) contains the eigenvectors of \( M(t_k) \)—it is more convenient to perform a joint diagonalization [14], \( M(t_k) = V D(t_k) V^T \), where now the eigenvectors are shared by all time channels; this allows us to extract more reliable total ONVMS values and reduce uncertainty.

By default, all data are inverted as one, two, and three sources, but in a case where more than three sources are suspected, then some sets of data are inverted as four, five and even six sources using the combined DE-ONVMS algorithm. Such multi-target inversion is crucial in the field for cases in which a signal from a UXO is mixed with EMI signals from nearby clutter. Our two-target inversion code yields three sets of location and total ONVMS estimates: one for Target 1, one for Target 2, and a combined estimate with Targets 1 and 2 represented by a single object. (In the case of 3-target inversion, seven sets of data are expected: only Target 1, only Target 2, only Target 3, Targets 1 and 2 as a single object, Targets 2 and 3 as a single object, Targets 1 and 3 as a single object, and all three targets acting as a single object. In the general case of \( n \) targets one expects \( mn(n-1)+1 \) sets of ONVMS curves). The extracted intrinsic (total ONVMS) and extrinsic (locations) from data using one, two and three sources inversions are used to cross validate inversion and classification results.

IV. SELECTION OF INTRINSIC PARAMETERS FOR CLASSIFICATION

Most UXO are bodies of revolution, and thus the two secondary polarizability elements are degenerate. However, live-site UXO discrimination studies have repeatedly shown that this symmetry can be compromised due to low SNR, especially for small or deep targets. A good classification of object features can then be obtained by using only the principal component of the total ONVMS (\( M_{zz} \)). Furthermore, to limit the number of relevant features for use in classification we extract parameters exclusively from the main polarizability \( M_{zz}(t_1) \), both to represent size \( M_{zz}(t_1) \) and wall thickness \( M_{zz}(t_n) / M_{zz}(t_1) \).

V. TRAINING

Our classification approach is based on custom training data, which is a crucial classification part. At the first stage of the process we used a semi-supervised clustering technique for identifying potential site-specific TOI. Below are the basic steps performed during training data selection;

(a) The targets’ intrinsic features (\( M_{zz}(t_i) \)), \( M_{zz}(t_n) / M_{zz}(t_1) \) are selected from the extracted total ONVMS; \( n \) is chosen based on feature separation.
(b) Initial clustering is performed. The ground truth is requested for all targets whose features are located closest to the corresponding cluster centroid and had TOI-like ONVMS features. Figure 2 shows clustered Fort Sill, OK targets classification features. Clustered grouped features with the same color correspond to each cluster. Note that the colors are repeated.

Classification feature for a Fort Sill, OK MEC anomaly, see Figure 3

(c) Clusters containing at least one TOI are identified, and a smaller domain is selected within the feature space for further interrogation.
(d) Additional clustering is performed within the selected domain, and those targets with features closest to the corresponding cluster centroids are probed for ground truth. The clusters with at least one identified UXO are marked as suspicious. The total ONVMS curves are inspected within the selected domain.
(e) All targets whose features (based on multi-object inversion and library matching) fell inside any of the suspicious clusters are used to train the statistical classifier and the library-matching procedure.

The above described training data selection approach allowed our group to identify and accurate classify the site specific Munition of Explosive Concern (MEC), Figure 3.

![Figure 4. Fort Sill, OK MM targets classification results in form of ROC curves obtained by our and other teams.](image)

VI. CLASSIFICATION

Once targets classification feature parameters are clustered and side specific training targets ground truth are obtained, then all anomalies are classified as following:

(a) Probability density functions are created for single- and multi-target scenarios.

(b) All of the unknown targets are scored based on the probability density functions.

(c) Dig lists are produced for both single-and multi-object cases and compared to each other to find similarities and differences.

(d) All items are further analyzed using library matching, and all total ONVMS time-decay curves are inspected visually.

(e) A set of anomalies are identified and if necessary additional training data sets are requested. The new information is incorporated into the classification model and all items are re-scored.

(f) Based on the previous steps, a classification threshold is selected and a final dig list produced.

Our classification approach was applied to Fort Sill, OK MM data sets. The classification results in form of Receiver Operating Characteristics (ROC) curves are depicted in Figure 4. The same data were analyzed by other two teams. The comparisons between the ROC curves clearly indicate that our team obtained much better classification results than other two teams. Namely, we were able to identify about 75% clutter items as “no dig”, where teams 1 and 2 identified only 5% and 48% of clutter as “no-dig”, respectively.

VII. CONCLUSIONS

In this paper the detailed UXO classification procedures are described for advanced sensors and models. First, advanced sensors EMI data are normalized to the transmitter currents, then data are background corrected; third the background corrected data are inverted and classification feature parameters are extracted. Fourth, the targets intrinsic feature parameters are clustered and site specific training targets lists are determined. Finally, once the training targets ground truth is obtained then all anomalies are classified as targets of interest and clutters. The comparisons between our and other team’s analysis for Fort Sill, OK site clearly indicates that our approach provides superior classification results.

REFERENCES


