IMAGE PROCESSING AND NEURAL NETWORK TECHNIQUES FOR AUTOMATIC DETECTION AND INTERPRETATION OF GROUND PENETRATING RADAR DATA

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Abstract -Ground penetrating radar (GPR) has gained a distinguished place during recent years as a tool for investigating subsurface objects, yet its output is of low resolution, and in need of further processing in order to make its output readily interpretable. Furthermore, GPR data collected in a typical survey is usually in large quantities, and dealing with such quantities manually to produce final interpretations would result in human inaccuracy, and time-consumption problems. In this paper we present an automatic target-detection and localisation system based on unsupervised neural network classifier along with some image processing techniques to extract useful data representing targets (such as pipes, tanks, reinforcement bars, and voids) and discard undesirable data (such as noise and clutter). The neural classifier is capable of returning 3-dimensional images outlining regions of extended targets and pinpointing the location of localised targets such as mines and pipes. This classifier was applied to a variety of GPR data sets gathered from a number of sites, and it achieved rapid and accurate results.

Key-Words: Ground penetrating radar, feature extraction, image processing, edge detection, neural networks.

1 Introduction

The use of ground-penetrating radar (GPR), as a rapid and non-destructive tool for detecting subsurface anomalies has proven this tool to be of high efficiency and practicality. The basis of GPR work is that it consists of two antennae (as shown in Fig. 1), one for transmission of electromagnetic pulses into the ground and the other for receiving the reflected signal. The transmitting antenna sends a sequence of pulses; the reflected energy is then detected by the receiving antenna. As the GPR is advanced in the direction of travel, a 2-dimensional map is generated consisting of returned adjacently lying signals (referred to as B-scan). A typical B-scan is shown in Fig. 2, with vertical and horizontal axes representing the two-way travel time and scan number. GPR returns are usually of low resolution and have noisy content, and hence not suitable for direct interpretation. To solve this problem, some pre-processing and post processing operations are performed to convert returned B-scans towards high resolution image data. These operations are usually performed by a skilled operator. Such operations would require considerable amounts of time and efforts, and this would make the whole process exposed to human inaccuracy and slowness. To overcome this situation, automatic handling of such operations is investigated.

In the recent years, many forms of automatic detection and interpretation systems were proposed and applied successfully (for example [1] and [2]).

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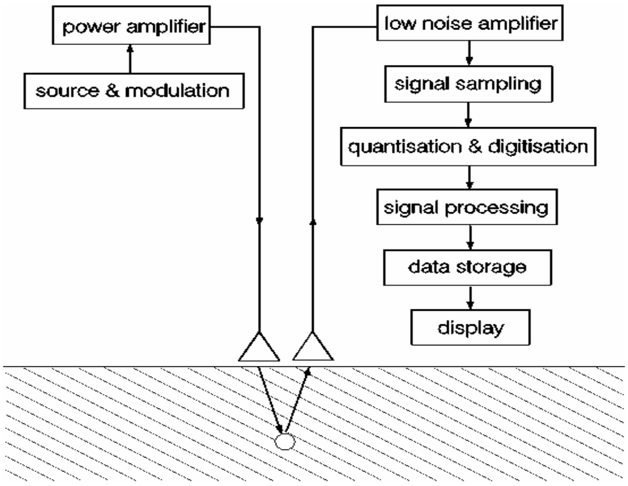


Fig. 1 Block diagram of ground penetrating radar system

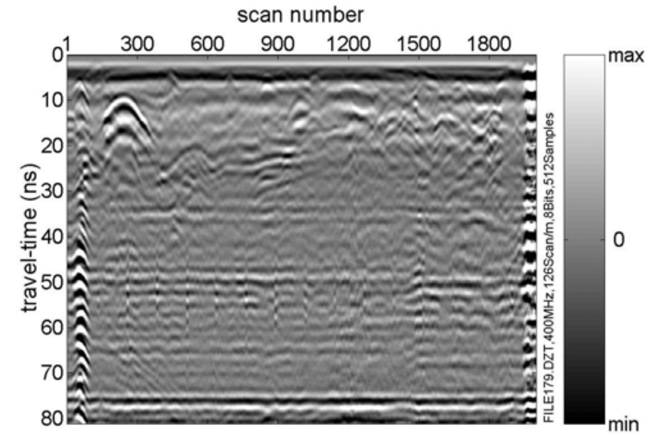


Fig. 2 Typical GPR scan indicating a buried tank to the upper left of the image.

In this paper we present an automatic system based on a combination of a neural network classifier and image processing techniques to perform detection and interpretation of GPR data. As shown in the following sections, this system has achieved high accuracy and low time consumptions, and this would make it favourable for on-site data processing.

2 Feature selection

In order to build a robust classifier, powerful discrimination features between desired classes must be selected. In this work, we dealt with the GPR scans as if they form a single image, and hence we have an image processing problem. A number of statistical features for images were investigated ([3] [4] [5]) for discrimination properties, from which some descriptors were chosen as they gave good discrimination bases. The investigated features were applied to a data set consisting of 100 (60×50)-bit image segments. These segments represent a number of different targets (such as pipes, tanks, voids, and reinforced-bars) and non-targets, provided by Zetica (UK) Ltd. Both the data set and the selected features formed the bases upon which the neural network classifier was trained.

The selected features are:

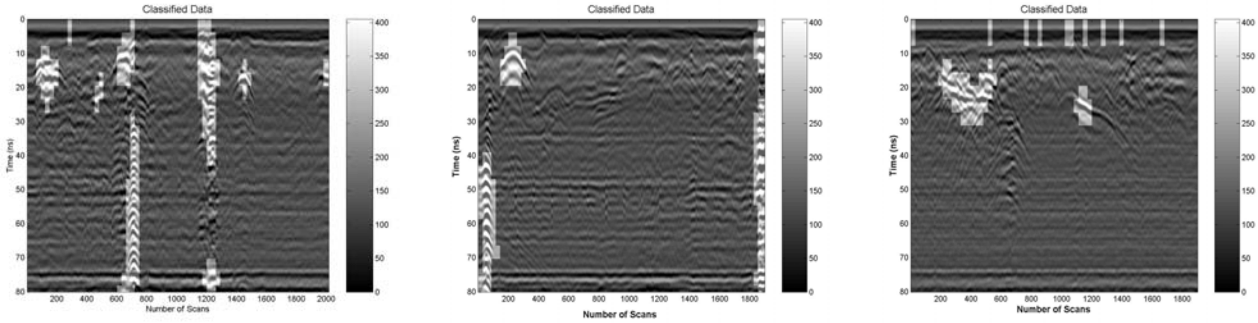
1. Variance of the histogram.
2. Third Moment of the histogram.
3. Kurtosis of the histogram.
4. Skewness of the histogram.
5. Entropy of the image.

3 Neural Network Classifier

After suitable features were selected, the task was to design and build a neural network classifier, and using the selected image descriptors as distinguishing bases for the network. A three-layer perceptron neural network was trained using backprobagation learning. The pre-collected data set was used for training and testing the classifier, and after good classification results were achieved, the networks parameters were saved. This classifier was then applied to a number of GPR scans collected from different sites, and returned from a variety of targets. The network has achieved high accuracy and rapid convergence, and its outputs were presented in a clear form, where the classified data are presented by highlighting the areas of interest on the original image data. Fig. 4 shows some classification results for different target types. It can be seen clearly that the sizes of highlighted areas are much smaller than those of rejected ones. On average about 80% of original data is reduced, and this of course is much desirable for the coming stages as the amounts of data to be processed is reduced, and hence less time consumption.

4 Image Processing

GPR images are low-resolution in nature due to the ratio of wavelength and the physical dimensions of targets. Thus, further image processing operations are yet necessary, despite the robust classification results achieved by the neural network. In Fig. 2, a target representing a buried tank and having a hyperbolic shape is shown to the left side of the image. In fact, this shape is formed due to incompatibility between the acquired data and the presented data. Thus, indicating targets areas is still insufficient in the sense of automatic localisation and interpretation of these targets; hence selected areas are in need of further treatment to produce a vivid final interpretation.



(a) (b) (c)

Fig. 3 Classification results indicating (a) buried pipes and ducts, (b) buried tank, and (c) disturbed soil.

4.1 Edge detection

The first stage in defining the shapes of the detected targets is to characterise the edges of these targets in order to extract targets-related information from them such as position and dimensions. This operation is based on detecting the boundary points that separate areas of different intensity-values. These boundary points appear when a sudden change in intensity values takes place. Although this operation may seem easy, in many cases when edges are investigated, the changes between different areas are so slight that makes it very difficult to detect the boundary points. This can be clearly seen in the low-resolution GPR images.

To overcome this problem, image enhancement procedures are needed. This can be accomplished by applying a sharpening procedure to the image to increase its contrast and hence emphasise the boundary pixels. Many standard image enhancement techniques can be found in image processing literature (for example [3] and [4]).

There are many edge detection methods presented and used in image processing operations. In this work, the Laplacian of Gaussian (LOG) method was used [3]. It involves convolving the image the second-order derivative of the Gaussian function.

If the Gaussian function *h(x,y)* is given by

$$h(x,y) = \exp\left(\frac{x^2+y^2}{2\sigma^2}\right) \qquad (1)$$

where σ is the standard deviation.

Then the Laplacian of *h(x,y)* is given by

$$\nabla^2 h = \left(\frac{r^2-\sigma^2}{\sigma^4}\right)\exp\left(\frac{r^2}{2\sigma^2}\right) \qquad (2)$$

where $r^2 = x^2 + y^2$.

Fig. 4 below shows the edge detection results of the detected pipes and ducts of Fig. 3 (a).

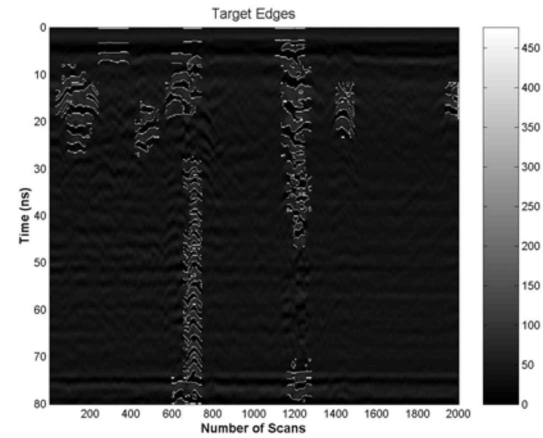


Fig. 4 Edge detection result for detected areas in the image data of Fig. 3 (a).

4.2 Target Localisation

Although the classification results were shown to be quite accurate, this achievement is still not enough, since our goal is to pinpoint the detected targets and calculate their depths, in order to achieve an automatic detection and interpretation system. For this reason, a further stage was added to process the areas highlighted as targets to verify whether they represent targets or not and produce a final report indicating positions of the targets and their depths. This stage was discussed in detail by Al-Nuaimy [2]. It involves applying the Hough Transform in a successive manner in order to pinpoint the targets and their depths, where each point in the edges of a classified binary image (t,x) is transferred into a curve in the parameter space

$$t_0 = \sqrt{t^2 - \frac{4}{v^2}(x-x_0)^2} \qquad (3)$$

where x is the horizontal distance, t represents time (vertical co-ordinate), (t_0, x_0) are the co-ordinates of the apex, and v is the propagation speed.

Fig. 5 below shows the pinpointing of the pipes and ducts detected by the classifier.

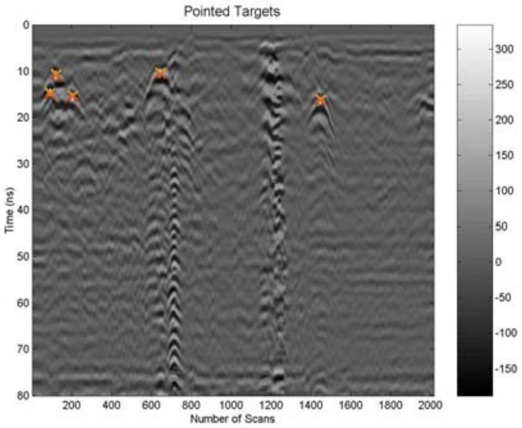


Fig. 5 GPR data of Fig. 3 (a) after verifying targets and pinpointing genuine ones.

Conclusions

The use of image descriptors as feature extraction tools along with artificial neural networks and targets locating stage has shown promising results in the sense of speed and accuracy. This would make the proposed system suitable for on-site processing of the data and visually reporting the interpretation results to the user. The image statistical descriptors used, has produced discrimination bases for the neural network classifier upon which its decisions would be made. Image processing techniques, and the Hough transform were applied in the final stage to verify targets in the selected areas, and to pinpoint the verified targets and calculate their corresponding depths.

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