Comparison of Neural Network Classification Methods Applied to Subsurface Radar Images Based on Single Echo and Hyperbolic Signature

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Abstract

This paper presents the comparison of two different classification methods for Ground Penetration Radar (GPR) images. Both methods are used for detection of the target hyperbola–like signatures on the GPR data, and both use artificial two layers feed-forward backpropogation Neural Network (NN). The first method is based on the Neural Network searching of the target responses in Echograms (NNE), produced by GPR. The second method is based on the Neural Network classification of Fourier Descriptors (FD) of the closed hyperbola/ non-hyperbola (FDNNH) shapes in the data. The comparison is made in terms of quality of the classification and computational time.

1. Introduction

GPR is a radar device whose goal is to detect and identify objects underneath the ground. GPR uses an electromagnetic (radio wave) antenna tuned to a frequency which can penetrate soils, rock, concrete, ice, and other common natural and manmade materials.

In this research, the data was obtained by Ground Penetration Radar SIR-2 equipment from the Geophysical Survey System, Inc. The data used in this research was supplied by NASA-SSC, obtained from a geographically referenced archeological site referred to as PC3d (Panama city, Fl.).

The NNE algorithms implemented in MatLab consists of algorithms for a) image noise filtering, b) scanning the echograms with sliding window of fixed size, c) a trained Neural Network. In this work, the NNE image classification result is compared with FDNNH [Tolstoy02] result.

In section 2, a description of the NNE method which was elaborated in detail in [Parsiani03] is presented. A brief description of the FDNNH is presented in section 3, for the purpose of appropriate comparison of both results in terms of quality and the computational intensiveness.

2. NNE Method

2.1 Echogram scanning of GPR images

The GPR data can be transformed and shown as 2D grey-level 8-bit image. The vertical axis shows delay time of the radar echo-signal, and horizontal axis shows the distance from the start point of the scan (Fig.1).

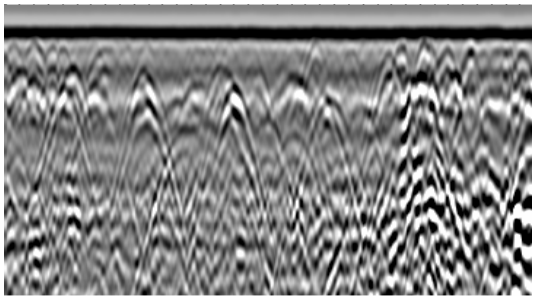

Figure 1 Typical GPR data in gray-level representation.

The types of information that can be observed in the GPR image of Fig. 1 are:
a) System response time (the smooth band above the straight black line),
b) The antenna ground coupling (light/dark line right below the smooth band).
c) The clear responses from the underground objects which come in forms of light-gray hyperbolas.
d) Responses from other deeper objects (less intensive gray signals in the middle part),
e) Noise, which has a large intensity in the lowest part of the image.
The same image could be shown in the form of a sequence of echograms, [Chen02], where signal amplitude replaces gray intensity, as in Fig.2:

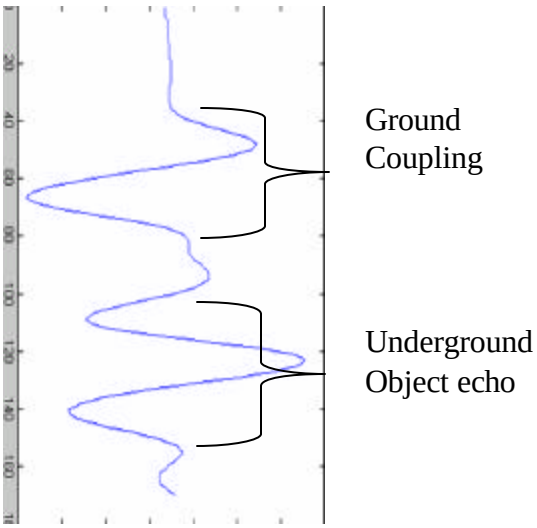

Figure 2 A fraction of a single echogram.

The sliding window of 50 points was used to select fractions of the echogram and use it as input to the trained NN.

2.2 Neural Network Description

The recognition system in both cases was implemented using Neural Network. The structure used here was two layers feed-forward backpropagation Neural Network, with different numbers of inputs for different classification methods. Fig.3 shows the structure of this network.

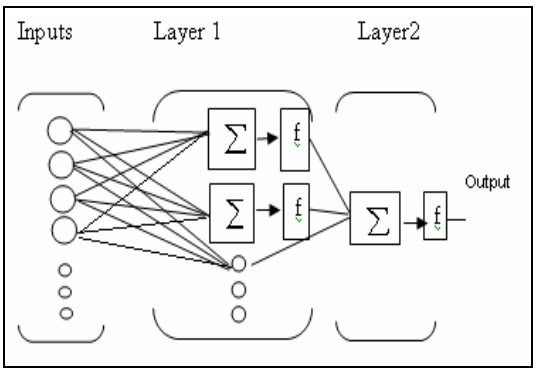

Figure 3 Neural Network

Neurons in the first layer use *logsig* transfer function. Initial weights and biases are generated randomly. Second layer includes only one neuron. Its transfer function is *purelin*, and output of this layer used to determine the pattern used on the input.

2.3 NN Training using echogram signals

The 50-points portions of the echogram were used as training samples for NNE method. Figure 4 shows training examples used in this algorithm:

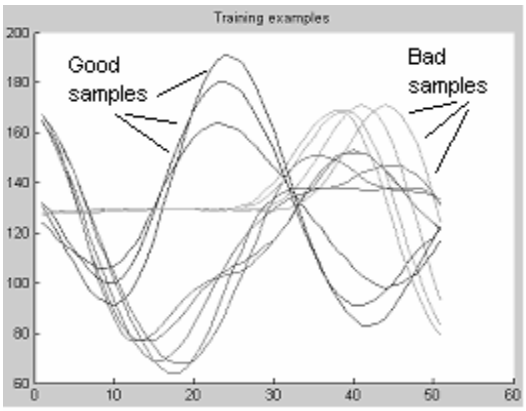

Figure 4. Training samples. "Good" samples represent echo from the objects, "bad" samples represent noise.

If a good target response is detected by the NN, its input which is a 50-point portion of the echogram is copied to the output image.

3. FDNNH method

3.1 Image Preparation & Fourier Descriptors

The background noise of the image was removed using a subjective threshold level of 180. Then, $N_8(p)$ algorithm was applied to find connected objects, as shown in Fig. 5. Next, these shapes were classified using FD.

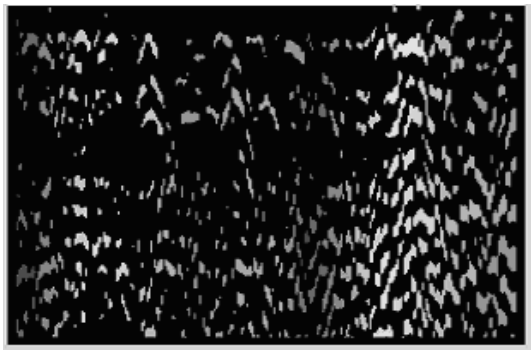

Figure 5: $N_8(p)$ algorithm finds all of the connected objects, shown in levels of gray.

There are many approaches to description and classification of contours of the pattern: statistical methods, based on method on moments, curve signatures, circular autoregressive model, etc. In this paper the shape of the pattern is described by coordinates of it contour in Cartesian (complex) coordinate system, and then the Discrete Fourier Transformation is applied to this data, to achieve the Fourier Descriptors of the shape [Ghorbel92], [Man90]. The advantage of FD is that they are easily computed and based on the well-developed theory of Fourier transformation [Ramesh95].

Let us suppose that we have closed contour in a complex X-Y plane. A point moving around the contour generates a sequence of coordinates (x(m), y(m)), where m=1,2,…,N, and N is a number of points in the boundary. Since boundary is a closed curve,

$$x(N)=x(1),\ y(N)=y(1) \qquad (1)$$

We can represent each coordinate pair as a complex number:

$$a(n) = x(n) + i * y(n) \qquad (2)$$

The Discrete Fourier transformation, u(n), for this coordinate sequence a(n) is defined as follow:

$$u(n) = \sum_{k=0}^{N-1} a(k) e^{\frac{i2pkn}{N}} \qquad (3)$$

Inverse Fourier transform is given by:

$$a(k) = \frac{1}{N} \sum_{n=0}^{N-1} u(n) e^{\frac{-i2pkn}{N}} \qquad (4)$$

$0 \le n \le N-1$

Fourier Descriptors s(n) are computed as follows:

$$s(n) = \frac{|u(n)|}{|u(1)|} \qquad (5)$$

To make Fourier Descriptors rotation- and shift- invariant, we have to use only absolute values of coefficients u(k), and in order to make them scale invariant, we normalize them by dividing each one by the first value. The most important Fourier Descriptors are the ones describing the lowest frequencies.

Ten lowest value descriptors were used to describe the shape in this work.

3.2 NN Training and classification for the FDNNH method.

The FDNNH method also used a two-layers feed-forward backpropagation Neural Network. Fourier Descriptors were obtained from the parabola/no-parabola-like images, and were used at the input of the Neural Network.

In the training of this NN, several closed contour shapes from the original image, representing hyperbolas and non-hyperbolas, after filtration, were selected, as shown in Figures 6 and 7.

Figure 6
Hyperbolas

Figure 7
Non-hyperbolas

4. Results and discussion

The NNE algorithm was applied to the data shown in Figure.1. Computation time for this algorithm is about 30 minutes on the Pentium 3 computer with 512 Mb of RAM. The computation time is high because of the successive sliding windows implemented. Fig. 8 shows the results of the classification with this method:

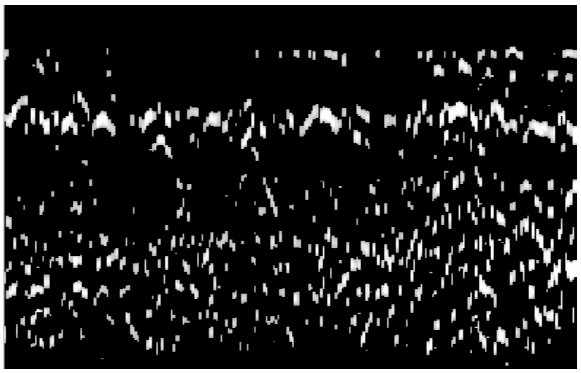

Figure 8. The result of the NNE method.

The FDNNH classification was applied to the same data. Computation time for this algorithm is about 5 minutes, including thresholding time and $N_8(p)$ algorithm on the same computer. The training time for 10 different images took less than one minute. The result of classification is shown in Figure 9.

Figure 9. Image after classification by FD-based algorithm.

Comparing these two images one can see that each method correctly classified a few very clear hyperbolas from the input data.
The result of the NNE method still has a lot of noise. The excessive noise is partially because of the low horizontal resolution of the data, hence, the responses from small objects produce short hyperbolas with weak amplitude at the tails, which can not be recognized by this method. Another reason is that after overlapping of the tails of different close hyperbolas, the final signature on the echogram becomes corrupted. It does not have high enough amplitude to be selected by NN, hence, hyperbolas become broken.
The image classified by FDNNH method is much cleaner. Most part of the noise, such as broken tails of overlapping hyperbolas, is eliminated. The final image has downward or upward hyperbolas. The reason for this is that FDs have rotation- invariant properties. Extra image processing would be necessary to select and keep only the downward

hyperbolas. In general, it can be conclude that the usage of FD can greatly improve the speed and quality of the classification.

5. Conclusions

The comparison of the two methods of classification of the GPR data was presented in this paper.
It was shown that FD contains a set of useful features, which can be used in classification and shape recognition.
The advantage of the FDNNH method over NNE method consists of better quality of the result and lower computation time.

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