Multi-Feature Based Landmine Detection Using Ground Penetration Radar

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Abstract- This paper presents a method for detection of multiple landmines by using a ground penetrating radar (GPR). Conventional algorithms mainly focus on detection of a single landmine, which cannot linearly extend to the multiple landmine case. The proposed algorithm is composed of four steps; estimation of the number of multiple objects buried in the ground, isolation of each object, feature extraction and detection of landmines. The number of objects in the GPR signal is estimated by using the energy projection method. Then signals for the individual objects are extracted. Features from each of the individual object scans are obtained. These features are tabulated and fed to the support vector machine(SVM) for the identification of landmine.

Keywords- Ground Penetrating Radar, multiple landmine detection, Support Vector Machine, PCA, geometric feature, multiple landmine.

I. INTRODUCTION

Landmines are the significant cause of suffering in many developing nations. They pose a great threat to individuals for years after conflict has ceased and can be a serious impediment to industrial and agricultural development. Many efforts have been made for developing methods for detecting landmines. Among them, detection using a ground penetrating radar (GPR) has attracted many researchers' attention due to its various advantages over other devices [7]. GPR can be used to detect both metal and non-metal materials without any changes in the configuration of the device. Moreover, it can be implemented as a stand-alone hand-held sensor or as a vehicle mounted device [3] – [4].

In this work, the problem of multiple landmine detection using the GPR is addressed, and a novel method is proposed, which detects multiple landmines from a GPR signal. The GPR scans a ground, to generate a signal. Next, the number of objects in the signal that are determined to be possible landmines is estimated. Once the number is computed, regions corresponding to each object are extracted, each of which is then processed to obtain features. Some of the popular techniques used for the process of feature extraction from the processed GPR signal include polynomial fitting [17], geometrical features of a landmine signal [13], texture-feature coding method (TFCM) [15], hidden Markov models (HMMs) [11], Spatial Features analysis [12], time-frequency features [16] and principal component analysis (PCA) [2], [5], [14]. In [2] and [5], multiple features for a landmine such as PCA and Fourier coefficients are used for high accuracy detection and identification. These conventional methods are designed to detect a single landmine from the GPR signal with some clutters. However, they are not intended to handle the case that multiple landmines are captured in one signal set. More than one landmine may be buried in the ground, yielding a GPR signal containing multiple landmines. It might happen that only one landmine might be detected, and the others would be ignored as obstacles when the number of landmines in the signal is not known. The features are then used to decide if the objects are landmines or not. The decision is made using a support vector machine scheme (SVM) [5].

II. OVERALL PROCEDURE

The overall procedure of multiple landmine detection is proposed as shown in figure (1). It consists of two major processes: segmentation and identification. The segmentation process in indicated by a green rectangle and the identification process is indicated by a blue rectangle.

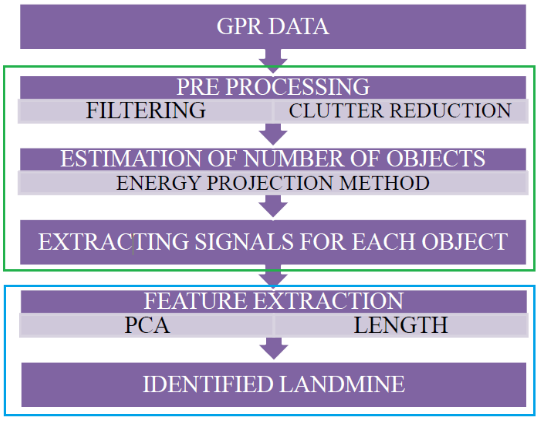

Figure 1: Block diagram

The segmentation process estimates the number of possible landmines in GPR data.

This step is important in the multiple landmine detection because it defines how many times the identification should be performed. Once the number of possible landmines is estimated, each segmented signal is processed for extracting features for identification. Once the features of each signal are computed, identification of the signal is performed. The first step is to reduce the clutter in the GPR signal in order to minimize the influence that might be caused by the difference of the hardware and the individual experimental environments. Next, the number of objects in the signal is estimated using the energy projection method. Once the number is estimated, signals for each individual object are extracted separately. Then features such as the principal components, depth and geometric features are computed for each signal [1] – [2]. These features are fed to the support vector machine for landmine identification.

III. SEGMENTATION

Segmentation is the first step in the proposed algorithm. The segmentation stage estimates the number of possible landmines in GPR data. This step is important in the multiple landmine detection because it defines how many times the identification should be performed. The two main sections in this stage are pre-processing and estimation of number of objects.

Pre-processing: A GPR signal is given as a set of intensity values at x and y positions as shown in figure (2).

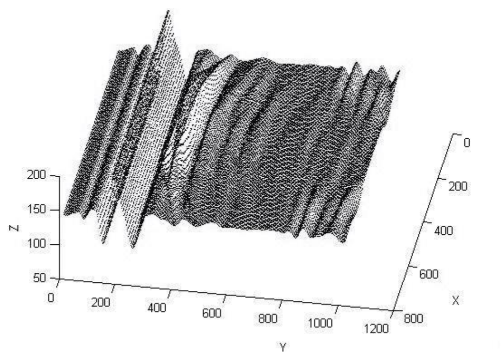

Figure 2: GPR signal in 3-d

Here, the x axis indicates the integer index of each sampling position (denoted as Column No.) for the width of the scanning area. The sampling interval of the two adjacent scanning positions is 5 mm. The y axis is the depth and the z axis is the strength of the signal. The strength of the GPR signal reflects the size and material type of a landmine in the ground. Therefore, it could be considered as a feature of a landmine. However, the strength can also be influenced by other factors such as the power of the GPR, the installation height of the radar and the properties of the ground. Therefore, clutter reduction and filtering algorithms are applied in order to effectively reduce the background clutter.

The signatures of shallowly buried landmines measured using GPR are normally obscured by a strong background signal comprised of reflections from the ground surface, surrounding noise and the antenna crosstalk, called clutter. The following methods are used to eliminate clutter that is observed in the b-scans, figure (6).

i. Subtract mean trace method: In the experimental setup, 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 superimposes 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. Hence, we remove transmitted wave using Subtract Mean Trace method. In this method, we define a kernel window of size 2x2, 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. Here f(x, y) is the input image , g(x, y) is the mean subtracted image [6].

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

ii. Filtering: To the mean subtracted data obtained from the above section, two different filtering techniques are applied in order to further enhance the noise reduction. This is essential to have a decluttered image in order to further process it for feature extraction. Here, initially we are using a mean filter in order to smoothen the data. The mean filter is a simple sliding-window spatial filter that replaces the centre value in the window with the average (mean) of all the pixel values in the window. The window, or kernel, is usually square but can be any shape. Here, a 7x7 window is defined with a pixel value of (1/49) in each of the windows. The multidimensional array given as input is filtered with this multidimensional filter. Later this output is convolved with the defined window and only the central part of the convolution is stored.

Then, a 3 by 3 Gaussian mean filter with the sigma of 8 is applied to this signal for noise reduction.

$$f(x,y) = \frac{1}{2\pi\sigma^2} e^{x^2+y^2/2\sigma^2}$$

The convolved output from the previous stage is filtered with this filter to yield the Gaussian mean filtered output. Thus, coupled with the mean filter the Gaussian filter yields a noise reduced output. Figure (6) is the original B-scan and figure (7) shows the scan after mean subtraction and the entire filtering process.

iii. Erosion: Erosion is one of two fundamental operations in morphological image processing from which all other morphological operations are based. The basic idea in binary morphology is to probe an image with a simple, pre-defined shape, drawing conclusions on how this shape fits or misses the shapes in the image. A structuring element is a matrix that identifies the pixel in the image being processed and defines the neighbourhood used in the processing of each pixel. A structuring element of the same size and shape as the objects is chosen in order to process in the input image. There are two types of structuring elements: *flat* and *non-flat*. A flat structuring element is a binary valued neighbourhood, either 2-D or multidimensional, in which the true pixels are included in the morphological computation, and the false pixels are not. The centre pixel of the structuring element, called the *origin*, identifies the pixel in the image being processed. Here, a flat structuring element in the form of a disk of radius 5 is used since morphological operations using disk approximations run much faster. This causes the focusing of target pixels by enhancing the image and thus results in efficient removal of background clutter and reflection [8]. Figure (8) shows the scan after erosion.

iv. Thresholding: A suitable threshold is decided on closer perusal of the pixel values of the eroded image. On experimentation, we map the minimum value of target pixels. This value is chosen as the threshold. Pixel values beyond the threshold are included in the target image and the pixel values with the lesser intensity than the threshold are ignored. This results in an image where the target pixels are focused with minimal noise or clutter. A threshold value of 90 is used. $h(x, y)$ is the image after thresholding. Figure (9) shows the scan after thresholding.

$$h(x, y) = \begin{cases} h(x, y) & h(x, y) \geq 90 \\ 0 & otherwise \end{cases}$$

Estimation of number of objects: In order to estimate the number of targets present in the given scanned area, we use a novel method called "Energy Projection method". Here, the edges obtained from the previous section, are projected onto the *y-z* and *x-z* planes, respectively. During the projection, the intensity values at the same projected positions are accumulated to produce the accumulated projected signatures in the *y-z* and *x-z* planes. The projected values form distinct groups. Then, the numbers of groups whose peaks are larger than a tolerance $T2$ in each of the *y-z* and *x-z* planes are counted to be $ny2$ and $nx2$. Next, among $ny2$ and $nx2$, the numbers of groups, which have ranges (widths) wider than a tolerance $T1$, are computed to be $ny1$ and $nx1$. The largest one between $ny1$ and $nx1$ is selected to be the number of objects in the signal, which is denoted by *n-obj*. This estimation procedure is called Energy projection method. $T1$ is the minimum width of the signal range in the projection planes. $T2$ is the minimum intensity in the GPR data. Signals either with narrower widths than $T1$ or with intensities smaller than $T2$ is ignored as noise. Basically, these values need to be chosen empirically with various landmines and objects. They should be so selected that the estimated number of objects in the signal becomes more than the actual number of landmines. In this case objects other than landmines can be discarded in the decision step. This way, the possibility that a landmine is missed, a dangerous case than the false alarm, can be minimized. Here, T1 is set as 8 mm and T2 is set as 15% of the value of the maximum signal strength. The value of *n-obj* is very significant as it governs the further stages in the algorithm. Hence, Energy projection method is the pivotal stage of this algorithm. Figure (10) and (11) show the projection of target signals in X-Z and Y-Z planes respectively.

IV. IDENTIFICATION

Extraction of signals for each object: This section deals with identification of the landmines detected in the previous stage. The value of *n-obj* governs the number of times the algorithms in this section are executed. From the output obtained by the above techniques, we extract the features of each of the objects. Here, a window of size *n* is used to slide across the image with no clutter and noise. The maximum intensity level of this image is found out and this window is centred on this pixel value and the target pixels within the defined window are extracted. These pixels are stored in a new matrix. The parent image is replaced with zeros for these corresponding pixels scanned by the window. The window is centred on the next maximum value detected in the parent image. Similarly, the pixels of the second target too are extracted and stored in a new matrix. The corresponding pixels are cleared in the parent image and this procedure is repeated for *n-obj* times. Thus, *n-obj* new matrices are created each storing the signatures of the corresponding target. Figures (12) and (13) show the extracted signals for individual objects.

Extracting features of the objects: The extracted signals for individual objects are subjected to feature extraction. Two geometric features and one statistical feature are considered. The two geometric features are the geometric dimensions of the signal intensity distribution. As a first feature the size, l_1 is measured along the horizontal axis as shown. It is related with the size of an object reflected in the signal. The bigger an object is, the larger l_1 becomes. This feature can differentiate objects with respect to their size. This value is measured as the number of columns that the horizontal size of the region covers. The second feature is the length, l_2, which is measured along the depth (y axis) in the figure. It is mainly dependent on permittivity and permeability of materials of an object. The radio wave transmittance is different according to the object materials. It is observed that the length l_2 of a plastic object is longer than that of a metallic one. Therefore, this feature can separate a steel object from a plastic one. The two geometrical features are as shown in figure (3).

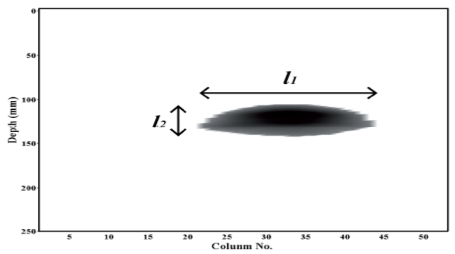

Figure 3: Representation of the two geometric features

As a third feature, a principal component by the principal component analysis (PCA) method is used. PCA method analyses discrete data points in *n*-dimensional space, producing *n* principal components in *n* principal directions, forming *n* pairs of the component value and its corresponding direction. Each component represents a pattern of the data in that direction.

Consider *m* sets of data, $\gamma_i = (x_{1i}, x_{2i}, \ldots x_{ni})$, i= 1,2…m in *n*-dimensional space. The average data of the *m* data sets are obtained by

$$\emptyset = \frac{1}{m}\sum_{i=1}^{m}\gamma_i$$

The difference of γ_i with $\emptyset$ is computed by $\emptyset_i = \gamma_i - \emptyset$. Then the covariance of the data sets is then

$$C_\emptyset = \frac{1}{(m-1)}\sum_{i=1}^{m}\emptyset_i\,\emptyset_i^T$$

The eigenvectors and eigenvalues of the covariance matrix are the principal components, which are computed by solving the following equation.

$$C_\emptyset u = \omega u$$

Here, u and ω are a vector and a scalar value, respectively. u and ω are the eigenvectors and their eigenvalues of the covariance matrix, serving as the principal components of the data. Now the above obtained eigen values of the covariance matrix are plotted in the form of a bar graph as shown. The eigen value with maximum magnitude is chosen as the third feature. Figure (4) shows a plot of the first fifty eigen values. [9].

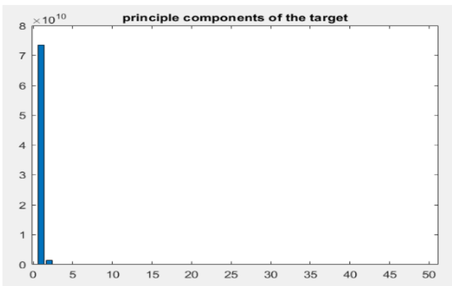

Figure 4: Bar-graph of eigen values

Experiment and results: In this work three land mine prototypes were constructed, prototypes of the M-14, PLMN-1 and PLMN-2 landmines. The experimental setup consists of Geophysical Survey Systems, Inc. (GSSI) GPR bistatic horn antenna system as shown in figure (5) with a centre frequency of 1.3 GHz and 40% bandwidth. The receiver and transmitter antennas are shielded, that is, direct coupling and interference from the surrounding systems is negligible. This setup just uses a VNA and a pair of horn antennas. Soil is filled in a wooden box of dimension 105cmx70cmx60cm. VNA used in the project works in the Range 9KHz to 4. 5GHz.We have used a distance mode of collection, 70 scans, and 1601 sample points per scan.

Figure 5: GPR and VNA set-up used in the experiment

The GPR unit is placed above the ground surface at a height of between 8cm to10cm. Its motion is controlled manually by shifting the position of each antenna by 5mm for each A-scan. In addition to the mine like objects, we also considered false targets, such as plastic pipes, metal cans, stones, wooden pieces, glass bottles and plastic boxes in order to test the efficiency of proposed algorithm. The readings were recorded and stored in polar coordinates using the E5071C VNA (Vector Network Analyzer) for each Ascan.1601 sample points were obtained for each A-scan. Totally 70 A-scans were generated with step size 5mm.The collected data was stored in CSV format. The readings were processed offline using MATLAB.

The following scans are the results of the various stages of the proposed algorithm. These scans include a metal mine and a plastic mine.

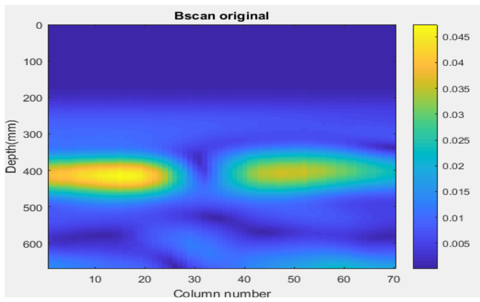

Figure 6: B-scan obtained by concatenating multiple A-scans

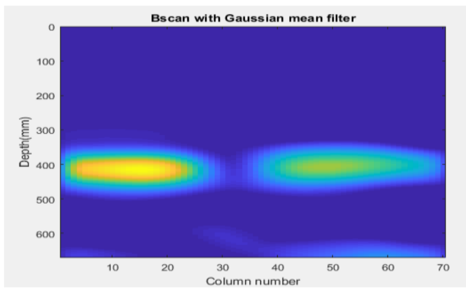

Figure 7: B-scan after complete filtering process

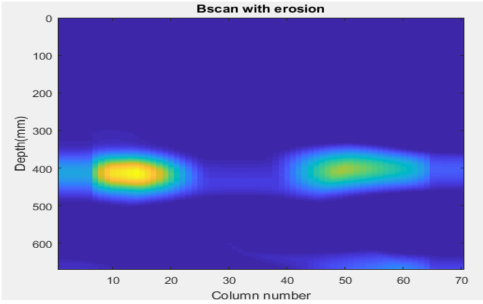

Figure 8: B-scan after erosion

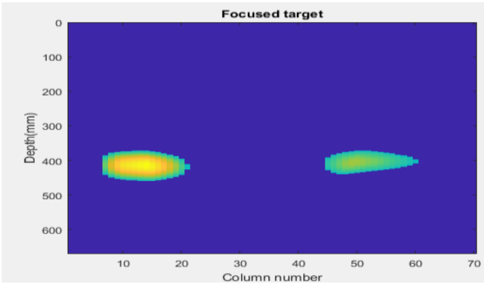

Figure 9: B-scan after thresholding

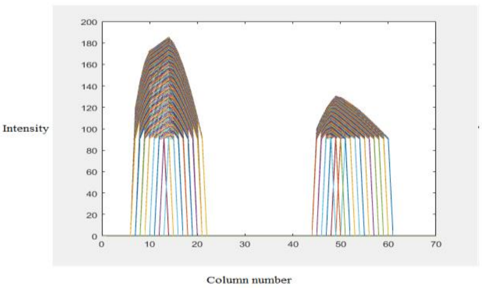

Figure 10: Projected signatures of the target in intensity vs column number(X-Z) planes

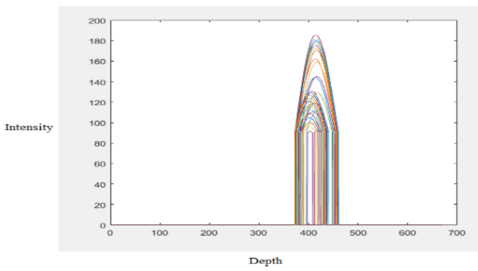

Figure 11: Projected signatures of the target in intensity vs depth(Y-Z) planes

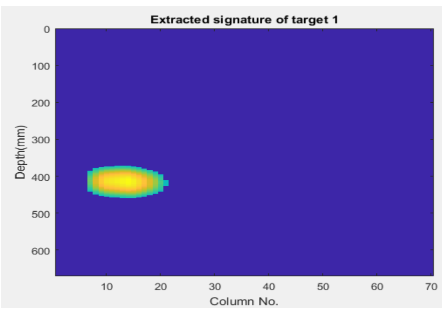

Figure 12: Extracted signature of target 1

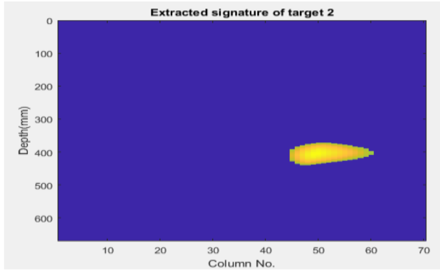

Figure 13: Extracted signature of target 2

In total, a database of 120 readings was considered. These readings include scans for both mine and non-mine objects. For each case three features are computed and stored in the database with their corresponding landmine information. In order to simulate real signals, input signals are prepared by adding various levels of Gaussian noise. The identification accuracy varies between 90 to 95% depending on the various levels of Gaussian noise. The SVM is trained on this database. Once the classifier is trained it is subjected to test input values, where the classifier must correctly classify the objects into the categories of landmines or non-mines [10].

Figures (14) is a scatter plot where every point represents an object. The red points stand for mines and the blue ones stand for non-mines. Correct classifications are marked by a point, wrong classifications are marked by a cross. Figure (15) includes an ROC curve and a confusion matrix. The marker on the curve shows the values of the false positive rate (FPR) and the true positive rate (TPR) for the classifier. A perfect result with no misclassified points is a right angle to the top left of the plot. A poor result that is no better than random is a line at 45 degrees. The Area Under Curve(AUC) number is a measure of the overall quality of the classifier. Larger Area Under Curve values indicate better classifier performance. The second fig in figure (15) and the figure (16) are confusion matrices which represent false positives, false negatives, true positives and true negatives. These four values can be used to calculate the accuracy of the classifier.

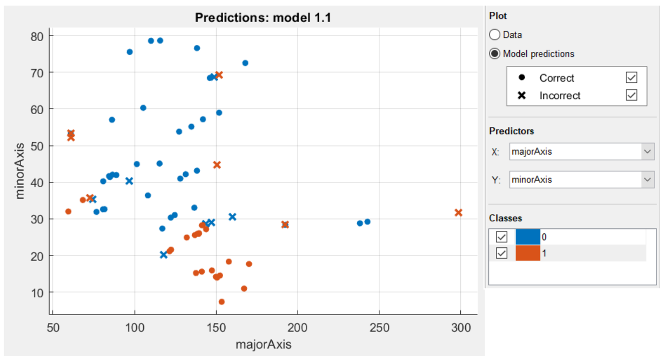

Figure 14: Scatter plot of the predicted data points

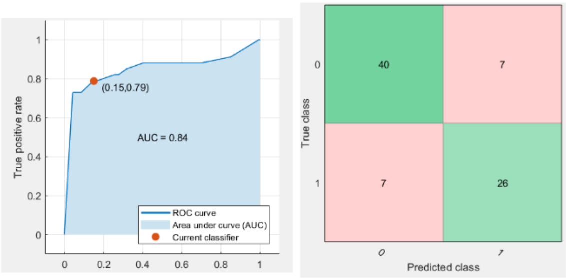

Figure 15: ROC curve and Confusion matrix

Figure 16: confusion matrix with true positive and false negative rates

V. CONCLUSION

This paper proposes a method for detecting multiple landmines buried in the ground using a GPR. The method consists of clutter reduction, estimation of the number of objects in the GPR data, isolation of object signals, feature extraction and detection. The tests show that the proposed method can mostly detect multiple landmines in various conditions. The proposed method has three limitations: choice of tolerances, database construction, and ignorance of different ground conditions. The method requires a couple of user-defined values such as threshold values for the estimation of the number of objects. These values mainly depend on the properties of the GPR hardware used. A larger database for landmines and various other foreign objects should be constructed for robust detection. There might be a false-alarm case that a non-landmine object is determined as a landmine due to the limited amount of data in the database. These two limitations can be overcome through extensive experiments with objects and landmines.

The overall procedure of the method is designed for general environments. However, the tests in the paper were performed in controlled conditions, suitable tolerances were chosen and the database was constructed for those conditions. Therefore, it is necessary to refine the tolerances and to improve the database by considering more realistic situations. A thorough evaluation of the method for selection of tolerances and enhancing the database using real field data is recommended for future work.

VI. REFERENCES

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