Classification of different materials for underground object using artificial neural network

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Abstract. Ground Penetrating Radar (GPR) is widely used for non-destructive investigation of the shallow subsurface exploration especially in locating the buried infrastructure such as pipes, cables and road inspections. However, the interpreting hyperbolic signature of buried object in GPR images remains a challenging task. Therefore, this paper presented the classification of different materials based on GPR images using artificial neural network (ANN). In this research, GPR images so called the B-scan radargram represented by hyperbolic signature are firstly acquired and pre-processed. Then, the hyperbolic signature features are extracted using statistical techniques. The extracted features is then fed up as input to the multilayer perceptron (MLP) neural network classifier. A series of experiments have been conducted based on extracted hyperbolic features of different materials and shapes. Based on the results, the proposed method in classifying different materials based on GPR images using neural network showed promising results.

1. Introduction
GPR is a non-destructive evaluation and imaging tools for shallow subsurface exploration based on the transmitting and receiving of electromagnetic (EM) wave. It is widely used in a variety of applications such as locating buried infrastructure such as pipes [1] and cables, road inspection, land mines [2] and also used in geological/ archeological studies. The GPR system transmits short pulses of high frequency EM from 100 MHz to 1 GHz into the ground. These wave propagate with a velocity that depends on the dielectric property of medium. If the wave hit a buried object with different reactive indices, some of the wave are reflected back and receiver processes them to create a time-series, known as an A-scan [2]. Consecutive patterns in A-scan can be concatenated to create images of the subsurface, called B-scan. Buried objects exhibit characteristic pattern in B-scan so called radargram/map, such as hyperbolas, which can be used for detection [3, 4] as shown in Figure 1.

In the literature, many approaches have been developed in computer vision to analyse hyperbolic signature in detecting and locating the buried object. Some of them utilized histogram of oriented gradient (HOG) [5], scale invariant feature transform [6], finite different time-domain [7], and Hough transform [8, 9]. For instance, Carlotto [8] have used Hough transform in GPR images to find the hyperbolic parameter for buried object. Although Hough transform was commonly used method in detecting hyperbolic signature, however this method is time consuming and low accuracy. Ni et al. [4]...
used discrete wavelet transform to detect underground buried pipe based on hyperbolic signature. They used multiresolution analysis of DWT to filter and enhance the GPR data for obtaining more information on the DWT profile. Further, they have used sample of buried pipe made of plastic and metal in their design.

One of the problems in GPR signal is that they easily corrupted with by environmental noise, which might mask the weak reflections from inhomogeneities located deep in the test structure. The scattering amplitudes of wavelengths in the GPR signal are functions of the relative antenna-to-target orientation, target and background properties, scattering angle and target thickness. Moreover deeper objects may be obscured by numerous shallower objects, which appear constructively interfering hyperbolic reflectors. This diffracted energy can mask other reflections of interest and cause misinterpretation of the size and geometry of subsurface object from the GPR raw signature [1]. Therefore, this paper proposed of using multilayer perceptron neural network to classify the materials and the shape based on statistical features extracted from hyperbolic signature. The rationale of using this method is that the neural network has the ability to learn effectively from the data. They have been used successfully in several field such as speech recognition and face recognition.

![Figure 1. Basic principle of GPR](image)

**2. Methodology**

The flowchart of the proposed method is depicted in Figure 2. It consists of data acquisition, pre-processing, feature extraction and classification. The detailed of each block is described at the subsequent sections.

![Figure 2: The flowchart of the proposed method.](image)

**2.1. Data Acquisition of GPR images**

Sample Preparation. Fabrication of different samples having different materials (i.e perspek and alluminium) and different shape (i.e cubic and cylinder) have been conducted. In this work, antenna of 800 MHz transmitter and receiver of Ramac GPR Mala system was used to collect the data. Figure 3 shows the basic GPR components that consist of antenna, battery pack, control unit, and a portable PC.
In this research, two shapes (cylindrical and cube) and two materials (aluminium (metal) and perspex (non-metal)) were used as target samples. These samples are buried in parallel with depth of 200 cm from the ground surface with 100 cm apart between them. Sand was used as soil medium. Figure 4 illustrates the location of the buried sample. The operation GPR system was guided by research officer at Non Destructive Test (NDT), Nuclear Agency Malaysia for collecting the GPR data. The acquisition of data was conducted and repeated with 100 times. The example of hyperbolic signature appear in GPR images with respect to the buried object is depicted in Figure 5.

**Figure 3**: Basic component of GPR system

**Figure 4**: The position of the buried samples

**Figure 5**: The hyperbolic signature of the buried object

### 2.2. Image Pre-Processing

The acquire image that contains irrelevant parts (noise) should be removed. For the purpose of analysis, the original GPR images needs to be preprocessed. The preprocessed is composed of two step:
2.2.1. **Filtering.** Original image firstly converted into grayscale images. Then, in this work, median filter was used to improve the quality of the image by preserving the edge as well as removing unwanted noise. Figure 6 shows the example of applied median filter from grayscale image.

![Example of applied median filter](image)

Figure 6: (a) original GPR images, (b) grayscale image, (c) Applied median filter

2.2.2. **Cropping.** In this work, the hyperbolic signatures of filtered image of the samples are manually cropped. Only the region of interest of hyperbolic signature will be extracted and used as features for further investigated. The example of cropped hyperbolic signature is depicted in Figure 7.

![Example of cropped hyperbolic signature](image)

Figure 7. Example of cropped hyperbolic signature for different samples

2.3. **Feature Extraction**

The hyperbolic signature of buried objects exhibit unique pattern with respect to the shape, size, materials and depth. Feature extraction needs to be done to extract important features. In this work, skewness, standard deviation, maximum peak and total number of peak are extracted from hyperbolic signature.

\[
Skewness, s = \mathbb{E} \left[ \frac{(x - \bar{x})^3}{\sigma^3} \right]
\]

Where \( \mathbb{E} \) is expectation operator, \( \bar{x} \) is the mean of the data, \( x \) in the position of amplitude in the x-axis, \( s \) is the skewness and \( \sigma \) is the standard deviation.

2.3.1. **Gray Level Co-Occurrence Matrix (GLCM).** In statistical texture analysis, texture features are computed from the statistical distribution of observed combinations of intensities at specified positions relative to each other in the image. According to the number of intensity points (pixels) in each combination, statistics are classified into first-order, second-order and higher-order statistics [10]. The Gray Level Co-Occurrence Matrix (GLCM) method is a way of extracting second order statistical texture features. In this work, the GLCM features such as contrast, correlation, energy and homogeneity are used to extract the information of the hyperbolic signatures. Contrast is used to measures the local variations in the GLCM, whereas the correlation is used to measures the joint probability occurrence of the specified pixel pairs. Meanwhile, energy provides the sum of squared elements in the GLCM and also known as uniformity or the angular second moment. Then, the homogeneity is used measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.
2.4. Neural Network Classification

Artificial neural network is one of the techniques in artificial intelligence (AI) which has a functional imitation of the human brain. It is based on simulated nerve cells or neuron, which joined together to form networks. In general, an ANN is characterized by its architecture, learning algorithm and activation functions. Figure 8 shows the example of multilayer perceptron neural network. It consists of an input layer that distributes the input data to the processing elements in next layer. The hidden layers where the nonlinear behavior comes from and the output layer. Both the input and output layers are directly accessible while the hidden layers are not. Each layer contains several processing units which are generally called neurons. In this work multilayer perceptron is used to classify different type of material. The MLP learning algorithm [11] works as follows:

i. Initialize the weights to random values on the interval [-1, +1].

ii. Present the first training pattern, and obtain the output

iii. Compare the network output with the target output.

iv. Propagate the error backwards

   a. Correct the output layer of weights using the following formula:
   
   \[ w_{ho}^{(new)} = w_{ho}^{(old)} + (\eta \delta_o \cdot o_h) \]
   
   where \( w_{ho} \) is the weight connecting hidden unit \( h \) with output unit \( o \), \( \eta \) is the learning rate, \( o_h \) is the output at hidden unit \( h \). \( \delta_o \) is given by the following:
   
   \[ \delta_o = o_o (1 - o_o) (t_o - o_o) \]
   
   where \( o_o \) is the output at node \( o \) of the output layer, and \( t-o \) is the target output for that node.

   b. Correct the input weights using the following formula:
   
   \[ w_{ih}^{(new)} = w_{ih}^{(old)} + (\eta \delta_h \cdot i_h) \]
   
   where \( w_{ih} \) is the weight connecting node \( i \) of the input layer with node \( h \) of the hidden layer, \( o_i \) is the input at node \( i \) of the input layer, \( \eta \) is the learning rate. \( \delta_h \) is calculated as follows:
   
   \[ \delta_h = o_h (1 - o_h) \sum_o (\delta_o w_{ho}) \]
   
   where \( p \) is the number of units in the output layer.

v. Calculate the error, by taking the average difference between the target and the output vector. For example the following function could be used:

\[ E = \frac{1}{p} \sum_{o=1}^{p} (t_o - o_o)^2 \]

vi. Repeat from 2 for each pattern in the training set to complete one epoch.

vii. Shuffle the training set randomly. This is important so as to prevent the network being influenced by the order of the data.

viii. Repeat from step 2 for a set number of epochs, or until the error ceases to change.
3. Experimental Results & Discussion

In this work, 100 GPR images have been acquired at Malaysia Nuclear Agency using Mala RAMAC GPR with 800 MHz antenna. Firstly, the raw data of GPR image so called radargram is preprocessed by using median filter to improve the quality of image as well as to remove the unwanted noise. Then, the region of hyperbolic signature of GPR images are manually cropped. In this research, eight features of hyperbolic signature of buried object are extracted such as maximum peak, total number of peak, skewness, standard deviation and GLCM features (contrast, correlation, energy and homogeneity). These features serve as input to fed into MLP NN for classification. The effectiveness of the proposed method was evaluated using based on extracted hyperbolic signature features. Further, we also examined four different types of learning algorithm adopted in MLP such as Bayesian Regulation (BR), Scale Conjugate Gradient (SCG), Lavernberg-Marquardt (LM), and Resilient Back-Propagation (RP). Meanwhile, the data was split into training and testing set based on conventional method with (80 %, 20 %), (70 %, 30 %) and (60 %, 40 %) strategy using 10 hidden layer.

Table 1 shows the value of skewness, standard deviation, maximum number of peak and number of peak with respect to the types of material and shape. It can be seen from Table 1 that, the aluminium exhibits higher value of skewness, standard deviation, maximum peak and total number of peak compared to the perspek material. This means that the metal (aluminium) possesses strong reflected value of EM when the EM hits the underground metal object. In addition, in terms of shape, cubic consistently shows higher value as compared to the cylindrical. This is inferred that the shape has unique pattern of the buried object. Based on the results we can summarize that the materials such as aluminium and perspek exhibit different value/pattern based on skewness, standard deviation, peak value and no of peak. In addition, cubic and cylinder are well distinguish in reveal their characteristic.

Table 1: The value of skewness of different sample.

| Materials | Geometry | Skewness | Standard Deviation | Maximum Peak value | Total No of Peak |
|-----------|----------|----------|--------------------|--------------------|-----------------|
| Aluminium | Cubic    | 0.64     | 2289.32            | 15853              | 68              |
|           | Cylindrical | 1.44     | 598.97             | 10363              | 63              |
| Perspek   | Cubic    | -0.85    | 632.64             | 9679               | 58              |
|           | Cylindrical | -0.39    | 96.06              | 6242               | 57              |

Table 2 presents the recognition rates using MLP NN with various learning algorithm based on aforementioned features. It can be seen from Table 2 that the recognition rates of training set give perfect classification for all strategy. For testing performance, the result of using skewness feature gives the highest recognition rates which is 98.32% using Lavernberg Marquard (LM) learning.
algorithm with 80% 20% strategy. In contrast, the total number of peak features has the lowest recognition rate which is 74.74% using the same strategy. Meanwhile, standard deviation and maximum no of peak features are comparable which are 94.8% and 90%, respectively. As overall, the computational time of MLP model is relatively short which less than 7s.

Table 3 presents the recognition rates of using GLCM features based on MLP NN with different learning algorithm. It can be seen from Table 3 that, all training performances gives perfect recognition rates. For testing performance, the correlation and homogeneity features achieved the best recognition rates which are 100% using BR, SCG, LM and RBP. Further, energy features contributes the recognition rate of 96.50%. This can be inferred that, the GLCM features able to characterize the pattern of hyperbolic signature of buried object having different material and shape distinctively. So, the proposed method shows the promising results in classifying different materials and shape. Further, the average time of MLP NN to train the network only required less than 7 second.

Table 2: The recognition rates using maximum no of peak, no of peak, skewness and standard deviation features MLP NN with different learning algorithm.

| L.A | Data (%,%)% | Max of Peak (%) | AT (s) | Total No. of peak (%) | AT (s) | Skewness (%) | AT (s) | $\sigma$ (%) | AT (s) |
|-----|-------------|-----------------|--------|-----------------------|--------|--------------|--------|-------------|--------|
|     | (Tr, Ts)    | Tr | Ts | Tr | Ts | Tr | Ts | Tr | Ts | Tr | Ts |
| BR  | (80, 20)    | 100 | 86.50 | 3.41 | 100 | 74.40 | 4.24 | 100 | 95.67 | 4.60 | 100 | 76.80 | 4.10 |
|     | (70, 30)    | 100 | 88.80 | 3.60 | 100 | 69.80 | 3.48 | 100 | 96.66 | 6.68 | 100 | 82.80 | 4.88 |
|     | (60, 40)    | 100 | 83.70 | 3.99 | 100 | 58.70 | 3.58 | 100 | 90.83 | 5.23 | 100 | 94.20 | 5.53 |
| SCG | (80, 20)    | 100 | 89.00 | 3.96 | 100 | 70.20 | 3.78 | 100 | 93.33 | 3.92 | 100 | 79.20 | 3.94 |
|     | (70, 30)    | 100 | 89.30 | 3.95 | 100 | 69.70 | 3.47 | 100 | 94.99 | 6.46 | 100 | 81.30 | 4.49 |
|     | (60, 40)    | 100 | 85.20 | 3.94 | 100 | 57.80 | 3.35 | 100 | 91.66 | 4.96 | 100 | 94.80 | 4.00 |
| LM  | (80, 20)    | 100 | 85.70 | 4.24 | 100 | 74.00 | 4.32 | 100 | 98.32 | 3.96 | 100 | 78.00 | 6.77 |
|     | (70, 30)    | 100 | 87.30 | 3.68 | 100 | 70.20 | 3.70 | 100 | 94.66 | 6.43 | 100 | 81.80 | 4.99 |
|     | (60, 40)    | 100 | 87.20 | 3.42 | 100 | 57.50 | 3.67 | 100 | 90.13 | 4.56 | 100 | 94.50 | 4.07 |
| RBP | (80, 20)    | 100 | 90.00 | 4.55 | 100 | 60.00 | 3.19 | 100 | 85.00 | 5.75 | 100 | 79.50 | 4.29 |
|     | (70, 30)    | 100 | 88.30 | 3.51 | 100 | 70.50 | 3.32 | 100 | 86.33 | 3.69 | 100 | 81.70 | 5.44 |
|     | (60, 40)    | 100 | 83.30 | 3.62 | 100 | 57.20 | 4.80 | 100 | 85.33 | 4.56 | 100 | 93.20 | 4.81 |

Note: L.A (Learning Algorithm), BR (Bayesian Regulation), SCG (Scale Conjugate Gradient), LM (Lavernberg Marquaardt), RBP (Resilient Back-Propagation), Tr (Training), Ts(Testing), AT(Average Time)

Table 3: Recognition rates of GLCM features based on MLP NN using different learning algorithm

| L.A | Data (%,%)% | Contrast (%) | AT (s) | Correlation (%) | AT (s) | Energy (%) | AT (s) | Homogeneity (%) | AT (s) |
|-----|-------------|--------------|--------|-----------------|--------|------------|--------|-----------------|--------|
|     | (Tr, Ts)    | Tr | Ts | Tr | Ts | Tr | Ts | Tr | Ts | Tr | Ts |
| BR  | (80, 20)    | 100 | 94.00 | 5.89 | 100 | 100.0 | 5.14 | 100 | 93.8 | 6.73 | 100 | 99.3 | 3.85 |
|     | (70, 30)    | 100 | 91.7 | 4.99 | 100 | 98.6 | 4.96 | 100 | 96.8 | 5.53 | 100 | 100.0 | 4.28 |
|     | (60, 40)    | 100 | 82.2 | 4.92 | 100 | 99.2 | 4.60 | 100 | 97.2 | 4.95 | 100 | 99.5 | 4.00 |
| SCG | (80, 20)    | 100 | 72.5 | 4.63 | 100 | 100.0 | 4.73 | 100 | 97.5 | 4.08 | 100 | 100.0 | 3.57 |
|     | (70, 30)    | 100 | 72.0 | 4.47 | 100 | 98.2 | 5.78 | 100 | 97.5 | 4.28 | 100 | 100.0 | 3.61 |
|     | (60, 40)    | 100 | 66.3 | 4.32 | 100 | 99.2 | 4.70 | 100 | 97.5 | 4.12 | 100 | 100.0 | 4.12 |
| LM  | (80, 20)    | 100 | 96.5 | 4.96 | 100 | 100.0 | 5.20 | 100 | 95.3 | 6.24 | 100 | 99.3 | 3.61 |
|     | (70, 30)    | 100 | 93.0 | 4.61 | 100 | 98.3 | 5.59 | 100 | 99.2 | 4.38 | 100 | 99.5 | 3.80 |
|     | (60, 40)    | 100 | 80.0 | 4.55 | 100 | 99.2 | 6.32 | 100 | 97.5 | 4.05 | 100 | 99.5 | 3.52 |
| RBP | (80, 20)    | 100 | 74.0 | 4.62 | 100 | 100.0 | 4.61 | 100 | 97.0 | 5.54 | 100 | 100.0 | 3.55 |
4. Conclusion

In this paper, classification of material using multilayer perceptron neural network based on extracted hyperbolic signature features of GPR images was presented. The extracted hyperbolic features: skewness, standard deviation, maximum peak, total number of peak and GLCM exhibits unique pattern for aluminium and perspek where the value for aluminium was higher. For cubic and cylinder shapes, distinctive features were revealed where cubic exhibited higher value. The use of statistical features was effective way to classify different material (i.e metal and nonmetal) due to unique pattern of hyperbolic signature. Effectiveness of the proposed method was evaluated using MLP NN classifier for various learning algorithm where, the GLCM features (correlation and homogeneity) achieved the best recognition rates which are 100% using BR, SCG, LM and RBP learning algorithm in classifying metal and nonmetal (i.e aluminium and perspek) for cubic and cylinder shapes. Thus, the proposed method shows promising results in crude classification of different material based on GPR images.

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