In this program, we investigated basic questions of interest to NVESD regarding landmine detection phenomenology, and developed algorithms for robust landmine detection for a variety of sensors, with primary focus on NIITEK radar based sensors. We have developed a highly effective “pre-screener” algorithm that has been tested on several field sites, blind tests, and several offroad sites. The performance of the algorithm on the blind tests were outstanding, and in conjunction with the radar showed one to two orders of magnitude improvement in false alarm rates over other deployed systems. This prescreener has been transitioned to NIITEK so that they can code it in their real-time processing system. We also
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List of papers submitted or published that acknowledge ARO support during this reporting period. List the papers, including journal references, in the following categories:

(a) Papers published in peer-reviewed journals (N/A for none)


Number of Papers published in peer-reviewed journals: 7.00

(b) Papers published in non-peer-reviewed journals or in conference proceedings (N/A for none)

Number of Papers published in non peer-reviewed journals: 0.00

(c) Presentations


Number of Presentations: 2.00

Non Peer-Reviewed Conference Proceeding publications (other than abstracts):


Number of Peer-Reviewed Conference Proceeding publications (other than abstracts): 23

(d) Manuscripts

Number of Manuscripts: 0.00

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### Student Metrics

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Number of graduating undergraduates who achieved a 3.5 GPA to 4.0 (4.0 max scale): ...... 1.00

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Sub Contractors (DD882)
Statement of the problem studied

The primary focus of this work is on developing robust algorithms and algorithm fusion architectures to reduce false alarm rates and improve detection rates for landmines. Two major systems were studied, the AMDS system and the GSTAMIDS/HMDS GPR. In the EMI-based systems, false alarm reductions were achieved algorithmically, and in the multi-sensor systems additional false alarm rate reduction was obtained when

Summary of the most important results

A list of the most important results is shown below, with relevant details following.

1. Robust pre-screener implemented for NIITEK radar.
2. Improved ground-bounce tracking algorithms developed
3. Alternative prescreeners for more difficult terrains developed and tested
4. Feature-based algorithms proposed and tested
5. Sensor and feature fusion algorithms proposed and tested

LMS-Based Prescreener

The Wichmann/Niitek radar is a very wide band (200 MHz to 7 GHz) impulse radar with extremely low radar cross section. Thus, the radar implicitly solves many of the problems previously associated with subsurface discrimination using ground penetrating radar based systems. Furthermore, due to the high bandwidth of this radar, accurate phenomenology of buried objects can often be discerned including some of their inner structure. This has lead us to hypothesize that sub-surface target identification and discrimination may be possible using the signals measured with this radar system. However target discrimination is often too computationally expensive to meet the real-time requirements of this, a vehicular system.

These real-time requirements have led us to develop a two stage algorithm which is divided into pre-screening and feature-processing stages. The goal of the pre-screening stage is to quickly flag potential locations of interest and to pass these locations along to the feature-processor. The feature processor will then attempt to separate targets from naturally occurring clutter and make final decisions regarding the confidence values for each of the alarms presented by the prescreener. Thus the amount of data which is analyzed by the feature processor is limited by the number of alarms the prescreener generates. Ideally, the splitting of data processing into two stages should allow for more complicated feature-based discrimination algorithms to operate on the small subset of pre-screener-flagged data in a real-time manner. In this paper, we present results from field and blind tests generated by both the pre-screener and the pre-screener followed by the feature-based processor.

A two-stage algorithm for landmine detection with a ground penetrating radar (GPR) system was developed and tested extensively under this effort. First, 3-D data sets are processed using a computationally inexpensive pre-screening algorithm which flags
potential locations of interest. These flagged locations are then passed to a feature-based processor which further discriminates target-like anomalies from naturally occurring clutter. Current field trial (over 6500 square meters) and blind test results (over 39000 square meters) were obtained and these show at least an order of magnitude improvement over other radar system-based detection algorithms on the same test lanes. Results from the blind lanes, which are the most realistic test, are summarized below. Note that this algorithm has been implemented in the real system and is currently operating in the field.

For blind test lanes, data was collected by Niitek and burned to CDs for processing. Resulting alarm files were presented to the independent contractor within 24 hours of receiving the data. No modifications were made to these algorithms at any point during or between the two separate test data collections. The ground truth for the blind lanes is sequestered and known only to the government sponsor. Blind test lanes consist of buried (no surface) plastic and metal-cased anti-tank landmines. Algorithm scores on the blind lanes were generated by the independent contractor.

In the eastern US site, blind lane performance was comparable to the calibration lane performance. These scores were generated by the third party contractor and represent aggregate scores over several lanes spanning 14000 square meters. At this site, the pre-screener achieves a Pd of 90% at a false alarm rate of approximately 0.0002 false alarms per meter squared, and the feature-based processor achieves a Pd of 90% at approximately 0.0001 false alarms per meter squared. This performance represents an improvement of approximately two orders of magnitude over other fielded radar systems.

Pre-screener results from the western US site also coincide with results on those calibration lanes. These results represent aggregate scores over several lanes spanning 25000 square meters. The pre-screener achieves a Pd of 90% at approximately 0.0001 false alarms per meter squared. The feature based processor was not run on this data due to insufficient training data. Again, this performance represents an improvement of approximately two orders of magnitude over other fielded radar systems.

**Ground Bounce Tracking**

In landmine detection applications, the goal is to localize all landmines with a minimum number of false alarms. This means that features that can distinguish the landmines from the background clutter have to be formulated and extracted. Historically, a combination of features from both the time-domain and the frequency domain are required to achieve low false alarm rates. One issue that has been a problem for landmine detection algorithms is eliminating the radar return from the ground, or the “ground bounce” (GB), as it is a significant source of false alarms. It is therefore generally accepted that the GB must be detected and removed.

Inaccurate location of the GB can also impact feature extraction. A number of algorithms have been proposed for GB tracking and clutter removal in order to increase the accuracy of landmine detection. Each of these approaches performed well in relatively benign conditions, but may encounter difficulties in more difficult scenarios. The main challenge
for GB tracking in the real world is that there are a variety of ground conditions, such as soil, sandy, gravel, asphalt surfaces, or ground covered with vegetation. These various ground surfaces often result in significant anomalies unrelated to the presence of a landmine. These anomalies are inhomogeneous and the statistical properties of the GB responses may vary with position. GB response characteristics are also influenced by weather conditions, such as soil humidity, rain and snow.

Due to the dielectric discontinuities between the ground and the air, the main feature of the GB is a sharp peak in each A scan. As a simple GB tracking algorithm, GB locations can be roughly estimated by finding the maximum response along each of these A scans, which will be referred to as the “global maximum” method. In most cases, particularly in benign environments, the ground/air interface does in fact generate the maximum response in the GPR signal. However, there are a number of cases where the maximum response is generated by other factors, such as the interface between snow and the air or surface metallic objects and the air. Other subsurface anomalies can also be problematic for a simple GB tracker. These anomalies cause GB tracking based on a global maximum to “jump” from one location to another, which significantly impacts the accuracy of landmine detection, particularly if GPS interference occurs in the vicinity of a landmine.

An alternative yet still simple ground tracker is based on finding local maximum responses, which will be referred to as the “constrained maximum” method. For every DT/XT location, this algorithm searches for the maximum radar response in a “safe” neighborhood based on the previous GB estimate in the adjacent A Scan, where the size of the neighborhood is defined with a pre-defined window size. For a given data set, this parameter can be chosen so that both the accuracy and the efficiency of the GB tracking are optimized. However, if a variety of data sets are blended, it is difficult to choose this parameter so as to make it fit all experimental conditions, which degrades the overall performance. Another choice is to apply a Kalman filter based on the global maximum, which potentially provides a more accurate GB tracker than the simple approaches mentioned above. In essence, the Kalman filtering formulation is the minimum mean squared error (MMSE) estimate to the global maximum with a Gaussian observation noise, in which linear models are required. However, sometimes it is hard to relate the GB locations to the observations with linear functions due to the inhomogeneous GB signatures. As Sequential Monte Carlo sampling is a technique to estimate the state of nonlinear/non-Gaussian stochastic systems, it is potentially a better choice for GB tracking problems. During this project we implemented each of these approaches and considered their efficacy on a wide variety of field data.

Generally speaking, and averaged over a wide variety of data, it appeared that the best choice for stable robust ground tracking was the Kalman filter, although we are currently continuing to investigate other techniques. The constrained maximum and global maximum are computationally simple, but subject to fairly significant error. The Kalman filter is computationally more expensive, but provides better results both in terms of error (when the data has been manually ground truthed) and in terms of ROC performance. Several of the more advanced techniques considered provided marginally better
performance, but required parameters to be set carefully and were considerably more computationally intense.

**Alternative Prescreeners**

Our initial research in detecting buried targets in government maintained lanes using the NIITEK radar resulted in the application of the LMS algorithm to GPR responses for anomaly detection. However since the LMS pre-screening algorithm was developed for anomaly detection in relatively homogeneous lane data, we expect some degree of performance degradation on heterogeneous off-road collections where anomalies are more prevalent and have stronger GPR responses.

To mediate the effects of more predominant clutter objects, we developed a new anomaly detection algorithm referred to as the "Segmented Shifting and Differencing" (SSAD) algorithm. The SSAD algorithm is an attempt to utilize nearby background responses to reduce the effects of background interference in a particular scan while simultaneously preserving responses from buried targets. This technique relies on the assumption that GPR responses from subsurface anomalies typically span a large physical distance, and have somewhat constant energy. This is in contrast to typical assumptions regarding responses from buried targets where GPR response energies vary widely over a short distance, and the target responses are located in a physically small area.

SSAD was tested on a large set of data. In relatively benign topologies, the performance of the SSAD algorithm and the LMS-based prescreener was similar. However, in more difficult environments where the terrain was rougher or the soil moisture was inconsistent, SSAD performed better than the LMS prescreener. Blind testing has not yet been performed, but recent theatre data suggests that SSAD may need to be revisited as a potential prescreener.

**Feature-based algorithms**

We considered an technique called the texture feature coding method, based out of the biomedical image processing literature, that uses texture features to classify data. The texture feature coding method developed by Horng is a technique for translating intensity images to class-number images based on thresholded gradients taken along different orientations of an intensity image. For each pixel \((i, j)\) in an image, we seek to generate a texture feature class number based on the 3-pixel by 3-pixel sub-image around \((i, j)\). We considered directly implementing the 2-D approach as initially posed, but then considered several 3-D extensions to apply it to GPR data.

Off-lane GPR data provides a more stringent test of energy-based pre-screening anomaly detection algorithms. However, due to the low computational complexity of these algorithms, we can utilize feature-based processing at flagged locations of interest to improve PD/FAR performance. We have developed a 3-D extension to the 2-D texture feature coding method originally developed by Horng and used for target identification by Liang et al. In this work we apply 3-D TFCM to GPR responses taken from pre-
screener flagged locations of interest. Several different features are then extracted from
the resulting TFCM class numbers. Relevance vector machines trained on these features
are then used to separate landmine feature sets from clutter feature sets. Current
PD/FAR curves indicate significant performance improvements for RVM-based feature
processing over energy-based pre-screening algorithms. Results also indicate
improvements in target discrimination for 3-D TFCM features compared to their 2-D
counterparts. Our future work in this area will include exploration of other TFCM
features, other feature sets, and different learning machines for target/clutter
classification.

Sensor/Feature Fusion

In collaboration with UFL, U Missouri, and U. Louisville we have shared features across
a wide variety of data sets and developed algorithms for performing feature level fusion.
To date, the algorithms developed at UFL have out-performed the algorithms we have
tested.

Bibliography
(2) Song, J., Liu, Q., Torrione, P., and Collins, L. M., “2D and 3D NUFFT Migration
Antennas and Propagation, 44 (6), June, 2006, 1462 - 1469.
(3) Torrione, P. and Throckmorton, C., and Collins, L., “Performance of an Adaptive
Feature-Based Processor for a Wideband Ground Penetrating Radar System”, IEEE
Landmine Detection using Quadrupole Resonance,” IEEE Trans. Geoscience and
(6) Torrione, P. and Collins, L., “The Performance of Matched Subspace Detectors and
Support Vector Machines for Induction-Based Landmine Detection”, Subsurface
Landmine Detection Using the Wichmann/Niitek Ground Penetrating Radar”, IEEE
frequency domain quadrupole and dipole electromagnetic induction sensors in a
landmine detection application,” 2008 International Symposium on
landmine detection in ground-penetrating radar data,” 2008 International Symposium


