Performance of a Four Parameter Model for Modeling Landmine Signatures in Frequency Domain Wideband Electromagnetic Induction Detection Systems

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ABSTRACT

This work explores possible performance enhancements for landmine detection algorithms using frequency domain wideband electromagnetic induction sensors. A pre-existing four parameter model for conducting objects based on empirically collected data for UXO[1] is discussed, and its application for accurately modeling landmine signatures is also considered. Discrimination of mines versus clutter based on the extracted model parameters is considered. Furthermore, this work will compare the effectiveness of discrimination based on the four parameter model to a matched subspace detection algorithm.[2,3] Experimental results using data from government run test sites will be presented.

Keywords: Landmine, EMI, Model, Detection, Pattern Recognition

1. INTRODUCTION

There are millions of buried landmines across the globe. Many landmines and other harmful devices left over from conflict situations remain in wait to claim unintended victims. Most landmine victims are civilians and of those many are children.[4] As a result of many years of effort the world has seen countries declare themselves mine-safe. As of 2004, Costa Rica, Djibouti, El Salvador, Kosovo and Moldova have all been declared mine safe.[4] Although the numbers of landmines are decreasing, there is still much room for improvement. Mitigation of false alarm rates is a fundamental criterion in the development of landmine detection systems. Further research into the development of improved landmine detection algorithms holds promise for the continued remediation of this global problem.

Many technologies have been developed over the years to confront the problem of buried landmines for both humanitarian and military de-mining purposes. Electromagnetic Induction (EMI) is one of the technologies that has had great success in the detection of buried landmines. These sensors, which typically function as anomaly detectors, have traditionally suffered from high false alarm rates due to metallic objects, ranging from spent munitions to aluminum cans. The application of physics based statistical models and other advanced algorithms to EMI data have shown significant improvements in clutter rejection.[5–11]

In this study we discuss a four parameter model developed by Miller et. al.[1] which has been successfully used for frequency domain EMI responses from unexploded ordnance (UXO). We begin by discussing the EMI system used to collect data for this analysis. This discussion is followed by a brief overview of the data collection process and ground truth. Next, the four parameter model is presented and introduced as a feature extraction process. Once these features have been extracted we discuss the k-Nearest Neighbor (kNN) classifier as applied to the four parameter model and the decision statistic used for landmine discrimination. These results are then compared to results of a matched subspace detector[2,3] for EMI data[12,13] and to a more traditional energy detector. Finally we summarize these results and discuss areas for further improvement.

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Figure 1. Wideband Electromagnetic Sensor Data Collection System (W. Scott, GA Tech)

2. WIDEBAND ELECTROMAGNETIC INDUCTION SENSOR

EMI sensors operate by emitting an electromagnetic field from a transmit coil. These EM fields produce eddy currents in buried conducting objects which emit EM fields of their own. These secondary fields are then recorded in the receive coil of the EMI sensor. Frequency domain EMI sensors emit a multi-sine EM field over broad ranges of the low frequency spectrum. By processing the received EM fields over these frequencies we attempt to identify an object based on its frequency domain response. The foundational concept in Electromagnetic Induction Spectroscopy (EMIS) is that an object's geometry, material make-up, and orientation drive this frequency domain response which can uniquely identify a target.[5] Unlike UXO responses which can greatly depend on the orientation of the target, in many cases, landmine symmetry can be exploited in order to identify the signature of a particular landmine type.

The EMI sensor used to collect data for this study is a prototype system being developed at the Georgia Institute of Technology and is shown in Fig. 1. The sensor uses simple dipole transmit and receive coils along with a secondary bucking transformer to cancel the coupling between the coils.[14] This configuration allows the system to have a simple detection region due to the dipole coils while benefiting improved sensitivity from the cancellation due to the bucking coil. Most other frequency domain systems use either a quardapole transmit or receive coil to cancel the coupling between the coils which make the detection region more complex.

The prototype system consists of a head constructed using PCB technology that has a transmit coil with a diameter of approximately 25 cm and a receive coil with a diameter of approximately 21 cm. The data was taken at 21 frequencies that were approximately logarithmically spaced from 330 HZ to 90.03 KHz. The frequencies deviated from logarithmic spacing to minimize interference from power line harmonics. A multi-sine excitation signal was generated using the 21 frequencies and used to excite the EMI sensor. The response due to this multi-sine excitation was recorded in 0.1 s increments. These time records were transformed into the frequency domain and used to construct the frequency domain response of the sensor.

3. DATA CONSIDERATIONS

Data was collected at an Eastern United States government test facility. This test facility contains a variety of background clutter items including metallic and non-metallic objects. Target responses arise from anti-personnel metal and low metal (APM and APLM) landmines as well as anti-tank metal and low metal (ATM and ATLM) landmines. Clutter responses cover a wide range of objects, from large and small amounts of metal to various shapes and sizes of non-metallic clutter that are usually difficult for EMI sensors and ground penetrating radar (GPR) systems respectively. This facility consists of a number of lanes each divided into 1.5 x 1.5 m squares. Table 1 shows the distribution of the previously mentioned objects as well as the locations where no object is buried at this facility.

Table 1. Test Facility Response Distribution

Object Type	Proportion
APM	7%
APLM	23%
ATM	4%
ATLM	17%
Metallic Clutter	15.5%
Non-metallic Clutter	15.5%
Blanks	18%

The data used in this study was collected in a lane based fashion, in which the sensor was carted down a track and the time gated response was recorded every 0.1s. Each frequency domain data vector was then stamped with the spatial location within the grid location along the lane. However for the purpose of this document the results herein only utilize background corrected data vectors, $\mathbf{s}$, from the center of each grid location. Linear background correction has been performed on the frequency domain data vector at each grid location such that the resulting background corrected WBEMI data vectors are

$$\mathbf{s} = \mathbf{s_c} - \mathbf{s_g}$$

This simple background correction process consists of the subtraction of a blank ground response at the beginning of each grid square, $\mathbf{s_g}$, from the grid location center response vector, $\mathbf{s_c}$. This helps to correct the data signal for sensor drift and changes in the ground response.

4. MODEL DESCRIPTION AND FEATURE EXTRACTION

The phenomenological model being considered has demonstrated significant improvements for the detection of buried unexploded ordnance, UXO.[1] The underlying signal response of an object for the model being considered is

$$S(\omega) = A(X(\omega) + jY(\omega))$$

in which A, the amplitude is dependent on object geometry and field strength, while $X(\omega) + jY(\omega)$ is the frequency dependent component. This response is highly dependent upon the geometry and material structure of the object. The four parameter model under consideration in this study has been shown by Miller et. al.[1] to be very accurate for objects of high permeability in the high frequency range of the response. The underlying model is based upon the relation between the known response of spheres and cylinders discussed by Grant and West.[15] It is interesting to note that the four parameter model is an extension of this relation, giving consideration to objects of non-compact shape. The parametric model under consideration is

$$X(\omega) + jY(\omega) = q\left(s + \frac{(j\omega\tau)^c - 2)}{(j\omega\tau)^c + 1)}\right)$$

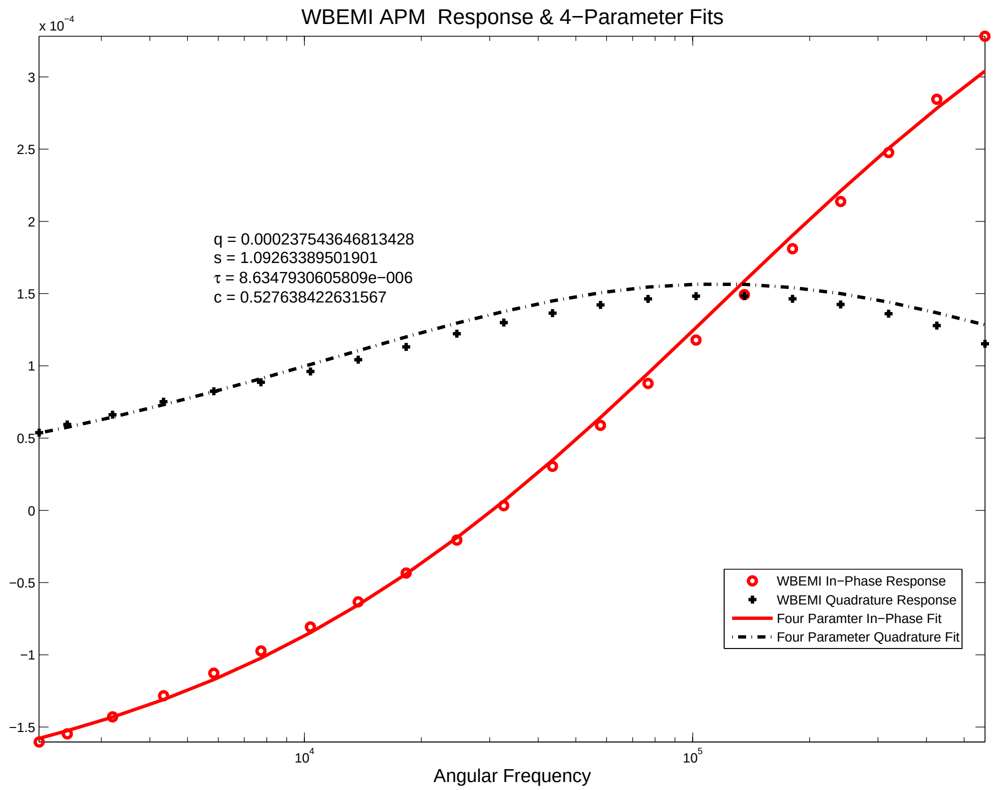

Figure 2. Example Landmine Response: The solid and dash-dot lines represent the four parameter fit for the in-phase and quadrature components of the WBEMI response, which are samples in frequency at the discrete points indicated by the o's and +'s

where the parameter q represents amplitude, τ is a time constant, s controls the asymptotes at low and high frequencies while the parameter c controls the width of the transition zone.[1] Parameters that are extracted from the model fit to the data will form the feature space used in the classification of landmines and discrimination from various forms of clutter. This model provides reasonable fits to WBEMI responses as illustrated in Fig. 2. Histograms of the absolute error, ϵ_{abs}, and squared error, ϵ_{sq}, for the model fits to the real and imaginary parts of the WBEMI data vectors are shown in Fig. 3.

$$\epsilon_{abs} = \sum_{\omega} \mid \hat{\mathbf{s}} - \mathbf{s} \mid$$

$$\epsilon_{sq} = \sum_{\omega} (\hat{\mathbf{s}} - \mathbf{s})^2$$

Where the vectors $\mathbf{s}$ and $\hat{\mathbf{s}}$ are the background corrected WBEMI data vectors and model fit vectors at the 21 approximately logarithmically spaced observation angular frequencies, ω, respectively.

This model is applied to background corrected WBEMI data vectors, $\mathbf{s}$, collected at each grid center. To extract the parameters we applied an iterative non-linear least squares curve fitting algorithm. Certain initial conditions and bounds have been found empirically to allow the curve fitting algorithm to fit landmine WBEMI responses with reasonable accuracy. These extracted features are then combined with the energy of the quadrature response into a length d = 5 observation vector, $\hat{\mathbf{x}} = (\hat{q}, \hat{t}, \hat{s}, \hat{c}, E_q) \in \mathbb{R}^5$, where the carat notation indicates estimated values.

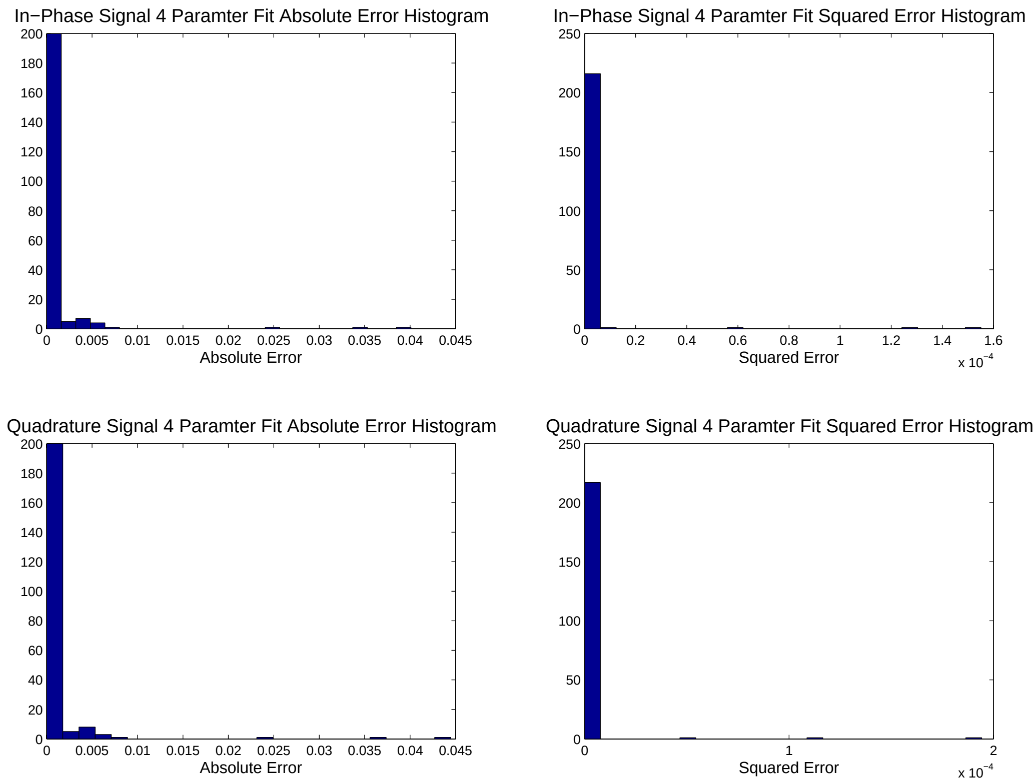

Figure 3. Error Histograms: In-phase signal absolute fitting error, In-phase signal squared fitting error, Quadrature signal absolute fitting error, Quadrature signal squared fitting error

5. CLASSIFICATION

The classifier chosen for this study is k-Nearest Neighbor (kNN).[16] In general the kNN rule states that the observation vector x is classified as the most abundant class type among the k nearest sample points in the training feature space. It is important to note that the kNN classifier is sensitive to scaling of the feature space dimensions. If the range of the features vary, it can be helpful to scale the data to obtain a more meaningful measure of distance.

To mitigate differences in scale, the feature vectors extracted from the background corrected WBEMI data are first rescaled logarithmically. The Euclidean distance is then computed between the observation vector and each vector in the training space, keeping the k nearest vectors for classification. The decision statistic used in this classifier is the difference between the average distance from the test point to k training points labeled H_0 (non-mines) and the average distance from the test point to k training points labeled H_1 (mines). Other distance metrics, scaling of the feature space and decision statistics may also be of interest. Computational complexity can be reduced through the combination of editing prototypes, search trees, and partial distance calculations.[16]

The performance of this classifier will be compared to the well-known matched subspace detector..[2,3] This has previously shown good performance on WBEMI data.[12,13] The matched subspace detection algorithm used here for the WBEMI data requires the creation of projection matrices for each mine type subspace. Each subspace consists of the average of the normalized frequency domain quadrature responses for each class. In this case we take the responses of each mine type from the training data and design the estimated subspace for the particular mine type. The projection matrix onto that subspace is then defined by

$$P_H = H(H^H H)^{-1} H^H$$

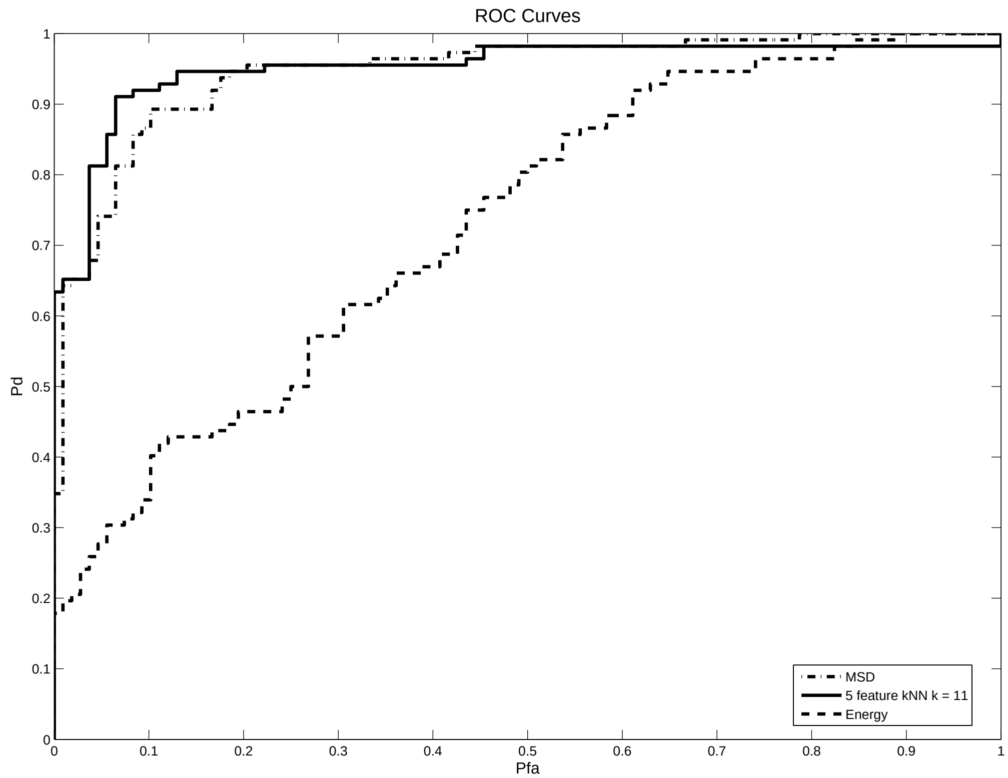

Figure 4. ROC Curves: MSD-Matched Subspace Detector, kNN, Energy Detector

where H is the subspace for a particular mine type and the superscript H represents the Hermitian transpose. Also during the training phase the minimum and maximum energies from each mine type in the training data are maintained for the detection process.

The matched subspace detection process for WBEMI data is two tier. The first tier consists of a pre-screening energy detector. If the observation vector falls below a certain multiple of the minimum energy or above a multiple of the maximum energy for a particular mine type, the decision statistic for that mine type is a assigned value of 0. The scale factor used in this work is 2. This energy detection helps to prevent the misclassification of clutter that appears as scaled versions of landmine responses. Otherwise, the quadrature observation vector, $\mathbf{s}_q = \Im\{\mathbf{s}\}$, is passed on to the second tier of our detector where the cosine decision statistic is computed.[2,3]

$$\lambda = \frac{\mathbf{s}_q^T P_H \mathbf{s}_q^T}{\mathbf{s}_q^T \mathbf{s}_q}$$

The matched subspace detector performance could possibly be enhanced through the creation of a blank, metallic and nonmetallic clutter projection matrices. The in-phase information from the WBEMI responses could also be combined with the quadrature information to improve performance.

6. RESULTS

The receiver operating characteristic (ROC) curve in Fig. 4 shows the performance of the kNN classifier on the five parameters for k = 11. Curves for the matched subspace detector and an energy detector are also plotted with these results. The training-testing method used to produce these results was leave one out, where the entire data set except for the current observation vector was used for training the kNN classifier and creating the mine type projection matrices in the matched subspace detector.

The performance of the four parameter model and classifier are comparable to the matched subspace detector, while performing considerably better than the energy detector. A particular point of interest is at 90% probability of detection, in which the kNN classifier suffers a 7% probability of false alarm (Pfa), the MSD yeilds a 17% Pfa and the energy detector undergoes a 61% Pfa. The four parameters are highly accurate in fitting WBEMI responses and for discriminating mines from non mines.

7. SUMMARY

A four parameter model was used as the framework for fitting WBEMI landmine responses. These four parameters were then used as features in a kNN pattern classification algorithm in order to discriminate landmines from clutter. This classifier was then compared to a two-tier WBEMI matched subspace detector and energy detector. Current results indicate that the four parameter model shows promise for lowering false alarm rates while sustaining high detectability in WBEMI systems.

Further research will be carried out to exploit these features. The sensitivity of this classifier will be investigated, to such issues as different training data and bad or missing features. There are many areas of interest in modifying the classifier. Different metrics can be applied to kNN to measure "closeness", typically ranging through L_p distances : $p \in [1, \infty]$ also known as Manhattan, Euclidean, various Minkowski, and Chebychev distances. Other non-L_p distance metrics exist as well. Many decision statistic choices are also available. One could diverge from the kNN framework altogether by applying discriminant analysis and other pattern classification techniques as well as machine learning and Bayesian approaches.

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