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Sean Goldberg, Taylor Glenn, Joseph N. Wilson, Paul D. Gader, "Landmine detection using two-tapped joint orthogonal matching pursuits," Proc. SPIE 8357, Detection and Sensing of Mines, Explosive Objects, and Obscured Targets XVII, 83570B (10 May 2012); doi: 10.1117/12.927443

Event: SPIE Defense, Security, and Sensing, 2012, Baltimore, Maryland, United States

Landmine Detection Using Two-Tapped Joint Orthogonal Matching Pursuits

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ABSTRACT

Joint Orthogonal Matching Pursuits (JOMP) is used here in the context of landmine detection using data obtained from an electromagnetic induction (EMI) sensor. The response from an object containing metal can be decomposed into a discrete spectrum of relaxation frequencies (DSRF) from which we construct a dictionary. A greedy iterative algorithm is proposed for computing successive residuals of a signal by subtracting away the highest matching dictionary element at each step. The final confidence of a particular signal is a combination of the reciprocal of this residual and the mean of the complex component. A two-tap approach comparing signals on opposite sides of the geometric location of the sensor is examined and found to produce better classification. It is found that using only a single pursuit does a comparable job, reducing complexity and allowing for real-time implementation in automated target recognition systems. JOMP is particularly highlighted in comparison with a previous EMI detection algorithm known as String Match.

Keywords: landmine, electromagnetic induction (EMI), Argand diagram

1. INTRODUCTION

The use of wideband electromagnetic induction (WEMI) for the detection and discrimination of land mines has been widely investigated. A WEMI sensor uses a primary trasmit coil to generate a time-varying electromagnetic field to penetrate the ground's surface. Interactions with subsurface elements cause induced reflections back to the sensor where they are picked up by one or more receive coils, indicating the presence or absence of a target containing metal.

The NIITEK Autonomous Mine Detection System (AMDS) uses EMI sensors in conjunction with ground-penetrating radar (GPR) sensors to perform landmine detection. This paper focuses on the use of EMI for conducting prescreening. Prescreening approaches have proven to be successful for specific classes of objects such as antitank landmines for both GPR[1] and EMI.[2]

The current incarnation of AMDS makes use of a prototype dictionary of known EMI frequency-domain responses for its String Match algorithm. The system checks each response and computes the gradient angle residual[3] to determine a confidence. By exploiting a new dictionary with a more physically significant foundation not based on predetermined mine types, we are able to generalize the applicability of the system and improve performance in terms of both an increase in probability of detection (PD) and lowering of the false alarm (FA) rate.

An additional novelty is to use a ”double tap” approach which utilizes the spatial extent of the signal and measures correlation both in front of and behind the sensor. This also reduces false alarm rate as opposed to using a single tap.

This paper is organized as follows. We begin in Section 2 with an introduction of the AMDS sensor and nature of the induced AMDS response. Next, in Section 3 the dictionary based on relaxation frequencies is discussed. Section 4 is devoted to a description of the Joint Orthogonal Matching Pursuit algorithm, while Section 5 describes a blobbing technique for confidence assignment and alarm detection. We list our experimental results in Section 6 followed by conclusions in Section 7.

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Detection and Sensing of Mines, Explosive Objects, and Obscured Targets XVII,
edited by J. Thomas Broach, John H. Holloway Jr., Proc. of SPIE Vol. 8357, 83570B
 · doi: 10.1117/12.927443

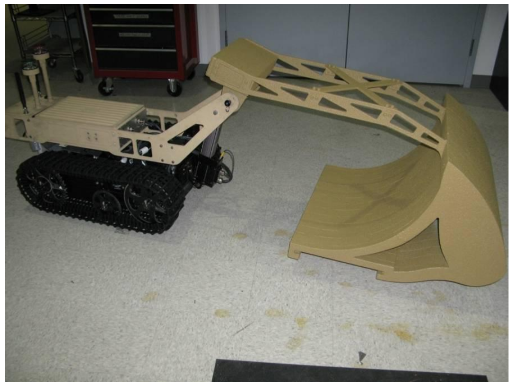

Figure 1. The NIITEK AMDS robotic platform. The GPR and EMI arrays are attached to the visor.

Figure 2. EMI Quadrapole Antenna Array

2. ELECTROMAGNETIC INDUCTION RESPONSE

2.1 AMDS Platform and Sensors

NIITEK's AMDS platform consists of a man-portable robot with an integrated GPR antenna array and wide-band EMI array sensor. The GPR antenna employs a twelve-channel array of low radar cross-section antennas. This antenna has been used successfully in the context of automated systems for the detection of antitank landmines.[1] Figure 1 shows the robotic platform and attached GPR/EMI antenna.

Figure 2 shows the organization of the rectangular broadband EMI antenna which consists of a single dipole transmit coil and three quadrapole receive coils. The antenna collects data at 21 logarithmically-spaced frequencies ranging from 330 Hz to 90.03 kHz. These data are filtered with a sine-wave filter for several reasons. The unfiltered response of the quadrapole antennas is near zero when the antenna is positioned directly above an object. Filtering also removes ground reponse through differencing and averages of the data to yield an increased signal-to-noise ratio.

Data from the sensor are collected at one centimeter increments in the direction of travel. Data from GPR antenna are spaced ever 5 centimeters laterally and the EMI receive centers are spaced 21.5 centimeters apart. Each A-scan of the radar antennae is discretized into 512 time increments.

Assuming a two-bye encoding of the data, complex data for the EMI and real data for the GPR, this means the system collects over 12,000 bytes of data per download track sample, and over 1.2 MB per meter downtrack. Performing any kind of complicated operation on each and every datum would be prohibitive in terms of speed and efficiency. The typical solution to this problem is to employ a prescreener. The prescreener's main task is to pare down the data into a more manageable number. The likely mine locations are then employed by the remainder of the algorithm's tasks such as feature extraction, discrimination, and fusion, to result in an even smaller number of decisions. Figure 3 outlines the full process.

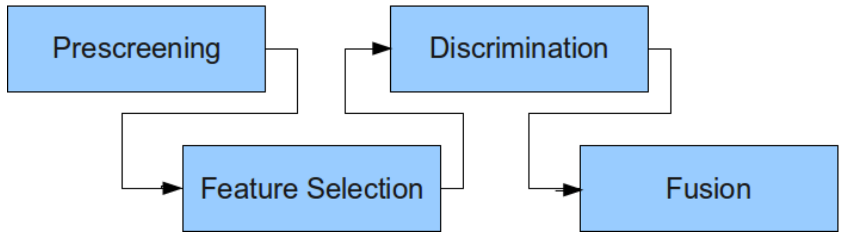

Figure 3. Typical landmine detection/discrimination algorithm.

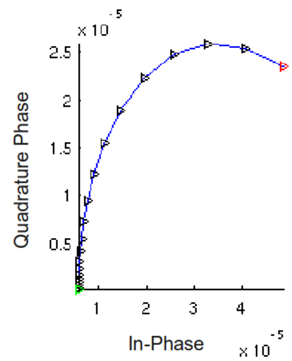

Figure 4. Sample Argand diagram of a low-metal antitank mine.

The critical properties of a prescreener are that it: i) uses few computation resources (efficient), ii) will generate an alarm (suspected target location) for almost all objects belonging to the class of interest, ie. targets (high true positive rate), iii) generates as few as possible alarms associated with non-target objects subject to condition ii (relatively low false alarm rate).

2.2 Frequency Reponse

Every centimeter the quadrapole EMI receive antenna collects data in the frequency domain which contain both an *in-phase* and *quadrature* part. Each sample contains the response from 21 frequencies. Figure 4 shows the response to a single antenna of a low-metal antitank landmine plotted as an Argand diagram. Each point represents the I/Q response associated with a specific frequency with neighboring points connected by a line moving from low frequency (green) to high frequency (red).

The response of the system to an infinitely small point reflector would be a perfect semicircle corresponding to a single relaxation. The simpler the structure of metallic objects in a subsurface object being sensed, the more its Argand will resemble that of a single relaxation. In practice, even though landmines have quite a complicated structure, their regular structure provides a relatively small set of relaxation Argand diagrams.

3. DICTIONARY

In general, metallic objects exhibit a coherent structure in their Argand diagrams while background shows more of a random pattern. Thus a key method in determining relevancy of a signal is to check for coherency. A dictionary of expected Argand responses corresponding to possible alarms can be enumerated for comparison. The ability of a sample to match any element of the dictionary can be used to signal a possible alarm.

Previous investigation has used a dictionary composed of previously sensed target Argands. This method is fundamentally flawed due to the ever changing types of mines and the growing number of homemade improvised explosive devices. We propose a new dictionary not dependent on the design of the mine, but determined by the material of which it's composed. This generalizes the algorithm to support detection of a far wider range of objects.

3.1 Discrete Spectrum of Relaxation Frequencies

An EMI model was developed by Baum[4] based on the discrete relaxations of a metallic target. Wei *et al.*[5] applied the model to landmine detection using support vector machines and k-nearest neighbors. The EMI frequency response is modeled as a sum as:

$$H(\omega) = c_0 + \sum_{k=1}^{L} \frac{c_k}{1 + \frac{j\omega}{\zeta_k}} \tag{1}$$

where c_0 is the shift, L the model order, c_k the real spectral amplitudes, and ζ_k the relaxation frequencies.

The spectral amplitudes depend on the orientation and position of a target, while the relaxation frequencies have the property of being invariant and are intrinsic to the object itself. Wei *et al.* also suggest that the c_k are consistent among different mines of the same type due to consistency in burial. For these reasons, the distinct parameter used as a dictionary feature are the relaxation frequencies ζ_k. Variation of the ζ_k parameter within a defined range produces frequency-dependent dictionary elements. Similarity of a target to any of these pre-defined elements proves the signal adheres to the model and represents a metallic object.

3.2 Soil Model

The dictionary described above contains prototypes signaling a positive match with a metallic object. In addition to these prototypes, our dictionary also contains a signal negative element based on the magnetic properties of the surrounding soil. Similarity with this element relegates the sample to an automatic background with zero confidence. Wei *et al.*[5] analyzed the frequency dependence of the soil response and noticed a similar trend among many different soils. With respect to the log-frequency, the real part varied linearly and the imaginary part remained constant. The soil model they proposed was:

$$R(\omega) = p_1 + p_2[ln(\frac{\omega}{\omega_0}) + j\frac{\pi}{2}] \tag{2}$$

where p_1 and p_2 are model parameters that are fit to the particular soil type and w_0 is the minimum frequency.

3.3 Composition of Dictionary

The dictionary is composed of 101 elements, 100 positive identifications corresponding to the EMI response model and a negative response corresponding to the soil model. In the EMI response model, only a single model was used, ie. $L = 1$. JOMP uses normalized signals for comparison and are mean subtracted, so the scale and shift parameters are irrelevant. Thus $c_0 = 0$ and $c_1 = 1$. The reduced equation defining the first 100 elements is:

$$H(\omega) = \frac{1}{1 + \frac{j\omega}{\zeta_k}} \tag{3}$$

Each element is parametrized by a value of ζ and contains a set of 21 modeled responses, one for each frequency collected by the EMI sensor. The ζ's are logarithmically spaced in the range from 45 Hz to 670 kHz. For the same reasons as above, the scale and shift are removed from the soil model. It can be seen from Figure 5 that the dictionary covers the range of expected semicircle responses from a metallic object. The soil model with its constant imaginary component is just a horizontal line with y-intercept $\frac{\pi}{2}$.

4. JOINT ORTHOGONAL MATCHING PURSUITS

The original use of the term *Matching Pursuit* introduced by Mallat and Zhang[6] comes from signal-processing and refers to the act of trying to decompose a signal into the "best matching" projections onto an over-complete dictionary using a greedy iterative process. The initial signal is scanned against the entire dictionary and the best match is subtracted from the original. The process repeats with the subtracted signal and continues iteratively until the entire signal has been sufficiently decomposed into a weighted collection of dictionary elements. An *Orthogonal Matching Pursuit* ensures that each new dictionary match is orthogonal to the previous matches. Finally, a *Joint Orthogonal Matching Pursuit* (JOMP) tries to map a pair of correlated signals to the same dictionary decomposition.

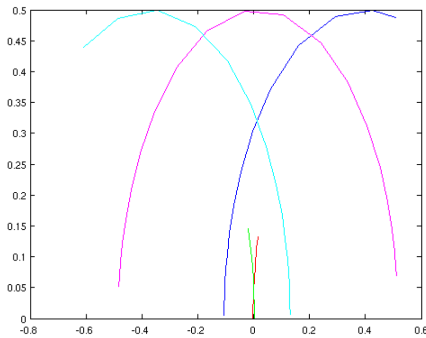

Figure 5. Sample dictionary elements corresponding to elements 1 (red), 25 (blue), 50 (magenta), 75 (cyan), and 100 (green).

Initially, preprocessing is done on the signal including passing it through a sine filter. Demeaning reduces the dependency of the model on the shift parameter c_0 and normalization reduces dependency on the scaling parameter c_1. The real and complex parts of the 21 frequencies are collected into a single 42x1 vector for both the signal and each dictionary element.

The EMI response is compared in turn to each prototype in the normalized dictionary with the greatest match weighted by the inner product being subtracted away for each pursuit. That is, given a signal S and a dictionary D containing elements d_i, for each iteration over the number of pursuits we have

$$S = S - \max_{d_i \in D} (< S, d_i >) * d_i. \tag{4}$$

The inverse of the final residual after subtracting p pursuits determines a confidence value for the input signal bounded in the range [0,1]:

$$conf = \frac{1}{S+1}. \tag{5}$$

Equation 4 refers to just the case of Matching Pursuits. Orthogonality ensures that an additional constraint is satisfied, ie.

$$\forall_{d_i, d_j \in A} < d_i, d_j >= 0, \tag{6}$$

where A is the set of dictionary elements found over all pursuits.

Given the relatively high frequency of sampling (every 1 centimeter), the spatial extent of mine-like targets extends over multiple correlated scans. Instead of assigning a confidence value to the point where the response was received, one could base the confidence around neighboring scans. The motivation is to only signal an alarm for signatures large enough to extend over multiple scans, lowering the false alarm rate attributed to a single anomalous coherent signal.

The double tap version of JOMP uses as input two signals 5 scans before and 5 scans after the center of the EMI antenna, respectively. The highest matching pursuit is the one that jointly matches both scans. The final residual is averaged between the two signals to give a confidence value to the location directly between them.

5. ALARM IDENTIFICATION

Figure 6 shows a sample confidence map after running JOMP double tap with a single pursuit. While cross-track has only three channels, interpolation is performed between channels to increase the number to 33. The image is then smoothed with a Gaussian filter.

Binary thresholding is performed on the smoothed image to determine "blobs" that might indicate the presence of an alarm. Morphological restructuring dilates the blobs and closes any holes small-sized holes. This

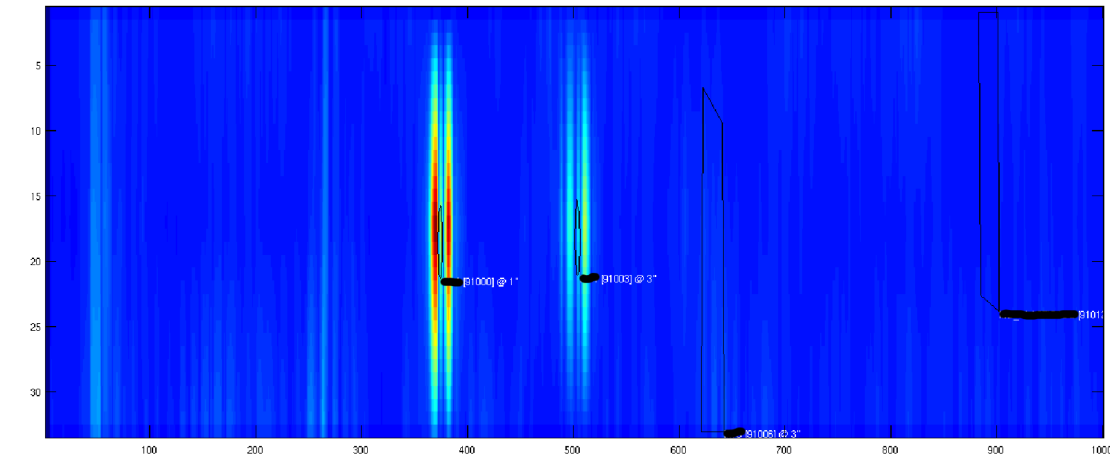

Figure 6. Sample confidence map containing two antipersonal low metal M14ss mines, an antitank low metal M19 mine, and a plastic jug. JOMP easily picks up the M14s, but has difficulty picking up the M19 in addition to the non-metal plastic jug.

has the desired effect that if two high confidence blobs occur in a small enough interval, we map them to the same alarm and create a single blob.

After image processing, each remaining blob of confidence values is considered an *alarm*. The location of the alarm is whichever scan in the blob has the highest confidence. This is also the single confidence value associated with the alarm itself. This prescreening step results in a number of alarms that are sent onto feature extraction and discrimination to lower the set of alarms even further.

One shortcoming to this method of alarm assignment is that in its current form it is essentially a post-processing step after the AMDS system has trekked over a complete lane. One can apply a causal blobbing method that can designate alarms during real-time performance based only on past data.

6. EXPERIMENTAL RESULTS

Experiments were performed on data collected by personnel from Niitek at a test facility with a desert climate in the western United States. The data included two different types of low metal antipersonnel mines and nine different types of antitank mines, containing both low and high metal. In total there were 88 objects containing metal. The goal is for JOMP to be able to designate each target object as an alarm with a low rate of false alarms.

JOMP's performance in differing incarnations are compared and summarized in a Receiver Operating Characteristic (ROC) curve as shown in Figure 7. The ROC curve measures probability of detection vs. false alarm rate. Shown also is the String Match method which utilizes a fixed dictionary of specific mine responses that have been seen previously. All methods use the same blobbing technique described in the previous section, but have different threshold values on the binary map. The threshold was chosen by selecting the value giving the best ROC.

It is an interesting result that taking more than one pursuit actually hurts the detection performance. Mine responses tend to be coherent while background is more random. A single response is more likely to resemble a single element of the dictionary than it is a superposition of elements. The background, however, may be able to eke out a smaller residual with two pursuits as opposed to one. This would lead to a larger false alarm rate to generate the same level of PD.

It can be seen that the double tap method improves upon the single tap considerably at low FAR, though the two roughly converge around 0.025. At the highest levels of confidence (low FAR), the double tap method is

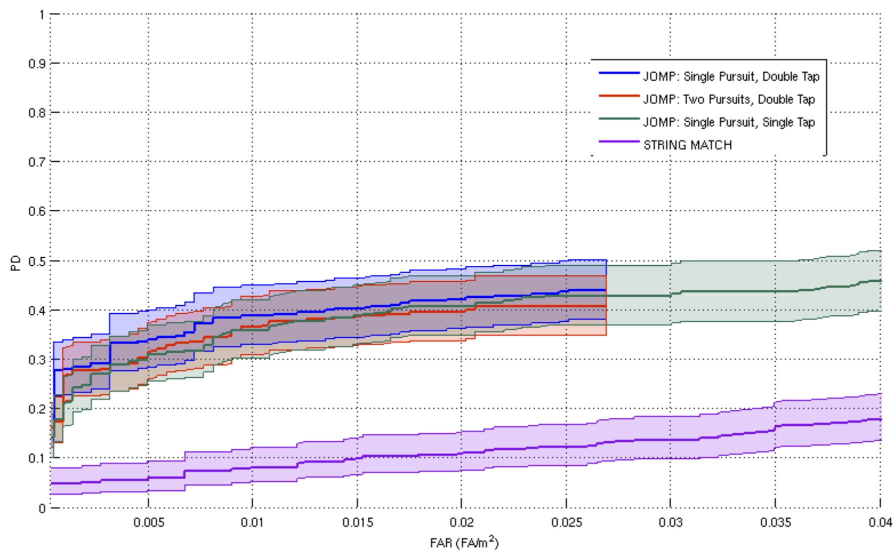

Figure 7. ROC curve comparing JOMP for various pursuits and taps to String Match.

able to distinguish between target and FA for certain objects to a greater degree than the single tap. Medium confidence alarms near the threshold (higher FAR) contain signatures that recognizable through either the double or single tap method.

In all cases, however, all of the JOMP methods significantly improve upon the String Match algorithm. String Match's dictionary is composed of hand selected prototypes of previously seen signatures, many of which didn't match anything contained in this experimental data set. Hence the incredibly low PD rate. JOMP's dictionary is based not on specific mine types, but on the physics underlying the metallic content. This makes it more adaptable and generalizable, giving a larger boost to all objects containing metal in the data set.

7. CONCLUSION

A computationally efficient prescreener for detecting metal-bearing subsurface objects has been created that uses data collected by a wideband electromagnetic induction sensor. Using a physics-based dictionary based on relaxation frequencies, joint orthogonal matching pursuits yield a residual that provides a better confidence value on data collected than previous EMI algorithms. Performance would see an even greater increase in effectiveness when used in conjunction with a GPR prescreener.

Further research will involve a real-time causal implementation of the blobbing technique. In addition, JOMP's merits as a discriminator are also being investigated.

ACKNOWLEDGMENTS

This work was supported in part by the Army Research Office under Grant W911NF-08-10410. The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the official policies either expressed or implied, of the Army Research Office, Army Research Laboratory, or the U.S. Government. The U.S. Government is authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation hereon. The authors would like to thank R. Harmon, R. Weaver, P. Howard, and T. Donzelli for their support of this work.

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