# Fundamental Shape Discrimination of Underground Metal Object Through One-Axis Ground Penetrating Radar (GPR) Scan

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***Abstract*—Ground Penetrating Radar (GPR) was used in this research to detect or recognize the buried objects underground. Hyperbolic signals formed by datagram of GPR after detection the buried objects which quite similar to each other in term of metal shapes. The research was tested on the metal cube and metal cylinder by using the A-scan of GPR. There are steps in this signal processing step which are pre-processing step, feature extraction, and classification process. The segmentation process hyperbolic signals were segmented one by one and normalize from the negative to positive signals. The hyperbole from the metal cylinder and metal cube that had been buried in the ground is differentiated using four features of their respective A-scans which are found the maximum value of amplitude signal graph, the number of peaks in the signals graph, skewness, and standard deviation values. Finally, the classification process used learning algorithm of Multi-Layer Perceptron (MLP) was a test on Bayesian Regulation Backpropagation (BR) was given the highest accuracy, 98.70% as a classifier to classify the metal shapes which are a metal cube and metal cylinder.**

***Index Terms*—A-Scan; Ground Penetrating Radar (GPR); Metal Shape; Recognition; Signal Processing; Statistical Features.**

## I. INTRODUCTION

The most popular device is to find or verify buried object which located underground which known as ground penetrating radar (GPR) device that defined one of the major concerns that occupy the minds of GPR operators when dealing with such objects. The GPR detections such as shape buried object, mines, pipes, tanks and cables, metal and non-metal which are characterized of parameters such as the depth of buried objects, the medium of permittivity, diameter, the soil condition and orientation of the target[1].

Nowadays, the technology of using GPR is most popular in many applications. But there are some problems occur when buried objects cannot detect by ground penetrating radar. When the image of GPR is producing, that image is not clear and undefined with the shape of the object that buried underground. But hyperbolic signals that formed by GPR only persons which have experience and professional can understand [2]. The condition of soil at the field site is very important. The GPR device cannot give the signal if the soil condition not in good condition [3]. The offsite of GPR also take main part which means the object buried near to each other will formed double hyperbolic signals by GPR datagram [4]. So this solution for this problem is developed by the methods to reduce signals with double hyperbolic so that the needed of buried objects is detected.

Recognition system of metal shape by using Artificial Neural Network (ANN) was used to analyze the result. The method that used for this project is to classify the metal shape which metal cube and metal cylinder. Method of extraction the image acquisition uses suitable image processing algorithms and then makes recognition and classification of metal shapes using Artificial Neural Network which is Multi-Layer Perceptron and several learning algorithms for examples Scale Conjugate Gradient (SCG) [5], Levenberg-Marquardt Backpropagation (LM) [6], Bayesian Regulation Backpropagation (BR) [7], and Resilient Backpropagation (RP) [8].

## II. LITERATURE REVIEW

### *A. Pre-Processing*

In pre-processing data, there are many methods to remove or filter noise from the signal. One of the methods is using background clutter removal [11]. This method was applied to data analysis of signals for examples, system ringing, surface reflection, and coupling of signals. The process is using the mathematical process to the image. The object signatures will produce higher contrast and higher signal to the clutter ratio of the image.

Hilbert Transform is used non-linear operation of envelope extraction [12]. This method is working to enlarge the element extraction from the undesirable signal for in the element extraction process.

### *B. Feature Extraction*

To extract the feature from signal means by the derivation of values that was developed and initial data that measured from signals. There are many methods to extract the feature from the signal pattern which using Fast Fourier Transform (FFT) [13]. Statistical features [14], use to differentiate between reflections representing target and non-target object buried. Then, to simplified and reduce the signals the time variable is removing. This method contents mathematical variables to analysis graph and curve. The statistical feature also will form the skewness and standard deviation from statistical method. This method is suitable for A-scan data.

### *C. Classification*

Image of datagram will undergo through the classification process also known as the image of feature and classifies that were analyzed into a small number of categories and numerical properties. K-Nearest Neighbor (k-NN) classifier was approved by the researcher [15]. k-NN was applied as input system in every image of leaves in the database. This classifier was tested on 640 leaves that come from 32 different of plants. As a result, the accuracy of 83.5% classifier and was upgraded to 87.25% using the matching colour of histogram. k-NN uses this classifier to classify the shape features of plan leaf. The accuracy, not higher compared to the next researcher.

Another classifier is Multi-Layer Perceptron (MLP) from researcher [16] used to classify seismic signals recorded by the local seismic network of Agadir (Morocco). Besides, MLP contains several learning algorithms which are Scale Conjugate Gradient (SCG) [17], Levenberg-Marquardt Backpropagation (LM) [18], Bayesian Regulation Backpropagation (BR) [19], and Resilient Backpropagation (RP) [20]. MLP also contains several layers which are output layer where the network indicates the predicted class, and hidden layers between the input and output layers. Data will train and test on a pair input/output set of data to learn to associate the inputs with the corresponding outputs. The result of this classification that tests on 343 a data set of seismic signals is above 85%.

Support Vector Machines (SVM) classifier was also used to test finding the hyperbolic or linear of pattern in ground penetrating radar (GPR) images. SVM gave good performance in object detection and material recognition. Based on the curse of the dimensionality, the margin maximization of principle and decision function by SVM was good in generalization in capability and low sensitivity [21].

Multi-Layer Perceptron (MLP) is the most suitable in classification algorithm MLP can be utilized as a part of the capability of approximate non-linear functions of inputs and can be verified by many samples of data signals.

## III. METHODOLOGY

The proses of the methodology are started with an explanation about three phase which are image acquisition, signal processing, and classification process. In the first phase, image acquisition was prepared by recording sample data. The samples that produce data used in this research are cylinder and cube which made up of metal. These objects are made with specific measurement and build in hollowed at the inner side. Then, followed by the second phase which is signal processing which includes pre-processing data and feature extraction process. The objects are buried beside each other with specific measurement and vertical and horizontal line to find midpoint which signals acquisition processes. Besides, RAMAC software is used for display GPR datagram, and ASCII array algorithm is used to convert from datagram to MATLAB software. In the process of features extraction, the statistical method is used. The third phase is classification process which used Multi-Layer Perceptron (MLP) for classifying the shape of metal objects. The three phases as shown in Figure 1 below.

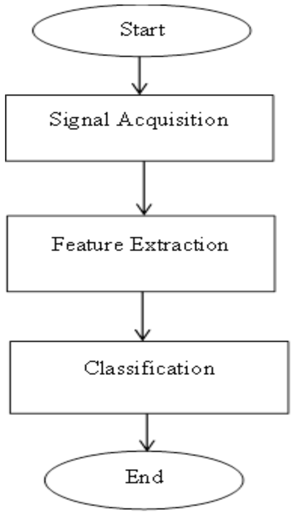
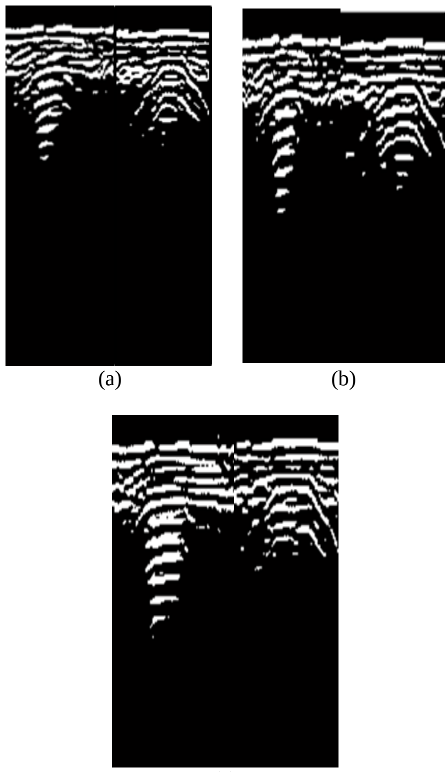



Figure 1: Flowchart of the system

There are steps in this signal processing step which are pre-processing step, feature extraction, and classification process. Firstly, for the segmentation process, hyperbolic signals were segmented one by one and normalized from the negative to positive signals. Secondly, the feature extraction process has four features which are found the maximum value of amplitude signal graph, the number of peaks in the signals graph, skewness and standard deviation values. Lastly, for the classification process used Multi-Layer Perceptron (MLP) as a classifier to classify the metal shapes which are a metal cube and metal cylinder.

### A. *Pre-Processing*

After done process collecting the signals by ground penetrating radar, results in form as shown in Figure 2.



(a) (b)

(c)

Figure 2: Datagram of GPR signal

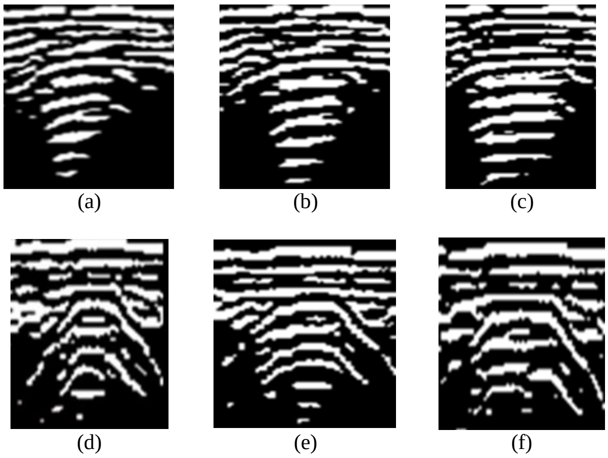



Figure 3: Cropped datagram of GPR signal

From the Figure 3, Cu01, Cu02, and Cu03 refer to datagrams of the metal cube, Cy01, Cy02, and Cy03 refers to datagrams of the metal cylinder. After done pre-processing process for both hyperbolic signals, these data form in negative values and positive values. Then, both data will normalize Fast Fourier Transform (FFT) which converts all negative value to positive value and constructed in the graph before extract the data.

### B. *Feature Extraction*

In feature extraction process there are four features that were chosen used to complete this processed. The first feature is to find the maximum value in signal data of metal cube and metal cylinder. This feature used to find the maximum value in each data signal object by referring the amplitude value in a signal graph using the command in MATLAB software. The second feature is to find the number of peaks in both data signal which each signal produce difference number of peaks. The third feature is to find the value of skewness among metal cube and metal cylinder by using the command in MATLAB. The fourth feature is standard deviation method using highest maximum amplitude in the data signal of the metal cube and metal cylinder.

Before starting the feature extraction process, the data is undergoing this step as below:

1) Determine the center of the hyperbolic signals as in Equation (1).

$$i_N = (Total\ Number\ of\ single\ signal)/2 \tag{1}$$

2) Assume the first right and left signal, where the separation between left and right signal with the center signal $i_0$ is n. Set n as 2 pixel. Thus, the left signal is $i_{-2}$ and the right signal is $i_2$.
3) Find the next consecutive signals for each left and right signals of $i_0$ by using Equations (2) and (3).

$$Right\ hand\ side\ signal = i_{0+Nn} \tag{2}$$

$$Left\ hand\ side\ signal = i_{0-Nn} \tag{3}$$

N is consecutive signals which the from 1 to 5.

4) Lastly, the signals are arranged as shown in Figure 4 and expressed as Equation (4).

$$i_n = [i_{-5} i_{-4} i_{-3} i_{-2} i_{-1} i_0 i_1 i_2 i_3 i_4 i_5] \tag{4}$$

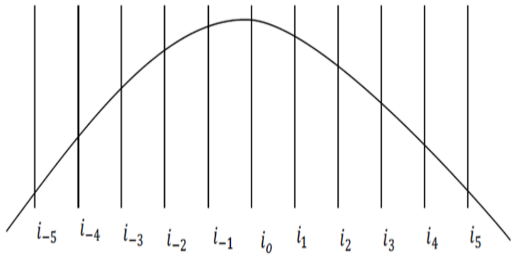



Figure 4: The hyperbolic signal of A-scan by 11 lines

The first feature is by finding the maximum values of data in a range of metal shape which are a metal cube and metal cylinder. The second feature is by finding the number of the peaks in the range of amplitude that form in the signal graph by both metal shapes as shown in Equation (5). Maximum value/amplitude

$$Max(i_{-5}) Max(i_{-4})\ Max(i_{-3}) \ldots Max(i_3)\ Max(i_4) Max(i_5) \tag{5}$$

The third feature is using skewness method that calculates A-scan's range of data of amplitude metal cube and metal cylinder. The fourth feature is identifying the value of standard deviation of amplitude that forms in the range of both metal shape. The skewness and standard deviation can be calculated to differentiate the signals of the metal cube and metal cylinder. Table 1 shows the features range of values between Cube and Cylinder

Table 1
Features Range of Values between Cube and Cylinder

| Features | Cube | Cylinder |
|---|---|---|
| Maximum Value | 111303>255777 | 3374>111303 |
| Maximum number of peaks | 24>37 | 14>24 |
| Skewness | 1.00>2.45 | 0.05>1.00 |
| Standard Deviation | 500>2264 | 238>500 |

If there have more data overlaps with each other will affected the accuracy of each feature in next step which classification method. The error will occur due to some data that overlap.

### C. *Classification*

After done finalized data of feature extraction process, a data signal of the metal cube and metal cylinder were classified by using Multi-Layer Perceptron, k-nearest neighbors (k-NN) and Support Vector Machine (SVM).

A small value of k means that noise will have a higher influence on the result which a large value make it computationally expensive and kind a defeats the basic philosophy behind k-NN (that points that are near might have similar densities or classes ). Data features of the metal cube and metal cylinder were divided into two classes which defined as class one and class two as input in command of k-nearest neighbors. For class two, the metal cube was defined as 0 and metal cylinder as 1.

Besides, 200 data also tested into Multi-Layer Perceptron (MLP) classifier; the samples were tested on four learning algorithms which are Scale Conjugate Gradient (SCG), Levenberg-Marquardt Backpropagation (LM), Bayesian Regulation Backpropagation (BR), and Resilient Backpropagation (RP).

## IV. RESULTS AND DISCUSSION

Table 2 shows that 97.5% of metal shapes are classified correctly in the case where the training samples are more than the test samples. The percentage error is 2.5%.

Table 2
Classification Efficiency of Scale Conjugate Gradient (SCG)

| Training Samples | Test Samples | Classification Efficiency SCG (%) |
|---|---|---|
| 90 | 10 | 97.50 |
| 80 | 20 | 95.50 |
| 30 | 70 | 93.00 |

Table 3 shows that 94% of metal shapes are classified correctly in the case where the training samples are more than the test samples. The percentage error is 6%.

Table 3
Classification Efficiency of Levenberg-Marquardt Backpropagation (LM)

| Training Samples | Test Samples | Classification Efficiency LM (%) |
|---|---|---|
| 90 | 10 | 94.00 |
| 80 | 20 | 93.00 |
| 30 | 70 | 92.00 |

Table 4 shows that 99.50% of metal shapes are classified correctly in the case where the training samples are more than the test samples. The percentage error is 0.05%.

Table 4
Classification Efficiency of Bayesian Regulation Backpropagation (BR)

| Training Samples | Test Samples | Classification Efficiency BR (%) |
|---|---|---|
| 90 | 10 | 99.50 |
| 80 | 20 | 99.00 |
| 30 | 70 | 95.50 |

Table 5 shows that 92.50% of metal shapes are classified correctly in the case where the training samples are more than the test samples. The percentage error is 7.5%.

Table 5
Classification Efficiency of Resilient Backpropagation (RP)

| Training Samples | Test Samples | Classification Efficiency RP (%) |
|---|---|---|
| 90 | 10 | 92.50 |
| 80 | 20 | 91.00 |
| 30 | 70 | 92.50 |

Table 6 shows that 92.50% of metal shapes are classified correctly in the case where the training samples are more than the test samples. The percentage error is 7.5%.

Table 6
Overall Accuracy of Classifications According to Different Network

| Ratio Training-Testing | 90-10 | 80-20 | 30-70 |
|---|---|---|---|
| MLP-SCG | 95.35 | 92.20 | 92.67 |
| MLP-LM | 93.55 | 93.10 | 92.17 |
| MLP-BR | 98.70 | 98.50 | 95.83 |
| MLP-RP | 94.80 | 94.30 | 92.50 |
| k-NN | | Accuracy 86.7 | |
| SVM | | Accuracy 57.7 | |

## V. CONCLUSION

Based on the step of signal acquisition, the condition of ground must be accountable when buried the object in the ground which cause will some disturbance and effect in signals that formed by ground penetrating radar(GPR). Therefore, more duration object buried in the ground will give the highest compactness soil, so that the GPR will form a high-quality image of datagram signals. In the step of signal processing, four features extraction process were used in this step. As for the last step, Bayesian Regulation Backpropagation was given the highest accuracy, 98.70% among three mains of classifications. Therefore, the methodology of this research was acceptable to define and predict the metal shape of objects in the ground.

## ACKNOWLEDGMENT

The author gratefully acknowledges the supervisor and co-supervisor for this final year project. Importantly, the author would like to express thankfulness to Non-Destructive Lab of Malaysian Nuclear Agency for the corporation for using RAMAC GPR at the lab compound and useful information during this research study.

## REFERENCES

[1] V. Rafael, N. Santos, W. Al-nuaimy, J. Luís, N. S. Tomita, and H. S. Alzubi.(2014). "Spectral analysis of ground penetrating radar signals in concrete, metallic and plastic targets," J. Appl. Geophys., vol. 100, pp. 32–43.

[2] K. C. Ho, S. Member, L. M. Collins, S. Member, L. G. Huettel, P. D. Gader, and S. Member.(2004). "Discrimination Mode Processing for EMI and GPR Sensors for Hand-Held Land Mine Detection," vol. 42, no. 1, pp. 249–263.

[3] A. Omran, A. Firas, S. Hameed, A. Abdulrazzaq, M. Suad, and M. Ali.(2013). "The Effect of Air Reflection on Ground Penetrating Radar ( GPR ) Data," no. 5.

[4] S. Perkins (2003), "Grafting : Fast , Incremental Feature Selection by Gradient Descent in Function Space," Journal of Machine Learning Research, vol. 3, pp. 1333–1356.

[5] S. Areerachakul and S. Sanguansintukul (2010). Classification and Regression Trees and MLP Neural Network to Classify Water Quality of Canals in Bangkok , Thailand. International Journal of Intelligent Computing Research, vol. 1, no. 1, pp. 43–50.

[6] A. A. Nasir, M. Y. Mashor, and R. Hassan (2013).Classification of Acute Leukaemia Cells Using Multilayer Perceptron and Simplified Fuzzy ARTMAP Neural Networks Classification of Acute Leukaemia Cells using Multilayer Perceptron and Simplified Fuzzy ARTMAP Neural Networks. The International Arab Journal of Information Technology no. July.

[7] F. Kurtulmu, İ. Aliba, and I. Kavdir (2016), "Classification of pepper seeds using machine vision based on neural network," vol. 9, no. 1.

[8] S. Shihab.(2004)."Radius Estimation For Subsurface Cylindrical Objects Detected By Ground Penetrating Radar," no. 2, pp. 19–22.

[9] Y. Xi, F. Yang, and X. Qiao, (2014), "Ground penetrating radar system applied in the underground concealed object detection," pp. 811–814.

[10] F. J. W. Podd, A. J. Peyton, and D. W. Armitage, (2015), "GPR combined with a positioning system to detect anti-personnel landmines," pp. 5–8.

[11] S. Shihab,(2004), "Radius Estimation For Subsurface Cylindrical Objects Detected By Ground Penetrating Radar," no. 2, pp. 19–22.

[12] H. Boche and U. J. MOnich (2012), "Extension of the hilbert transform," Acoust. Speech Signal Process, pp. 3697–3700.

[13] M. Devi and a a Shinde(2013), "Signal Analysis of Real Time Signals to Remove Noise," no. October, pp. 426–428.

[14] S. Shihab, W. Al-Nuaimy, Y. Huang, and A. Eriksen (2003), "A comparison of segmentation techniques for target extraction in ground-penetrating radar data," 2nd Int. Work. Adv. GPR, pp. 14–16.

[15] A. Vehtari and J. Lampinen (2000), "Bayesian MLP Neural Networks for Image Analysis," no. September.

[16] A. Ebrahimzadeh, M. Ahmadi, and M. Safarnejad (2016).Classification of ECG signals using Hermite functions and MLP neural networks. Journal of AI and Data Miningvol. 4, no. 1, pp. 55–65.

[17] E. Pasolli, F. Melgani, and M. Donelli (2008), "Automatic Detection and Classification of Buried Objects in Gpr Images Using Genetic Algorithms," Computer (Long. Beach. Calif)., no. 1, pp. 525–528.

[18] T. Munisami, M. Ramsurn, S. Kishnah, and S. Pudaruth (2105), "Plant Leaf Recognition Using Shape Features and Colour Histogram with K-nearest Neighbour Classifiers," Procedia Comput. Sci., vol. 58, pp. 740–747.

[19] E. Hassan (2013), "Seismic Signal Classification using Multi-Layer Perceptron Neural Network," vol. 79, no. 15, pp. 35–43.

[20] S. Arora, L. Malik, D. Bhattacharjee, and M. Nasipuri (2014), "Classification Of Gradient Change Features Using MLP For Handwritten Character Recognition," pp. 3–6.

[21] C. Science and S. Engineering.Feature Selection for Plant Leaf Classification Based on Information Gain. International Journal of Advanced Research in Computer Science and Software Engineering vol. 4, no. 10, pp. 856–861.