Metal shape classification of buried object using multilayer perceptron neural network in GPR data

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Abstract. Ground penetrating radar (GPR) is a non-destructive tool for subsurface investigation becomes an emerging trend in many applications especially in detecting infrastructure utilities. However, interpreting of GPR data in terms of target’s geometry is remained a challenging task due to the existence intra/inter-class variations and subtle changes of hyperbolic signature pattern in GPR data. To addressed this issue, this paper proposes to classify the basic shape (i.e. cubic, cylindrical and disc) of buried object using multilayer perceptron neural network. The GPR raw data firstly is pre-processed based on A-scan and B-scan GPR data. Then, the combined statistical features with gray level co-occurrence matrix (GLCM) and Hu moment invariants are extracted from A-scan and B-scan. The extracted features are then fed as input to multilayer perceptron to classify the shapes (cubic, cylindrical and disc) of buried object. Based on the experiment conducted, the highest recognition rate has been achieved is about 83.3%. Thus, the proposed method of using combined statistical with GLCM and Hu moment invariants features to classify shape of buried object using multilayer perceptron is promising.

1. Introduction

GPR is one of the most popular and reliable geophysical devices in shallow subsurface exploration. It successfully used in detecting and locating the subsurface utilities such as pipes and cables [1] and land mines [2]. It produces cross-sectional profile of subsurface without the need of digging or drilling on the ground surveyed. Figure 1 shows the basic principle of GPR system. It transmits short electromagnetic pulses of high frequency electromagnetic wave (EM) into the surveyed ground. These waves propagate with a velocity that depends on the dielectric property of medium. Pulses will be reflected back to the receiver when EM waves hit the materials with different dielectric constant [3]. When antenna is located above a target (i.e. at $x_0$), the travel time to the target will be minimum (i.e. $t_0$). Therefore, it creates a hyperbolic signature in GPR images.
Basically, there are three methods in running the GPR system to acquire the data which are A-scan, B-scan and C-scan as illustrated in Figure 2 [4]. A-scan signal is created from time-series of reflected wave signal that collide with buried object. The 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. The C-scan is equal to a multiple parallel of B-scan results.

In previous work, many techniques have been proposed in pattern recognition in order to detect and recognize the buried objects. Some of them adopted histogram of oriented gradient (HOG) [3, 5], scale invariant feature transform [6], finite different time-domain [7], and Hough transform [8, 9]. For example, Lee & Mokji [3] have used histogram of oriented gradient to automatically detect the hyperbolic signature in GPR data that contains the reflections from target of buried object by narrow down the data into possible reflections with the aid of linear SVM. Syambas [10] proposed decision tree method for predicting the shape and size of a buried object on surface GPR. 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.

This paper presents classifying the metal shape of buried objects in GPR data using combined statistical features derived from A-scan and GLCM and Hu moments invariant features derived from B-scan. The extracted features then served as input to multilayer perceptron neural network to classify the metal shape of buried objects based on hyperbolic signature.

2. Methodology

Figure 3 illustrates the flowchart of the proposed method. It consists of data acquisition, pre-processing, feature extraction and classification. The detailed of each block is described at the subsequent sections.

Figure 1. Basic principle of GPR system.

Figure 2. Representation of GPR system: (a) A-scan, (b) B-scan, & (c) C-scan.

Figure 3. The flowchart of the proposed method.
2.1. Data Acquisition

This research consists of hardware and software development. In hardware development, preparation of samples is required and material of metal specifically aluminum was used in this investigation. Sample fabrication has focused on three basic shapes which are cubic, cylindrical and disc. For GPR system, antenna of 800 MHz transmitter and receiver of Ramac GPR Mala system was used to acquire the GPR images. Figure 4 shows the basic GPR components that consist of antenna, battery pack, control unit, and a portable PC.

![Figure 4. Basic component of GPR system.](image)

The location of buried object is depicted in Figure 5. These samples consist of spherical, disc, cubic and cylindrical shape from material aluminium and perspex. These samples are buried in parallel with depth of 200 cm from the ground surface with 100 cm apart between them. Dry sand was used as soil medium. The operation GPR system was guided by research officer at Non Destructive Test (NDT), Nuclear Agency Malaysia for collecting the GPR data.

In this work, we proposed to investigate the behavior of three different shapes which are cubic, cylindrical and disc for material aluminium (metal) based on GPR images. About 150 GPR images have been recorded in which 50 cubic images, 50 cylindrical images and 50 disc images. Figure 6 illustrates the example of A-scan signal for three different shapes. Meanwhile, Figure 7 shows the B-scan images reveal unique hyperbolic signatures appear in GPR images with respect to the buried object.

![Figure 5. The position of the buried samples.](image)
Figure 6. The example of A-scan signal of the buried objects based on the shape: (a) cubic, (b) cylindrical & (c) disk.

Figure 7. The B-scan of the buried objects reveal the hyperbolic signature pattern.

2.2. Signal & Image Pre-Processing
The acquired signal or image that contains irrelevant parts (noise) should be removed. For the purpose of analysis, the original GPR images needs to be pre-processed. This technique involved for signal pre-processing (A-scan) and image pre-processing (B-scan).

2.2.1. Signal Pre-processing. Figure 8 shows the pre-processed technique for A-scan signal. It consists of cropping, filtering, absolute and normalize of the signal. An example of pre-processed is shown in Figure 9. While for the image, filtering and cropping the specific region to extract the hyperbolic signature was done.

Figure 8. Signal preprocessing technique for the proposed method.
2.2.2. Image Pre-processing. The original GPR image was converted to grayscale image as illustrated in Figure 10. To reduce the noise and preserve useful details in the image, filtering technique was adopted in this work. In this work, we investigate three type of filters which are median filter, average filter and Gaussian filters. The median filter is a non-linear digital filtering technique often used to reduce the noise of an image and preserves useful details in the image, whereas average and Gaussian filter are linear filter. An example of filtered image for cubic metal shape is depicted in Figure 11. Then, the filtered images were further cropping to extract the hyperbolic signature of GPR images. Figure 12 shows the example of the cropped hyperbolic signature image.
2.3. Feature Extraction

The hyperbolic signature of buried objects exhibits unique pattern with respect to the shape, size, materials and depth. Feature extraction needs to be done to extract important features. In this work, statistical features such as skewness, standard deviation, maximum value and total number of peaks were extracted from A-scan signal. While, texture and shape features of GLCM and Hu moment invariant were extracted from the hyperbolic signature.

2.3.1. GLCM. Gray Level Co-Occurrence Matrix proposed by Haralick [11] consists of 24 parameters from co-occurrence matrix. The parameter such as energy, contrast, local homogeneity, and correlation will be used as features in this work.

2.3.2. Hu Moment Invariant. Moment invariants have been widely used to image pattern recognition in various applications due to its invariant features on image translation, scaling and rotation [12]. Moment can provide characteristics of an object that uniquely represent its shape. Hu introduced seven nonlinear functions which are invariants under object’s translation, scale and rotation [12]. The set of seven third order boundary central moments are given by the following equations.

\[ M1 = \eta_{20} + \eta_{02} \]  
\[ M2 = (\eta_{20} - \eta_{02})^2 + 4 \eta_{11}^2 \]  
\[ M3 = (\eta_{30} - \eta_{12})^2 + (3 \eta_{21} - \eta_{03})^2 \]  
\[ M4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \]  
\[ M5 = (\eta_{30} - 3 \eta_{12})(\eta_{30} + \eta_{12})[(\eta_{20} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + 3(\eta_{21} + \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{20} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \]  
\[ M6 = (\eta_{30} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4 \eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \]  
\[ M7 = (3 \eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{20} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3 \eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \]

The set of seven boundary moments are treated as feature vectors. The moment 1 (M1) to moment 6 (M6) are moment that invariant to translation, size and rotation. There are analogous to the moment of inertia around the images centroid, where the pixels intensities are analogous to physical density. While moment 7 (M7) is skew invariant, which enables to distinguish mirror images of otherwise identical images. These features are then used for the classification.

Figure 12. The radargram for three shapes: (a) cubic, (b) cylindrical, and (c) disc.
2.4. Multilayer Perceptron Neural Network.
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 13 shows the structure of multilayer perceptron neural network used in this project. 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 [13] works as follows:

1. Initialize the weights to random values on the interval [-1, +1].
2. Present the first training pattern, and obtain the output
3. Compare the network output with the target output
4. Propagate the error backwards
   a. Correct the output layer of weights using the following formula.

   $\Delta_{ho} = \eta \delta_o o_h$  

   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.

   $\Delta_{ih} = \eta \delta_h i_h$  

   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.

   $\delta_h = o_h (1 - o_h) \sum o_o \delta_o w_{ho}$  

   where $p$ is the number of units in the output layer.
5. Calculate the error, by taking the average difference between the target and the output vector. For example, the following function could be used.

   $E = \frac{\sqrt{\sum_{n=1}^{p} (t_o - o_o)^2}}{p}$  

6. Repeat from 2 for each pattern in the training set to complete one epoch.
7. Shuffle the training set randomly. This is important so as to prevent the network being influenced by the order of the data.
8. Repeat from step 2 for a set number of epochs, or until the error ceases to change.
3. Experimental results and discussion

To evaluate the effectiveness of the proposed method, 150 recorded GRP data have been used. Three basic shape (cubic, cylindrical and disc) shape from metal specifically aluminum has been adopted. Firstly, the GPR data need to pre-process so that any noise and irrelevant data can be minimized. The statistical features such as skewness, standard deviation, maximum value and total number of peaks were extracted. In addition, GLCM and Hu moment invariant features were extracted from GPR images based on hyperbolic signature. These features then were combined to form one dimensional feature vector that served as input to the multilayer perceptron (MLP). For the MLP NN structure, 50 hidden layers were used at 50 epochs. A series of experiments has been conducted using different learning algorithm such as Bayesian Regulation (BR), Scale Conjugate Gradient (SCG) and Lavernberg Marquardt (LM). In this experiment, the training and testing data was split into 3 strategies which are (90% training, 10% testing), (80% training, 20% testing) and (70% training, 30% testing).

Table 1 shows the average recognition rates based on the combined statistical features with GLCM and Hu moment invariant using MPL NN with different learning algorithms in classifying metal shape of buried object. It can be seen from Table 2 that all training data achieved perfect recognition rates. For testing performance, the proposed method achieved the highest recognition rate which is 83.30% using Scale Conjugate Gradient learning algorithm with (90% training, 10% testing) strategy. When we change the training and testing data to (80% training, 20% testing) the results slightly decrease to 81.30%. Based on the result, it shows that the combined features able to classify the metal shape of buried object in GPR data using MLP NN, thus it shows a promising result of the proposed method.

**Table 1.** The recognition rates of using combined statistical features with GLCM and Hu moment invariants. using MPL NN with different learning algorithm.

| L A      | Data (%) (%) | Recognition Rates (%) |
|----------|--------------|-----------------------|
|          | (Tr, Ts)     | Tr                    | Ts                    |
| BR       | (90, 10)     | 100                   | 66.00                 |
|          | (80, 20)     | 100                   | 70.70                 |
|          | (70, 30)     | 100                   | 62.20                 |
| MLP NN   | SCG          | (90, 10)              | 100                   | 83.30                 |
|          | (80, 20)     | 100                   | 81.30                 |
|          | (70, 30)     | 100                   | 77.20                 |
| LM       | (90, 10)     | 100                   | 48.70                 |
|          | (80, 20)     | 100                   | 40.70                 |
|          | (70, 30)     | 100                   | 48.10                 |

Note: LA (Learning Algorithm), BR (Bayesian Regulation), SCG (Scale Conjugate Gradient), LM (Lavernberg Marquardt), Tr (Training), Ts (Testing)
4. Conclusion

This paper has presented the classification of metal shape of buried object using multilayer perceptron based on the combined hyperbolic features extracted from GPR data. The combined of statistical features (skewness, standard deviation, maximum value and total number of peak) with GLCM and Hu moment invariants are extracted and used to classify the metal shape object using MPL NN with different learning algorithms. Based on the results, it shows that, the highest recognition rate which gives 83.30% has been achieved using Scale Conjugate Gradient learning algorithm with (90% training, 10% testing) strategy. Thus, the proposed method shows a promising result in classifying metal shape of buried objects specifically cubic, cylindrical and disc from GPR images. However, further study should be conducted to enhance the performance of the proposed method by utilizing optimization technique of the proposed method.

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