

# FINAL REPORT

Classification Study Using a Handheld,  
Three-element EMI Sensor

SERDP Project MR-2201

APRIL 2013

Thomas Bell  
Science Applications International Corporation

*This document has been cleared for public release*



## Report Documentation Page

*Form Approved*  
*OMB No. 0704-0188*

Public reporting burden for the collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington Headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington VA 22202-4302. Respondents should be aware that notwithstanding any other provision of law, no person shall be subject to a penalty for failing to comply with a collection of information if it does not display a currently valid OMB control number.

1. REPORT DATE <b>APR 2013</b>	2. REPORT TYPE	3. DATES COVERED <b>00-00-2013 to 00-00-2013</b>			
4. TITLE AND SUBTITLE <b>Classification Study Using a Handheld, Three-element EMI Sensor</b>		5a. CONTRACT NUMBER			
		5b. GRANT NUMBER			
		5c. PROGRAM ELEMENT NUMBER			
6. AUTHOR(S)		5d. PROJECT NUMBER			
		5e. TASK NUMBER			
		5f. WORK UNIT NUMBER			
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) <b>Science Applications International Corporation, 1710 SAIC Drive , McLean, VA, 22102</b>		8. PERFORMING ORGANIZATION REPORT NUMBER			
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)		10. SPONSOR/MONITOR'S ACRONYM(S)			
		11. SPONSOR/MONITOR'S REPORT NUMBER(S)			
12. DISTRIBUTION/AVAILABILITY STATEMENT <b>Approved for public release; distribution unlimited</b>					
13. SUPPLEMENTARY NOTES					
14. ABSTRACT <b>Typical library matching procedures used for classification ask how much a given target's principal axis polarizabilities resemble those of targets of interest (TOIs). The polarizabilities are calculated from sensor array data using dipole inversion. In conventional dipole inversion, given a set of measurements of the EMI response we simultaneously search out the location orientation, and principal axis polarizabilities that produce signals that best match the measured target response. Unfortunately you need a lot of data to reliably constrain the target location in dipole inversion. The eigenvalues of the data matrix for an array of paired transmit and receive loop are easy to compute and need a much less extensive sensor array than the polarizabilities. This research project has focused on whether or not the data eigenvalues from a simple handheld sensor can serve as surrogates for principal axis polarizabilities. We conclude that they cannot. In general, the data eigenvalues are built up of linear combinations of the principal axis polarizabilities. This means that a classification scheme based on data eigenvalues would have to accommodate arbitrary linear combinations of TOI polarizabilities. The loss of classification performance to clutter items whose principal axis polarizabilities can be closely reproduced using linear combinations of TOI polarizabilities is just too large.</b>					
15. SUBJECT TERMS					
16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT <b>Same as Report (SAR)</b>	18. NUMBER OF PAGES <b>44</b>	19a. NAME OF RESPONSIBLE PERSON
a. REPORT <b>unclassified</b>	b. ABSTRACT <b>unclassified</b>	c. THIS PAGE <b>unclassified</b>			

This report was prepared under contract to the Department of Defense Strategic Environmental Research and Development Program (SERDP). The publication of this report does not indicate endorsement by the Department of Defense, nor should the contents be construed as reflecting the official policy or position of the Department of Defense. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise, does not necessarily constitute or imply its endorsement, recommendation, or favoring by the Department of Defense.

## Abstract

Typical library matching procedures used for classification ask how much a given target's principal axis polarizabilities resemble those of targets of interest (TOIs). The polarizabilities are calculated from sensor array data using dipole inversion. In conventional dipole inversion, given a set of measurements of the EMI response we simultaneously search out the location, orientation, and principal axis polarizabilities that produce signals that best match the measured target response. Unfortunately you need a lot of data to reliably constrain the target location in dipole inversion. The eigenvalues of the data matrix for an array of paired transmit and receive loop are easy to compute and need a much less extensive sensor array than the polarizabilities. This research project has focused on whether or not the data eigenvalues from a simple hand-held sensor can serve as surrogates for principal axis polarizabilities. We conclude that they cannot. In general, the data eigenvalues are built up of linear combinations of the principal axis polarizabilities. This means that a classification scheme based on data eigenvalues would have to accommodate arbitrary linear combinations of TOI polarizabilities. The loss of classification performance to clutter items whose principal axis polarizabilities can be closely reproduced using linear combinations of TOI polarizabilities is just too large.

## Table of Contents

Abstract .....	i
Table of Contents .....	ii
List of Figures .....	iii
List of Acronyms .....	iii
Keywords .....	iv
Acknowledgements .....	v
Objective .....	1
Background .....	2
Introduction .....	2
Data Eigenvalues .....	3
Examples .....	5
Materials and Methods .....	7
Data Eigenvalue Calculations .....	7
Classification Performance Evaluation .....	8
Results and Discussion .....	11
Polarizability Mixing in Data Eigenvalues .....	11
Classification Performance with Linear Combinations of Polarizabilities .....	12
Conclusions and Implications for Future Research/Implementation .....	14
Literature Cited .....	15
Appendix .....	A1

## List of Figures

Figure 1. Principal axis polarizabilities (blue) and data eigenvalues (red, gray) calculated from TEMTADS array data collected over 37mm projectiles at former Camp Butner. ....	6
Figure 2. Basic three-element array. Red circles represent three transmitter loops and blue circles represent three receiver loops. ....	7
Figure 3. Examples of data eigenvalues from the three-element array with a 37mm projectile target at various locations and orientations below the array. ....	8
Figure 4. Simulation results for relative strengths of axial and transverse polarizability in data eigenvalues (primary eigenvalue in red, secondary in green and blue). Target locations distributed uniformly $\pm dxyz$ about a point centered 27cm below the array. ....	12
Figure 5. Classification performance for former Camp Beale based on library matching of principal axis polarizabilities (blue) and linear combinations of polarizabilities (red). ....	13

## List of Acronyms

EMI	Electromagnetic Induction
ESTCP	Environmental Security Technology Certification Program
FOM	Figure of Merit
IMU	Inertial Measurement Unit
MPV	Man Portable Vector
MR	Munitions Response
Rx	Receive
SERDP	Strategic Environmental Research and Development Program
TEM	Transient Electromagnetic
TEMTADS	Transient Electromagnetic Towed Array Discrimination System
TOI	Target of Interest
Tx	Transmit
UXO	Unexploded Ordnance

## **Keywords**

Camp Beale

Classification

Data Eigenvalue

Dipole Inversion

Electromagnetic Induction

Joint Diagonalization

Polarizability

TEM Array

## **Acknowledgements**

We gratefully acknowledge financial support from the Strategic Environmental Research and Development Program for this project.

## Objective

This project represents an attempt to address the challenge of classification in conditions involving difficult terrain and vegetation that make it difficult to collect high quality data with currently available sensors. Current hand-held sensors suitable for use in such environments must be supported by costly and/or cumbersome ancillary systems capable of precisely determining sensor location while data are being collected. Here we document the findings of a proof of concept study for a simple hand-held electromagnetic induction (EMI) sensor that would be capable of detecting and classifying buried objects and that does not require precise sensor position information. The basic system concept is a compact three-element hand-held EMI array that can simply be waved over some suspected target location and then classify the target on the basis of its intrinsic EMI response in real time using a simple procedure initially introduced in the Strategic Environmental Research and Development (SERDP) project MR-1572 for purposes of estimating the number of targets within a sensor array's field of view [1].

Target classification using standard physics-based processing of EMI data collected over a target entails inverting the data to determine the target's location, orientation, and three principal axis polarizability curves. The inversion is based on a dipole response model in which the polarizabilities specify the target's intrinsic electromagnetic response. In order for this procedure to yield accurate results, measurements of the response at many locations and/or from many directions are needed, and the locations of the sensor readings relative to each other must be precisely known. However, it turns out that using the MR-1572 joint diagonalization procedure you can easily calculate a set of data eigenvalues that often mimic the shapes of the principal axis polarizabilities. This research project has focused on whether or not these data eigenvalues can serve as surrogates for principal axis polarizabilities for purposes of target classification.

# Background

## Introduction

Recent large scale ESTCP demonstrations have shown that the new multi-axis EMI sensor systems can be used to successfully distinguish between buried munitions and clutter when they are operated in a cued interrogation mode. In cued interrogation, the sensor is parked over an anomaly of interest, the transmit coils are excited sequentially, and the response from the target at the various receive coils is recorded. These data are inverted using a dipole response model to estimate object parameters, which are then supplied to classification engines that decide whether they are more likely associated with munitions or clutter. The large vehicle-mounted or towed systems that have been successfully demonstrated cannot be used at sites with rugged terrain or extensive brush and tree cover. ESTCP is currently testing more compact, cart-based versions of these systems which will expand the range of accessible environments somewhat, but some especially difficult sites or portions of sites will remain accessible only to operators using hand-held sensors.

Two hand-held sensor concepts which might be effectively deployed at such sites are being investigated by ESTCP. Both rely on accurate spatial mapping of the data. The hand-held transient electromagnetic (TEM) sensor in ESTCP project MR-200807 has a single Tx/Rx coil pair. It can be used with a rigid 6x6 point grid template placed on the ground over the target, or with a tactical grade inertial measurement unit (IMU) to collect classification-grade data [2]. Data collection using the grid template is cumbersome and time-consuming. The IMU-based positioning system is also cumbersome, and quite expensive. The man-portable vector (MPV) EMI sensor developed and tested in project MR-201005 uses a single-axis transmitter and several multi-axis receivers. Sensor positioning is based on monitoring the primary field, acting as a beacon, with a pair of EMI receivers placed at a base station [3]. Again, this is cumbersome and not particularly well suited to tight quarters.

The sensor concept considered here is based on the joint diagonalization processing technique for multisensor array data introduced by Fridon Shubitidze in SERDP project MR-1572 [1]. A joint diagonalization algorithm [4] is used to simultaneously calculate the eigenvalues and eigenvectors of a square multistatic response matrix of measured EMI array data at a set of time gates. In SERDP project MR-1572 and a subsequent ESTCP project MR-201101 [5] it was shown that the eigenvalues of the multistatic data matrix can be useful for purposes of estimating the number of targets within the sensor array's field of view. It was further observed that "in a good number of cases" the data eigenvalues could provide "quick inversion-free characterization and classification of the targets". Specifically, "the number of nonzero eigenvalues of the matrix (i.e., those above a noise threshold) is related to the number of elementary sources in the illuminated cell; moreover, the time-decay patterns of these non-vanishing eigenvalues are

intrinsic properties of the targets to which the sources correspond and can ultimately provide dependable classification features.”

It is this “inversion-free” information useful for target classification that we wish to exploit. In conventional dipole inversion, given a set of measurements of the EMI response we simultaneously search out the location, orientation, and principal axis polarizabilities that produce signals that best match the measured target response [6]. We found in ESTCP Project MR-200909 that you need a lot of data to reliably constrain the target location in dipole inversion [7]. The MR-200909 2x2x3 configuration comprising an array of four transmit loops and four three-axis receivers is probably the minimum practicable system. This is currently deployed in a man-portable, roughly one meter square cart-mounted arrangement. The size could conceivably be reduced somewhat, but it would still be cumbersome for handheld operation. If the joint diagonalization procedure does in fact produce dependable classification information without dipole inversion, then perhaps we can get by with a simpler, more compact sensor array suitable for use in the more challenging areas.

### Data Eigenvalues

The standard expression for the EMI signal measured by an ideal time domain sensor at the  $k^{\text{th}}$  time gate is

(1)

$$s(t_k) = \mu_0 n_R n_T I_0 C_R \cdot C_T B(t_k)$$

where  $n_T$  and  $n_R$  are the number of turns in the transmit and receive loops,  $I_0$  is the transmit current,  $B(t)$  is the polarizability tensor with eigenvalues  $\beta_x(t)$ ,  $\beta_y(t)$  and  $\beta_z(t)$ , and  $C_T$  and  $C_R$  are (vector) transmit and receive coil response functions given by Biot-Savart integrals over the transmitter and receiver loops

(2)

$$C_T(r) = \frac{1}{4\pi} \oint_T \frac{dl_T \times (r - r_T)}{|r - r_T|^3} \quad \text{and} \quad C_R(r) = \frac{1}{4\pi} \oint_R \frac{dl_R \times (r - r_R)}{|r - r_R|^3}.$$

For a multi-static array of transmitters and receivers, the signal at receiver  $j$  due to transmitter  $i$  is then

(3)

$$s_{ij}(t_k) = \mu_0 n_R n_T I_0 \{C_{Tix} C_{Rjx} \beta_x(t_k) + C_{Tiy} C_{Rjy} \beta_y(t_k) + C_{Tiz} C_{Rjz} \beta_z(t_k)\}$$

in a target-fixed coordinate system (coordinate axes aligned with the target’s principal axes). The complete measurement then consists of a set of  $k=0, 1, 2, \dots, n-1$  signal matrices

(4)

$$S(t_k) = \begin{pmatrix} s_{11}(t_k) & s_{12}(t_k) & s_{13}(t_k) & \cdots \\ s_{21}(t_k) & s_{22}(t_k) & s_{23}(t_k) & \cdots \\ s_{31}(t_k) & s_{32}(t_k) & s_{33}(t_k) & \cdots \\ \cdots & \cdots & \cdots & \cdots \end{pmatrix},$$

where  $n$  is the number of time gates. The number of rows and columns in  $S$  are equal to the number of transmit and receive elements in the array. With conventional processing, the data  $S$  are inverted to determine the target  $x, y, z$  location and the polarizability tensor  $B$  [6]. The eigenvalues of  $B$ , considered as functions of decay time  $t$ , are the principal axis response functions used to classify the target.

Now consider the conceptual sensor array shown in Figure 2. With three Tx/Rx coil pairs, a measurement over a target can be expressed by a  $3 \times 3$  matrix

(5)

$$H_d(t_k) = \begin{pmatrix} h_{11}(t_k) & h_{12}(t_k) & h_{13}(t_k) \\ h_{21}(t_k) & h_{22}(t_k) & h_{23}(t_k) \\ h_{31}(t_k) & h_{32}(t_k) & h_{33}(t_k) \end{pmatrix}$$

at each time gate  $k$ , with rows and columns corresponding to the different transmitters and receivers. If the transmit and receive coils have the same size and shape and are arranged in co-located Tx/Rx pairs, then because of the electromagnetic reciprocity principle the data matrix  $H_d(t_k)$  is symmetric and can be represented as

(6)

$$H_d(t_k) = VD(t_k)V^T$$

where  $D(t_k)$  is diagonal and  $V$  is a rotation matrix common to all the data matrices (i.e. is the same for all time gates). The individual elements of the data matrix are then given by

(7)

$$h_{ij}(t_k) = v_{i1}v_{j1}d_1(t_k) + v_{i2}v_{j2}d_2(t_k) + v_{i3}v_{j3}d_3(t_k)$$

where the  $d_i$  are the (diagonal) elements of  $D$  and the  $v_{ij}$  are elements of the rotation matrix  $V$ . This has precisely the same form as the elements of the dipole model's signal matrix  $S$  above, with  $\alpha = 1, 2, 3$  corresponding to the  $x, y, z$  coordinate directions and rotation matrix elements replacing the coil response functions. The central issue here is whether or not the similarity between equations (3) and (7) implies that the relationship between the polarizabilities and data eigenvalues is sufficiently simple and direct that the data eigenvalues are as useful for classification as the polarizabilities. If so, then we should be able to devise a simple classification sensor which exploits this effect.

## Examples

The original use of the joint diagonalization technique was at the ESTCP classification demonstration at former Camp Butner [8] using data from the TEMTADS transient electromagnetic towed array discrimination system [9]. TEMTADS has 25 pairs of transmit and receive loops arranged in a 5x5 element array. To illustrate the correspondence between data eigenvalues and polarizabilities we processed TEMTADS data collected over 121 37mm projectile targets at former Camp Butner using the joint diagonalization technique. The appendix contains plots of the TEMTADS data eigenvalues and corresponding polarizabilities from dipole inversion of the TEMTADS data for all of the 37mm targets. Examples are shown in Figure 1. Heavy blue curves are principal axis polarizabilities from standard dipole inversion of the data, and heavy red curves are the dominant three data eigenvalues from joint diagonalization of the TEMTADS data matrix. Other data eigenvalues are shown by the light gray curves. The scale for the polarizabilities is shown on the left axis and the scale for the data eigenvalues is shown on the right axis. The scales are aligned so that the polarizabilities and eigenvalues can be easily compared. In many cases the polarizabilities and data eigenvalues are essentially the same except for a single scaling factor (a). More generally, the shapes of the curves are similar, but with different scaling factors (b). In some cases there is not a simple one-to-one correspondence between data eigenvalues and polarizabilities (c). This is in fact the rule. The coil response matrices in equation (3) are not simply scaled versions of the rotation matrices in equation (7), and depending on the target/array geometry they can produce data eigenvalues which have a mix of the different principal axis polarizabilities. The final example (d) is a case where the dipole inversion sort of failed and the data eigenvalues actually give a better sense of the target's identity. In this case the target's driving band is intact, and one of the data eigenvalues shows the tell-tale bow typical of the primary (axial) polarizability of a 37mm projectile with an intact driving band.

In general the data eigenvalues are linear combinations of the principal axis polarizabilities, not simply scaled replicas of the polarizabilities. The details depend on the location and orientation of the target relative to the sensor array. As noted in [1] and can be observed in the plots in the appendix, in many cases each combination is dominated by a different polarizability component and the data eigenvalues look much like the polarizabilities. Classification is based on deciding whether or not an unknown target's polarizabilities look like those of a target of interest. In what follows we will evaluate how much the data eigenvalues are distorted relative to the polarizabilities and, when all is said and done (i.e. when the distortion is accounted for) how useful the data eigenvalues are for classification.

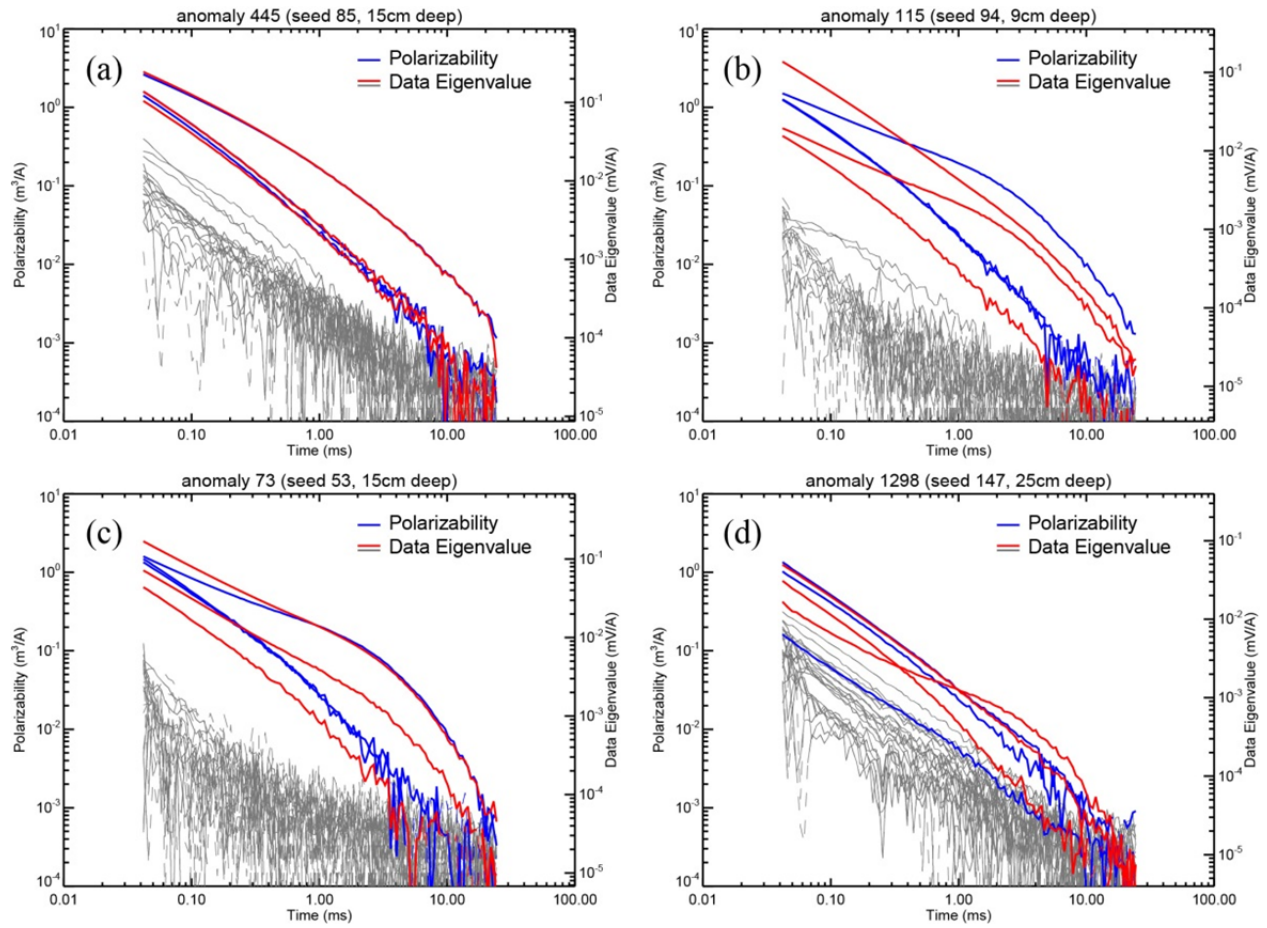


Figure 1. Principal axis polarizabilities (blue) and data eigenvalues (red, gray) calculated from TEMTADS array data collected over 37mm projectiles at former Camp Butner.

## Materials and Methods

### Data Eigenvalue Calculations

The relationship between data eigenvalues and principal axis polarizabilities depends on the location of the target relative to the array elements and on the target orientation. To systematically examine the effects, we ran numerical experiments using the simple three-element array shown schematically in Figure 2. Red circles represent transmitter loops and blue circles represent receiver loops. In the simulations we used 20cm radius transmit and receive loops positioned 25cm from the center of the array.

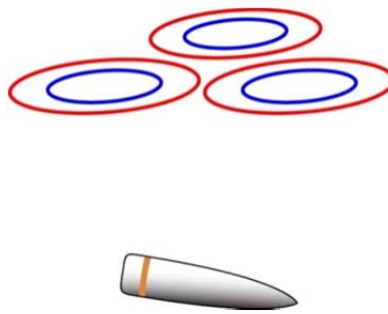


Figure 2. Basic three-element array. Red circles represent three transmitter loops and blue circles represent three receiver loops.

The simulations were run using a 37mm target at various locations and orientations below the array. Figure 3 gives examples of the results for several different locations and orientations. As in Figure 1, blue lines show the polarizabilities and red lines show the data eigenvalues. In each plot a single scale factor is applied to the set of data eigenvalues to get them lined up with the polarizabilities. Target location and orientation are indicated on each plot. There is a sweet spot 27cm directly below the center of the array where the data eigenvalues match the polarizabilities perfectly (a). Moving off from the sweet spot introduces differential scaling of the data eigenvalues (b) and mixing of the polarizabilities contributing to the different data eigenvalues (c). These effects can even be perverse enough to make the data eigenvalues look like the polarizabilities for a plate-like object (d).

Target orientation has no effect on the data eigenvalues at the sweet spot, but can exert a significant influence at locations where the data eigenvalues are not scaled replicas of the polarizabilities. The dominant effect appears to be target location relative to the array elements. We ran Monte Carlo simulations to quantify the effects, looking at the extent of polarizability mixing in the data eigenvalues. The results are reported in the Results and Discussion section below.

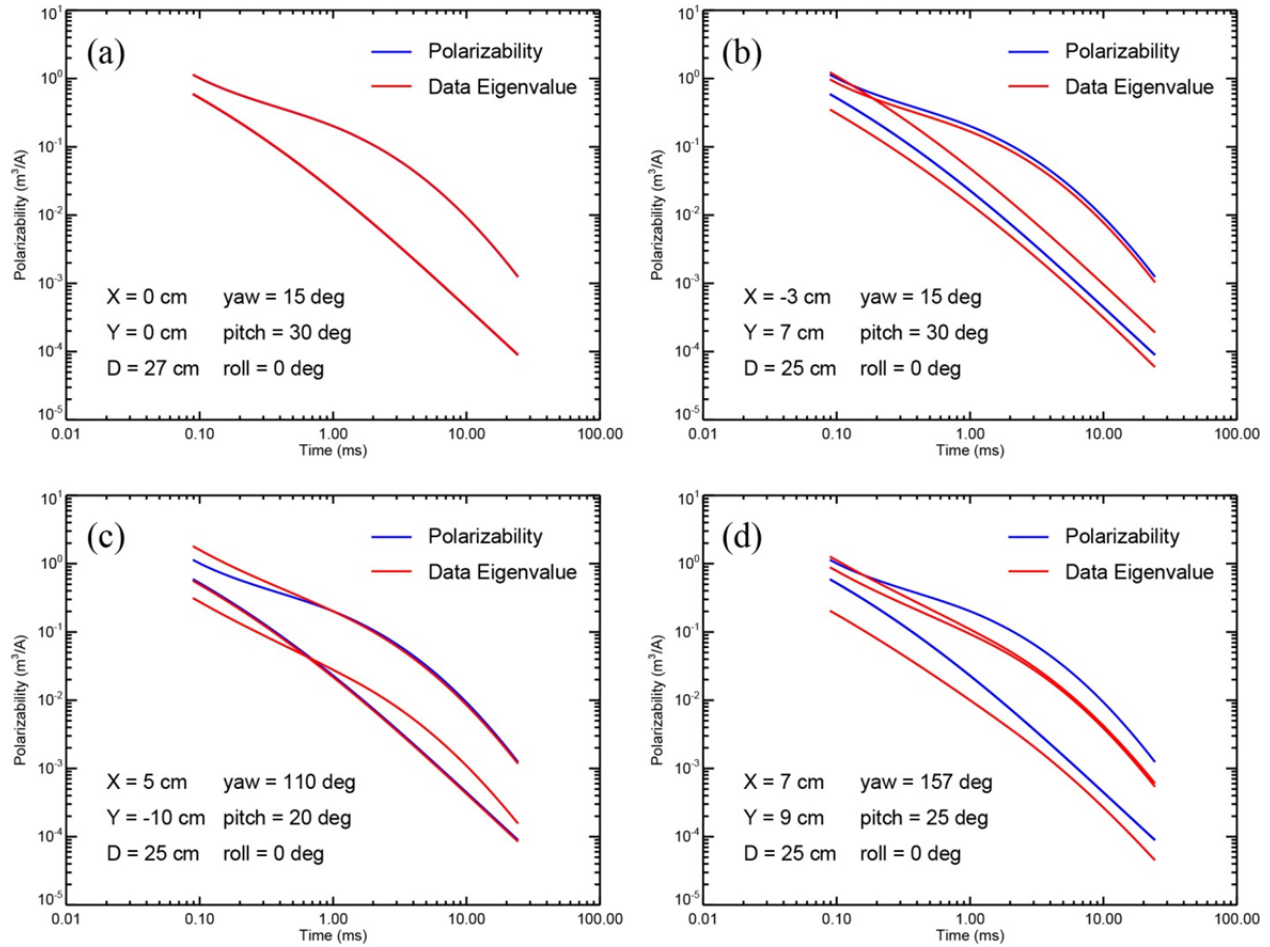


Figure 3. Examples of data eigenvalues from the three-element array with a 37mm projectile target at various locations and orientations below the array.

### Classification Performance Evaluation

In general the data eigenvalues are linear combinations of the polarizabilities rather than simply scaled replicas of the polarizabilities. This can have a significant effect on their usefulness for target classification, which is usually done by comparing an unknown target's polarizabilities with those of targets of interest (TOIs). If the unknown target's polarizabilities look like TOI polarizabilities then the target is classified as a possible TOI. If not, then it is classified as likely clutter. Classification based on data eigenvalues would have to accommodate arbitrary linear combinations of the polarizabilities.

Library matching methods employing various procedures to compare polarizabilities of unknown targets with those of TOIs are commonly used for classification. Ours, developed in SERDP project MR-1658, exploits the fact that an object's polarizability tensor  $\beta_{ij}(t) = V\alpha_{ij}(t)$  is a product of two factors: the volume  $V$  of the object and a tensor  $\alpha_{ij}(t)$  whose eigenvalues  $\alpha_i(t)$ ,  $i = 1, 2, 3$  depend only on the shape and composition of the object. Confronted with an unknown target, we compare its apparent size and EMI "shape" with the sizes and shapes of the TOI.

Given the set (spanning three axes and N time gates) of principal axis polarizabilities  $\beta_0$  for a TOI and the set of principal axis polarizabilities  $\beta$  for an unknown target, we calculate a size ratio  $s$  as

(8)

$$s = \text{median} \left( \frac{\sqrt[3]{\beta}}{\sqrt[3]{\beta_0}} \right)$$

where the median is taken over all axes and time gates for which  $\beta > 0$ . If  $\beta < 0$  for more than some threshold fraction (typically 25-50%) of the available terms, then the target is put in the “can’t analyze” category. The size mismatch parameter  $\Delta_{size}$  is then

(9)

$$\Delta_{size} = \log(s)$$

which is equal to zero if the EMI sizes of the target and the reference TOI are the same, The shape mismatch parameter  $\Delta_{shape}$  is determined by comparing the unknown target’s polarizability with the reference polarizability scaled by the size mismatch

(10)

$$\Delta_{shape} = \frac{\sum |\sqrt[3]{\beta} - s \sqrt[3]{\beta_0}|}{\sum \sqrt[3]{\beta}}$$

in which the sums are over all terms with positive  $\beta$ . For each target, size and shape mismatch parameters are calculated for each TOI. Classification is based on thresholding a figure of merit (FOM) parameter

(11)

$$FOM = \min_{TOI} \{ |\Delta_{size}| + k \log(\Delta_{shape}) \}.$$

We find that using a parameter value  $k \approx 0.3$  gives the best classification performance. Minimizing the FOM over the set of TOI finds the best match to any TOI.

With data eigenvalues  $p$  we have to consider linear combinations of the  $\beta$ s. The shape parameter (10) must then be modified to

(12)

$$\Delta_{shape} = \frac{\sum |\sqrt[3]{p} - \sum a_i \sqrt[3]{\beta_{0i}}|}{\sum \sqrt[3]{p}}$$

and the size parameter goes away, being subsumed in the term  $\sum a_i \sqrt[3]{\beta_{0i}}$  in equation (12), which represents the best fit linear combination of TOI polarizabilities  $\beta_0$  for to the data eigenvalues  $p$ . The figure of merit for classification is then simply

(13)

$$FOM = \min_{TOI} \{\Delta_{shape}\}.$$

In order to determine the effect of having to use arbitrary linear combinations of the polarizabilities we have re-classified polarizabilities from the former Camp Beale classification demonstration [10] using the FOMs in equations (11) and (13). Since the data eigenvalues are linear combinations of the polarizabilities, replacing the unknown target data eigenvalues with the unknown target polarizabilities in equation (12) has no effect on classification performance. The issue is how many additional clutter digs are introduced with the less restrictive classification procedure. The former Camp Beale polarizabilities simply provide a representative set of TOI and clutter for analysis. The results are reported in the Results and Discussion section below.

## Results and Discussion

### Polarizability Mixing in Data Eigenvalues

We ran Monte Carlo simulations using the notional three-element array (Figure 2) to determine the extent of polarizability mixing in the data eigenvalues. For the calculations reported here we used 20cm radius transmit/receive loop pairs set in a circle of radius 25cm. Other calculations confirmed that array geometry details have no effect on the general conclusions. We used a 37mm target and randomly varied its location and orientation relative to the sweet spot 27cm directly below the center of the array. At each location/orientation combination data matrices for each time gate were calculated using the standard forward model in equation (3). Each set was then jointly diagonalized for all the time gates to get data eigenvalues as functions of decay time. These data were reduced by calculating the best fit linear combinations of the 37mm's transverse and axial polarizabilities to the data eigenvalues. Some typical results for different spreads in the target location ( $d_{xyz}$ ) are shown in Figure 4. Each plot shows the results of 1000 simulations with the target distance below the array varied in a uniform random distribution over  $\pm d_{xyz}$  and the X,Y location varied in a uniform random distribution with radius  $d_{xyz}$ . Target yaw and pitch were uniformly distributed over all solid angles. Red symbols show the relative strengths of axial and transverse polarizabilities in the primary data eigenvalue; green and blue show their relative strengths in the secondary data eigenvalues. With no polarizability mixing (e.g. at the sweet spot) red points would plot at (1, 0), while green and blue points would plot at (0, 1).

When the target is near the sweet spot (Figure 4a,  $d_{xyz} = 2.5\text{cm}$ ) the data eigenvalues cluster about their respective no-mixing locations (1, 0) and (0, 1). In this case the data eigenvalues are pretty much just scaled replicas of the principal axis polarizabilities. As the spread of locations progressively increases (Figure 4b-d) the data eigenvalues can no longer be considered as scaled replicas of the individual principal axis polarizabilities, but rather must be recognized as linear combinations of all of the target's polarizabilities.

Looking back at the TEMTADS results in the appendix we can see plenty of examples of polarizability mixing. Adding more sensors does not alter our conclusions regarding the relationship between data eigenvalues and principal axis polarizabilities.

With the target location unknown, the sensor array cannot be positioned in the "optimum" location where data eigenvalues are simply scaled replicas of the polarizabilities. Classification using data eigenvalues has to accommodate arbitrary linear combinations of the polarizabilities. This is not much different than the scheme advanced by Norton et al. [11] for classification in which individual sensor readings are matched to linear combinations of polarizabilities. In the next section we show that classification performance is seriously degraded when we are forced to admit arbitrary linear combinations of polarizabilities in the classification algorithm.

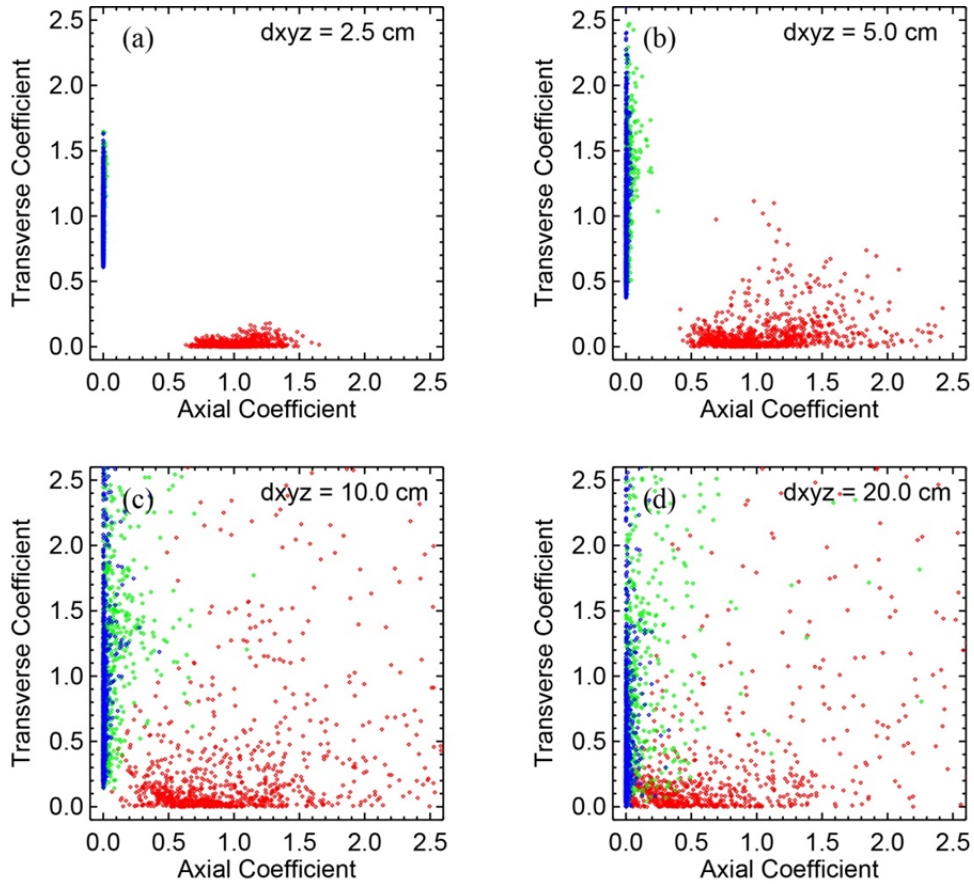


Figure 4. Simulation results for relative strengths of axial and transverse polarizability in data eigenvalues (primary eigenvalue in red, secondary in green and blue). Target locations distributed uniformly  $\pm d_{xyz}$  about a point centered 27cm below the array.

### Classification Performance with Linear Combinations of Polarizabilities

In order to determine the effect of having to use arbitrary linear combinations of the polarizabilities we have re-classified polarizabilities from the former Camp Beale classification demonstration [10] using the figures of merit in equations (11) and (13). Since the data eigenvalues are linear combinations of the polarizabilities, replacing the unknown target data eigenvalues with the unknown target polarizabilities in equation (12) has no effect on classification performance. The issue is how many additional clutter digs are introduced with the less restrictive classification procedure. The former Camp Beale polarizabilities simply provide a representative set of TOI and clutter for analysis.

Classification performance results are shown in Figure 5. The blue curve corresponds to classification based on library matching of principal axis polarizabilities and the red curve corresponds to classification performance based on linear combinations of principal axis polarizabilities. The plots are standard receiver operating characteristic (ROC) curves. They show how the number of properly identified targets of interest varies with the number of clutter

items incorrectly identified as targets of interest as the figure of merit decision threshold is increased. A good ROC rises quickly to 100% TOI recovered with few incorrectly classified clutter items. A really bad ROC runs diagonally from lower left to upper right. In that case decisions are basically coin flips. Directly comparing a target's principal axis polarizabilities to those of the TOIs (blue curve) produces very good classification performance. Matching a target's principal axis polarizabilities to linear combinations of TOI polarizabilities (equivalent to matching data eigenvalues to linear combinations of polarizabilities) significantly degrades the classification performance. The extra degrees of freedom simply allow too many clutter items to masquerade as TOIs.

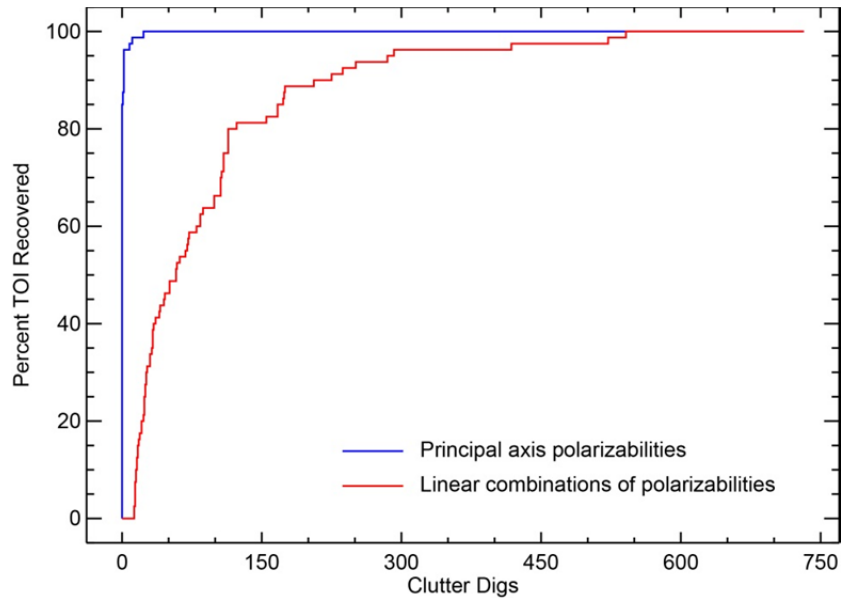


Figure 5. Classification performance for former Camp Beale based on library matching of principal axis polarizabilities (blue) and linear combinations of polarizabilities (red).

## **Conclusions and Implications for Future Research/Implementation**

Typical library matching procedures used for classification ask how much a given target's principal axis polarizabilities resemble those of targets of interest. The polarizabilities are calculated from sensor array data using dipole inversion. In conventional dipole inversion, given a set of measurements of the EMI response we simultaneously search out the location, orientation, and principal axis polarizabilities that produce signals that best match the measured target response. Unfortunately you need a lot of data to reliably constrain the target location in dipole inversion. The eigenvalues of the data matrix for an array of paired transmit and receive loop are easy to compute and need a much less extensive sensor array than the polarizabilities. This research project has focused on whether or not these data eigenvalues can serve as surrogates for principal axis polarizabilities.

In general, the data eigenvalues are built up of linear combinations of the principal axis polarizabilities. This means that a classification scheme based on data eigenvalues would have to accommodate arbitrary linear combinations of TOI polarizabilities. We re-classified data from the former Camp Beale classification demonstration using comparable procedures based on principal axis polarizabilities and linear combinations of polarizabilities. Classification performance was significantly degraded when we had to accommodate linear combinations of the polarizabilities.

Although the data eigenvalues have proved useful for identifying situations where there are multiple targets in the sensor's field of view and often give an indication that a target of interest may be present [1], they cannot replace principal axis polarizabilities as the primary data-derived parameters for classification. The loss of classification performance to clutter items whose principal axis polarizabilities can be closely reproduced using linear combinations of TOI polarizabilities is just too large. Consequently, a simple hand-held EMI sensor that relies on data eigenvalues to reliably classify targets without precise sensor position information is not realistic.

The polarizabilities needed for reliable classification can only be obtained by inverting the data, and you need a lot of data to reliably constrain the target location in the inversion process. The MR-200909 2x2x3 configuration comprising an array of four transmit loops and four three-axis receivers is probably the minimum practicable system. This is currently deployed in a man-portable, roughly one meter square cart-mounted arrangement. The size could conceivably be reduced somewhat, but it would still be cumbersome for handheld operation.

## Literature Cited

1. Fridon Shubitidze, "A Complex Approach to UXO Discrimination: Combining Advanced EMI Forward Models and Statistical Signal Processing," SERDP Project MR-1572 Final Report, January 2012.
2. "Advancing Discrimination Performance by integrating an Inertial Measurement Unit with a handheld EMI Sensor," ESTCP Project MR-200810 Interim Technical Report, July 2012.
3. Nicolas Lhomme, "Man-Portable Vector EMI Sensor for Full UXO Characterization," ESTCP Project MR-201005 Technical Report, March 2012.
4. Jean-Francois Cardoso and Antoine Souloumiac, "Jacobi angles for simultaneous diagonalization," *SIAM Journal on Matrix Analysis and Applications*, vol. 17, no. 1, pp. 161-164, January 1995.
5. Fridon Shubitidze, "Advanced EMI Models for Live-site UXO Discrimination at Former Camp Beale," ESTCP Project MR-201101 Demonstration Report, February 2012.
6. Thomas H. Bell, Bruce J. Barrow and Jonathan T. Miller, "Subsurface Discrimination Using Electromagnetic Induction Sensors," *IEEE Trans. Geoscience and Remote Sensing*, vol. 39, no. 6, pp. 1286-1293, June 2001.
7. James B. Kingdon, Bruce J. Barrow, Thomas H. Bell, David C. George, Glenn R. Harbaugh and Daniel A. Steinhurst, "TEMTADS Adjunct Sensor Systems: Hand-held EMI Sensor for Cued UXO Discrimination (ESTCP MR-200807) and Man-Portable EMI Array for UXO Detection and Discrimination (ESTCP MR-200909)," Final Report, April 5, 2012.
8. Fridon Shubitidze, "Demonstration of Advanced EMI Models for Live-Site UXO Discrimination at Former Camp Butner, North Carolina," SERDP Project MR-1572 Technical Report, May 2012.
9. Nagi Khadr, James B. Kingdon, Glenn R. Harbaugh and Daniel A. Steinhurst, "2010 ESTCP UXO Classification Study Rougemont, NC," ESTCP MR-1034 Demonstration Data Report, Former Camp Butner MTADS Discrimination Array (TEMTADS) Survey, October 20, 2011.
10. "ESTCP Live Site Demonstrations Former Camp Beale, Marysville, CA," ESTCP MR-201165 Demonstration Data Report, Former Camp Beale TEMTADS MP 2x2 Cart Survey, August 23, 2011.
11. Stephen J. Norton, I.J. Won and Ernesto R. Cespedes, "Spectral Identification of Buried Unexploded Ordnance from Low-Frequency Electromagnetic Data," *Subsurface Sensing Technologies and Applications*, vol. 2, no. 3, pp. 177-189, July 2001.

## Appendix

This appendix contains plots of the TEMTADS data eigenvalues and corresponding polarizabilities from dipole inversion of the TEMTADS data for all of the 37mm targets at the former Camp Butner classification demonstration. Heavy blue curves are principal axis polarizabilities from standard dipole inversion of the data, and heavy red curves are the dominant three data eigenvalues from joint diagonalization of the TEMTADS data matrix. Other data eigenvalues are shown by the light gray curves. The scale for the polarizabilities is shown on the left axis and the scale for the data eigenvalues is shown on the right axis. The scales are aligned so that the polarizabilities and eigenvalues can be easily compared. In many cases the polarizabilities and data eigenvalues are essentially the same except for a single scaling factor. More generally, the shapes of the curves are similar, but with different scaling factors. In some cases there is not a simple one-to-one correspondence between data eigenvalues and polarizabilities. This is in fact the rule. The coil response matrices in equation (1) which relate individual sensor readings to the principal polarizabilities are not simply scaled versions of rotation matrices in equation (6). Depending on the target/array geometry they can produce data eigenvalues which have a mix of the different principal axis polarizabilities.

