MULTIPLE SUBSURFACE TARGETS LOCALIZATION FROM NEXT-GENERATION EMI SENSOR DATA USING MUSIC ALGORITHM

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1. INTRODUCTION

This paper utilizes the multiple signal classification (MUSIC) algorithm for localizing subsurface metallic targets such as unexploded ordnances (UXO) using next generation time domain electromagnetic induction (EMI) sensor data. First, the method takes EMI data and decomposes it into eigenvectors and singular values. Then, the resulting eigenvectors are divided into two groups: the noise and signal subspaces. Next, the model defines a localizer operator that projects the estimated EM signal into the noise subspace, and finally it minimizes the localizer operator by utilizing the fact that the modeled magnetic field at each actual source location is orthogonal the noise subspace. The method is applied to next generation EMI sensor data for estimating number of targets in the sensor's field of view and pinpointing their location (i.e. localizing) them. The results for overlapping EMI signals demonstrate the method's effectiveness in determining the locations of multiple targets.

Clean-up of unexploded ordnance (UXO) contaminated lands at Department of Defense (DoD) and Department of Energy (DoE) has been identified as one of the military's most pressing environmental problems. As a result of past military and weapon-testing activities, UXO is found at both active and formerly used defense sites (closed, transferred and transferring ranges, munitions burning and open detonation areas). In the United States alone, more than 900 sites (about 11 million acres of land) are potentially contaminated with UXO. The costs of excavating all geophysical anomalies are well-known and are one of the greatest impediments to the efficient clean-up of UXO, particularly at highly contaminated UXO sites, when the multiple objects are present simultaneously in the sensor's field of view.

Although, various forward EMI models (such as s dipole, multi dipole, normalized surface magnetic source) have demonstrated great UXO discrimination capabilities for well isolated single targets using next generation EMI sensors data sets, single target discrimination capability is considerably limited for overlapping EMI signals, i.e. when sensors detect EMI signals from two or more targets simultaneously. The obvious extension of current EMI modeling to accommodate overlapping EMI signatures is multiple targets modeling. However, if we apply multi-target modeling to the data, the accuracy of the solution is generally limited by the ill-posed nature of the inverse problem and, thus, multi-target modeling with more than two targets is seldom applied in UXO detection and discrimination practice.

Even when two target EMI forward modeling is applied to high fidelity next generation sensor EMI data, estimating the parameters of multiple targets generally requires a highly multidimensional nonlinear optimization search for which no existing technique can guarantee that the true solution will be attained within the practical limits of computational time. Therefore, the success of multiple target parameter estimation greatly depends on how close the initial target locations are set to the actual locations of the targets in this search. One clever way to avoid this highly multidimensional search is to use the multiple signal classification (MUSIC) algorithm, which provides suboptimal estimates for the locations of multiple scatters by using a single three-dimensional (3-D) search, regardless of the number of scatters. This algorithm was proposed by Schmidt [1], in the field of antenna-array processing, then introduced to the magnetoencephalographic (MEG) inverse problem by Mosher *et al.* [2], and recently applied to buried targets localization problem by Ammari et al [3]. This paper combines a MUSIC type algorithm with next generation EMI sensor data for locating multiple subsurface metallic targets such as UXO in the present of clutter. The algorithm estimates the number of targets and their locations without solving a traditional ill posed inverse scattering problem.

2. MUSIC ALGORITHM APPLIED TO NEXT GENERATION EMI SENSOR DATA

Recently, under the Strategic Environmental Research and Development Program (SERDP), next generation EMI sensors have been developed for discriminating between subsurface UXO and clutter. One such sensors is the Time domain Electromagnetic Multi-Sensor Towed Array Detection Systems (TEMTADS). The system consists of 25 transmit/receive pairs of square coil antennas arranged in a 5 x 5 grid, each consisting of a 35-cm transmitter loop and a 25 cm receiver loop. The sensor activates the transmitter loops in sequence, one at a time, and for each transmitter all receivers receive, measuring the complete transient response over a wide dynamic range of time: from approximately 100 μs to 25 ms distributed in 123 time gates. The sensor thus provides 625 spatial data points at each instrument location, with unprecedented positional accuracy. Recent TEMTADS blind data sets discrimination studies [ ] show perfect performances when the number of targets was known as prior information. However determining the number of potential targets and locating them is still a challenging problem. To take advantage of the high fidelity TEMTADS data set, here the MUSIC type algorithm is employed for the simultaneous localization of multiple subsurface metallic targets. Let us briefly describe the MUSIC algorithm for the TEMTADS system. Let us define the Hz (z component) of the magnetic field measured by the m-th receivers coil when the k-th Transmitter is active as H_m, and a matrix [d]=[$H_{k,m,..,}$ $H_{k,M}$]as a set of measured data/vector for k-th transmitter, where k=1,2, .., K. M is the number of receivers and K is the number of transmitters. We assume that a total p targets generate measured EMI signals. In addition and for simplicity, each target is assumed to be a magnetic dipole source. Then, the relationship between the measurement tensor data d and the magnetic dipole field intensity is expressed as

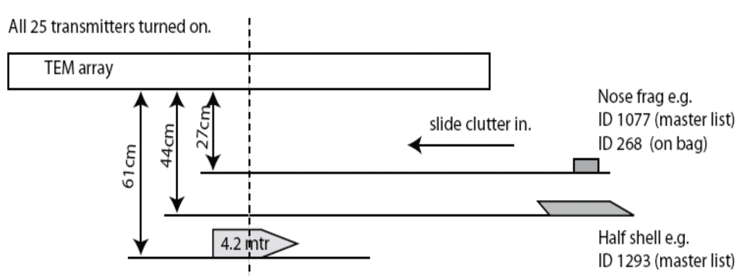
$$d = [G][S]+[N] \qquad (1)$$

where[G] is the magnetic dipoles Greens function tensor, [N] is additive noise, and [S] are the amplitudes of the responding magnetic dipoles. The conventional way of estimating the locations of the dipole sources is to minimize misfit between the actual and modeled data using a least square approximation. This minimization, however, requires a 3P dimensional search where P is the number of targets. Generally, for such a highly multidimensional search, there is no guarantee of obtaining the correct solution unless we can set the initial estimate very close to the true solution.

The MUSIC algorithm [1] has been introduced to avoid this highly multidimensional search. A distinct advantage of this algorithm is that, regardless of the number of dipole sources, it can give a suboptimal estimate of the source locations by using only one 3-D search in the solution space. The MUSIC algorithm first finds the eigenvalue decomposition of the measured-data matrix [d]. We denote the eigenvectors of [d] as $\{U_i\}$ where i=1,2,.., M. Unless some of the source activities are perfectly correlated with each other, [d] has P eigenvalues arising from the signal sources and M-P eigenvalues arising from the noise. Let us define the matrices $[E_s]$ and $[E_n]$ as $[E_s]=[U_1, U_2, \ldots,]$ and $[E_n]=[U_{p+1}, \ldots U_M,]$ respectively. The span of the columns of $[E_s]$ is called the signal subspace and that of $[E_n]$ is called the noise subspace. To estimate the locations of the dipole sources, the MUSIC algorithm uses the fact that the lead field vector at each source location is orthogonal to the noise subspace. The source locations are estimated by checking the orthogonality between the modeled field and the noise subspace projector. In practice, some kind of measure to evaluate the orthogonality is needed to implement the MUSIC algorithm; we can use [6]

$$F = \frac{1}{\lambda_{\max} \left\| W_s^T W_s \right\|}, \qquad [\mathbf{W}_s] = [([\mathbf{I}] - [E_s][E_s]^T)]\ [G(\mathbf{r}_{obj}, \mathbf{r}_{sen})] \qquad (2)$$

where $\lambda_{\max}$ indicates the generalized maximum eigenvalue of the matrix pair given in parenthesis||…||. The MUSIC localizer is calculated in a volume where sources can exist, and the locations where the localizer reaches a peak are chosen as the source locations.



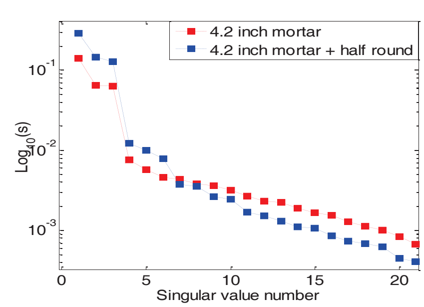


Fig. 1. (Left) Experimental setup for TEMTADS multi targets scenarios. (Right) The distribution of the singular values of [d] for 4.2 inch mortar with and without present half shell.

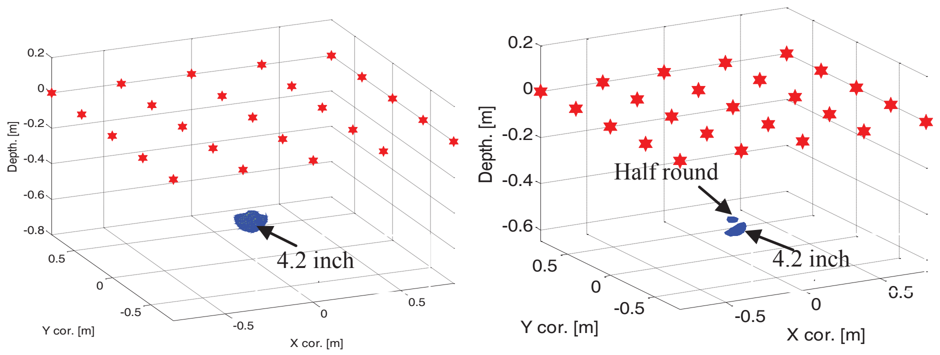


Fig. 2. Reconstructed three dimensional plot of F function obtained from actual TEMTADS data for the 4.2 inch mortar without (left) and with (right) half round clutter. For the mortar only: actual location is x=y=0; z=-61 cm, Predicted location: x=y=0; z=-61 cm; for both: Mortar actual location is mortar: x=y=0; z=-61 cm, predicted x=y=0; z=-56 cm; Clutter: actual location: **x=y=0**; z=-47 cm; Predicted location: **x=y=0**; z=-47cm

3. RESULTS

We applied the proposed approach to actual multi-object TEMTADS data. The schematic diagram of the experimental setup is depicted oi Figure 1 (left). The data were acquired by NRL personnel at the Blossom Point site. The sensor was stationary, and the 4.2 inch mortar was placed horizontally at 61 cm under array centerline while the half shell was lying horizontally and placed under the array center line at 47 cm depth. We used the first time channel data to invert for the objects' locations with the algorithm above. The singular values are displayed in Figure 1 (right) for the mortar with and without the clutter. The results clearly show the existence of a single and two targets i.e. only 3 singular values is emerging for a single targets and 6 singular values are important for two targets. The corresponding 3d maps of F function are given ias Figure 2. The peaks of the F function correctly corresponding to the targets actual location for a single object, and for the case of two targets, it identifies correctly the shallow target's position while it underestimates the deeper target's location.

4. CONCLUSION

We have employed a MUSIC-type algorithm for localizing multiple subsurface metallic targets. EMI data from the targets were acquired by the TEMTADS sensor: a bi-static system with 25x25 Tx/Rx combinations. This data yields the d matrix for each time channel. By examining the eigenvalue structure of this matrix at a given time channel, we can efficiently locate the subsurface targets with this algorithm. In the future we plan to combine this approach with existing models to more efficiently determine parameters from multiple targets such as the polarization tensors, or the total NSMS which yields information about the size and orientation of the scatterers.

5. REFERENCES

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