A Survey of Modern Signal Processing Methods and their Application to Ground Penetrating Radar to Sustainable Humanitarian Demining

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Abstract: This paper surveys several modern signal processing methods which may be applied to the problems of detecting and classifying minimum-metal anti-personnel (AP) land mines. The methods are applied to measured Ground Penetrating Radar (GPR) responses of two common and widely-used AP mines. Preliminary results of this on-going research, obtained from GPR responses of T72 and PMN-1 mines buried in sand and soil indicate that time-frequency representations (TFRs) may provide valuable information which, if applied to a competitive neural network, may facilitate identification/classification of the buried object. Additional signal processing methods are discussed as potential candidates for the mine detection/classification problem. Although the methods herein are applied to GPR data, they are not limited to that application, but can also be applied to infrared (IR) and other sensors.

Introduction

Detecting and classifying minimum-metal mines buried in sand and soil offers considerable challenges for signal processing algorithms. The clutter background is severe and the medium is lossy and dispersive. The mine detection equipment used for sustainable humanitarian demining is often constrained to be portable. The equipment should provide the operator with reliable information with which a decision may be made. Signal and image processing algorithms used for such demining must aid the operator in achieving very high levels of detection, currently 99.6 to 99.9% [1],[2]. False alarm rates must also be reduced. False-alarm rates in Afghanistan, for example, approach 1,000:1 [3], using manual means.

Technical means of detecting buried objects have shown a consistently poor ability to classify the object into categories of threatening and non-threatening objects. For example, three Advanced Technology Demonstrations (ATDs) for unexploded ordnance (UXO) detection conducted at the U.S. Jefferson Proving Ground (JPG) between 1994 and 1997 showed “In general, demonstrators lack a capability to distinguish ordnance and the emplanted nonordnance....” [4].

GPR Measurements at EPFL/DeTec

GPR can be used for detecting buried land mines ([5],[6]) and GPR measured data are used for the analyses in this paper. However, these analyses can also be applied to any other type of sensor, including magnetic induction, infrared, etc.

Portions of the radar data used for the analysis in this report were collected at the École

Polytechnique Fédérale de Lausanne (EPFL) Demining Technology Program (DeTec) laboratory, by laboratory personnel. The equipment used is the commercial SPRScan pulse radar produced by ERA Technologies, LTD. A detailed description of the experimental set-up is described in [7]. These data and MATLAB m-files with which to read the SEG-2 formatted data files are freely available from http:\\diwww. epfl.ch/lami/detec.

Each mine file consists of 21 stacked B-scans taken at 2.0 cm intervals for a total swath width of 42 cm. For the analysis presented here, only the first 20 B-Scans are used. Each B-Scan consists of 98 A-Scans, with each A-Scan taken every 1.0 cm. The number of signal samples for each A-Scan is 512 with an effective sampling rate of 40 GHz. Thus the time resolution for each A-Scan is 25 picoseconds (ps), and the total time duration is 12.8 nanoseconds (ns). The layout of the grid is shown in Figure 1. The data for this report are from either the x- or y- scan direction, given by the file names on the following plots.

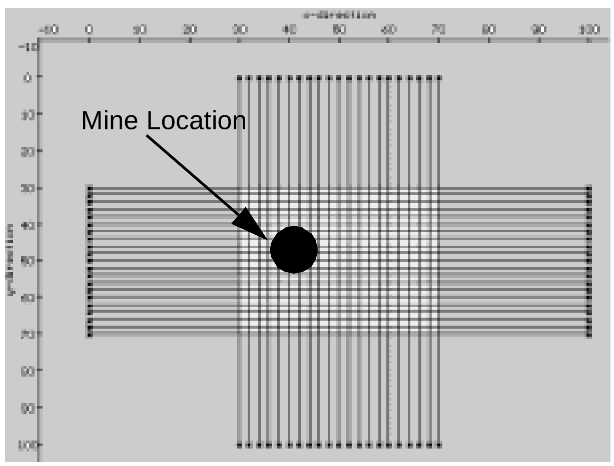


Figure 1. Perspective of DeTec Sand Box Scan Grid

Two types of AP mines are considered: The T72 and the PMN (Figure 2). The T72 mine is a small cylindrical plastic mine with diameter of 78 mm and a height of 37 mm, and contains 34 g of explosive. The PMN mine is widely used, and is a minimum-metal mine with a diameter of 112 mm and a height of 56 mm, and contains 240 g of TNT. The metal retaining cap is not available for the radar scans in this paper.

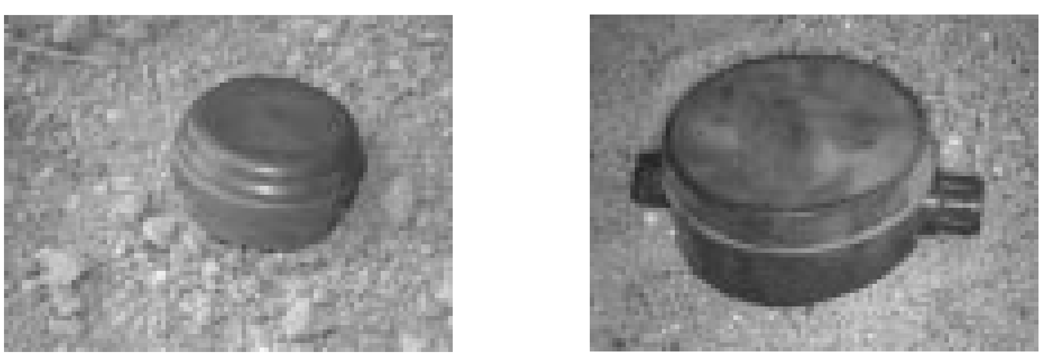
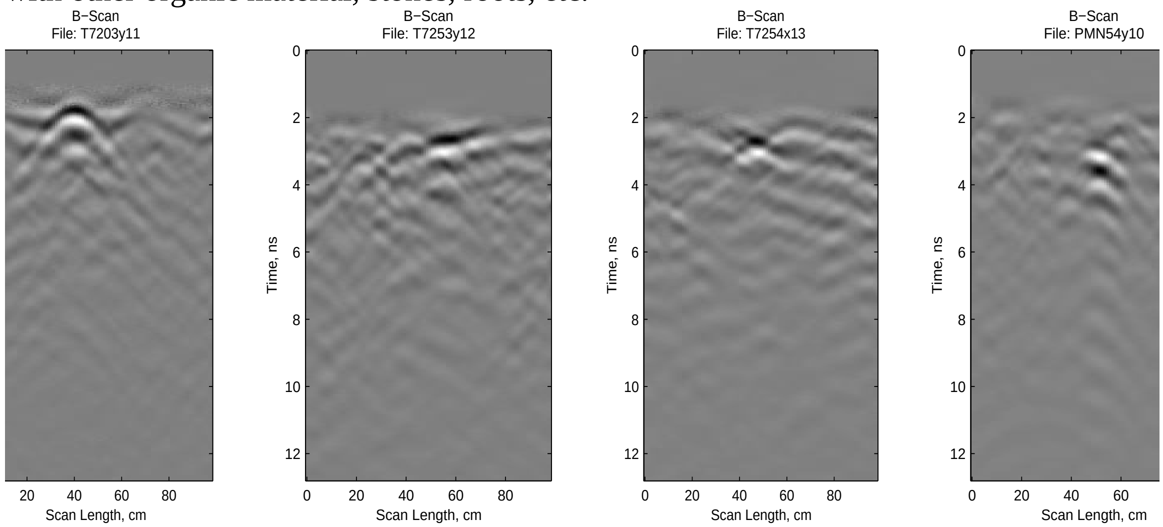


Figure 2. Type 72 Anti-personnel Mine, Left, and PMN Mine, Right

Figure 3 shows typical B-Scans of the two mines buried in two types of media. The T72 in image (a) is buried in sand, whereas the other three images show the mines buried in soil. The image of the mine in sand shows a clearly defined hyperbola [5], whereas the images of the mines in soil do not. Sand is more homogeneous than soil, the latter being mixed with other organic material, stones, roots, etc.



a. b. c. d.

Figure 3. Typical B-Scans for: T72 in (a) 5 cm Sand, (b) 5 cm Soil, (c) 10 cm Soil. PMN (d) in 10 cm Soil

Figure 4 shows successive C-Scans of the T72 corresponding to Figure 3(b), while Figure 5 and Figure 6 represent the C-Scans of Figure 3 (c) and (d), respectively. A C-Scan is produced by taking a specific time slice from the collection of B-Scans, and plotting the intensity in the form of an image. These C-Scans are represented as a 3-dimensional surface to highlight the texture of the plot. Each plot represents a 40cm-by-98cm scan grid, as shown in Figure 1. Each figure consists of three time slices. The first time slice represents the first peak value observed in the mine response; the second represents the minimum response, and the third time slice is the second maximum response. From Figure 3, there are several additional fluctuations, but, in all cases observed so far, the first two dominate, and may be easily determined by observing the modified C-Scans

In a laboratory situation, when the soil or sand is nicely homogeneous, such well-defined peaks and valleys are common, and one may be led to draw conclusions about algorithms which show promise based on “pattern analysis”. One may conclude, for example, that surrounding clutter does not have the same characteristic as does the mine response. In the “real world”, however, there are more subtle effects, as shown in the next section.

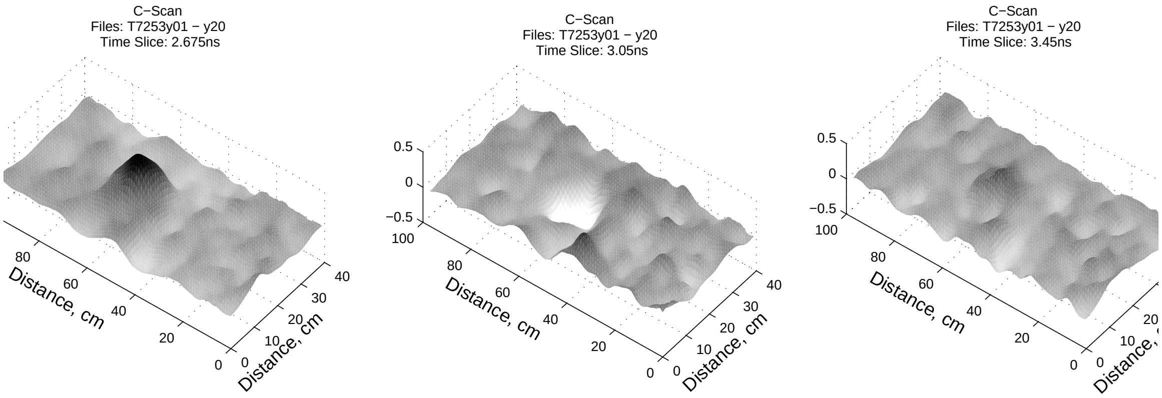


Figure 4. C-Scans for Type T72 Mine Buried 5 cm in Soil

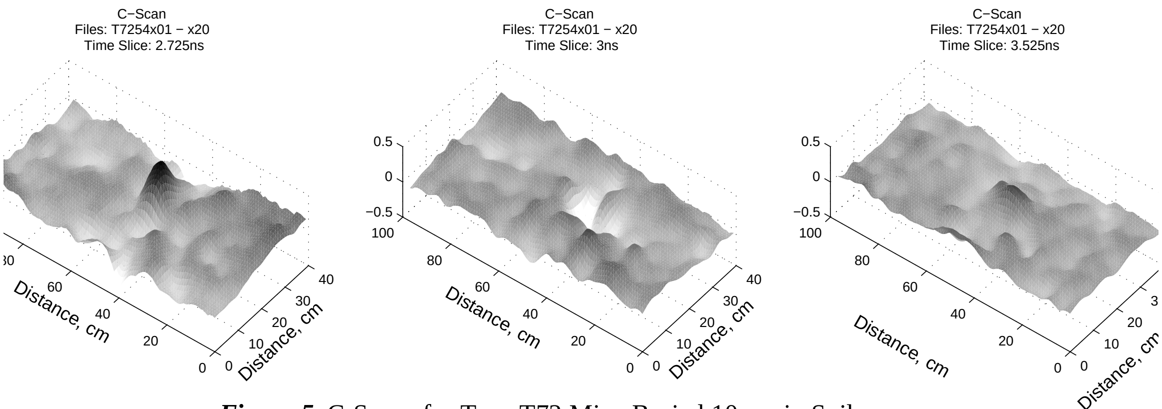


Figure 5. C-Scans for Type T72 Mine Buried 10 cm in Soil

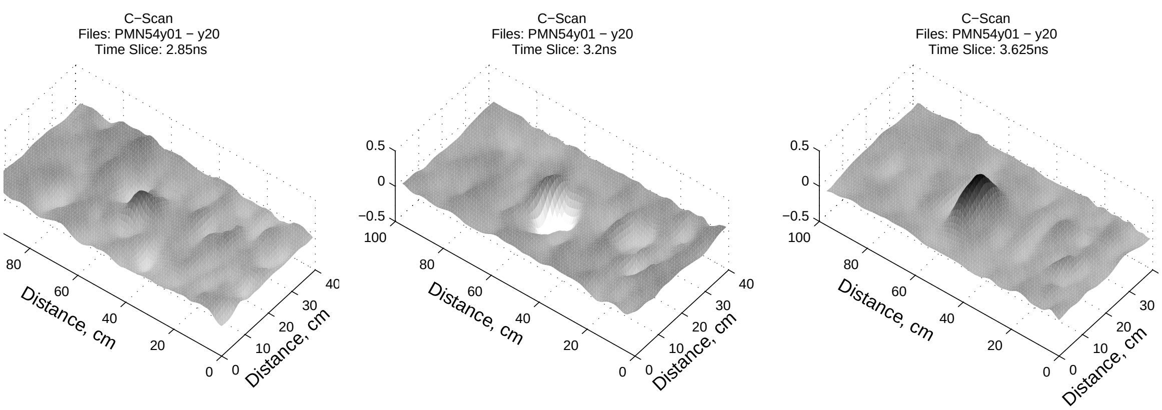


Figure 6. C-Scans for Type PMN Mine Buried 10 cm in Soil

SIGNAL PROCESSING APPROACHES

For the remainder of this paper, only the laboratory data is considered; efforts are currently underway to address the field data, and results are not yet available. The methods described here may not be appropriate to the analysis of the field data.

Several innovative advances have been made in the field of signal processing over the last decade. The long-time mainstay of signal processing, Fourier analysis, while still useful, is limited by the inability to localize events within a signal in both the time and frequency domain. Classical image processing, while offering more flexibility, also suffers from some of the same limitations.

To attempt to minimize the false alarm rate while maintaining a high detection rate, automatic target recognition (ATR) algorithms are often implemented. The basis for ATR is the determination of a set of measurable features (“feature vectors”) which characterize the target uniquely. For example, the size and/or shape of an object may be used to identify it. Other examples include electromagnetic resonances. In this case, the feature vectors are the ordered pairs representing the locations of the resonant poles in the complex frequency plane. Other features may be a particular pattern in the time-frequency plane associated with a wavelet decomposition of the return signal or image which is found to uniquely identify a particular target.

In the following sections, a number of detection/classification schemes are introduced, with special emphasis on the processing of the measured data presented in the previous section. The depth of technical detail, however, must remain rather shallow due to space constraints. The reader is encouraged to examine the references at the end of this paper. [8]-[12].

Time-Frequency Methods

The localization of a specific frequency at a particular time is the basic principle of time-frequency analysis [13],[14]. The wavelet transform is a subclass of the general class of time-frequency domain analysis. It can be shown that the human ear is mathematically equivalent to a wavelet transformer [15].

The wavelet transform ([13]-[27]) is proving to be a highly useful tool in signal and image analysis, with hundreds of papers presented on the subject. The International Society for Optical Engineering (SPIE) has devoted four conferences on wavelet applications to date [20].

Consider the continuous Fourier Transform,

$$(\omega) = \int_{-\infty}^{\infty} f(t)e^{-j\omega t}c \tag{1}$$

is taken over all time. The details of exactly when certain events take place, and the effects of those events on the signal, are smeared over the duration of the signal. This is due to the infinite support, or time duration, of the exponential kernel $e^{-j\omega t}$.

The continuous wavelet transform (CWT) [16] is

$${}_{\psi}(b, a) = \frac{1}{\sqrt{|a|}}\int_{-\infty}^{\infty} f(t)\psi\left(\frac{t-b}{a}\right) \tag{2}$$

where the wavelet kernel $\frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right)$ has replaced the exponential kernel $e^{-j\omega t}$ of the FT, and is specified to have finite support, or finite duration in time and bandwidth. Thus, by scaling and shifting the wavelet, selective portions of the time-frequency plane may be analyzed.

Several approaches may be applied in the analysis of the mine data with the purpose of developing a detection/classification scheme. One-Dimensional analysis may be applied to the he individual A-Scans or slices of the C-Scans. 1- or 2-D analysis may be applied to the B-Scans or C-Scans. This is clarified in the following examples.

Wavelet Packet Analysis of T72 Mine

Wavelet packet analysis ([21]-[23]) is an extension of the standard WT method. A wavelet packet breaks the time-frequency plane into smaller, more refined sections and permits even better localization of a signal event than does the WT. Wavelet packets do not preserve some of the orthogonality aspects of the WT, but are better suited to the analysis at hand. The approach of Donoho, et. al. [22] is applied to the 1-D analysis in this paper. MATLAB m-files, Wavelab 0.701, are available free at http://playfair.stanford.edu/~wavelab/. The Mathworks also sells the Wavelet Toolbox for MATLAB, which was used in the 2-D analysis presented here.

To assess the presence of the T72 mine, and to discriminate against clutter, the T72 mine in 5 cm sand and at 10 cm soil (Figure 5) were selected for the current analysis. The T72 was selected to be a “worst-case” detection/discrimination scenario due to its’ size.

Wavelet packet analysis was applied to consecutive 1-D slices of the C-Scan at the mine location and also to a representative clutter slice, as shown in Figure 7.

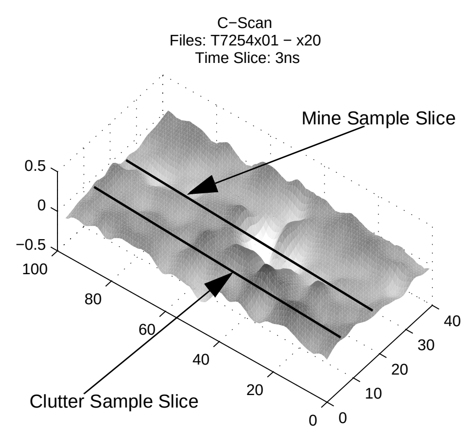


Figure 7. Selection of Mine and Clutter Slice

A Fourier power spectrum of both mine and clutter slices was produced; the clutter and mine power spectra are quite similar, making discrimination based on Fourier techniques problematic.

Figure 8 shows the localization behavior of the wavelet packet analysis. The clutter signal (top plot in each figure) is more evenly distributed throughout the scan length, but the mine signal shows a local intensity at the second scale in both cases (arrow). Extending this approach to classifying the target will require considerably more research; however, the approach appears promising.

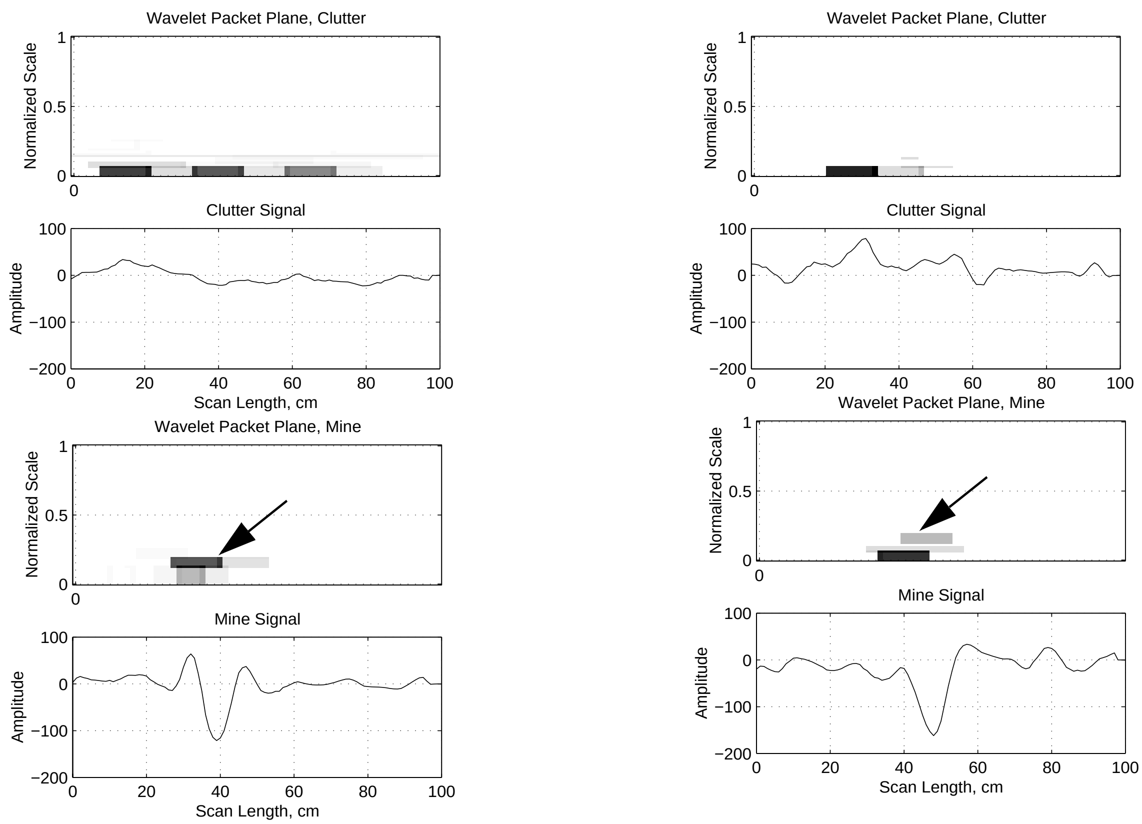


Figure 8. Wavelet Packet, T72 Mine 5 cm Sand (Left) and10 cm Soil (Right)

Wigner Transform Analysis of T72 Mine

The Wigner (Distribution) Transform (WD) [13], [14], [24] is another subclass of time-frequency analysis. The WD is classified as a quadratic time-frequency representation (TFR) [14], whereas the WT is a linear TFR. Because the WD is a quadratic function, it contains cross-terms which are usually undesirable. The Choi-Williams modified WD removes these cross-terms, and is used in the following analysis.

Figure 9 show the WD corresponding to the two cases analyzed above. The different patterns in the t-f plane between the clutter signal and the mine signal are not so distinct in the heavy clutter case when the mine is 10 cm in soil. Additional work is necessary to refine the results.

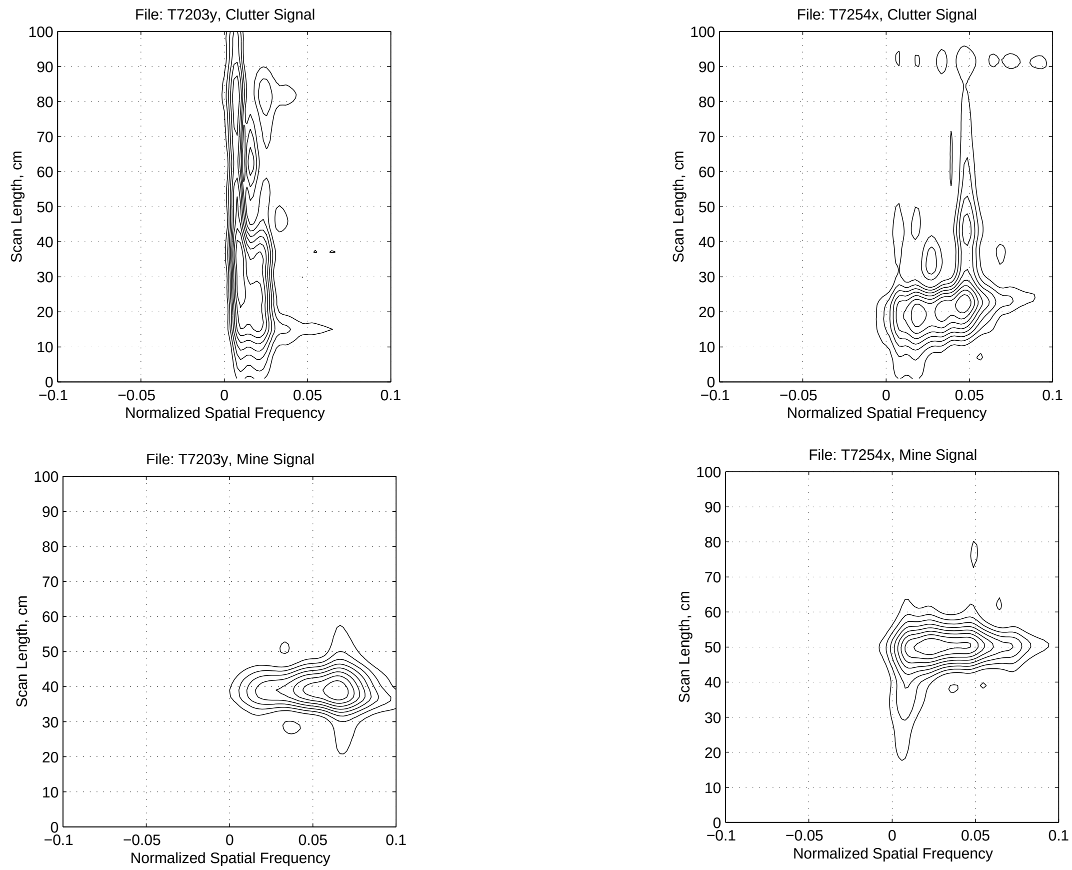


Figure 9. WD of T72 in 5 cm Sand (Left) and 10 cm Soil (Right)

2-D Wavelet Decomposition of Mine Data

The previous sections described 1-D time-frequency analysis methods applied to radar scans within a specific time slice of the C-Scan. Such techniques require that each of the (in this case, 20) parallel radar scans be processed (Refer to Figure 7). There are now very fast algorithms which perform the DWT, so it is possible that such a 1-D analysis approach is acceptable. This section presents 2-D processing applied to the C-Scans; conventional image processing techniques and the 2-D DWT.

The 2-D wavelet transform (2-D WT) extends the basic principles of wavelet analysis to an image. The 2-D WT decomposes an image into a set of low-frequency coefficients and high-frequency detail coefficients for the horizontal, vertical and diagonal components of the original image. If there is noise in the image which is preferentially oriented, it will show up in the detail coefficients of the decomposed image.

Figure 10 shows these effects on a sample of C-Scan for the T72 mine buried in 10 cm of soil. The axes are not labeled, as the numbers are the indices of the wavelet coefficients. (The dark stripes on the detail subimages are artifacts of the decomposition process.) The "approximation" or low-frequency subimage in the upper left corner of the figure can be used in an automatic detection/classification algorithm; the coefficient values represent the feature vectors of the image. An additional decomposition of the image will reduce the number of wavelet coefficients in the approximation image further, thus reducing the processing for the classification unit (neural network, etc.). The 2-D WT accomplishes this reduction of processing load while maintaining good retention of features.

The mine image does not appear perfectly round because the original image is not square; it is 40 x 98, so the approximation coefficients will reflect this aspect ratio.

Figure 11 shows the 2-D wavelet decomposition of the PMN mine buried in 10 cm of soil. The high-frequency quadrants now begin to display faint images of the mine. Thus, the detail coefficients may possibly be used as a further discriminant to identify/classify targets.

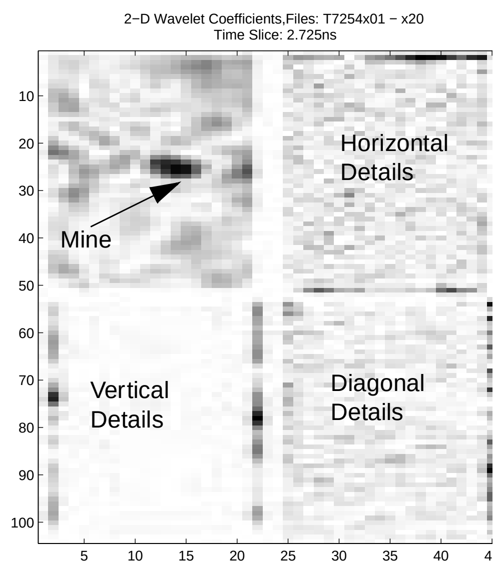


Figure 10. 2-D WT Decomposition of T72 Mine
10 cm Soil

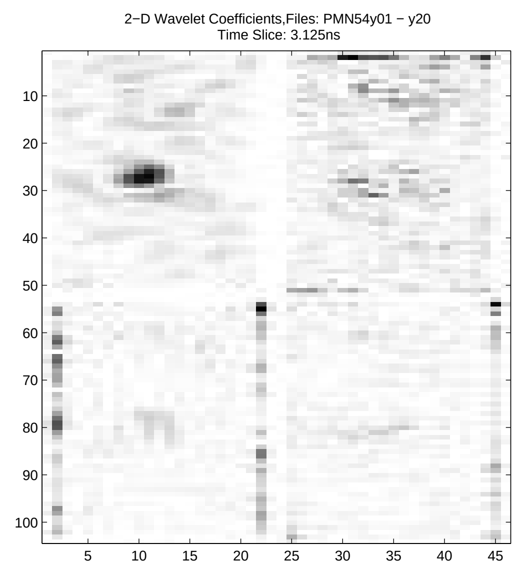


Figure 11. 2-D WT Decomposition of PMN Mine in 10 cm Soil

ADDITIONAL PROCESSING METHODS

Electromagnetic Resonance Methods

In 1971 Baum [28] postulated that the solution for electromagnetic interaction of currents due to an incident field, and the resulting scattered fields, could be formulated in terms of the singularities (poles) of the current distribution in the complex plane (The Singularity Expansion Method, or SEM). A key result of this postulate is that the pole locations, and resulting summation of exponentially damped sinusoids in the time domain, would be invariant with target orientation relative to the radar. SEM parameters for conducting bodies of revolution (BOR) were determined [29]-[31], and a classification method was devised in [32], [33] which permitted the discrimination between two classes of conducting BOR. Studies of SEM parameters applied to dielectric materials have been conducted [34]-[36], but, as shown in [37], the SEM parameters of conducting BOR vary considerably with burial depth when the object is placed in a lossy dispersive medium such as the ground. Additional research is required to determine whether electromagnetic resonances are a viable means of detection/classification of buried objects.

Bispectra and Cumulant Methods

The bispectrum is a subset of higher-order spectral (polyspectra) analysis ([38]-[44]). The bispectrum has been proposed for detection of buried dielectric objects [43],[44]. The bispectrum, defined as the Fourier transform of the third-order cumulant of the data set, suppresses additive noise which has a symmetric probability distribution function. Thus, Gaussian noise is automatically suppressed when the Bispectrum of a signal is calculated. The bispectrum is often used in radar array analysis to suppress false targets which appear as a result of correlated clutter effects. Higher-order spectral analysis was applied to the mine data sets, but no conclusive results were obtained. Additional research is proceeding to determine the utility of these methods

Neural Network Applications

Each of the techniques described above may be applied to a classification/target identification processor [25]-[27]. A series of controlled experiments would need to be conducted in order to develop a set of templates for each mine type, and also for different types of potential false targets such as debris, etc. The features of the target under investigation would then be compared to the library of templates in order to make a decision regarding the identification of the target.

Neural networks have become prominent in target classification research within the past decade. In particular, learning vector quantization (LVQ) as a type of competitive network shows considerable promise for the task of mine detection and classification ([45]-[49][49]). LVQ trains a competitive network in a supervised manner, and is able to identify a class which is represented by disjoint or non-intersecting feature vectors.

Conclusions

This paper has presented a number of modern signal processing methods which are subjects of current research for sustainable humanitarian demining purposes. Time-Frequency representations, combined with neural networks, are technologies which show considerable promise in the challenging problem of detecting and classifying minimum-metal mines. Additional research is currently underway to determine performance bounds for the methods described herein.

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