Automatic detection of buried utilities and solid objects with GPR using neural networks and pattern recognition

W. Al-Nuaimy a,*, Y. Huang a, M. Nakhkash a, M.T.C. Fang a, V.T. Nguyen b, A. Eriksen c

a University of Liverpool, PO Box 147, Brownlow Hill, Liverpool L69 3BX, UK
b Shell Research, Shell Research and Technology Centre, PO Box 1, Thornton CH1 3SH, UK
c Geo-Services International (UK), 26 Bridge Street, Witney, Oxon OX8 6HY, UK

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Abstract

The task of locating buried utilities using ground penetrating radar is addressed, and a novel processing technique computationally suitable for on-site imaging is proposed. The developed system comprises a neural network classifier, a pattern recognition stage, and additional pre-processing, feature-extraction and image processing stages. Automatic selection of the areas of the radargram containing useful information results in a reduced data set and hence a reduction in computation time. A backpropagation neural network is employed to identify portions of the radar image corresponding to target reflections by training it to recognise the Welch power spectral density estimate of signal segments reflected from various types of buried target. This results in a classification of the radargram into useful and redundant sections, and further processing is performed only on the former. The Hough Transform is then applied to the edges of these reflections, in order to accurately identify the depth and position of the buried targets. This allows a high resolution reconstruction of the subsurface with reduced computation time. The system was tested on data containing pipes, cables and anti-personnel landmines, and the results indicate that automatic and effective detection and mapping of such structures can be achieved in near real-time. © 2000 Elsevier Science B.V. All rights reserved.

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1. Introduction

Ground penetrating radar (GPR) has been widely used as a non-destructive tool for the investigation of the shallow subsurface, and is particularly useful in the detection and mapping of subsurface utilities and other solid objects. GPR displays are usually either manually scaled and interpreted, or stored and subsequently processed off-line. Separating out clutter, and accounting for various system and subsurface effects require considerable operator skill, experience and time. The processing aids that have been developed to aid in data interpretation are generally computationally expensive systems inadequate for on-site application.

As GPR is becoming more and more popular as a shallow subsurface mapping tool, the volume of raw data that must be analysed and interpreted is causing more of a challenge. There
is thus a growing demand for automated subsurface mapping techniques that are both robust and rapid. The system outlined in this paper provides such a solution.

The proposed system employs a combination of neural network, signal and image processing techniques to provide a high-resolution image of the sub-surface in near real-time facilitating straightforward data interpretation and providing accurate depth and azimuth location information. The three major stages are preprocessing, image segmentation and pattern recognition. As shown in Fig. 1, these three software stages work together in the above order to achieve the highest resolution and accuracy possible within the limitations of real-time operation.

2. Pre-processing

Before the information in the raw radargram can be utilised correctly, it must first be preprocessed to remove undesired system and ground effects. This involves background clutter removal, path loss compensation, antenna-separation rectification and low-pass filtering. Background clutter removal eliminates commonalities present in the data, such as the coupling pulse, surface reflection, and system ringing, and is achieved by dividing the image into vertical strips equivalent to about 3 m, and then subtracting the ensemble mean of each row of pixel intensities across each strip. This results in a higher signal-to-clutter ratio of the image and improves the contrast of the object signatures of interest. Path loss compensation involves applying a time-varying gain to each scan to compensate for the attenuation caused by the propagation of the expanding spherical wavefront (Johansson and Mast, 1994) and has the effect of visually enhancing the appearance of the lower portion of the radargrams.

The radar configuration used for this study was the GSSI SIR®-2 system with a 400 MHz centre-frequency antenna pair. The antenna as-
semblage consists of a transmitting and receiving antenna pair a finite distance apart. This finite separation of the transmitting and receiving antennae is not taken into account by the radar system, and must therefore be considered during processing. As can be seen in Fig. 2, neglecting this separation can lead to an erroneous judgement of the depth of the target and the shape of the signature. An initial velocity estimate is used to rectify this problem by computing the ‘ideal’ time of arrival of each reflection assuming co-located antennae. Referring to Fig. 2, with the assumption of a constant propagation velocity \( v \) (in scans per sample), and antenna separation \( \delta \) (exaggerated), each sample recorded at a time \( t_s \) is translated to an earlier corrected time \( t_c \), where \( t_c \) and \( t_s \) are related as follows:

\[
t_c = \sqrt{t_s^2 - \frac{\delta^2}{v^2}}
\]  

The effect of this correction applied to a hyperbolic target signature are shown in Fig. 3.

High-frequency system noise, especially visible in the lower portion of the image where the time-varying gain is maximum, is removed by rejecting frequencies beyond the frequency bandwidth of the radar, in the range of 2–2.5 times the antenna centre frequency Nakhkash, 1996. This further improves the SNR at the later arrival times. Fig. 4 illustrates the effects of the above pre-processing techniques on a radargram containing reflections over three pipes.

3. Feature extraction

In order to successfully identify the subsurface targets amidst the surrounding clutter, it is necessary to locate and distinguish the genuine target reflections from spurious reflections. As typically only a relatively small area of the radargram contains useful reflections corresponding to the pipes, and the remainder of the image is redundant in many ways. Automatic selection of these anomalous zones can significantly reduce the dimensions of the data set with which one must deal, hence alleviating the computational burden during later processing and pattern recognition stages. In order to automate this selection process, attributes must be identified that characterise the sought signals and distinguish them from other undesirable reflections.

Pattern recognition is used to discriminate between echoes from buried targets and unwanted signals. Different representations of the time series data facilitate the pattern recognition task by extracting different features of the signal. As it is not known which features are directly relevant to the above discrimination, various spectral representations were investigated. Since the radar scans are non-stationary, and are neither periodic nor transient, they cannot be dealt with effectively by direct application of the Fourier integral Kanasewich, 1975. The following spectral estimates were computed:

-Periodogram of full scans
-Periodogram of signal segments
-Welch averaged periodograms of full scans
-Welch averaged overlapping periodograms of signal segments
Although each of these methods provided a valid measure of the spectral content of the signals, the latter estimate proved the most effective in discriminating and locating the required echo signals. It is computed as follows: the signal $s(n)$ is first subdivided into 8 segments of length $N = 64$, which are then sectioned into $K = 2N/(M - 1) = 7$ subsets of length $M = 16$ with 50% overlap, as illustrated in Fig. 5. Each subset is tapered with a suitable window function $w(n)$ such as a Hanning window or pair of cosine bells. The Welch power spectral estimate $P_w$ for each segment is then given by Eq. (2) (Kanasewich, 1975; Oppenheim and Schafer, 1975):

$$P_w(\omega) = \frac{1}{MUK} \sum_{i=1}^{K} S_i(\omega) S_i(\omega)^*$$

(2)

where

$$S_i(\omega) = \sum_{n=0}^{M-1} s_i(n) w(n) e^{-j \frac{2\pi}{M} \omega n}$$

(3)

is the discrete FT used in computation, and where

$$U = \frac{1}{M} \sum_{n=0}^{M-1} w^2(n)$$

(4)
is the average power in the window, and the star indicates the complex conjugate. A 64-point FFT was used resulting in 33 spectral values. Retaining the first 12 of these was found to be sufficient for discrimination.

Although there are other more advanced methods of spectral estimation (Grant et al., 1989; Kanasewich, 1975), the above procedure is particularly suited to power spectrum estimation using the FFT (Oppenheim and Schafer, 1975), and by windowing the time series segments before computing the periodograms, it achieves both a reduction in the variance and a smoothing of the spectrum. Segmenting the scans before computing the features (spectra) reduces the feature size, and the result is more sensitive to the presence and the location of the target.

The data set used for this study consists of eight radargrams acquired from two different sites, over pipes of different materials buried in soil, in addition to two radargrams obtained from [DeTeC] containing reflections over two landmines with a 1-GHz antenna. The feature set was compiled as follows: the 10 radargrams were first normalised to the same range scale and range gain function. Three percent of the scans were selected at random, and for each scan, two others were selected, m scans to the left and right, where m was chosen to represent 10 cm. This is in order to take into account their relative spatial location. For each scan the above spectrum was computed for the 8 time-segments, and each three corresponding spectra augmented to form one feature vector. This feature set was divided into training and testing sets of equal sizes (1120 × 36), used successively to train and test the neural network classifier.

4. Neural network classification

This stage provides the subsequent stages with a continuous measure of confidence as to whether a particular scan segment is the result of reflection from a target or no, by first training an artificial neural network to recognise certain distinctive features of the frequency domain representation of the reflected signal. A data reduction is thus achieved and only the image portions containing useful reflections are considered for subsequent processing, significantly reducing the computation time required. Knowledge compiled from example feature vector sets is compiled from the training set in a training or learning stage. This knowledge is then used to construct a rule for the labelling of new data into two classes. Unseen examples presented to the classifier during the training or recall stage, result in an output of class membership.

After first normalising the training and testing feature sets to confine all vectors to the range −1 to 1, a three-layer fully-connected feed-forward perception neural network (as in Fig. 6) was trained with the backpropagation learning algorithm (Patterson, 1996; Zurada, 1992). The input layer consists of 3 × 12 = 36 input neurons, one for each spectral value, and the output layer contains two neurons to indicate either a target reflection (−1, 1) or otherwise (1, −1). The number of neurons in the ‘hidden’ layer is determined empirically by monitoring the network performance with dif-
ferent numbers of hidden nodes. As shown in Fig. 7, six hidden nodes achieves the fastest convergence with minimum error.

The training procedure was interrupted at regular intervals in order to cross-validate the network performance with the (unseen) test data, to constantly monitor for over-training and locate the optimum network training time. The performance of a classifier is its ability to label new or unseen data correctly. As this data is not yet available, only an estimate may be made of this performance using the classification of the data that is available. This estimate is accurate only if the data in the examples are representative of the data that will be encountered during application. This estimate, referred to as generalisation error, is estimated using the hold-out technique described in Patterson (1996). This problem of memorising the inputs is evident for one and two hidden nodes in Fig. 7, which shows the generalisation (test) error plotted against training epochs for different numbers of hidden nodes. The moment the test error is observed to cease decreasing, training is stopped.

The trained neural network can then be applied to classify a full radargram feature set from a radargram new to the neural network, and the output (generated instantaneously in a feed-forward manner) then used to ‘highlight’

sections of the image classified as corresponding to target reflections, as shown in Fig. 8 below. This selection is done by assigning a threshold value of $\pm 0.8$ at the network output, as the neurons’ saturating transfer function prevents the output from reaching $\pm 1$. The entire radargram would thus be segmented into regions belonging to one of two classes. Those regions classified as target reflections are further processing by subsequent stages.

5. Image processing

As evident in Fig. 8, each target exhibits a characteristic hyperbolic signature in the radargram, caused by the large beamwidth of the radar antenna. The goal of the image processing stage is to locate, separate and identify these hyperbolic anomalies amidst the surrounding clutter within the regions selected by the neural network classifier. The geometrical setting giving rise to these hyperbolae is illustrated in Fig. 9. A point or localised cylindrical target is considered in a homogenous medium, and due to the corrective pre-processing, the distance between the transmitting and receiving antennae is assumed small compared to the depth of the target. Although in practice the soil type will
vary across a scan, for the volume in the immediate vicinity of the target this variation is small, and the assumption is valid for most practical cases.

6. Edge detection

This stage involves the detection of the outline or envelope of the main peaks of the reflected wavefronts. This is achieved by computing the gradient of the image regions containing the reflected wavelets, and then applying peak tracing techniques to the gradient image. This results in a binary image representing the edges of the main curves present. This leads to a significant reduction in the amount of data to be processed, and it is this reduction which makes the system feasible for near real-time operation.

7. Pattern recognition

The Hough Transform (Illingworth and Kittler, 1988) is a well-tested method for detecting complex patterns of points in binary image data, and has been known to perform well in the presence of noise and occlusions. Spatially extended patterns are transformed so that they

![Fig. 8. Neural network classification of radargrams containing reflections over (a) three pipes (steel, plastic and clay), and (b) an anti-personnel landmine (of metal and plastic).](image)

![Fig. 9. Formation of hyperbolic anomalies.](image)
produce spatially compact features in parameter space.

Successful application of the HT requires a definite knowledge of the type of curves sought in order to obtain analytic relationships between image- and transformation-space parameters. The shape of these hyperbolic diffraction curves depends on the propagation velocity of the radar pulses and the position of the buried reflectors, as illustrated in Fig. 9, and Eq. (5):

\[ t^2 = t_0^2 + \frac{4}{v^2} (x - x_0)^2 \]  

(5)

where \( x \) is the horizontal displacement, \( t \) is the image-space time (vertical ordinate), \( (x_0, t_0) \) are the coordinates of the apex, and \( v \) is the apparent speed of propagation, in scans per sample, because the horizontal and vertical dimensions of the radargram are respectively scans and samples.

To increase the computational efficiency, the HT is performed in two dimensions \( (x_0, \ t_0) \) with the value of the third parameter \( v \) varied between the limits of possible velocities, corresponding to propagation velocities of \( c/\sqrt{2} \) and \( c/9 \), where \( c \) is the speed of electromagnetic propagation in free-space. Each point \( (x, t) \) in the binary edge image is transformed into a curve in \( x_0 - t_0 \) parameter space

\[ t_0 = \sqrt{t^2 - \frac{4}{v^2} (x - x_0)^2} \]  

(6)

For each speed, these curves are superimposed over each other in a discretised accumulator functioning as a two-dimensional histogram. The highest peak of each histogram represents the most likely coordinates of the apex of a hyperbola at that speed. For each of these peaks, a measure of histogram spread, is computed, and the required parameters \( (x_0, t_0 \text{ and } v) \) are obtained from that peak exhibiting the minimum spread.

This successive application of the HT is equivalent to iterative synthetic aperture time domain focusing, which reconstructs the subsurface representation by focusing each diffraction hyperbola into a single point (Johansson and Mast, 1994). The reflections along each hyperbolic wavefront are focused to the apex, where the target would be expected to exist. This summation greatly increases the signal-to-clutter and signal-to-noise ratios, resulting in a corresponding reduction in uncertainty. The results of both techniques are similar but the amount of processing required by the current approach is considerably less, principally because of the large amount of data reduction achieved by converting the hyperbolae into binary outlines.

An image is generated to report these findings to the user, with the positions of the located targets clearly indicated. The results of applying these processing stages to the radargrams above are shown in Fig. 10, where the pipes and the landmine are clearly displayed with accurate depth and azimuthal position information. The complete mapping process from the raw radargram to the output in Fig. 10 took approximately 8 s on a 233-MHz PC.

![Fig. 10. Subsurface report showing location of (a) the three pipes, and (b) the anti-personnel landmine.](image-url)
8. Conclusions

Neural networks and pattern recognition techniques are combined in the proposed system to automatically produce a high resolution image of the shallow subsurface in a highly reduced computation time, suitable for on-site GPR mapping of utilities and other objects such as landmines. The neural network makes use of the spectral features of the data to identify areas in the radargram containing useful reflections. The Hough Transform is applied as a pattern recognition technique to locate and identify the hyperbolic anomalies associated with buried targets, generating high resolution images suitable for precise location and mapping of subsurface utilities and ordnance. Results reported from a number of sites indicate a degree of robustness and encourage further research into this technique as an automated target detector and mapper.

References