TARGET PRIORITIZATION IN TEM SURVEYS FOR SUB-SURFACE UXO INVESTIGATIONS USING RESPONSE AMPLITUDE, DECAY CURVE SLOPE, SIGNAL TO NOISE RATIO, AND SPATIAL MATCH FILTERING

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Abstract

To reduce the number of false-positives in identifying UXOs and related debris for ongoing Site Investigation, a target prioritization routine was developed based on the likelihood of a metallic source. Numerous parameters were evaluated statistically using over 2000 existing intrusive investigation results. Those showing the best ability to discriminate between metallic and non-metallic sources were incorporated into the scheme, including peak amplitude response, power-law decay slope, signal to noise ratio, and spatial match filter response. Parameters were assigned increasing numeric values based on likelihood of a metallic source, and summed to produce a target rank. Subsequent application to over 4000 new intrusive investigations revealed that the highest ranked 25% of targets were nearly five times more likely to yield a metallic source when investigated than the lowest ranked 25%. These results show that target selection routines in UXO investigations would benefit from using more parameters than just magnitude response, allowing more aggressive target identification and reduced costs by lowering the number of false positives that are investigated. Proposed refinements may further increase predictive capabilities.

Introduction

Background

Time Domain Electro-Magnetic (TEM) methods are widely used in surveys for unexploded ordnance (UXO). Since typically most anomalous TEM responses are not associated with UXOs, significant effort in recent years has been directed towards discriminating the source of anomalies. The question of which responses should be targeted for intrusive investigation remains open.

Often surveys will simply target all responses that exceed a specified amplitude for a given time-gate after the pulse. This results in the selection of numerous responses that physically do not correspond to a subsurface metallic source. Further, some responses that are due to a subsurface metallic source can be missed because the peak amplitude does not exceed the specified threshold. An ongoing Site Investigation (SI) for UXO provided an opportunity to develop a target prioritization scheme to discriminate between metallic and non-metallic and thus, help to reduce the number of ‘false positives’ (i.e., no metallic source could be identified after intrusive investigation of a given target).

Objectives

Several issues specific to our SI led to the development of a ranking process to help prioritize which previously targeted responses should be dug first. The overall project objective is to delineate areas of military use that might result in UXO hazards, such as target areas used for live fire exercises. This means that the primary geophysical target is munitions fragments (frag) scattered mainly in the shallow subsurface. Frag are typically very small and difficult to detect because their responses are often indistinguishable over background noise levels.

Aggressive target selection in the initial ~2000 intrusive investigations resulted in a large number of false positives. Most of the targeted responses returned as false positives have been attributed to noise rather than a metallic source. Background geology comprises a significant noise source, including magnetically polarized rocks that also precluded the use of magnetometers for data acquisition. Although less influenced than magnetometer systems, higher TEM noise levels correlated with areas of exposed bedrock and larger magnetic gradients observed using handheld magnetometers. Additional noise sources include a nearby high-powered radar array and high voltage power lines transiting portions of the SI area.

Investigation of only a portion of anomalous responses is required as part of the SI, and the 'dig teams' are directed to leave an area once any UXO or munitions related items are recovered since a determination of military use for that area can be made. Therefore, prioritizing targets most likely to have metallic sources significantly reduces cost by finding munitions related items more quickly, allowing teams to move on into the next area. It also improves overall confidence in the SI results by ensuring that possible munitions related items are not missed because of limited sampling among potentially numerous false positives.

Instrumentation

TEM data were acquired along widely spaced transects using hand pulled Geonics EM 61 Mk 2 cart systems with coincident rectangular transmitter and receiver coils measuring 1 x 0.5m. Data were collected at 10 Hz at the four available time gates (216, 366, 660, and 1260 μs) using only the bottom receiver coil. Additional test data were acquired using the Zonge Dynamic nano-TEM (DNT) 1 x 1m three-component configuration sampling at 64 Hz across 31 time gates. All data were collected at an ordinary walking pace or slower, with difficult terrain (e.g., rock outcrops, steep slopes, and rutted drainages), generally avoided. Data were processed to include interpolated RTK GPS locations. Data leveling, along with the removal of instrument drift, and longer period background responses, was accomplished using a 100 fiducial demedian filter.

Method

Given the huge range of possible characteristics for frag due to their varied shape, size, orientation, and depth - and the limited discrimination/ modeling potential of TEM data collected across only four time gates, we decided to focus on distinguishing between metallic and non-metallic sources. The simplest approach would have been to prioritize responses based on the highest peak amplitude. However, this would bias our sampling away from the small, difficult to detect frag that are the primary geophysical target. Instead, we applied a statistical approach to identify parameters useful in distinguishing between metallic and non-metallic sources. Using available intrusive investigation results from the SI (approximately 2000 records), we selected four parameters as the basis for prioritization: peak amplitude response, power-law decay slope, signal to noise (SNR), and a spatial match filter response.

Peak Amplitude Response

Peak amplitude responses were calculated using a temporal matched filter based on a simplified Pasion-Oldenburg model (Pasion, 1999 and 2001). The transient from a typical UXO can be modeled by

$$\frac{\partial B}{\partial t}(t) = \frac{k}{(a-t)^b} \tag{1}$$

at the EM 61 Mk2 time gates, where a = 0, b = 1 and t is set to the time-gate values. A linear least-squares inversion for the magnitude parameter k can be calculated ahead of time, effectively creating a set of weights (k/t) for a temporal matched filter. The filter coefficients were normalized to scale the filter output to the equivalent of a transient model response at the third time gate (660 μs). Once a set of filter coefficients were established, a peak amplitude response R could be quickly calculated as,

$$R = \sum_{i=1}^{4} w_i \cdot d_i \tag{2}$$

where d_i and w_i are respectively, measured data and temporal matched filter weights for each of the four time gates. Summing all four time gates together acts to reduce noise, and using the modeled weights tends to equalize the contribution from each time gate where an un-weighted sum would be dominated by the earliest time gate.

Power-Law Decay Slope

This parameter is calculated based on fitting the exponent in the power law decay relation with the measured data. The relation,

$$\frac{\partial B}{\partial t}(t) = kt^{-b}, \tag{3}$$

the same as Eq. (1) where a = 0 for the EM 61 Mk 2, models the change in the measured decay $\partial B/\partial t$ as a straight line in log/log space, with slope -b (larger b values correspond to a faster decay) and an intercept k. The slope –b is calculated independent of k using linear regression to find a 'best fit' line in log/log space.

Signal to Noise Ratio

Using the simplified Pasion-Oldenburg transient model used for the temporal matched-filter, model values for k are calculated at each record for an assumed b. "Noise" is characterized as the sum of squared differences between transient model and measured data values, while "signal" is characterized as the sum of squared transient model values. The ratio is reported as a signal to noise ratio percentage:

$$SNR = 100 \cdot \frac{\sum (m_i)^2}{\sum (d_i - m_i)^2} \tag{4}$$

Spatial Match Filter

The spatial match filter uses the measured response generated by a 37 mm seed at 19" depth (at the limit of our detection capability) as the basis for a band-pass spatial convolution filter. The filter shape is loosely based on a sinc function, with the seed response as the central peak and troughs of the same width and ½ the amplitude on both sides of the peak such that the integral across the entire filter is zero. The effect of the filter is to amplify small, discrete responses with wavelengths less than the seed response, and smooth broader responses more typical of geologic or instrument noise.

Prioritization

To generate the prioritization scheme used by the dig teams, the potential range of values for each parameter were first divided into four ranks based on the statistical association that the parameters values had shown to metallic sources. The ranks were then assigned a letter value, A, B, C, or D, with A being most likely to contain a metallic source and D being least likely. Typically, the 'A' rank was assigned to eliminate roughly 85% of false positive responses while still identifying about 50% of the metallic sources. The 'D' rank was assigned such that only 15% of the metallic sources remained, with roughly 50% of the 'false positive" responses remaining. The remaining range was spread across the two middle categories.

The four ranks were then assigned numeric values and summed together to produce a combined prioritization parameter. The potential range of values for the prioritization parameter was divided into four roughly equal categories, and also labeled A, B, C, or D following the parameter ranking, to create a priority level. A simple sum of the parameter ranks was chosen because despite some differences, the parameters were relatively uniform in their ability to distinguish between metallic and non-metallic sources. Interestingly though, as shown in Table 1, the best discriminator (highlighted in bold) was not the peak amplitude response; instead, the power-law decay slope proved to be best at identifying which responses had non-metallic sources.

Table 1: Percentage of non-Metallic Sources by Parameter and Rank

	Peak Amplitude Response	**Power-Law Decay Slope**	**NSR**	**Spatial Match Filter**
A	24%	32%	24%	19%
B	66%	42%	45%	45%
C	72%	65%	57%	60%
D	71%	**90**%	71%	73%

Results

After development of the prioritization scheme, another 6000 targets have been intrusively investigated. Targeted responses from the top priority, A, were at least five times more likely than the lowest priority to have a metallic source (see Figure 1). The number of targeted responses falling into each priority is roughly equal. However, after introducing prioritization, roughly 40% of the targeted anomalies actually investigated were from the top priority, resulting in an estimated 1500 fewer intrusive investigations over the SI.

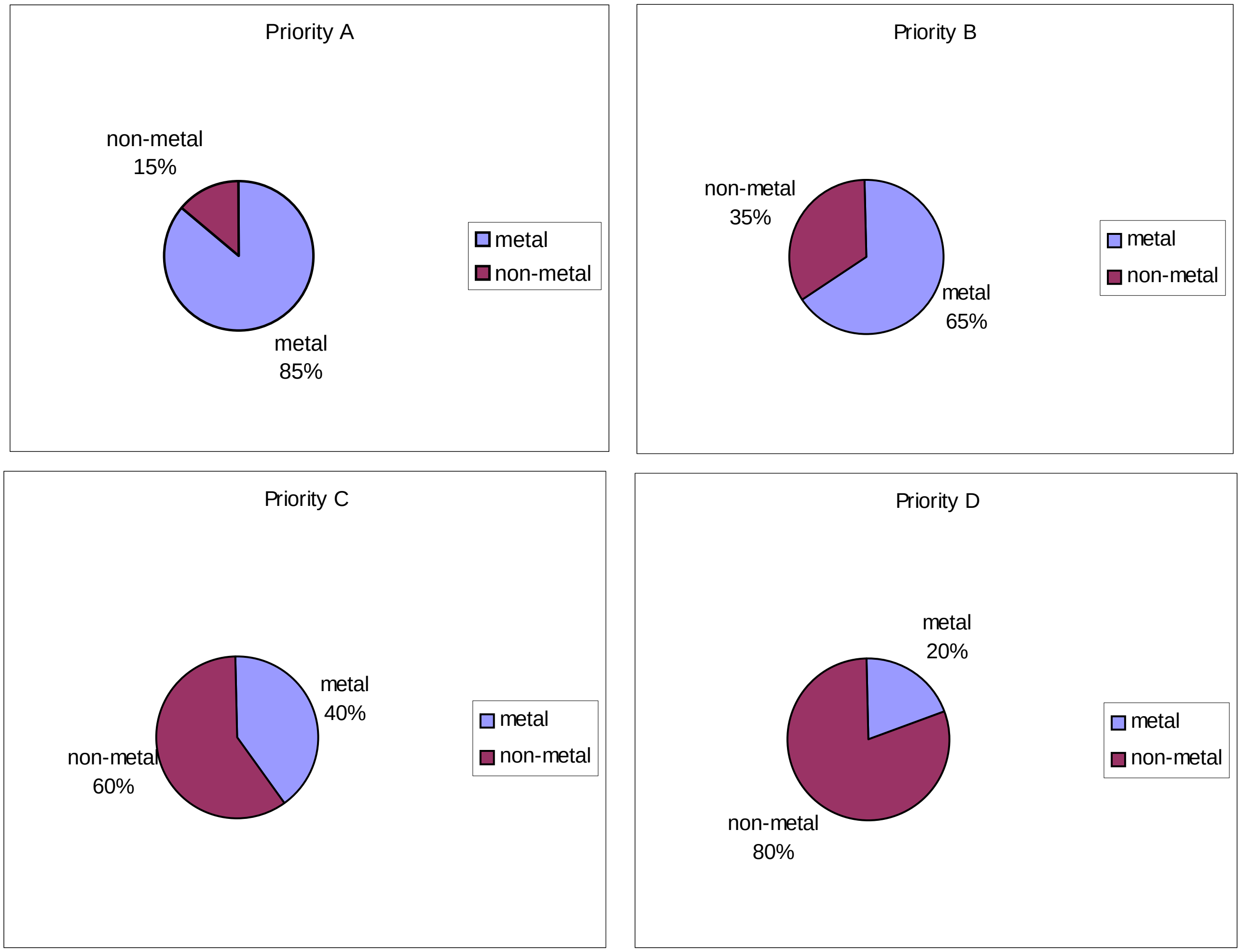

Figure 1: Percentage of metallic and non-metallic sources found for each priority level.

Current Research

Power-Law Decay Slope Modeling

Two of the four parameters in our prioritization scheme, including the one that best discriminates between metallic and non-metallic sources, depend on calculations of power-law decay slope (b). This suggests a possibility that power-law decay curve slope and/or modeling based on this relationship may be a better tool than response amplitude in identifying subsurface metal. Unfortunately, the EM 61 Mk 2 system – the industry standard- records a maximum of only 4 relatively late time gates, thus limiting our ability to fully explore its potential.

To pursue this line of research, we have collected test data using the DNT system, which offers 31 time gates including responses much earlier in time than are otherwise available. These early time responses are particularly valuable in helping to identify small, shallow sources. Figure 2 depicts typical DNT test data plotted in log/log space to show the linear relationship as predicted by the power-law decay model. At later times (not shown due to negative values), the slope becomes flat as constant background noise overwhelms the decaying signal. In this example, the response is mostly lost in the noise by the later time gates available with the EM 61 Mk 2. Also apparent is a distinct break in slope near the middle of the plotted curve, suggesting that a more complete Pasion-Oldenburg model is needed to model transient shapes.

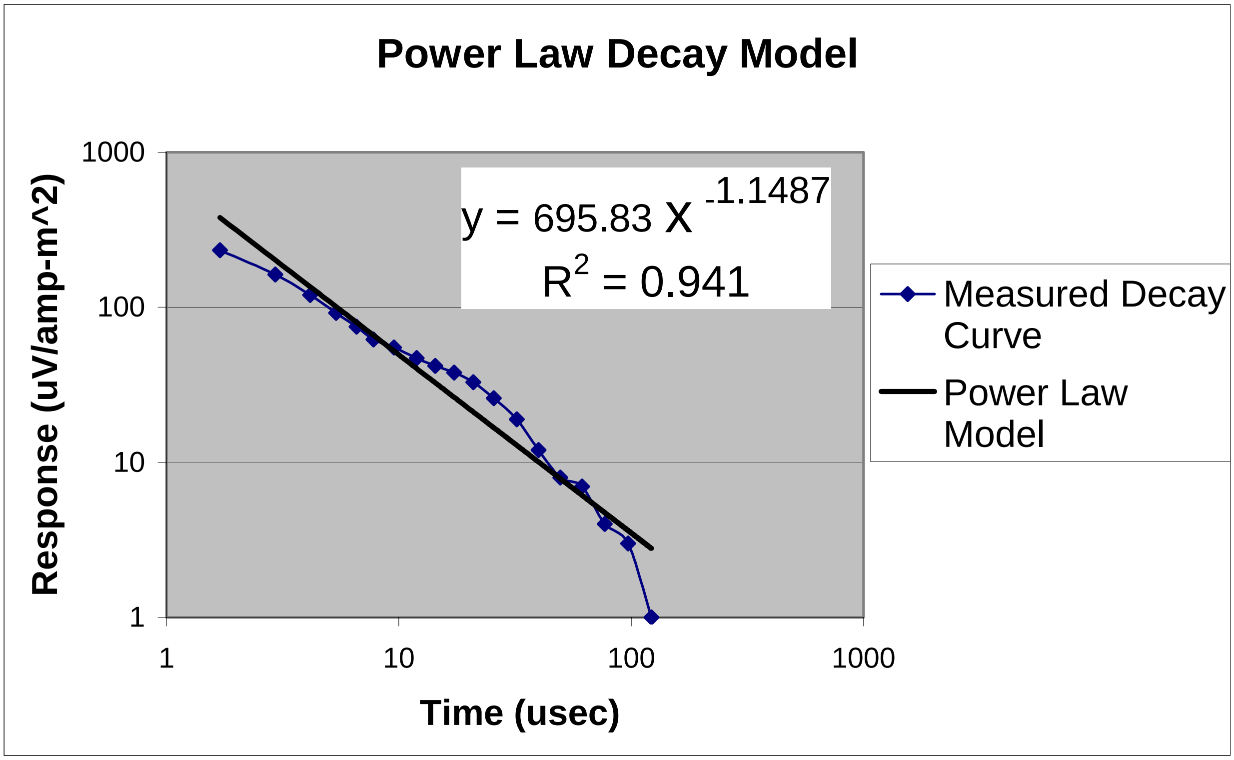

Figure 2: Typical DNT data, plotted in log response vs. log time. The diamonds are measured data, and the solid heavy line linear best fit. The equation matches the power law decay formulation given by Eq. (3), with the slope given as the exponent. R^2 is a measure of the quality of fit and is analogous to the SNR parameter.

Noise Sensitive Thresholds

Most of the target selection in our SI targeted responses that exceeded a 'noise sensitive' threshold, rather than the more typical 'fixed' threshold. Noise levels in TEM data often vary dramatically as a function of location, the result of geologic and cultural sources often grouped together as 'site conditions'. The goal in developing a noise sensitive threshold was to only target higher amplitude responses (or other parameter being used for target selection) in noisy areas, while targeting much weaker responses in less noisy areas.

The simple example used in our SI can be represented mathematically as

$$Target\ if\ 0 \leq Data - C_N\left[Std(100) - |Mean(100)|\right] - C_I \qquad (5)$$

where *Std*(100) and *Mean*(100) are rolling statistics, standard deviation and mean respectively, that are calculated over a 100 data record widow at each data record. Taking the difference between the standard deviation and absolute mean is a simple way to quantify noise over a small window of data. The noise threshold and instrument threshold constants, C_N and C_I respectively, also have some physical basis. C_I is based on the amplitude of the noise when the instrument is not moving; it represents the resolution of the static instrument for detecting anomalous signal. C_N marks the level above which a particular response is likely not to be randomly generated noise, but rather indicative of an anomalous source.

Conclusions

Target selection and discrimination between possible sources for UXO investigations using TEM surveying remains a challenging area of research for geophysicists. Our relatively simple approach to prioritizing targets yielded significant benefits, and several avenues of further work remain open. Power-law decay curve modeling in particular shows promise towards improving target identification and discrimination. However, current industry standard tools do not collect enough data to fully exploit the possibilities of this approach. There are potentially significant cost savings to be gained developing and exploiting a new generation of data acquisition and targeting identification tools capable of collecting and interpreting richer data sets.

References

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