Shape classification of ground penetrating radar using discrete wavelet transform and principle component analysis

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Abstract. Ground penetrating radar is one of the promising non-destructive investigation for shallow subsurface exploration in locating buried utilities. However, interpreting hyperbolic signature of buried objects in GPR images remains a challenging task since the GPR signals are easily corrupted by environmental noise and cause misinterpretation of the size and geometry of subsurface object from the GPR raw profile. Therefore, this paper proposes Discrete Wavelet Transform (DWT) and principal component analysis (PCA) to classify geometry of buried object using k-nearest neighbour. (k-NN). The GPR images firstly being pre-processed. Then, the GPR images are decomposed using DWT into four sub-bands which are LL (Low-Low), LH (Low-High), HL (High-Low) and HH (High-High). The sub-bands LL or a coarse approximation coefficients was extracted as DWT features in order to classify the shape of buried objects. Since DWT features do contain high dimensional data, thus PCA is used to reduce the dimensional features from higher to lower space by linear transformation. The new projected features were then classify using k-NN classifier into four shapes which is cubic, cylinder, disc and sphere. A series of experiments have been conducted on extracted DWT and PCA features from hyperbolic signature of buried objects having different shapes. Based on the results, the proposed method had achieved the average recognition rate of 99.41%.

1. Introduction

The ground penetrating radar utilizes high frequency electromagnetic (EM) wave propagation which transmits waves into the ground by means of moving the antenna along the surface. Whenever wave strikes the object or boundary interface of contrast dielectrics, a portion of the wave reflects back to the surface, and receiving antenna. Figure 1 shows the imaging process of GPR data. It is widely used in a variety of applications such as locating buried utilities infrastructure such as pipes and cables [1], road inspection, land mines [2] and potential collapse area [3].

In previous work, many techniques have been attempted to analyse the hyperbolic signature for detecting and locating the buried object. Carlotto [4] 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.
In [3], they used the logarithmic transformed ensemble empirical mode decomposition for subsurface GPR imaging able to assess the risk of potential collapse area in urban environments. Irving & Knight [5] used numerical modeling (finite-difference time-domain) of ground penetrating radar by exploring the link between subsurface properties and GPR data in two dimensions using MATLAB environment. Ni et al. [6] 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. Lee & Mokji [7] 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 [8] proposed decision tree method for predicting the shape and size of a buried object on surface GPR. One of the issues of GPR signals is that they easily corrupted by noisy environment, which cause misinterpretation of the size and geometry of subsurface objects from GPR raw profile.

Therefore, this paper proposes the used of DWT to decompose the GPR images into four sub-bands. Due to advantages of DWT which analyzes the signal at different resolutions by decomposing the signal into a coarse approximation and detailed information, thus generated wavelet coefficients able to reveal signal characteristic enhancement by means of applying a low pass filter to obtain approximation coefficients and high pass filter for detailed coefficients [6]. In this work, LL sub-bands or approximation coefficients at first level decomposition is extracted. Since DWT features have higher dimensional space, thus PCA is adopted to reduce the dimension from higher to lower space. The new projected features were then used to classify the geometry of buried objects using kNN.

\begin{figure}
\centering
\includegraphics[width=0.6\textwidth]{gpr_process.png}
\caption{Imaging process of GPR data (left to right) [8].}
\end{figure}

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

\begin{figure}
\centering
\includegraphics[width=0.7\textwidth]{methodology.png}
\caption{Block diagram of the proposed method}
\end{figure}

2.1. Data Acquisition
Totally, 340 GPR images are collected from 87 cubic images, 82 cylinder images, 86 disc images and 85 sphere images from aluminium material (metal) using Ramac GPR Mala system with antenna of 800 MHz transmitter and receiver. Figure 3 shows the basic GPR components that consist of antenna, battery pack, control unit, and a portable PC. These samples are buried in parallel with depth of 20 cm from the top surface in the rig test setup at Non Destructive Test (NDT), Nuclear Agency Malaysia as
shown in Figure 4, with 40 cm apart between them. Sand is used as soil medium. The operation of GPR system was guided by research officer of NDT, Nuclear Agency Malaysia.

Figure 3. Basic component of GPR system

Figure 4. The rig test setup by NDT, Nuclear Agency Malaysia.

2.2. Image Preprocessing
Pre-processing is an important stage in every image analysis which can boost the overall performance of the system. In this work, the original image is firstly scaled and cropped into a fixed size in order to have uniformity in size is achieved. Figure 5 shows the original binary images and the preprocessed GPR images. The preprocessed images are then subjected to the DWT for extracting the GPR features.

Figure 5. (a) Binary images of cubic, cylinder, disc and sphere (left to right), (b) cropped hyperbolic signature images of cubic, cylinder (top) and disc, sphere (bottom).
2.3. Feature Extraction: Discrete Wavelet Transform

Discrete Wavelet Transform (DWT) offers advantage of using variables size time-scale for different frequency subbands. Thus, it is a powerful tool for analyzing nonstationary signals like GPR signals which reveals subtle changes of temporal variations in low frequency and abrupt temporal changes in high frequency [6]. The DWT involves some signal processing for example filtering, downsampling and upsampling. The DWT analyzes the signal at different resolutions by decomposing it into a coarse approximation and detailed information. The approximation coefficients are resulted by allowing the signal through a low pass filter, which removes the high frequency component. The process was repeated same for detailed coefficients resulted by allowing the signal through a high pass filter. The extracted wavelet coefficients can then be adopted for signal behavior enhancement. This method has advantages over generating the signal behavior the, especially for a GPR signal with noise and/or a masked target. Based on this rationale, this study aims to link the behavior of GPR signal with DWT to classify the shape of buried objects based on hyperbolic signature pattern.

In 2D image framework, DWT decomposes images by first applying 1D filtering along rows of the image and then along columns [9]. The output of the analysis decomposition is a set of four \( N/2 \times M/2 \) subimages so-called LL (low low), LH (low high), HL (high low) and HH (high high) sub-bands which correspond to different spatial frequency band in the image [9]. The decomposition of binary GPR image into such four sub-bands is shown in Figure 6. It can be observed that, the LL sub-bands is a coarse (low resolution) version of the original image, and that the HL, LH and HH sub-bands, respectively contain details with vertical, horizontal and diagonal orientation. The total number of pixels in the four sub-bands is equal to the original number of pixels, \( NM \).

![Figure 6](image.png)

**Figure 6.** Decomposition of \( N \times M \) image into four \( N/2 \times M/2 \) sub-bands, (a) the original image of cubic shape, (b) first level DWT decomposition on GPR image of cubic shape.

2.4. Feature Reduction: Principal Component Analysis

The goal of PCA is to mapped higher dimensional space into a lower dimensional space by means of linear projection that maximizes the scatter of all projected samples [10]. Let \( X \) be a random vector with observations \( x_i \in \mathbb{R}^d \).

Step 1: Determine the mean of the data matrix \( \mu \).
Step 2: Determine the covariance matrix \( S \).
Step 3: Calculate both the eigenvalues \( \lambda \) and eigenvectors \( v_i \) of \( S \),
Step 4: Sort the eigenvectors in descending order associated with largest eigenvalues. The projected sample in the new space is defined as $y = W^T \ast x$. Figure 7 illustrates the number of components (no of eigenvectors) with respect to the variance accounted. In this work, the first 250 principal components with 98.37% of variability were investigated.

![Figure 7. The plot of principal components analysis.](image)

2.5. Classification: K-Nearest Neighbour

The k-Nearest Neighbor algorithm (k-NN) [11] is a nonparametric method used in pattern recognition for both classification and regression by assigning the class label to the input pattern based on the class labels that represented by k-closest neighbour vector. The input pattern is classified by a majority vote of its neighbours.

3. Results and Discussion

In this section, the effectiveness of the proposed method was evaluated based on DWT features and PCA using k-NN. About 340 GPR images of buried objects are collected from 87 cubic images, 82 cylinder images, 86 disc images and 85 sphere images from aluminium material (metal). The GPR images firstly being preprocessed. Then, the GPR images are decomposed using DWT into four sub bands which are LL, LH, HL and HH. The sub-bands LL or a coarse approximation coefficients were extracted as DWT features in order to classify the shape of buried objects. Since DWT features do contain high dimensional data, thus PCA is used to reduce the dimensional features from higher to lower space by linear transformation. The new projected features were then classify using k-NN classifier into four shape which is cubic, cylinder, disc and sphere. In general, the performance of the DWT features using PCA method varies with the number of principal components. Thus before evaluating the DWT, we firstly performed an experiment using PCA. In this work, the first 250 principal components with 98.37% of variability were investigated.

Figure 8 shows the recognition rates of different shapes which are cube, cylinder, disc and sphere of GPR images based on DWT and PCA features using k-NN classifier. One can observe that both cube and cylindrical shapes have achieved the highest recognition rates which is 100% using DWT and PCA features. In addition, both disc and sphere shapes have achieved the recognition rates which are 98.84% and 98.82%, respectively. Further, Table 1 shows the confusion matrix of DWT features and PCA using k-NN classifier. As observed in Table 1, about 1 out of 86 disc shape was misclassified with cylindrical shape, whereas about 1 out of 85 sphere shape was misclassified with cylindrical shape. This can be inferred that, the geometry of cylindrical shape has tendency to be confused with geometry of disc and sphere shapes since they possess similar hyperbolic pattern in GPR images. As overall, the average recognition rates for four different shapes (cubic, cylinder, disc, and sphere) using
DWT and PCA features on GPR images produced 99.41% recognition rates. Thus, the proposed method shows a promising results.

![Shape classification](image)

**Figure 8.** The recognition rates of different shape (metal) based on DWT and PCA features using k-NN classifier.

|                  | Cubic | Cylindrical | Disc | Sphere | Average |
|------------------|-------|-------------|------|--------|---------|
| **Cubic**        | 87    | 0           | 0    | 0      |         |
| **Cylindrical**  | 0     | 82          | 1    | 1      |         |
| **Disc**         | 0     | 0           | 85   | 0      |         |
| **Sphere**       | 0     | 0           | 0    | 84     |         |
| **Total**        | 87    | 82          | 86   | 85     | **99.41%** |

4. Conclusion

This paper has presented the use of discrete wavelet transform and principal component analysis in classifying different shapes such as cubic, cylindrical, disc and sphere using k-NN classifier. Initially, the original image is preprocessed to have uniform size and shape. DWT is adopted to decompose the GPR images into four sub-bands. The LL sub-bands which is a coarse approximation coefficients are extracted and used as features. To reduce the redundancy of the features, PCA was adopted. Then, the reduced features is classify using k-NN classifier. Based on the results obtained, the average recognition rate achieved is 99.41% which cubic and cylinder shapes gave perfect recognition rates of 100%. While, the disc and sphere were achieved 98.84% and 98.82%, respectively. This shows that the DWT and PCA features able to discriminate as well as exhibit the signal characteristic of hyperbolic signature of buried object in GPR images. Thus, the proposed method shown a promising results in classifying the GPR images. However, further study needs to be conducted to automatically...
recognize the GPR images by applying artificial intelligence so that it can be utilized in real environments investigation.

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