Ground penetrating radar for buried utilities detection and mapping: a review

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Abstract. This paper presents a review on Ground Penetrating Radar (GPR) detection and mapping of buried utilities which have been widely used as non-destructive investigation and efficiently in terms of usage. The reviews cover on experimental design in GPR data collection and survey, pre-processing, extracting hyperbolic feature using image processing and machine learning techniques. Some of the issues and challenges facing by the GPR interpretation particularly in extracting the hyperbolas pattern of underground utilities have also been highlighted.

1. Introduction

Ground penetrating radar (GPR) has been acknowledged as an effective non-destructive imaging tools for shallow subsurface exploration such as locating and mapping the buried objects. Over the last decades, the usage of GPR has widely used in landmines detection [1], archaeological works [2] and geological explorations [3]. Due to its fast speed and minimal intrusive, it becomes popular NDT in civil engineering as routine tools used for structural health monitoring. Besides, the applications of GPR have been extended to rebar inspections in building concrete construction, mapping and locating underground utilities pipes/cables, inspection of road pavements and asphalts, as well as bridge structures [4]. Generally, GPR utilizes high frequency electromagnetic waves (EM) propagation ranging from 100 MHz to 1 GHz in which it transmits the waves into the ground having different indices. Figure 1 (a) illustrates GPR survey in which the working principle is based on the propagation and scattering of EM in solid matter. If the waves strikes the buried targets, the reflected signal will be presented in the form of hyperbola shape in the recorded B-scans. Figure 1(b) shows example of hyperbola shape of buried objects.

The GPR problem consists of the problem of retrieving the hyperbola pattern in the received signal which is a convolution of several impulse response. It also known that, the velocity of the EM propagating through a media (having different indices) is a function of dielectrics which acts as an insulator. For instance, the dielectric constants in air, water, rocks, sand dry, clay wet, and concrete have the wave velocities of 0.3 m/ns, 0.033 m/ns, (0.15-0.87) m/ns, (0.15-0.12) m/ns, 0.052 m/ns and (0.10-0.087) m/ns, respectively [5]. These characteristics reveal important observations in which, the harder the material the slower the velocity, the higher water content the slower velocity and the velocity in material can vary significantly. Thus, prediction the objects’ depth is considered extremely hard due to
the variations in velocities of media. In addition, the selection of antenna frequency has also influenced the detection of hyperbola region in which there are exist compromising between the maximum depth and the expected object resolution. The higher frequencies of antenna give a higher resolution. However, in terms of penetration depth, it can penetrate a medium shallower than the lower frequencies and vice-versa [6]. Figure 1 (c) illustrates the penetration depth and target resolutions for a frequency range.

![Figure 1. GPR working principle: (a) GPR survey [7], (b) hyperbola signature and, (c) the penetration depth versus frequency [6].](image)

GPR, as a NDT investigation tool, transmits short pulse of EM waves that can penetrate the building structure. The transmitted EM waves are reflected by underground boundaries at which there are electrical property contrasts. Then, the reflected EM waves are received by an antenna and used successfully in civil engineering inspections. For details survey one can refer to [4]. Data processing techniques are considered the key of the GPR data interpretation based on applications of interest. Generally, the traditional techniques of GPR data interpretation can be categorized into two types: signal-based techniques and image-based techniques. In the signal-based techniques (A-scan data), the task are focusing on reducing the effects of background noise and interference scenarios belong to heterogeneous mediums. While in image-based techniques using B-scans data, the tasks are focused to image received waves by background removal and velocity analysis [4]. In addition, image-based techniques have also been applied to C-scan data, in which results of the consecutive of 2D B-scan data. Although the imaging techniques in GPR have been calibrated with high precision, the utility of GPR systems still mainly depend on human experiments. For instance, the interpretation of the GPR data in underground utilities construction remains a challenging task. As far as we concern, in the process of civil infrastructure for example, the unseen network of underground utilities is quite complex man-made in any urban city. Positioning and mapping underground utilities in urban areas perhaps is the most complicated and ongoing research in ground penetrating radar. It is because the interpretation on hyperbolas reflector of underground utilities in B-scan images are highly subjective and depend greatly upon the operator knowledge and experience to extract diagnostic information. Thus, in this paper, we presents a review of the related works on GPR data with respect to the underground utilities that covers the data collections, feature extraction and machine learning classifier. Besides, some of the issues and challenges facing in interpreting the GPR data have also been highlighted.

### 2. Previous works on GPR in Underground Utilities Detection

Figure 2 shows the general framework of previous studies in GPR using image processing approach. It consists of GPR data acquisition and data collection, GPR pre-processing on B-scan images, features extraction on hyperbolas pattern, classification and detection of buried utilities.

![Figure 2. General framework of GPR using image processing approach](image)
2.1. Data Acquisition: GPR Mapping and Surveying

As reported in previous studies, various sites and experimental setups have been conducted by researchers for GPR mapping and surveying. Some of them conducted in real environment [8], controlled environment [9] and simulated software [10]. For example, Lu et al. [11] have conducted the investigation of GPR utility mapping in real environment located in University of Jilin, China (Figure 3 (a)). The road contains complex distribution of pipeline beneath in it. The subsurface pipe trench is along the road which contains asphalt pavement, coarse aggregates, fine aggregates and concrete layer as illustrated in Figure 3 (b). MALA proEX GPR with 500 MHz as centre frequency antenna has been used in the mapping. Besides, Hashim et al. [8] conducted the GPR mapping and surveying in real environment to determine the depth of water pipe and electric cable. Two instruments of single channel GPR have been compared, one is NOGGIN Plus and another is MALA RAMAC as for the accuracy assessment in terms of depth and time interval. The surveying design was conducted on the specified test base (6 x 6 meters) as illustrated in Figure 3(c). The original depth of water pipe and electric cable are 1.5 m and 1.4 m, respectively. The antenna of 250 MHz and velocity of 100m/µsec have been applied to estimate the depth of water pipe and the electric cable. In similar study, Saharudin et al. [12] have conducted the GPR surveying at University Sains Malaysia, Penang under uncontrolled environment to detect the buried targets at four different locations. Figure 3(d) illustrates the study areas denoted as location A (subsurface cavity), B (drainage), C (pipe) and D (concrete bunker). They have setup a few survey lines for location A, B and C into 30 meters length while at location D is about 12 meters length with setup antenna frequency of 250 MHz. The estimated depth of target of interest were then verified using the information of amplitude versus depth information. On the other hand, in the controlled environment, Alshamly et al. [9] conducted the GPR mapping in detecting the buried objects having different materials size, depth and location angle. A practical model has been built for GPR scanning as illustrated in Figure 3(e). The shielded antenna of 1 GHz using MALA have been applied in their study. They conducted three tests experiment for different types of material (metal, plastic and pottery), different depth for each buried object of the same material. On the other hand, Lei et al. [10] have conducted both simulated and field GPR dataset collection in detecting underground cylindrical objects and diameter identification. In simulated GPR, they generated B-Scan data using gprMax software toolbox with rebars as the target embedded inside the concrete. While in field GPR dataset collection, the rebars with different sizes were buried in the dry sand as illustrated in Figure 3 (f). The nine rebars having different diameters that mimicking the civil building were used. In short, the experimental design in GPR surveying and mapping is considered as important aspect in obtaining precise GPR dataset either in controlled environment or uncontrolled environment. Due to minimal intrusive, and its fast speed GPR offers significantly better depth penetration on any subsurface.

Figure 3. Experimental setup of GPR utility mapping and surveying for data acquisition of previous studies.
2.2. GPR Pre-processing

GPR data pre-processing is one of the important process for successful GPR data interpretation. The GPR raw data commonly contaminated by clutter background and ground effects [13], noisy environment such as the presence of roots trees and bricks, heterogeneity of subsurface medium and mutual wave interactions [14]. The clutter The GPR image processing tries to locate the exact position of hyperbolic curve and eliminate the unwanted background noise such as subsurface ground echoes due to existing heterogeneous of the medium. In [7], the ensemble mean and moving average filter are used to remove the bright ground surface reflectance and to reduce the noise, respectively. While, Dou et al. [15] used threshold method to segment foreground and background based on edge points values. The pre-processed data, then were further subjected to the next feature extraction method.

2.3. Feature Extraction of GPR data

The development of robust techniques to automatically detect the hyperbolas have received a great attention from the GPR research community. Data feature extraction of GPR raw data are very important to interpret the significant information of hyperbolic curve of underground targets. In the scientific literature, many techniques have been attempted to locate (position and depth) and characterize (size and material) the hyperbolas in GPR images particularly, in utility mapping applications. Some of them were attempted to used template matching [16, 17], Hough transform [18, 19], histogram oriented gradient [15, 20, 21], wavelet transform [7, 35], Viola Jones detection [15], curve fitting [26] scale invariant feature transform [27], genetic algorithm [28] and neural network [13, 14, 16, 31, 32, 33].

2.3.1. Template matching. Template matching has been widely used in computer vision and do tolerate in terms of computational time provided that the image and the template are not too large. The template does not need to contain the exact hyperbola curve, but it only does need to be able to discriminate between the hyperbola and the background. For example, in [16] they utilized template matching to detect and localize the pipe signatures in two perpendicular antenna polarizations. In the first step, they have defined a template using finite-difference time domain simulation of hyperbolic area with mean size of the objects. In the second step, pre-processed of raw radaragam, template matching in detecting hyperbola signatures (noisy environment), map distance calculation and thresholding have been employed. Then, the extrema (max and min) discrete amplitudes of hyperbola curves are extracted and lastly, these discrete hyperbolas are being fitted using a parametric hyperbola model. Although their work are feasible, however the presence of overlapping hyperbolic signatures, weak image quality and noisy environments make the hyperbola detections even more difficult. In different work, Syambas [17] predicted the shape and size of a buried object on surface GPR using decision three method. The geometrical representation from B-scan of hyperbolic signatures were interpreted using template matching as the hyperbolic signature of each type of buried object has a unique pattern before comparing to its training data. This template matching, however may result in missing data and false detection.

2.3.2. Hough Transform. Hough transform is the method used to transform the global curve detection into efficient peak detection in the Hough parameter space. For example, Carlotto [19] have used Hough transform of pre-processed input GPR images in finding the parameters of hyperbola for buried mines. Simi et al. [18] utilized modified Hough transform to recognize the presence of the buried targets by looking the hyperbolic pattern and mark the hyperbola. Although Hough transform is commonly-used method in detecting hyperbolic signature, however this method is computational cost expensive due to the higher resolution of B-scan images and produce random results in noisy environment.

2.3.3. Histogram Oriented Gradient. The histogram of oriented gradients (HOG) features are widely used for object detection. HOG decomposes an image into small squared cells, computes histogram of oriented gradients in each cell, normalizes the result using a block-wise pattern, and then return a descriptor for each that cell. In GPR application, HOG features typically applied as a dense-feature extraction technique, thus enables the HOG features to be extracted without previous interest point
identification. Lee and Mokji [15] developed an automated hyperbolic detection in GPR data using histograms of oriented gradients (HOG). The hyperbolic signature whose contains the reflections from target of buried object were narrow down into possible reflections with the aid of linear SVM. Also, Noreen and Khan [22] utilized the HOG features to exhibit the shapes of hyperbolic signatures in GPR images. Their features were fed to Adaboost as learning classification and classify the signature using SVM. Meanwhile, Torrione et al. [20] have utilized the HOG features for landmine detection in GPR images. These features are seem fairly robust to moderate changes in GPR object detection.

2.3.4. Edge Detection. In detecting the hyperbolic pattern, the edge detection such as Canny operator is considered the most-effective operator as compared to Robert, Prewit, Sobel, Laplacian due to better performance. Application of Canny operator in early stage, significantly improve the overall performance. For example, Bugarinovic [23] have used Canny edge detector as the first step of an advanced imaging algorithm for automated detection of hyperbolic reflections in B-scan data. In Canny edge processed image, several edge pixels are presence in the hyperbolic reflection. These edge pixels, are useful for the purposes of identifying and characterizing hyperbola and noise elimination.

2.3.5. Viola Jones Detection. The Viola-Jones algorithm or boosted cascade algorithm was first introduced for object detection [29]. Later, it has been successfully applied in face detection because of the capability in processing the image with extremely rapid and achieving high detection rates. Thus, it was been utilized recently in detecting the hyperbola region of underground utilities. In [15], Viola-Jones based detector has been adopted to detect the candidates of hyperbola regions before subjected to the generalized Hough transform to extract hyperbola parameters by fitting hyperbolic edges of each candidate region.

2.3.6. Scale Invariant Feature Transform (SIFT). SIFT is a method used to find the interest points and feature descriptors to describe the objects. Besides, SIFT offers the advantages of having invariance to scale, rotation, illumination and affine distortion. In [27], SIFT has been used to identify the potential interest points of GPR B-scan profile and Hough transform for detection process. In their work, four stages of SIFT have been employed including scale-space extrema detection via difference of Gaussian (DoG), keypoint localization, orientation of image gradient and key point descriptor. Based on the results using simulated GPR profile, their proposed method are able to localize and detect the hyperbolic region of GPR B-scan images with accuracy of 83%.

2.4. Machine Learning Classifier in GPR Detection

2.4.1. Artificial Neural Network (ANN). ANN is an artificial intelligence function that imitates the workings of the human brain in processing data and creating patterns for use in decision making. In early work of NN in GPR applications, Costamagna et al. [30] have utilized neural network for searching objects signatures by adapting the inputs data using back-propagation learning algorithm. Their results shown that the underground pipe signatures present the same degree of accuracy by a human operator. Besides, Singh and Nene [13] utilized neural network with curve fitting technique to estimate the position of the buried objects in GPR images. A total of 20-50 samples was set as initial training in their works with 1200 inputs that fed into the two layer feedforward neural network. They observed that 75% of the objects have been detected by net was similar to the operator, in contrast 14% of the extracted positions are not represent the hyperbole. The overall accuracy of 91% has been reported. The localization of buried objects were proceed with curve fitting using migration technique. By utilizing this the depth of the target able to be estimated by knowing the apex and the ground permittivity. Recently, the current trends of NN have received great attentions among GPR researchers community. The introduction of deep learning neural network concept for GPR underground utilities have shown successfully prospect [34]. Deep learning is a subset of machine learning in artificial intelligence that has networks capable of learning unsupervised from data that is unstructured or unlabelled. For example,
Isthitsuka [31] applied deep learning convolutional neural network in GPR images to detect behaviour of hyperbolic curves inside the embedded objects. Lie et al. [14] proposed Faster Region-based Convolutional Neural Network (Faster RCNN) together with data argumentation method in identifying the hyperbolic signatures for automate detection and fitting hyperbola detection. Then, Tham and Lefevre [32] used similar framework of Faster RCNN for detection underground buried objects using simulated and real GPR data. Liu et al. [26] used deep learning model to automatically detect and locate the rebars embedded inside the concrete of residential building under construction. A total of 13,026 rebar targets in 3992 images has been trained using deep learning model on real GPR data. Lei et al. [33] developed the integrated convolution neural network with long short-term memory to extract the hyperbolic region of buried rebars with different diameters both in simulated data (gprMax toolbox) and controlled environments (test bed).

2.4.2. Support Vector Machines. Support Vector Machine (SVM) is a supervised machine learning algorithm capable of performing classification, regression and even outlier detection. The goal of SVM is to find the optimal hyperplane that maximize the margin between the classes. The linear SVM classifier works by drawing a straight line between two classes. SVM has been used in all machine learning algorithm especially in object detector. Noreen and Khan [22] used SVM classifier with HOG features to automatically detect the hyperbola pattern in GPR images with reported accuracy of 75.8%. Qin and Huang [35] utilized SVM classifier with discrete cosine transform and polarization attributes features to identify the voids underground in GPR images. Recently, Ali et al. [36] adopted SVM classifier for shape recognition using extracted hybrid features of wavelet and empirical mode decomposition. The results show promising technique in recognizing the shapes via hybrid features and SVM classifier.

3. Issues and Challenges
Although the GPR has achieved a remarkable success in various applications, extracting significant information however remains a challenging tasks. In urban city for example, the unseen network of underground utilities is quite complex. Positioning and mapping underground utilities in urban areas perhaps is the most complicated and ongoing research in ground penetrating radar. It is because the interpretation on hyperbolas reflector of underground utilities in B-scan images are highly subjective and depend greatly upon the operator knowledge and experience to extract diagnostic information. Inconsistent and subjective classification performance associated with human factor lead to misclassification error [37]. In addition manual operator have to look and interpret a huge number of B-scan images. This requires an enamours efforts, about two days are needed for analysing B-scan data collected from 3000 m² wide site [7], thus leading to computational time consuming. The problem was further hampered by the presence of noise-corrupted images in B-scan. The GPR signal of underground utilities easily corrupted by environmental noise like roots tree, rock or bricks which might mask the weak reflections from heterogeneities located deep in the test structure [15]. Moreover, the deeper underground utilities may be obscured numerous shallower objects which appear as constructive interfering hyperbolic reflectors. Thus may cause difficulty in extracting the discriminative hyperbolic reflector features, thereby leading to confusion or false detection [7]. As overall, robust techniques for GPR data interpretation still needs to be constantly proposed to ensure that the proposed techniques able to sustain the unpredictable subsurface environment and help to build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation by investigating the algorithm for solving/monitoring in infrastructure fields.

4. Conclusion
The progressive development of GPR techniques with desirable capabilities poses unique chances, as well as new challenges to non-destructive tool in underground utilities applications. Even though GPR systems provide precise and stable representation of buried utilities and backgrounds, its intricate data structures leads to the exploitation using complex image-based techniques not easy. Positioning and
mapping underground utilities in any urban areas perhaps is the most complicated and ongoing research in ground penetrating radar. In this survey, the GPR data interpretation for underground utilities including data collection, extracting hyperbolic feature using image processing and machine learning techniques either in controlled environment or real environments have been reported. Some of the issues and challenges facing by the GPR interpretation particularly in extracting the hyperbolas pattern have also been highlighted. As summarize, robust techniques need further attentions for GPR data interpretation to resolve the issues and also to ensure the proposed techniques able to sustain unpredictable subsurface disturbances.

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