CLASSIFICATION OF LANDMINE-LIKE METAL TARGETS USING WIDEBAND ELECTROMAGNETIC INDUCTION

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ABSTRACT

Our previous work has indicated that the careful application of signal detection theory can dramatically improve detectability of landmines using time-domain electromagnetic induction (EMI) data [L. Collins, P. Gao, and L. Carin, IEEE Trans. Geosc. Remote Sens., in press]. In this paper, classification of various metal targets via signal detection theory is investigated using a prototype wideband frequency-domain EMI sensor [I.J. Won, D.A. Keiswetter, and D.R. Hansen, J. Envir. Engin. Geophysics, **2**:53-64 (1997)]. An algorithm that incorporates both the uncertainties regarding the target-sensor orientation and a theoretical model of the response of such a sensor is developed. The performance of this approach is evaluated using both simulated and experimental data. The results show that this approach affords substantial classification performance gains over the traditional matched filter approach, on the average by 60%.

1. INTRODUCTION

A persistent problem with traditional narrowband EMI sensors involves not just detection of metal objects, but discrimination of targets of interest from clutter. Until recently, the energy in the output of such sensors was calculated, and a decision regarding the presence or absence of a target was made based on this statistic [1]. This approach leads to excessively large false alarm rates. When each piece of buried metal must be excavated in order to determine whether it is a target of interest, significant costs are incurred both due to lost time, and costs associated with digging. This problem is particularly pernicious in real world landmine detection. In order to facilitate the discrimination of targets of interest from other pieces of metal, several modifications to traditional EMI sensors have been considered [1-6]. One promising approach is to operate the sensor in the frequency-domain by utilizing wideband excitation. The frequency dependence of the induced fields excited by buried conducting targets can then be exploited by a detector.

This paper is organized as follows. In Section 2 we discuss a model which calculates wideband EMI responses. In Section 3 we describe a new prototype wideband frequency-domain EMI sensor, the GEM-3 [7]. A model-based Bayesian approach for discriminating targets is discussed, and results from both the simulated and measured data are shown in Section 4. Finally we summarize our major findings and suggest areas for future work.

2. MODEL

In this paper, a model-based Bayesian decision-theoretic approach is investigated to discriminate four man-made metal targets of different shapes, sizes and metal types under conditions where the target/sensor orientation is unknown. In order to model the signature of these targets, a method of moment (MoM) analysis is used to predict the theoretical response from the target [8][9]. The theoretical calculations are appropriate for highly (but not perfectly) conducting and permeable targets that can be characterized by body of revolution (BOR), *i.e.* a target that is rotationally symmetric about an axis [10]. The excitation is from a current-loop. Inputs to the model include the exact shape, size, constitutive parameters of the target, and the horizontal and vertical distance from the center of the sensor to that of the target. When the above parameters are specified, the theoretical wideband EMI response can be calculated.

The calculation provides the theoretical induced voltage (magnitude and phase, or in-phase and quadrature components) for each target and frequency considered. Later in this paper, it is shown that by incorporating the model into the detector formulation the classification performance is improved dramatically under uncertain environmental conditions.

3. SENSOR

Using data collected from a prototype wideband frequency-domain EMI sensor, the GEM-3, developed by Geophex, Ltd., the effectiveness of the model is tested and a decision-theoretic discrimination algorithm is applied to both simulated data and real data measured by the sensor. Instead of using a pulse excitation (as is the case for time-domain EMI sensors), the transmitting coils of the frequency-domain EMI sensor send out a complex waveform consisting of a user-defined set of frequencies [7][11]. The sensor records the real and imaginary parts (in-phase and quadrature) of the induced voltage at the receiving coil, relative to that on the transmitting coils. This ratio is multiplied by 10^6, and expressed in units termed parts-per-million (ppm). Thus, sensor output is subject only to the noise at the frequencies of interest, not within the whole frequency band, as is the case for time-domain EMI sensors. Frequency-domain EMI sensors can thereby achieve much higher signal-to-noise ratios (SNRs) compared to time-domain systems. In addition to the improved SNR, it has also been shown that the frequency-domain EMI signatures differ significantly across targets [8], which provides the underlying physical mechanisms important for discriminating, identifying, or classifying targets.

The model output and the sensor output are not reported in the same units. Therefore, the response predicted by the model is converted into ppm. Let $c(\omega)$ represent the calibration constant for frequency ω, the M by 1 vector $\boldsymbol{A}$ represent a set of measurements obtained at several (M) positions, and the M by 1 vector $\boldsymbol{B}$ represent model outputs for the same target and positions. We set $\boldsymbol{B}c=\boldsymbol{A}$, and a least-squares method is used to obtain the calibration constants as a function of frequency.

4. MODEL-BASED RESULTS

The uncertainty inherent in the sensor output for a particular object is not only due to the additive noise, but also the fact that the relative position between the sensor and the target is unknown. In this work, we investigate the classification performance of a Bayesian detector that incorporates modeled wideband EMI signatures as well as orientation uncertainties.

4.1 Problem Setup & Solution

Four metal targets are used for both the simulations and experimental measurements: an aluminum bar-bell, an aluminum disk, a thick brass disk, and a thin brass disk. The diameter of each of these targets is 5.08 cm. The heights of the targets are 2.897 cm, 2.667 cm, 2.34 cm, and 0.3175 cm for the aluminum bar-bell, the aluminum disk, the thick and thin brass disk, respectively. The response from a target depends on the constitutive parameters, geometry of the target, as well as the horizontal and vertical distance from the center of the sensor to that of the target. In the calculations, six frequencies: 3,990, 8,010, 12,030, 14,990, 20,010, and 23,970 Hz are chosen to avoid 60 Hz power disturbances. It is assumed that the sensor is subject to a small amount of additive Gaussian white noise. This assumption is verified by the experimental data. We exploit Bayesian decision theory to formulate an optimal classifier to discriminate these targets.

Since the sensor is subject to noise which is assumed to follow a Gaussian distribution, the distribution of the sensor outputs at a known height and horizontal position is a Gaussian random vector. The mean is the theoretical response and the variance is equal to that of the additive noise. Let H_i represent the hypothesis that the ith target is present, where $i=1,2,3,4$. The received data from the ith target can be modeled as:

$$x_{ij} = A_{ij} + n_j \qquad (1)$$

where j corresponds to frequency, $j=1,2,\ldots,6$, x_{ij} is the received data from the sensor, A_{ij} is the predicted response obtained from model for the ith target at the jth frequency at a known depth and horizontal position relative to the center of the sensor, and n_j is i.i.d. white Gaussian noise with zero mean and variance of σ_n^2. Let q_i represent the *a priori* probability that hypothesis H_i is true. We further assume that the cost of a correct decision is zero, and the cost of any wrong decision equals 1. Bayes' solution for this classification problem [12][13] is to decide that H_i is true if

$$\frac{p(H_i \mid x)}{p(H_k \mid x)} = \frac{q_i p(x \mid H_i)}{q_k p(x \mid H_k)} > 1 \qquad (2)$$

is satisfied for any $k \neq i$, where $p(x|H_i)$ is the probability density or likelihood function of data x given H_i, $p(H_i|x)$ is the *a posteriori* distribution or discriminant function [14], and x is the received data from the sensor at a known position. Assuming the magnitude and phase of the frequency response are independent, x is a vector containing both the magnitude and phase information. Therefore, when sampled data x is received, we decide in favor of hypothesis H_i where

$$q_i p(x \mid H_i) = \max_k \{q_k p(x \mid H_k)\} \qquad k = 1,2,3,4 \qquad (3)$$

Thus, we decide in favor of a hypothesis that has the largest *a posteriori* probability at x among the 4 pdfs. Since we have no *a priori* knowledge on q_i, an equal probability assumption for each target results in $q_i=1/4$. Therefore, the alternative discriminant function [14] is:

$$p(x \mid H_i) = (2\pi)^{-N} |\Sigma|^{-1/2} \exp[-\frac{1}{2}(x - A_i)^T \Sigma^{-1} (x - A_i)] \, (4)$$

where N is the number of frequencies, x and A_i are $2N$ by 1 vectors, and Σ is the covariance matrix of x. Given the assumptions on the noise process, Σ is a diagonal matrix. After taking the logarithm and incorporating the constant into the threshold, the alternative discriminant function simplifies to:

$$\log p'(x \mid H_i) = (x - A_i)^T \Sigma^{-1} (x - A_i) \qquad (5)$$

The discriminant function obtained above is for a known height and horizontal position, and can be implemented as a bank of matched filters. This solution is optimal only under the assumptions that all the parameters are known, and the sensor is subject only to Gaussian white noise.

A more accurate assumption is that the height and horizontal position is uncertain, since the exact position where measurements are obtained is unknown in practice. In this case, the matched filter bank is not the optimal solution. Hence, in order to obtain the alternative discriminant function for the received data, the effect of these random factors must be integrated out, *i.e.*

$$p(x \mid H_i) = \iiint p(x \mid H_i, h, x, y) p(h) p(x, y) dh dx dy \quad (6)$$

where h represents the height of the sensor from the target; x, y represent the horizontal position of the sensor; and $p(h)$ and $p(x,y)$ are the *a priori* distributions of the position factors. Monte Carlo integration was used to calculate this integral.

The performance of both the matched filter bank and the optimal classifier is investigated by using simulations and measurements. The results are shown in Sec. 4.2 and 4.3.

4.2 Simulations

In order to test whether the classification performance is improved by incorporating the model into the classification formulation, several cases, such as 1) fixed position, 2) random height, 3) random horizontal position, and 4) both height and horizontal position random are simulated. Both the matched filter classifier and the optimal classifier are then applied to the data. After obtaining the theoretical model of each target at different positions, Gaussian distributed white noise with parameters similar to those measured experimentally is added to the theoretically predicted values. The synthetic data is generated and the classification procedure as described in Sec. 4.1 is applied.

4.2.1 Fixed Height and Horizontal Position

First, the case where all the position parameters are known exactly is considered. The model of each target at the same position and all desired frequencies is calculated. Then, by adding Gaussian random noise with zero mean and variance of σ_n^2, 10,000 realizations for each target are generated. The decision of which target is present is made based on Eqn. (3) by using the calculation of a matched filter expressed in Eqn. (5). Because of the fact that the wideband EMI signature of these targets is significantly different [8] and the experimentally derived σ_n^2 is low, the performance is perfect.

4.2.2 Height Uncertain, Fixed Horizontal Position

Next, the case where only the height of the sensor from the target is unknown and the target is located under the center of the sensor is considered. This situation occurs in a real detection scenario when the sensor operator can accurately center the sensor, but the burial depth of the mine is unknown. The height of the sensor was modeled as a Gaussian distributed random variable with mean of 15 cm and variance of 1.94^2. Fig. 1 shows the performance of filters matched to the modeled response of each target at the mean height along with that of the optimal classifier. Clearly, substantial improvements in classification performance are obtained by the optimal classifier.

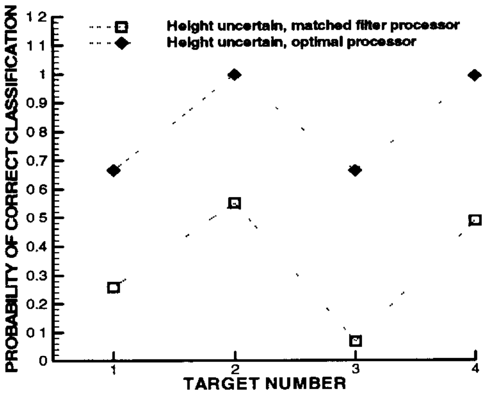

Figure 1. Comparison of matched filters and the optimal processor under uncertain height, fixed horizontal position conditions.

4.2.3 Horizontal Position Uncertain, Fixed Height

Thirdly, we simulated the case where horizontal position is uncertain. It is assumed that the sensor is located at a known, fixed height. Because the exact positions of mines are unknown to the sensor operator during detection, we assumed a uniform distribution in the horizontal plane. Fig. 2 shows the simulation results of the matched filter and the optimal classifier when the horizontal positions of targets are uniformly distributed. Again, the performance of the optimal classifier is substantially better than that of the matched filter.

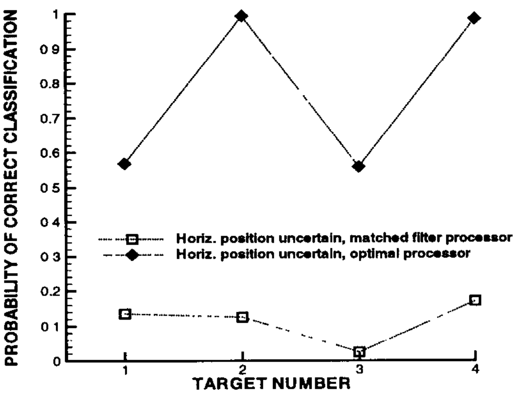

Figure 2. Comparison of matched filters and optimal processor performance under the uncertain horizontal position, but fixed height condition.

4.2.4 Both Height and Horizontal Position Uncertain

In the final simulation, both height and horizontal position are uncertain. The height is assumed to follow a Gaussian distribution with mean of 15 cm and variance of 1.94^2. The horizontal position follows a uniform distribution (within a 20cm by 20cm square). Fig. 3 illustrates the performance of the two processors. The results in Fig. 1, 2 and 3 indicate that for the matched filter bank the performance becomes progressively worse as the position uncertainty increases. Clearly, incorporating the uncertainty of these environmental parameters into the processor affords a significant performance gain over the matched filter.

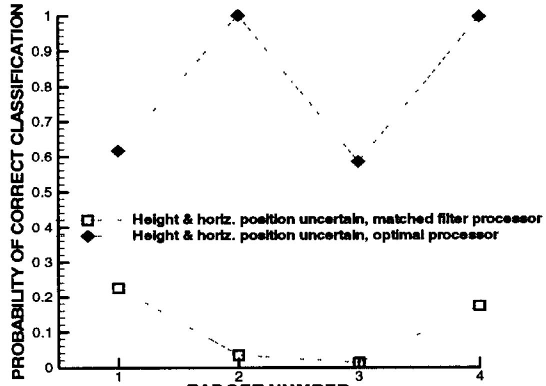

Figure 3. Comparison of matched filter and optimal processor performance when both height and horizontal position are uncertain.

4.3 Real Data

Simulation has shown that performance improvements can be achieved when the environmental uncertainty is incorporated into the detector. To verify this result, real data was collected using the GEM-3. In this sub-section, the results of implementing these processors using the measured data are described.

The measurements were taken in free-space. The GEM-3 was mounted on a wooden rack with the sensor head approximately 1.8 m above the wooden base of a platform. Both rack and platform contained no metal parts. The rack assembly allows placement of a target on a wooden shelf at various distances beneath the sensor head.

In order to convert the theoretical predictions to ppm the measurements with the four targets at known positions were taken so the calibration coefficients could be calculated. Each target was placed beneath the center of the sensor head at distances of 17 cm, 19 cm, 20 cm, 21 cm, and 23 cm. Using these 20 measurements, calibration coefficients were calculated by the least-squares method. Fig. 4 shows the theoretical model predictions and the measurements. As has been noted previously, the model predicts the GEM-3 response well [8].

To obtain the remaining data, measurements were taken at 7 heights from 17cm to 23cm in 1 cm increments. The distribution of height is assumed to be Gaussian with mean of 20 cm and variance of 1.94^2 (the mean is different from the simulation, because for some targets the height cannot be less than 15 cm, otherwise the sensor response saturates). At each height, between 11 and 36 measurements were taken. The exact count was calculated based on the assumed distribution. At each height the position of each measurement is uniformly distributed within a 20 cm by 20 cm square. For each target, there were a total of 328 measurements taken.

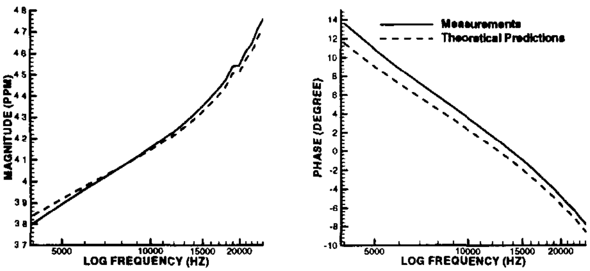

Figure 4. Comparison of measurements and theoretical predictions for the thin brass disk when the distance from the target to the sensor is 20 cm.

Two signal processing techniques are investigated: matched filters that match to the response at the mean position for each target and the optimal classifier that incorporates the uncertainty into the processor. Fig. 5 illustrates the performance of these two methods. Clearly, better performance is achieved by the optimal processor; performance improves on the average by 60%.

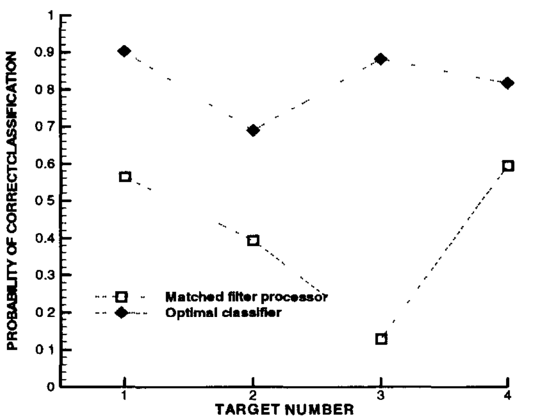

Figure 5. Comparison of matched filters and optimal processor performance under the condition of both height and horizontal position unknown for measured data.

5. SUMMARY

In this paper, we utilize a Bayesian decision-theoretic approach to classify metal targets using wideband EMI data. Four man-made metal targets were used. Results from both simulation and measured data, shown in Sec. 4, indicate that incorporating the uncertainty associated with the target/sensor orientation into the processor affords a significant performance gain over a processor that is matched to the predicted response at the mean expected target position. It is also noted that, as expected under conditions of uncertainty, the performance of both the matched filter bank and the optimal processor drops compared to that of the signal known exactly case. Though the optimal classifier can improve performance under uncertain conditions over matched filters, it will never achieve the performance obtained when no uncertainty is present.

Our preliminary work indicates that we can effectively discriminate different metal targets using wideband EMI signals by incorporating an accurate physical model and uncertainty of environmental parameters into the classifier. Performance can be dramatically improved over the standard approach that ignores environmental uncertainty. The simulations and measurements are performed in free-space; in the future, measurements and analysis from buried targets will be taken.

6. ACKNOWLEDGEMENT

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