Advanced Signal Analysis for Forensic Applications of Ground Penetrating Radar

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***Abstract*—**Ground penetrating radar (GPR) systems have traditionally been used to image subsurface objects. The main focus of this paper is to evaluate an advanced signal analysis technique. Instead of compiling spatial data for the analysis, this technique conducts object recognition procedures based on spectral statistics. The identification feature of an object type is formed from the training vectors by a singular-value decomposition procedure. To illustrate its capability, this procedure is applied to experimental data and compared to the performance of the neural-network approach.

Keywords-GPR, object recognition, neural networks, forensics, signal analysis

I. Introduction

Ground penetrating radars (GPRs) have proved to be valuable tools for forensic investigators in search of subsurface objects [1]. The operation of geophysical tools and the interpretation of data often require extensive training of personnel. Therefore, advancing quantitative recognition techniques will not only improve the accuracy of data analysis and decrease interpretation time for evidence recovery teams, but also lessen the need for manpower. Understandably, this is in the best interest of forensic and evidence recovery teams, which are frequently confronted with time and manpower constraints.

In support of the FBI Evidence Response Team, Special Technologies Laboratory, operated by Bechtel Nevada, initiated a collaborative forensic-GPR research effort with the University of California at Santa Barbara, the University of Florida, and the University of Tennessee [2]. For this project, GPR advancements in image formation and recognition techniques are applied to forensic targets, for the objective of improving the efficiency of evidence recovery.

Object recognition has been an active field in image processing and computer vision for many years. The standard recognition process mainly focuses on the object's spatial features. This method of reconstruction is based on the object's RF reflectivity profile, which does not always resemble its true surface configuration, especially after decomposition and degeneration. Thus, recognition based on spatial variations has not been an effective approach in this application.

One potential method for object recognition by GPR imaging devices is based on the spectral contents of the target. Each material type reacts to RF illumination in a unique manner, resulting in a unique variation within the operating frequency band. Given a set of training signals, a correlation matrix can be constructed. Subsequently, a singular-value decomposition (SVD) procedure can be conducted. The most common feature among the training set can be identified by a linear combination of the training vectors. The elements of the eigenvector corresponding to the most significant SVD component produce the coefficients of the combination. This signal pattern can then be utilized as the identification feature for object recognition.

The recognition with spectral contents is most suitable to stepped FM-CW systems because of the structure of the backward-propagation image formation algorithm, where the spectral variation of the reconstructed images is readily available [3]. Therefore, with an identification-feature-pattern, a probability distribution corresponding to an object type can be formed for each GPR image with simple modification of the image reconstruction algorithm.

Typically, GPR object recognition with the use of neural networks is based on spatial variation and can be used to detect UXO and utility pipelines [4]. The tasks often involve visual processing of the image shape in the GPR profiles. Most recently, automatic target detection algorithms and neural networks that incorporate pattern recognition have been applied to GPR profiles for *clutter and noise reduction* [5] and *edge enhancement and detection* [6].

This paper will provide an overview of the application of advanced signal analysis and neural network techniques to experimental GPR return signals. In one case, the spectral content of the GPR return signals is evaluated with the SVD procedure for a quantitative and statistical result. In the other case, the statistics of the reflected GPR signal are analyzed and used as the inputs to a neural network [7]. In both cases, the raw GPR data are pre-processed using position data with a synthetic-aperture radar (SAR) algorithm [8].

II. Background of Study and Experiments

For the initial phase of the research, forensic specimens were buried at two locations and GPR data were acquired on a monthly basis over a 24 month period. The Anthropological Research Facility operated by the Department of Anthropology at the University of Tennessee at Knoxville used GPR to collect data from human cadavers covered with soil and

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concrete slabs [9, 10]. The Department of Anthropology at the University of Florida also performed similar data-acquisition experiments with pig cadavers in Entisol and Ultisol [11]. Data from the latter were chosen for the first attempt with the object recognition and neural networks techniques due to the larger size of the test pits and grid data collected. Additionally, the larger amount of *non-target* data at the University of Florida site would be required for the training sets.

The data were acquired with a stepped-frequency GPR system over the frequency range of 200-700 MHz with 85 frequency steps [12]. A 6.1 m x 4.9 m grid was constructed over the test site. Ten transects were taken at each site with the middle two transects crossing over the width of the target. Data were acquired with an increment of 15 cm along each gridline and 60 cm spacing between gridlines. The initial results successfully demonstrated the feasibility of detecting the cadavers [13, 14]. GPR depth profiles from a pig cadaver buried for 4-11 months, 1 m deep in Entisol, is shown in Fig. 1.

III. OBJECT RECOGNITION

One of the important extensions to GPR imaging is to include the capability of object recognition. The basic procedure of a recognition task is the matching of the detected signals against the identification pattern. The identification pattern is often termed the *ID feature*, or *ID vector* for multi-dimensional cases. The crucial step in object recognition is not necessarily the matching process. Instead, it is the formulation and formation of the ID features, which is the key to the successful execution of the recognition task.

The development of the pattern recognition associated with imaging systems has been largely in the area of recognizing objects based on two- or three-dimensional spatial features. This approach is based on the functions and concepts of the human visual and perception processes. However, this technique has limited capability because GPR images are quite different from typical visual images due to the bandwidth, resolution, operating configurations of the data-acquisition systems, as well as the physical interactions between the targets and RF illumination. Thus, in this paper, an alternative approach is utilized to facilitate the recognition process, which is to operate the recognition procedure based on the spectral statistics at a target position, instead of the spatial features.

The image reconstruction procedure is implemented based on the multi-frequency tomographic version of the backward propagation algorithm [8]. The final image is the superposition of all coherent sub-images, so that at any target location, the spectral content of the superposition is readily available [3].

As mentioned earlier, the most crucial step is the formation of the ID features, which can be conducted in different ways. One is to formulate the ID features completely based on theoretical models. Another approach is to construct the ID features from a set of *training vectors*. If feasible, the collection of the training vectors is typically performed through laboratory experiments in a controlled manner to ensure high accuracy. Previous results have shown that when trained correctly, the SVD method can reach equilibrium in as few as 50 training sets [15]. Yet, when the theoretical model or laboratory experimental data are not available, field-test data can be used as the training vectors, which is common practice.

The most common and robust approach to the formation of an ID vector from a set of training vectors is direct averaging. In many applications it is adequate in terms of accuracy and convergence, especially when the training data are obtained in controlled laboratory experiments and the data set is sufficiently large. When field-test data are used for training, this approach is often ineffective due to the phase perturbation associated in wave propagation and variation of magnitude due to different range distances. Thus, instead, a SVD technique is used for the training process for improved accuracy and consistency.

From a set of training vectors, a cross-correlation matrix R is formed from data corresponding to one unique target type. R is an NxN square Hermitian-symmetric matrix and the elements of the matrix represent the correlation among the training vectors.

$$R = E\{SS^H\} \tag{1}$$

where S is the vector representing the collection of training vectors. Subsequently, a SVD is performed and the correlation matrix R is partitioned in the form of

$$R = U \Lambda U^H \tag{2}$$

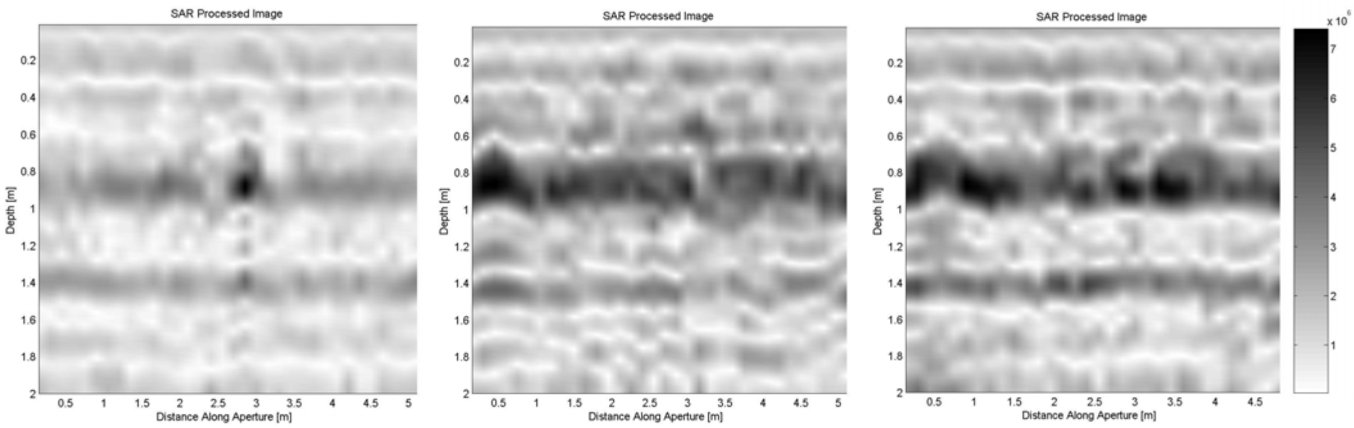

Figure 1. Depth profiles at 4, 8, and 11 months of a buried pig cadaver. Target is at 3 m along aperture.

where U is the orthonormal matrix, which is the collection of the eigenvectors, and Λ is a square matrix and its diagonal elements are the singular values. The variation of the singular values provides important information in terms of the quality of the training vectors. If the training vectors are of good quality, the singular values will be clustered with one or very few dominant components. If the training vectors are not well correlated, the singular values spread. This also means the magnitude of the most significant singular value

$$s^* = s_1/u_{11} + s_2/u_{12} + \ldots + s_N/u_{1N} \tag{3}$$

is an indication of the level of commonality among the training vectors, which represents the degree of confidence as well as the upper bound of the recognition process.

In (3) u_{1k} is the kth element of the eigenvector corresponding to the most significant singular value. In practice, the elements are often complex. The magnitude of the elements provides the normalization factor to equalize the variation among the training vectors and the phase provides correction of various phase perturbations in wave propagation and data acquisition.

A GPR image is formed by completing the backward propagation image formation procedure, and if any particular location is of interest, it can be selected for the recognition procedure. Once a target location is selected, the algorithm traces back to obtain its spectral contents prior to the superposition process to be used as the test vector. Then the test vector is normalized and matched against the ID vector by a simple inner-product operation. Since both the test and ID vectors are normalized, the magnitude of the inner product is bounded between 1.0 and zero, which represents the probability of the match.

It should be noted that the recognition produces a quantitative indicator as the probability of the match, instead of the traditional binary outcomes in many recognizers, which provides the opportunity for further analysis and investigation. In many GPR field operations, this technique provides 1) the confidence level of the ID vector from the magnitude of the most significant singular value, and 2) the numerical result of the matching process, which is proven to be of great importance. It should also be pointed out that the computation of the recognition procedure is the inner product of the normalized spectral content at a particular location with that of the ID feature. Thus, the result of the recognition process is independent of the variations in the image profiles.

The technical description of this section is focused on the formation of the ID vector and matching operation corresponding to one object type. Yet, with minor modifications, this concept can be extended to the recognition tasks for multiple object types by expanding the SVD procedure to analyze the commonality as well as differences among the ID vectors corresponding to multiple object types for further improvement of recognition performance.

IV. Neural Networks

Neural networks have been widely utilized as a classification tool, capable of adapting and generalizing to perform recognition tasks. Neural networks learn to formulate complex input and output relationships directly from the data, and can approximate a function to designated accuracy [16]. These relationships are identified through *training*, with input data repeatedly presented to the neural network.

In this study, a back-propagation neural network from NeuralWare's NeuralWorks Predict software was selected to facilitate the training on a data set from field-generated targets and non-targets. The raw GPR data was utilized for the multi-frequency image reconstruction, and then analyzed with statistical functions designed to discriminate between signals returned from targets and non-targets [17, 18] as explored by Shihab, et al. [6]. The three functions utilized in the process are 1) the mean absolute deviation, 2) the variance, and 3) the fourth moment of the signals. Input into the neural network for training consisted of the three statistical results from five consecutive returns, establishing change over distance within the data (Fig. 2). Feeding this data into a back-propagation neural network results in the ability to differentiate signal returns from a target versus a non-target.

V. Discussion

Fig. 3 shows a SAR processed image and an image with an ID feature produced by the SVD method. When SVD processing is compared to the traditional averaging of the training vectors, the results show more distinct matches of the target and less false identification of non-targets. The recognition process is typically performed subsequent to the image reconstruction. With the identification feature formulated by the SVD algorithm from the training vector set, the recognition procedure produces an image showing only the profile matched to the spectral statistics, which is a different profile than the reconstructed image. The quantitative recognition results provide an accurate numerical indicator reflecting the confidence level of the match, which is important to the overall assessment of the images.

The neural network was trained on data collected from several pits in months 4, 5, and 6, and then tested on different pits in the following months. In each test in Entisol, the neural network correctly detected and classified targets within the GPR return signal. In Ultisol, the clay layer was also detected as a target because it exhibited similar statistical properties.

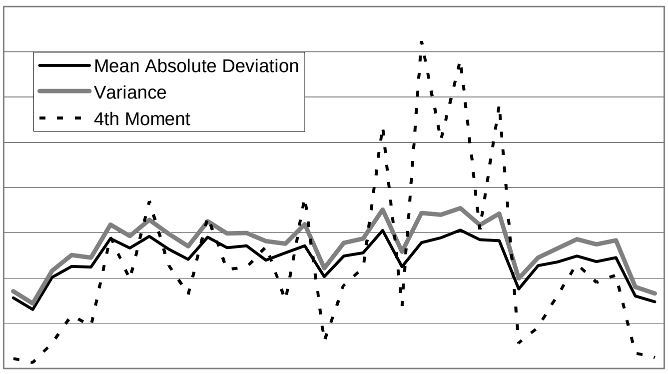

Figure 2. Statistical results of analysis on signal return over a target.

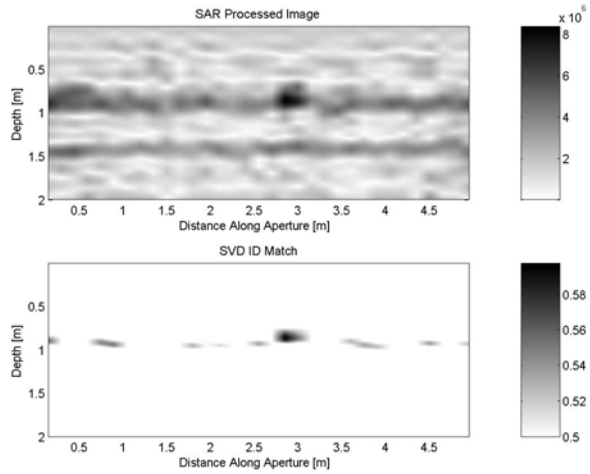

Figure 3. SAR and SVD processed image of a pig 1 m deep.

VI. Conclusion

This paper reports the results of the experiments on the feasibility of object recognition with step-frequency GPR. Two methods, the SVD approach and the neural network technique, are selected for the experiments to formulate the identification feature of the recognition process. The experiments were based on data collected at experiment sites over a period of 24 months and both methods demonstrated the feasibility. The SVD object recognition procedure demonstrated better accuracy than the neural networks. This is because the SVD procedure trains and analyzes the specific frequency content, while the neural network analyzes the total return, which is a sum of contributions from the entire frequency coverage. The SVD algorithm can be effectively incorporated into the image reconstruction process due to the structure of the image formation algorithm and recognition process. Future plans are to use the SVD method for object recognition for multiple object types and compare the performance with respect to that of the neural network techniques.

Acknowledgment

The authors would like to thank Todd McCall and the FBI Evidence Response Team for project funding. This work was supported by the U.S. Department of Energy, National Nuclear Security Administration Nevada Site Office, under contract DE-AC08-96NV11718. **DOE/NV/11718—874**.

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