MODEL-BASED STATISTICAL SIGNAL PROCESSING USING ELECTROMAGNETIC INDUCTION DATA FOR LANDMINE DETECTION AND CLASSIFICATION

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ABSTRACT

Traditionally, electromagnetic induction (EMI) sensors are operated in the time-domain and the response strength is related to the amount of metal present in the object. These sensors have been used almost exclusively for landmine detection. Unfortunately, there is often a significant amount of metallic clutter in the environment that also induces an EMI response. Consequently, EMI sensors employing detection algorithms based solely on metal content suffer from large false alarm rates. A second issue regarding processing of data collected on highly cluttered sites is that anomalies are often in close proximity, and the measured EMI signal consists of a weighted sum of responses from each anomaly. To mitigate the false alarm problem, statistical algorithms have been developed which exploit models of the underlying physics for mines with substantial metal content. In such models it is commonly assumed that the soil has a negligible effect on the sensor response, thus the object is modeled in "free space". To date, such advanced algorithms have not been applied specifically to the problem of detecting of low-metal mines in a cluttered environment. Addressing this problem requires considering the effects of soil on signatures, separating the multiple signatures constituting the measured EMI response as well as discriminating between landmine signatures and clutter signatures. In this paper, we consider statistically based approaches to the landmine detection and classification problem for frequency-domain EMI sensors. We also develop a preliminary statistical approach based on independent components analysis (ICA) for separating the signals of multiple objects that are within the field of view of the sensor and illustrate the performance of this approach on measured data.

1. INTRODUCTION

Land mines and unexploded ordnance (UXO) present a significant threat to individuals around the world. Currently deployed methods of clearing subsurface threat items are slow and less than 100% accurate. A variety of sensors for landmine and UXO detection have been proposed and utilized, each of which exploits a different fundamental phenomenology. The most commonly deployed sensor is an electromagnetic induction (EMI) sensor that operates by detecting the metal present in land mines. The high level of risk associated with the landmine detection problem requires 100% detection performance for any viable sensor for all possible targets. However, there are hundreds of varieties of land mines that vary in their construction from metal-cased varieties with a large mass of metal to plastic-cased varieties with very small amounts of metal. In addition, there is often a significant amount of metallic debris (clutter) present in the environment. Consequently, EMI sensors that utilize traditional detection algorithms based solely on the metal content operating at a high enough detection rate to satisfy performance requirements suffer from very high false alarm rates.

To address the false alarm issue, several groups have investigated target identification, or discrimination, using EMI sensors, while other groups have considered alternative sensor modalities and sensor fusion [1-8]. In [1,7], classification of metal targets using frequency-domain EMI sensors is considered, and a Bayesian approach is applied to address the inherent uncertainties concerning the target/sensor orientation. In [2], this same sensor is utilized to investigate the frequency-domain signatures of landmines. In the work presented here, a statistically-motivated approach is evaluated in a blind field trial, which is a better method of evaluating robustness than evaluating algorithms solely on synthesized, laboratory, or fully ground-truthed data.

Some statistical approaches to this problem may be ineffective since a statistical model is needed to describe the null hypothesis, and there is often insufficient data available to adequately develop an accurate statistical model [6]. Although the response to the ground can be characterized statistically, it is very likely that it is inappropriate to model discrete clutter in the same manner. Recent results from the signal processing community have indicated that an adaptive coherence detector [10] has optimality properties under a set of conditions that are applicable to the landmine detection problem considered here. Specifically, when detecting a signal of known form but unknown amplitude in zero-mean Gaussian noise with a known covariance structure but unknown gain, a correlation coefficient, or cosine statistic, provides a uniformly most powerful invariant test statistic [9,10]. Since the subspace algorithm is predicated on an assumption that the null hypothesis follows a zero mean Gaussian distribution, this particular detector is not directly applicable to the problem of landmine detection in the presence of anthropic clutter. However, the invariance class associated with this algorithm does address some of the issues associated with the detection problem and the sensor that we are considering.

In this paper, performance of an algorithm based on a subspace detector was evaluated on data collected in a blind field test. We have modified the original formulation of the detector to consider both a multi-component alternative hypothesis and a null hypothesis that does not follow a zero-mean multivariate normal model. We developed a set of features that could be used to robustly differentiate between landmines and discrete clutter and that could also be extracted from the EMI data in real time.

2. SENSOR AND DATA

The GEM-3 is a prototype wide-band frequency-domain EMI sensor manufactured by Geophex, Ltd. The GEM-3 uses a pair of concentric, circular coils to transmit a continuous, wideband, electromagnetic waveform [8]. The resulting field induces a secondary current in the earth as well as in any buried objects.

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The set of two transmitter coils has been designed so that they create a magnetic cavity at the center of the two coils. A third receiving coil is placed within the magnetic cavity so that it senses only the weak secondary field returned from the earth and buried objects. The frequency-domain in-phase and quadrature components are obtained from the received signal by convolving the received time-series with a sine time-series (for in-phase) and cosine time-series (for quadrature) at the frequency of interest.

When a mine is present, the response of the sensor consists of the sum of a response due to the mine and a response due to the background. To obtain the response due to the mine alone, it is necessary to determine the response of the sensor to the background alone. The GEM-3 sensor has some level of thermal drift in its background response [6], so the sensor noise cannot be treated with a simple statistical model (e.g. zero mean Gaussian). This drift must be tracked so that the background response can be removed from the measured signature.

Details of the data collection plan can be found in [11], however the most salient points are summarized here. A 50 meter by 20 meter plot of ground was selected for construction of the test grid, and a calibration area was created in an adjacent 5 meter by 25 meter plot. Initially, all indigenous clutter was removed from the site. Mine targets emplaced in the test grids were predominately "low metal" mines since these are the most challenging targets to detect using EMI sensors. Samples of the indigenous clutter were re-emplaced in the grids to provide discrete opportunities for false alarms. The ground truth associated with the calibration area is available; however, the ground truth associated with the main, or blind, test grid is sequestered. Algorithm developers provide the output of their algorithms for each grid square or "decision opportunity" to JUXOCO for scoring. The GEM-3 EMI sensor was programmed to measure responses at 20 frequencies spaced logarithmically between 270 and 23,790 Hz. Ten spatial positions in a '+' pattern were measured in each grid point, since spatial information has been shown to improved detection and discrimination performance [1]. Samples were taken every 2".

In order to track the background signature, background measurements were taken at one of four grid squares that had been set aside as known "blanks" by JUXOCO. The closest "blank" square was used as the background for each grid square while the measurements were taken in the lanes. A background measurement was taken before and after signature data was collected in each grid square. In order to compensate for sensor drift, a linear prediction algorithm was used to predict the background signature during each of the 10 measurements made in the grid square using the background data measured before and after data was collected in each square. These "corrected" data were the input to the algorithm described in the next section.

3. ALGORITHM DEVELOPMENT

Kraut, Sharf et al. have used the theory of generalized likelihood ratio tests to show that previously proposed matched subspace detectors can be employed in the case of unknown noise covariance and unknown scaling of a mean vector [9,10]. They have described what they term "adaptive" matched subspace detectors, where adaptive implies an estimation of the covariance structure using training data, and have investigated their optimality properties. The invariance to overall data scaling as well as the optimality when testing and training sets have a different scaling factor applied to the covariance matrix is one of the most appealing properties of this set of detectors for landmine detection problem. As the authors state, what these detectors sacrifice in high-SNR performance they gain in robustness to uncertain and *changeable* prior information regarding the signal and noise model and statistics.

The general detection problem addressed by Sharf and his colleagues is one in which a N-element signal, s, is located in a signal subspace of dimension p. The signal is scaled by an unknown constant k and scaled noise, $g\mathbf{w}$ is added to the signal where, the scaling factor g is unknown. The measured signal, $\boldsymbol{r}$, is given by $\mathbf{r} = k\mathbf{s} + g\mathbf{w}$ which follows a complex normal (CN) distribution $\mathbf{r} \sim CN_N(k\mathbf{s}, g^2\Sigma)$. This formulation admits a solution ranging in complexity from a rank 1 matched filter (p=1) to rank p subspace detectors where $\mathbf{s} = \Psi\boldsymbol{\theta}$, Ψ denotes the signal subspace and $\boldsymbol{\theta}$ is the known or unknown parameter vector which locates the signal in the subspace. Under the signal hypothesis, H_1, $k \neq 0$ while under the null hypothesis, H_0, $k = 0$. Previous work has addressed this detection problem under various assumptions regarding the parameters Ψ, Σ, g^2, and $\boldsymbol{\theta}$.

For the mine detection problem, we know $\mathbf{s}$, but do not know k, g, or Σ. It was shown in [9] that the optimal test under these uncertainties is given by a cosine-squared statistic

$$\cos^2 = \frac{(\mathbf{r}^T\hat{\Sigma}^{-1}\mathbf{s})^2}{(\mathbf{r}^T\hat{\Sigma}^{-1}\mathbf{r})(\mathbf{s}^T\hat{\Sigma}^{-1}\mathbf{s})}$$

and is termed a coherent CFAR adaptive subspace detector (ASD). In the formulation, Σ is estimated using maximum likelihood techniques and then used in the formulation of the detector. This approach is generally associated with a generalized likelihood ratio test, however it was shown in [9] that this detector is in fact optimal and uniformly most powerful.

To apply the subspace method described above we first consider only the data measured at the center point of each grid sqare, and if we assume the data follows the model

$$H_1 : r_i \sim N(k\mathbf{s}_i, g\Sigma)$$
$$H_0 : r_i \sim N(0, g\Sigma)$$

where the subscript denotes the ith target and k and g are arbitrary scaling factors on the mean and covariance matrix. For the mine detection problem considered here, the phenomenology inherent in the physical problem allows us to interpret the scalar k as uncertainty in object depth and the scalar g as uncertainty in the strength of the noise process resulting from the thermal drift. Under these assumptions, the detector for each spatial position is given by

$$\beta_i = \frac{(\mathbf{r}^T\hat{\Sigma}^{-1}\mathbf{s}_i)^2}{(\mathbf{r}^T\hat{\Sigma}^{-1}\mathbf{r})(\mathbf{s}_i^T\hat{\Sigma}^{-1}\mathbf{s}_i)}$$

This detector would be appropriate for finding a single mine type at the center position in a zero mean background. To extend the formulation to consider N possible mine types at the center position in zero mean background (corresponding to prior knowledge regarding the form of θ) a bank of such detectors is used and the maximum output is selected:

$$\beta = \max_{i} \beta_i$$

This formulation also allows classification of the mine by type.

When clutter is encountered, the zero mean assumption on the measured signal under the null hypothesis is clearly invalid. There are two mechanisms by which to modify the detector described above to consider the case of discrete clutter. In the first, we considered an approach described in [10] wherein clutter is assumed to lie in a rank t "interference" subspace and is thus treated separately from the noise or background. Although this is probably an accurate model, in the application we are considering there was not enough data to accurately model the subspace. For example, for the M=20 clutter items contained in the data set, it is not usually possible to write one of the clutter signals as a linear combination of the other M-1 signals, i.e. the measured signals do not span the clutter subspace.

The second approach, which was adopted here, is to utilize the output of the bank of cosine-filters as a feature set and to develop statistics for that feature set under the two hypotheses. These statistics can then be used in the formulation of a likelihood ratio. Let $\boldsymbol{t}$ be the 11 x 1 data vector formed by concatenating the sorted β_i then the likelihood ratio for this data set is

$$\lambda(\mathbf{t}) = \frac{f(\mathbf{t}/H_1)}{f(\mathbf{t}/H_0)}$$

To complete the formulation of this detector, the pdfs of $\boldsymbol{t}$ under each hypothesis must be estimated. These estimates were obtained using the calibration data collected in conjunction with the JUXOCO experiment. A uniform distribution with independent components was used to model $f(t/H_1)$ and a Gaussian distribution (both the mean and the covariance structure were estimated) was used to model $f(t/H_0)$. A simple extension of this approach allows the incorporation of spatial data.

4. RESULTS

In Figure 1, ROC curves are presented for three algorithms. The performance of the baseline algorithm is shown with a solid line and represents the performance obtained when EMI detectors are operated in a traditional energy-detection mode. The energy of the signal measured at the center of each grid square was reported to JUXOCO for scoring. Clearly, energy, which is proportional to metal content and inversely proportional to distance between the object and the sensor, does not provide a good discriminator between landmines and clutter or ground at this site. The performance of the cosine detector operating on the signal measured at the center of each grid square is shown with the dashed line. This algorithm is the coherent CFAR ASD described in [9] modified to utilize the maximum statistic over each of the signals, $\mathbf{s_i}$. Also shown is the performance of the modified algorithm that utilizes the output of the coherent CFAR ASD for each potential mine signal as the input to the likelihood ratio. It is labeled with the notation 'clutter' to indicate that for this formulation the statistics of the discrete clutter objects are included in the formulation, which is not true for the standard coherent CFAR ASD. Including a clutter model improves the performance of this algorithm, and both approaches perform dramatically better than the baseline.

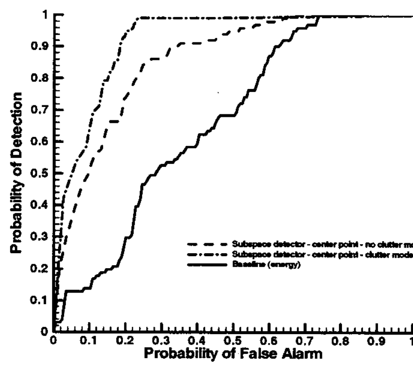

Figure 1. ROCs for the energy detector, CFAR ASD detector and the modified CFAR ASD detector on center point data.

In Figure 2, a similar set of curves is provided; however, in this figure the spatial information has been incorporated into the two CFAR ASD formulations. Again, including a clutter model improves the performance of this algorithm, and both approaches perform dramatically better than the baseline algorithm. In the lower false alarm rate region there is little difference between the performance of the two algorithms. This may be a result of the fact that spatial information for the low-metal mines falls off into the noise floor faster than for the larger metal mines. In the high Pd range, the modified ASD detector performs better than the standard ASD detector.

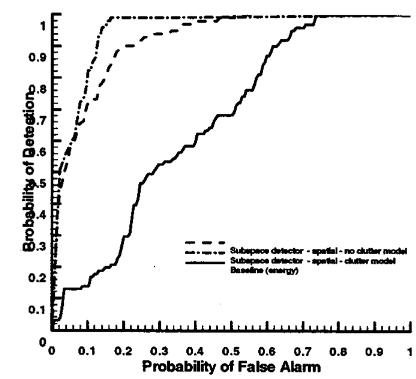

Figure 1. ROCs for the energy detector, CFAR ASD detector and the modified CFAR ASD detector on center point data.

As mentioned previously, it is possible to obtain classification information as the detector is implemented as a bank of processors, each tuned to a particular mine. We utilized the processor which has the maximum output to name the mine and this information was sent to JUXOCO for scoring. Using this approach, the mines were "named" correctly 65% of the time.

5. SIGNAL SEPARATION

One issue not considered in the above development is the case of overlapping signals. In actual field environments, objects are often in close proximity and thus the measured response will consist of a combination of the responses from the individual objects. For algorithms such as those described above, these signals must be separated prior to their application. Independent Components Analysis (ICA) has also been proposed as a viable solution for the problem of blind source separation [12-15], although it has not been explored in the subsurface sensing application. Therefore, an ICA algorithm has been implemented to test the feasibility of this approach for the problem of separating two landmine signatures from a set of measured responses.

We considered the signature of two ordnance items, where in-phase (solid black) and quadrature (dashed black) measured data as a function of frequency for the objects in isolation are shown in the top two panels of Figure 3. These signals were then "mixed", and the two of the resultant signals are plotted in the middle two panels of Figure 3. The mixing coefficients were selected so that the mixing is consistent with signatures that could be expected for EMI data measured at eleven different spatial locations. The bottom two panels show the two "independent components" extracted by a simple implementation of the ICA algorithm. As is typical with ICA algorithms, the signal with the highest energy is extracted first and with the highest fidelity. Clearly, this simple implementation, which has not been optimized for this problem, does an excellent job of extracting the signature of one of the objects and a reasonable job of extracting the second.

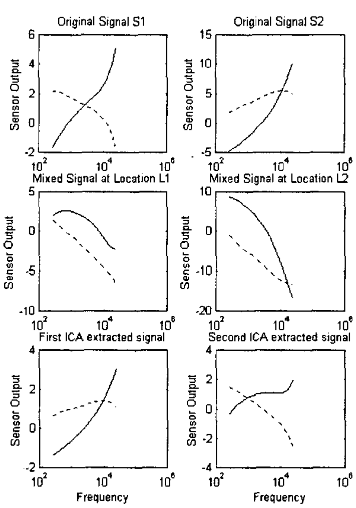

Figure 3. ICA Results. Top panel shows signals measured using the GEM3 from a Valmara landmine (left) and VS50 landmine (right). Middle panel shows two examples of the mixed signals that were supplied to the ICA algorithm. Bottom panel shows the signals as separated by the ICA algorithm.

6. ACKNOWLEDGEMENT

The authors would like to thank J. Cary, J. Moulton, L. Makowsky, D. Reidy, and D. Weaver for their help and support on the data collection and scoring effort. This work was supported by the Joint UXO Coordination Office and the Night Vision and Electronic Systems Directorate of the US Army.

7. REFERENCES

[1] P. Gao, L. Collins, P. Garber, N. Geng, and L. Carin, "Classification of Landmine-Like Metal Targets Using Wideband Electromagnetic Induction". IEEE Trans. Geosc. Remote Sens., Vol. 38, No. 3, May, 2000, 1352-1361.

[2] D.Keiswetter, I.J. Won, B.Barrow, and T.Bell, "Object identification using multifrequency EMI data," UXO Forum '99, Atlanta, GA, May 1999.

[3] L.S. Riggs, J.E. Mooney, and D.E. Lawrence, "Identification of metallic mine-like objects using low frequency magnetic fields," IEEE Trans. Geosc. Remote Sens., vol. 39, no. 1, pp. 56—66.

[4] G.D. Sower and S.P. Cave, "Detection and identification of mines from natural magnetic and electromagnetic resonances," Proceedings of SPIE, Orlando, FL, April 1995.

[5] A.H. Trang, P.V. Czipott, and D.A. Waldron, "Characterization of small metallic objects and non-metallic anit-personnel mines," Proceedings of SPIE, Orlando, FL, April 1997.

[6] L.M. Collins, P. Gao, S. Tantum, L. Makowsky, J. Moulton, D. Reidy, R.C, Weaverm=, "Improving Detection of Low-Metallic Content Landmines Using EMI Data" Proceedings of SPIE, Orlando, FL, April 2000.

[7] P. Gao and L. Collins, "A Comparison of Optimal and Sub-Optimal Processors for Classification of Buried Metal Objects," IEEE Signal Processing Letters, Volume 6, Issue 8, August, 1999, 216-218.

[8] I. J. Won, D. A. Keiswetter, and D. R. Hansen, "GEM-3: A Monostatic Broadband Electromagnetic Induction Sensor". Journal of Envir. Engin. Geophys., 2: 53-64, Aug. 1997.

[9] S. Kraut, L.L. Scharf, and T. McWhorter, "Adaptive Subspace Detectors", IEEE Trans. Sig. Proc., Vo. 49, January 2001, 1-16.

[10] L.L. Scharf and B. Friedlander, "Matched Subspace Detectors", IEEE Trans. Sig. Proc., Vol 42, August 1994, 2146-2157.

[11] "Hand Held Metallic Mine Detector Performance Baselining Collection Plan", JUXOCO, Ft. Belvoir, VA, December 1998.

[12] A. Bell and T. Sejnowski, "An information-maximization approach to blind separation and blind deconvolution," Neural Computation, vol 7, 1995.

[13] Hyvarinen, A., and Oja, E., "Independent Component Analysis: Algorithms and Applications," in press, Neural Networks.

[14] S.-I. Amari, A. Cichocki, and H.H. Yang. "A new learning algorithm for blind source separation", In Advances in Neural Information Processing Systems 8, pages 757-763. MIT Press, Cambridge, MA, 1996.

[15] 41. J.-F. Cardoso. "Infomax and maximum likelihood for source separation", IEEE Letters on Signal Processing, 4:112-114, 1997.