Buried Object Detection and Analysis of GPR Images: Using Neural Network and Curve Fitting

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Abstract—Recent live campaign applications involve the real-time location and identification of buried Improvised Explosive Devices (IEDs) and buried fusing mechanisms for the needs of national security. Ground Penetrating Radar (GPR) is an instrument used in the construction of underground images. In principle, images of subsurface objects such as mines and pipes may be detected and potentially measured. Noise and clutter are the influential irregularities that are present during GPR raw data collection where the sampling rate is 8+ frames per sec. Preprocessing techniques on this voluminous data has been proposed. The reflection from mines or pipes in the ground is characterized by a hyperbola on the underground radar image. The work is focused to simplify the interpretation of the hyperbolic pattern found in GPR image and estimate the position of the objects using neural networks and curve fitting techniques. We devise an efficient dynamic runtime buried object detection algorithm and verify results.

Keywords—GPR, Preprocessing, Neural Network, Curve Fitting, Migration algorithm.

I. INTRODUCTION

GPR is an instrument that is used for subsurface mapping using high frequency Electromagnetic (EM) waves. An attempt has been made to use GPR to detect and locate buried objects. Using GPR images we can identify metallic and non metallic buried utilities like primary mines, pipes, cables etc. Further, the GPR images can be used to obtain more quantitative information about the location, shape and size of buried objects reflecting the radar signals [1]. The images obtained using GPR are full of information, however these images contain undesired elements like: ground echo, noise and clutters [2]. Raw images obtained using GPR are called B-scan. The patterns appearing in the B-scan have shapes, which is obtained by the propagation of short pulses into a medium with certain electrical properties. The task of identifying buried objects using GPR can be realized in two ways. Firstly, by processing the received raw images from GPR, secondly, by improving and customizing the hardware used in GPR system to suit the needs of an application. The first option is feasible using various image processing techniques, whereas, second option is economically infeasible. The important task always is to visualize the image conveniently. Hence, to identify and automatically detect the object becomes challenging.

II. OUR WORK

GPR data are usually contaminated by clutter and noise. Clutter represents any unwanted reflections present in the GPR signal, hence rendering GPR data interpretation is more difficult. Noise is predominantly caused by interference from other radio-wave-emitting devices, like cell phones, CB radio etc. that are present during data collection. Before the information in the raw datagram can be utilized correctly, it must first be processed to remove the undesired signals and ground effects.

Our work focuses on devising an efficient algorithm. Using image processing techniques we propose and implement an algorithm which is a preliminary step to perform two important tasks. One, to detect the existence of buried object. Two, to estimate the location and depth of buried object. Since the need is to detect buried object at run time dynamically, the aim is also to optimize on the detection time of buried object by incorporating appropriate steps and computing environment. Performing the objectives as mentioned above is challenging, especially when the sampling rate is high.

Motivation: The detection of buried objects like land mines, explosive devices and other utility lines is a task that has been requested by security concerned organization.

In any life saving application, it is desired to have a faster location detection of buried objects. To the best of our knowledge none of the research paper describes time and platform required to process it. It is of at most importance to get location of buried object detected as early as possible with such high sampling rate.

III. METHODOLOGY

A brief outline of the methodology for the problem at hand is shown in Fig. 1.

The objective is to detect, locate and identify a buried object in GPR image dynamically when sampling rate is 8+ frames/sec. Before undergoing the detection process, the images are first subjected to enhancement of its visualization using preprocessing technique.
A sample of GPR image is shown in Fig. 2. To identify a buried object in such image is a non-trivial task. Hence, efficient processing on such images require a methodology with which conclusions can be derived.

Fig. 3 shows multiple frames that are received by GPR device based on its sampling rate. There are multiple frames in a received GPR image, where $t$ is round trip travel time of reflected EM wave, $v$ is velocity of EM wave and $x$ is horizontal position of buried objects.

A. Preprocessing

A preprocessing procedure is implemented for the following: 1) Clutter removal; 2) Noise reduction; 3) Undesired ground echo reduction.

1) Clutter removal: The received data contains the direct wave, reflected wave and external noise. The instrument is designed such that the receiver continues to listen even as the transmitter sends out the pulses. This effect is primarily due to the close proximity of the transmitting and receiving antenna. As a result, the receiver picks up the transmitted wave and superimpose it on the reflected signals. Since the transmitted signal is strong due to the close proximity of the antenna to the receiver, it is very bright and thus it is difficult to identify gradients in the image [3]. Hence, we remove transmitted wave using Subtract Mean Trace method. In this method, we define a kernel window of size $w_{pxy}$, compute its mean and subtract all the value in this window from its mean. The window is moved along and the procedure is repeated until the entire image is covered, as given in Eq. 1.

$$g(x, y) = f(x, y) - \frac{1}{M} \sum_{j=-m/2}^{i=m/2} f(x + i, y) \quad (1)$$

where $M$ is total no. of pixels in the original image, and $m$ is total no. pixel in the kernel window $w$.

2) Filtering: Filtering is applied to the GPR data to remove noise and improve its visual quality. Mean filtering technique is applied to the raw data to eliminate background. Further, Gaussian filter is applied to smoothen the input image.

Mean filter is applied with the following assumptions:
- Define kernel window $(k, l)$
- $c$ is centre of kernel window $\left(\frac{k}{2}, \frac{l}{2}\right)$
- $N \in (k, l)$ are such that excluding $c$, the rest are neighbours of $c$.

Compute Mean of pixel values of $N$, let $M_i$ be the Mean of values of $N$.

$$M_i = \frac{1}{M} \sum_{(k,l) \in N} f(k, l) \quad (2)$$

$$c = M_i \quad (3)$$

where, $M$ is the total number of pixels in the neighborhood $N$. 

Figure 1. Overview of the Methodology

Figure 2. A sample of original GPR image

Figure 3. Multiple frames are received by GPR Device.
Gaussian filters are a class of low-pass filters, all based on the Gaussian probability distribution function. A two dimensional Gaussian function is given by:

\[ g(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \]  

(4)

where \( x \) is the distance from the origin in the horizontal axis, \( y \) is the distance from the origin in the vertical axis, \( \sigma \) is standard deviation.

The absolute value of each image pixel is kept for the successive processing tasks. After that, the image is thresholded to discriminate between objects and the background. Further, object detection technique are applied on these preprocessed data frame.

B. Object Detection

The automatic detection of a buried object requires self learning capability and hence we employ neural networks for the proposed task. Further, to estimate the location and depth position of buried object curve fitting technique is used.

Neural network

Neural networks, with their ability to derive meaning from complicated or imprecise data, can be used to extract patterns. A trained neural network can be thought as an expert in the category of information it has been given to analyse. There are two types of learning strategies used with neural networks. These are supervised and unsupervised learning. In supervised learning the network is trained by providing it with matching output patterns, whereas in unsupervised learning which has self-organization ability, the system discovers statically salient features of the input population with no a priori set of classification categories.

a) The basic artificial model

All artificial neural networks take numeric input and produce numeric output. To capture the essence of biological neural systems, an artificial neuron receives a weighted number of inputs either from original data, or from the output of other neurons, and responds by producing an activation signal. The activation signal is passed through a transfer function also known as an activation function to produce the output of the neuron [4].

Consider a neuron with \( n \) inputs \( n_1, n_2, n_3, \ldots, n_n \) and corresponding weight \( w_1, w_2, \ldots, w_n \). The activation signal is given by

\[ \text{net} = w_1n_1 + w_2n_2 + \cdots + w_nn_n \]  

(5)

\[ = \sum_{i=1}^{n} w_in_i \]  

(6)

This activation is subjected to a (usually) nonlinear activation function, and the result is the output of the network. This transfer function is selected so as to accept input of an unlimited range, and produce the output on a restricted range. Saturating nonlinearity is the logistic S-shaped (sigmoidal) function defined as:

\[ \text{out} = f_{\text{sig}}(\text{net}) = \frac{1}{1+e^{-\text{net}}} \]  

(7)

![Fig. 4. Neural network structure: a two layer feedforward network with 1200 input nodes and one output.](image)

b) Training set

The training phase of a neural network is the processing step during which the neural network is “trained” to provide the desired output when a given, known input pattern is fed to it [5]. The reflection from mines or pipes in the ground is characterized by a hyperbola on the under ground radar image. In this particular application, for instance, a major problem is how to train the network not only to give a good result when a signature similar to a hyperbola is provided to the input nodes, but also to give better results when this signature has its peak exactly at the top of the input window when it has some offset. This need depends on the desire not only to detect, but also to localize the hyperbola as much as possible.

c) Validation of network

Consider a feedforward network trained by minimizing a sum-of-squares error function [6]. If we denote the joint probability density functions for the training data by \( p(x, t_j) \), then we can write the error in the form

\[ E = \sum_{j=1}^{m} \int \left[ y_j(x, w) - t_j \right]^2 p(x, t_j)dx \]  

(8)

where \( j = 1, \ldots, e \) labels the output units, \( x \) is the input vector to the network, \( y_j \) denotes the output from unit \( j \), and \( t_j \)
is the target value for that unit. The network corresponds to a set of functional mappings \( y(x, w) \), parametrised by a set of weights and biases \( w \) whose values are found by minimizing \( E \).

C. Object Localization

In this section, formula to measure target depth of GPR data is presented. Specifically, the formula related to the propagation velocity of EM wave is presented so that the depth information of buried object can be obtained. The velocity of a transmitting EM wave depends on the ground material.

Properties of ground materials/medium:

The type of ground material in which the waves of the GPR propagates have a strong effect on the signal penetration and clarity of the received wave. The GPR data consist of a continuous graphic display of reflected energy over a set time interval. This set time interval is the round trip travel time, measured in nanoseconds. The depth of the material in which the wave penetrates can be determined if the velocity of the electromagnetic energy \( Vm \) through the material is known. Using the dielectric constant of the material, the velocity of the wave can be calculated using the formula \[ Vm = \frac{c}{\sqrt{\varepsilon_r}} \] (9) where \( \varepsilon_r \) is the dielectric constant of the medium and \( c \) is speed of light. The depth of a buried object in the GPR image can be calculated by using the formula

\[ d_r = \frac{Vm t_r}{2} \] (10)

where \( d_r \) is depth of the target and \( t_r \) is round trip travel time from GPR to object.

The distance \( R \) from the antenna to the buried object is

\[ R = \sqrt{x^2 + (d + r)^2} \] (11)

The round trip time \( t_r \) is

\[ t_r = \frac{2.0.\sqrt{\varepsilon_r} 10^9}{c} \]
\[ = \frac{2(R - r) \cdot \sqrt{\varepsilon_r} 10^9}{c} \] (12)

where
- \( x \) is horizontal offset distance
- \( d \) is depth position of buried object
- \( R \) is distance from the antenna to buried object.
- \( r \) is radius of buried objects.
- \( c \) is speed of light.

Table 1. REFLECTIVE PERMITTIVITY FOR MATERIALS [2]

<table>
<thead>
<tr>
<th>Material</th>
<th>Relative permittivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Air</td>
<td>1</td>
</tr>
<tr>
<td>Water</td>
<td>81</td>
</tr>
<tr>
<td>Clay</td>
<td>5/40</td>
</tr>
<tr>
<td>Concrete</td>
<td>6/12</td>
</tr>
<tr>
<td>Sand</td>
<td>3/30</td>
</tr>
</tbody>
</table>

Curve Fitting

Using a curve fitting technique, it is possible to reasonably determine accurately the permittivity of the medium, and hence the propagation velocity. By using the curve fitter as an intermediate process, a narrow band of velocities can be selected. Migration is a technique used to get an accurate picture of underground layers. It involves the repositioning of the return signals. Hence, using migration technique the reflection point is retained by moving the energy of EM wave back to its true reflection point. This help to locate the position of object in ground material accurately [8].

For buried object localization, the reflective permittivity of ground material is considered as shown in Table 1.

Hence based on the selected ground material its relative permittivity is used for the following.

First, the corresponding velocity of EM wave is calculated from Eq.(9). Secondly, using this velocity and round trip travel time in Eq.(10), the corresponding buried object depth
is calculated. Using this propagation velocity and corresponding depth, a test curve is generated. If the slope of the test curve match the slope of hyperbola, it means that the permittivity, velocity and depth are valid. Hence, the buried object is detected and localized from the GPR data.

IV. EXPERIMENT & RESULTS

The proposed methodology is implemented and the result are verified using single processor and quad core processor computing environments in Matlab and CUDA using C++ environment, respectively.

Fig. 7(a) shows the initial raw data image received from GPR.

Fig. 7(b), 7(c) and 7(d) show the effect of applying preprocessing techniques: Subtract Mean Trace, Mean and Gaussian Filter respectively, on Fig. 7(a). With these preprocessing techniques clutter and noise is eliminated.

To detect the buried object, the proposed neural network based detection algorithm, as shown in Fig. 5, is applied on Fig. 7(d). The neural network is set with initial training set of 40-50 samples. Further, a two layer feedforward network with 1200 input nodes and one output is devised. The result of the neural network based detection algorithm is shown in Fig. 8(a). The highlighted hyperbola represents the object detection in Fig. 8(a) verified with manual interpretation as shown in Fig. 8(b). The overall correct classification rate for this image is 91%, confirming that the neural network classifies the shapes in a substantially exact way. We observe that nearly all the objects detected by the operator are also seen by the neural net (precisely 75%), and that the net finds some false occurrences (14% of the extracted positions are not actually hyperbolae). These percentages can be considered as acceptable, especially because the latter error is surely less important than missing an occurrence.

To localize the buried object, the proposed curve fitting and migration technique is applied on Fig. 8(b). While using the curve fitting technique, we have to fit the curve to the hyperbola found in Fig. 8(b). This is shown in Figure 9(a). The highlighted curve in Fig. 9(a) shows the position of buried object computed using Fig. 9(b) which shows velocity profile of GPR data.

The position estimated in Fig 9(a) is computed based on Eq. 9, 10 and 11, using reflective permittivity of ground material as described in Table 1. Based on the apex and ground permittivity the depth of target is estimated as shown in Table 2.

The object detection program for buried object detection was implemented on sequential system using Matlab and quad core system using CUDA programming environment in C++. It was observed that the required runtime for successful object detection was 42 minutes and 8 sec. respectively.
The techniques assist to detect and estimate the position of buried objects. Noise and clutter are the influential irregularities that are present during GPR raw data collection. Eliminating these types of irregularities is done by preprocessing. After the preprocessing stage, neural networks approach is employed to detect buried object.

Further, an algorithm to estimate the position of the buried objects using a curve fitting approach is implemented and verified. We implement and compare its performance on sequential and parallel computing platforms. We report in this research paper the improvement observed in computing time for detecting the location and depth of buried object.

**FUTURE WORK:** There is an intense need to explore automatic buried object detection and localization using various techniques and parallel algorithms.

**REFERENCES**


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