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AUTOMATIC MULTIPLE LANDMINE DETECTION USING GPR

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ABSTRACT

The land mine crisis is all over frightening since there are presently 500 million unexploded, buried mines in about 70 countries. Governments are noticing this situation seriously since land mines are claiming the limbs and lives of civilians' very day. A multiple of landmine extraction from the data which are obtained from the Ground Penetrating Radar (GPR). Traditional algorithms targets on obtaining a single landmine. The landmine, however, is not buried beneath the ground alone in the real cases; it is entombed with stones or alternative landmines. Therefore, detection of multiple landmines is an important problem. Thus the multiple landmine detection is composed of steps. Here, finds the number of buried landmines. Detection of a landmine in the GPR signal, to extract landmine features by using stacking algorithm and time domain. This shows that the proposed algorithm manifesting the potential of encounter the multiple landmines

Keywords: landmine detection, ground penetrating radar, stacking algorithm, time domain.

INTRODUCTION

The detection and efficient removal of landmine is a major problem around the world. Removal of landmines desires revelation, which can be done in numerous ways and a method to detect without digging the ground is preferable for a safety reason. Several research groups are investigating different approaches to solve this problem with the ground penetrating radar (GPR), which is a non- touch based sensor, has high resolution and can be made portable for handheld devices. In the GPR signal, the detection of a landmine requires different ways to extract landmine features by using different filters such as kalman filter, Wavelet, symmetric filtering, principal component analysis (PCA), side row subtraction and independent Component Analysis (ICA). Process this case that input GPR signal contain multiple landmine detection. Therefore, different processing methods are using to process the obtained GPR signal and detecting multiple landmines is necessary. This paper proposes a novel method for processing the GPR signal with multiple objects for landmine detection.

The GPR image is highly dependent on the propagation characteristics of the ground as well as the antenna characteristics. Consider the idealized case where we are detecting a point source; here, we have the point spread activity of the target being convoluted with the antenna beam function, and this spreads the received signal in time and space, causing the well-known diffraction hyperbola.

GPR uses high-frequency (usually polarized) radio crests, consistently in the range 10 MHz to 1 GHz. A GPR transmitter emits electromagnetic energy into the ground. When the energy encounters an entombed object or a boundary among the materials having different permittivity's, it may be reflected or deflected or dispersed back to the surface. A receiving antenna can then record the variations in the return signal. The principals muddled are similar to seismology, exempting GPR methods implement electromagnetic energy rather than phonic energy, and energy may be echoed at circumference where subsurface electrical properties change rather than subsurface mechanical properties.

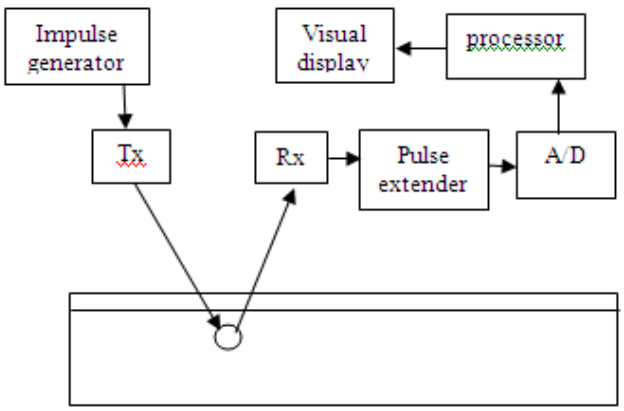

Figure-1. Block diagram of GPR.

a) Impulse generator generates pulses and the transmitter delivers out an array of EM pulses then listens with the receiver connected to high speed samples.

b) Pulse extender will exaggerate the ground rumination signal up to the superlative level seized A/D converter.

c) The A/D converter converts the samples from Nano sec to milli sec.

d) Processor filters the signals; it shows the presence or absence of surrogate mine in the soil. Processor preferred the mine detecting signal and passes to the visual display.

e) Visual display helps to see the range of targets and displays the position of landmine.

f) The operating principal of Ground penetrating radar is straightforward. A GPR sets EM waves in the ground and fragments the backscattered echoes.

The first step practices the hierarchal scheme to evaluate the number of objects in the input signal. The second step isolates the areas containing features of each object from the signal. The proposed method can use the methods for individual landmine detection from the input data.

This paper primarily focuses on a method of detecting number of landmines and separating a data set containing an individual object from the input signal.

RELATED WORKS

Landmines Ground Penetrating Radar Signal Enhancement by Digital Filtering

A digital high-pass filter that is adapted to Bscan data has been proposed to reduce clutter. The efficiency of such a filter to remove clutter while protecting the landmine signatures, even for landmines whose reply are hidden by clutter. The attainment of this method were evaluated due to a comparison with the commonly used CCRA method, and that presents that our approach gives an improved tradeoff in terms of clutter reduction and landmine signatures protection. The only concern is that should be analyzed before employing this filter to any Bscan data is that the width of the buried item in the BScan image is small in correlation with the image diameter. Moreover, the implementation of such a filter is simple, and its computational cost is low [1].

Localization of anti-personnel landmines using multi-bistatic ground-coupled ground penetrating radar

Ground-penetrating radar is a mature technology which has a promising application in humanitarian demining. The use of ground-contact antennas, which greatly improves signal penetration and reduces the rough ground disarrays, thereby simplifying data analysis. Accomplishing contact between the surface and antennas can be done by integrating the antennas against the feet of a non-articulated ambulatory robotic platform. By using fewer scans and simpler data processing approaches, this method is efficient of rising the surveying speed of traditional GPR methods. Using the expected localization method, metallic barrel-shaped targets, 4cm in height and 4cm in radius buried in dry sand at depths changeable between 5 and 15cm, were profitably located.
Although this method has not yet been evaluated experimentally for non-metallic targets [2].

Signal processing techniques for landmine detection using impulse ground penetrating radar

Some signal processing approaches for use along GPR and correlated their detection performance using receiver operating characteristic curves. An analyst should consider plotting the ROC curves for all techniques for the precise habitat they are working in (type of soil, type of target, declination, target size, etc.) before deciding on the best algorithm to use. It is examining from the ROCs shown here that the Kalman filter based detector provides the best overall performance. The Kalman filter approach decidedly assimilates the background component of the signal return into its model, while the rest of are essentially distinctive methods of detecting a change in a background-accustom trace. The cost of the admirable performance of the modified Kalman filter approach is the substantial increase in computational load. After the Kalman filter, the trimmed average power appears to achieve good detection performance for a relatively light computational load. The detection performance comparison framework developed here will greatly assist in the refinement, development and expansion of extant and new spotters for the detection of landmines. Analogous detection algorithms need to be matured and certified for other sensors [3].

Multi-feature based detection of landmines using ground penetrating radar

The procedure consists of data preprocessing, feature extraction and detection. Data are obtained by using a GPR. They are then processed in order to reduce unnecessary signals in order to isolate signals for landmines. Three features based on SVD, DFT and PCA are extracted to each signal for landmine detection, which is performed by using Mahalanobis distance method. The proposed procedure is tested with three different landmines and various ground conditions [4].

A Multiple Migration and Stacking Algorithm Designed for Land Mine Detection

A multiple migration and stacking algorithm has been matured to boost the probability of detection of AT landmines at a false alarm rate of 0.01. The algorithm affords a probability of disclosure of 0.85 compared with 0.6 before processing, hence professed a massive enhancement. The intent of this approach was to disqualify the hyperbolic scattering present when detecting landmines in GPR images for a range of distinctive ground conditions. The crucial factor of this modern access is the stacking technique which scales down the consequence of inconstancies of the ground conditions and in the movement of the detector operator [5].

A multiple instance learning technique for landmine detection using ground penetrating radar

MIL approach to landmine detection using GPR data. The bag of representative mines is then used to map the data into a new feature space where different classifiers could be applied. We have illustrated our approach with two different classifiers. The first one is based on a simple aggregation of the features in the mapped space while the second one is based on RVM. The standard EHD detector, the proposed approach has the supplementary asset of being simple and generic. In fact, it can be easily adapted to include multiple features from different sensors. Using different bags of instances from different sensors, our approach could be used to perform multi-sensor fusion

where data from different sensors could be captured at different resolutions and does not need to be aligned accurately [6].

OVERVIEW OF SYSTEM AND DATA COLLECTION

A series of measurements has been taken using a set of targets buried in various types of soil. An FR-127-MSCBimpulse GPR system developed has been used for this measurement. The structure gathers 127 returns, or soundings, per second, each tranquil of 512 samples with 12-bit efficiency. The deepness order may differ from 4 ns to 32 ns. The GPR structure uses bistatic bow-tie antennas which transmit wideband, ultrashort continuation pulses (Figure-1).

A dielectric abnormality in the soil may motivate the signal to be reflected behind to a separate receiver antenna. This knowledge is transformed from nanoseconds to milliseconds so that it may be digitized by a conventional A/D converter for processing and presentation. The center frequency and bandwidth of the transmitted pulse can be varied by changing the antenna and are preferred as regards to the required depth of penetration, soil type and size of the object to be detected. In this observation, we used receiver with a center frequency 1.4 GHz and 80% bandwidth.

The GPR entity is drooping over the ground surface at a pinnacle of between 0.5 to 2 cm. Its motion is controlled by a stepper motor entity functioning along a trail at a constant velocity. Since the motion of the GPR is controlled by a stepper motor, with consistent speed, running on a successive track, these samples correspond to distances from the starting point of the run. The assessments model a two dimensional matrix, invoked to as a radar gram or B scan. A sample radar gram showing two targets at approximately 55 cm and 100 cm is displayed. A return at a certain position along the distance axis is called an A scan.

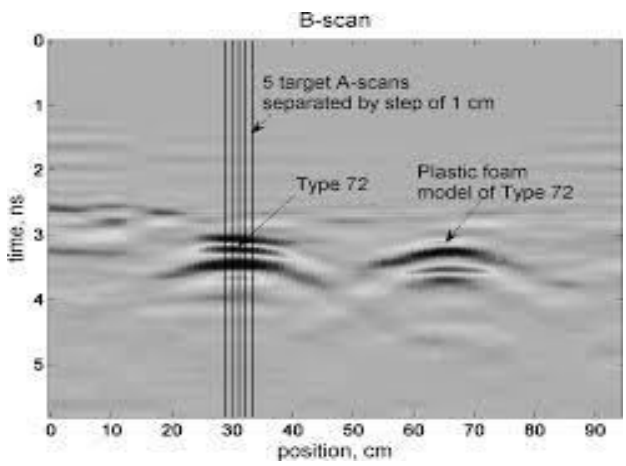

Figure-2. Radargram showing target positions.

DETECTION ALGORITHM

In this project, we proposed an algorithm is based on a hierarchical scheme such as the one in MMCA. First collect all the input images from GPR, next denoising the images. Later convert the images into graphs for easy processing. Convert the graphs into pixels. Compare the local dictionaries with global dictionaries to get the count. Here we are stacking algorithm and also time domain to display the count.

A. MMCA Algorithm

MMCA is clearly able to efficiently separate the initial source signals. For blind source separation, this MMCA algorithm is shown to behave well contribute the authentic sources are morphologically different meaning that the sources are comparatively represented in different bases. The MMCA algorithm is given below:

1. set # of iterations L_{max} and thresholds for all k, $\delta_k = L_{max}.\lambda_k/2$
2. While $\delta_k > \lambda_k/2$

For k= 1…., n_s

- Renormalize a^k, s_k and δ_κ
- Update of s_k assuming all $S\kappa^1 \neq \kappa$ and $a^{\kappa'}$ are fixed.
- Compute the residual $D_k = X - \sum_{k' \neq k} a^{k'} s_{k'}$
- Project $D_k : s_k = \frac{1}{a^{k^T} \Gamma_n^{-1} a^k} a^{k^T} \Gamma_n^{-1} D_k$
- Compute $\alpha_k = \dot{\vec{s}}_k T_k$
- Soft threshold α_k with threshold $=\delta_k$ $gives\ \hat{\alpha}_{-k}$
- Reconstruct s_k by $s_k = \hat{\alpha}_k R_k$
- Update of a^k assuming all $s_{k'}$ and $a^{k' \neq k}$ are fixed:

$$a^k = \frac{1}{s_k s_{k^T}} D_k s_{k^T}$$

lower the thresholds: $\delta_k = \delta_k - \lambda_{k/2}$

The block diagram of MMCA is given as:

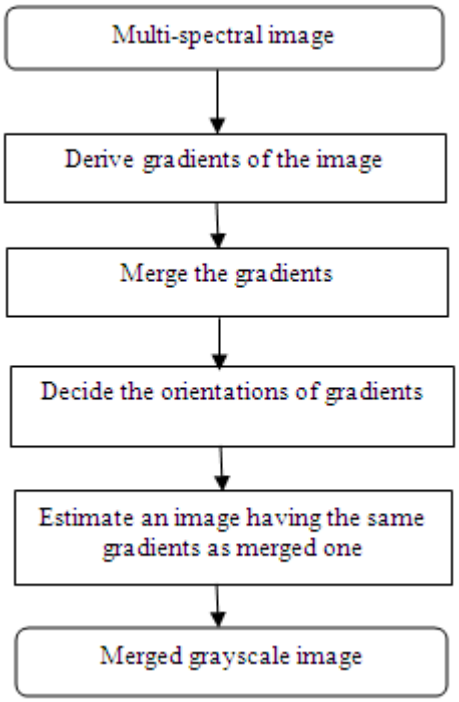

Figure-3(a). Block diagram of MMCA algorithm.

B. Time domain

Time domain is the analysis of mathematical functions, physical signals or time series of economic or environmental data, with respect to time. In the time domain, the signal or function's value is known for all real numbers, for the case of continuous time, or at various separate instants in the case of discrete time. An oscilloscope is a tool commonly used to visualize real-world signals in the time domain. A time-domain graph shows how a signal changes with time, whereas a frequency-domain graph shows how much of the signal lies within each given frequency band over a range of frequencies.

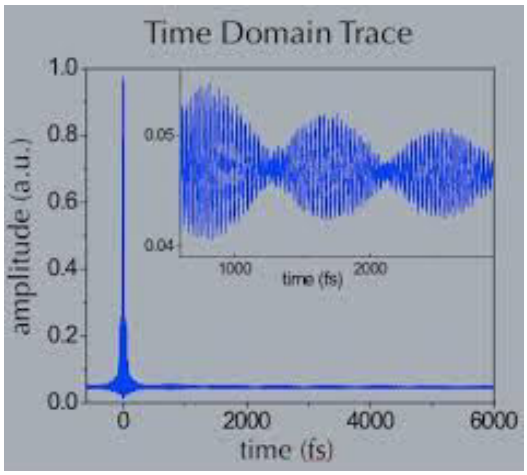

Figure-3(b). Model response of time domain.

c. stackin algorithm

The stacking algorithm is given as:

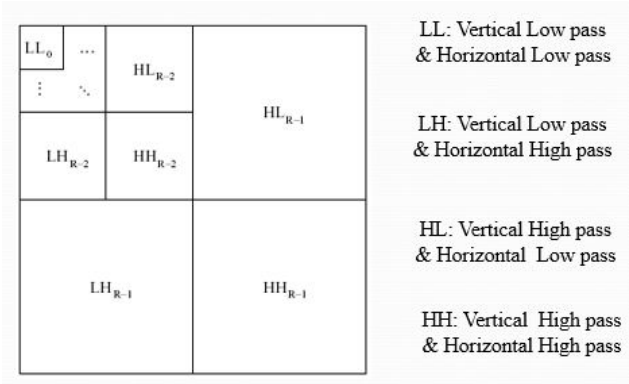

Figure-3(c). representation of stacking algorithm.

a) In module 1 the given input is a mixture of image and in that the process under goes on image denosing, image separation and we get the output from Multichannel Source Separation.
b) In module 2 the given input is Multichannel Source Separation to the proposed algorithm and the output we get is processed output from the algorithm.
c) In module 3 the output of algorithm is given to the global dictionaries versus local dictionaries
d) In module 4 the output from the global dictionaries versus local dictionaries is given to the practical issue. In these this process under goes on noise, dictionary and patch sizes and complexity Analysis.

5. SIMULATION RESULTS

In this experiment, we are considering some input images and then denoising the image. Convert the image into graphs. After remove the noise get the separated output of MMCA. The local dictionaries are compared with global dictionaries. Convert the graphs into pixels for more clarity. Then display the count i.e., number of landmines in the ground.

RESULTS

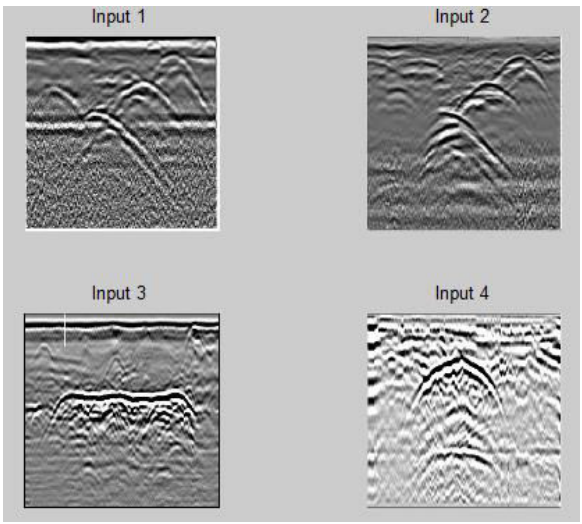

Figure-4(a). Input images.

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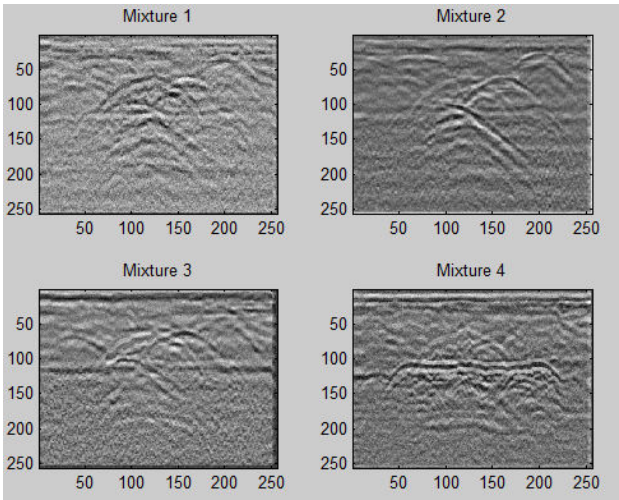

Figure-4(b). Denoising images.

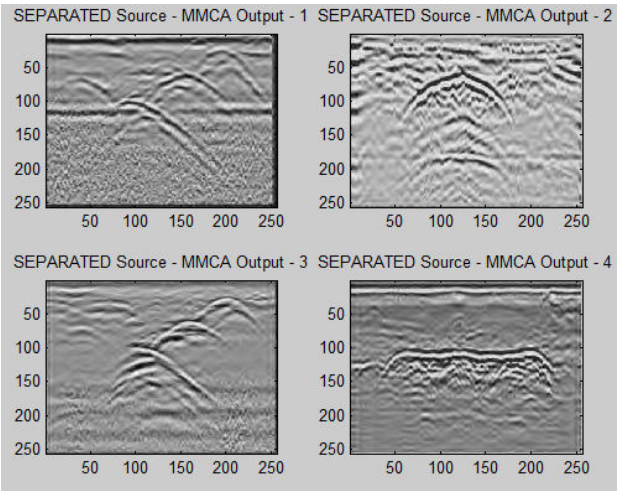

Figure-4(c). Separated source-MMCA outputs.

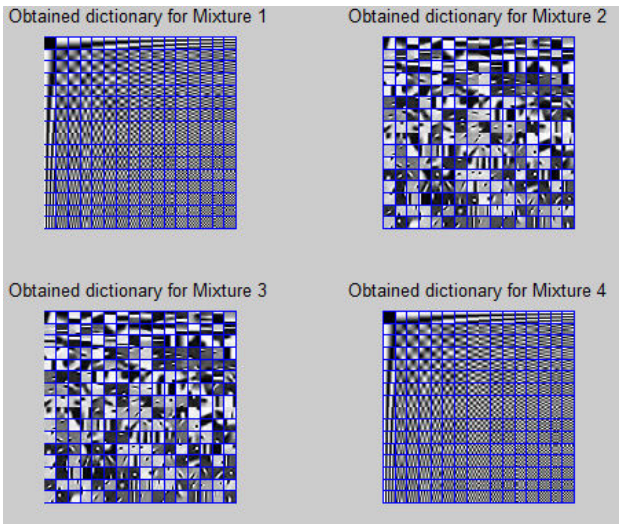

Figure-4(d). Dictionary output for MMCA images.

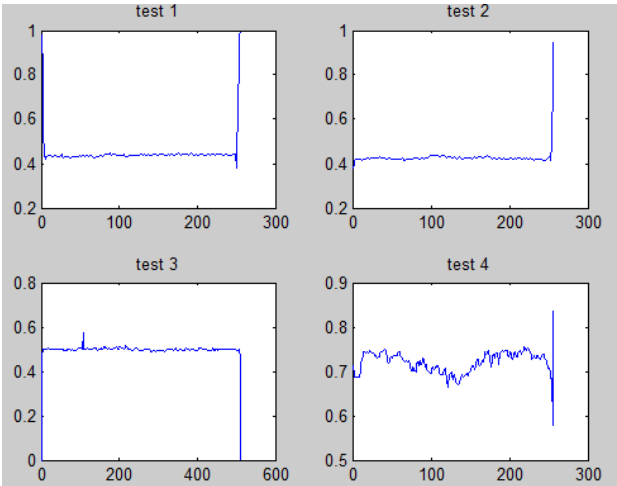

Figure-4(e). Graphical output of images.

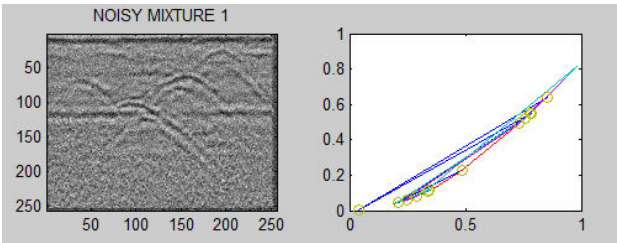

Figure-4(f). Adding pseudo noise in image.

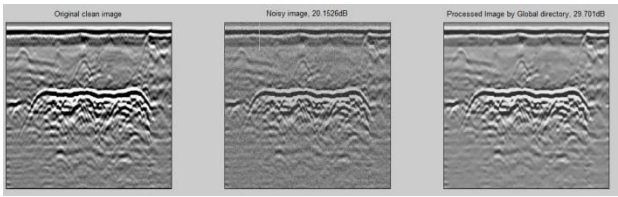

Figure-4(g). Comparing with global dictionaries.

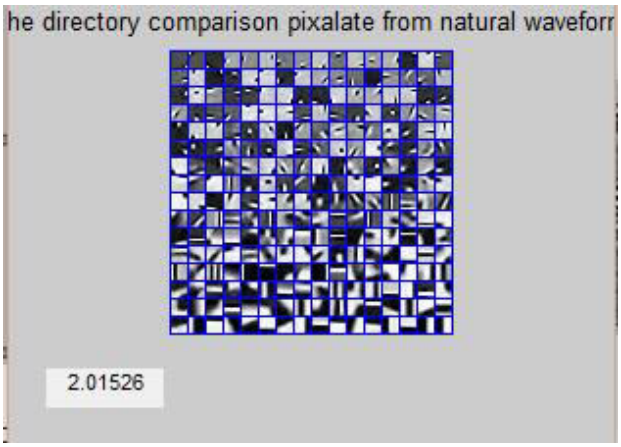

Figure-4(h). Displaying count.

The raw data considered in this test are shown in Figure-4(a). These data are generated by combining the data of each landmine. Figure-4(a) shows the raw data with the clutter removed. Figure-4(b) shows the denoising of the data and Figure-5(c) shows the separated output and

the MMCA outputs of the data. Figure-4(d) shows the dictionary output of the data and Figure-4(e) shows the graphical outputs of the data. Figure-4(f) and Figure-4(g) shows the adding of the pseudo noise to the raw data and compare the local dictionaries with global dictionaries. Finally, in Figure-4(h) shows the count i.e., number of landmines in the ground.

The experiments for various cases show that the proposed method can be used for multiple landmine detection.

6. CONCLUSION AND FUTURE SCOPE

This paper proposes a novel procedure for processing the GPR signal with multiple objects and presents a preliminary result using a simulated example. The essence of the proposed method lies in the estimation of the number of objects and isolation of the patterns of each object from the input GPR signal. The method can provide data sets for efficient landmine detection using various landmine detection methods. The proposed method is limited in that it requires a couple of user-defined values: a peak value for the estimation of the number of objects by using stacking algorithm and time domain. These values mainly depend on the properties of the GPR hardware used in the system. Therefore, such values should be determined and refined through various experiments with real field data. The proposed method is the first step toward the multiple landmine detection. Thorough evaluation of the method with extensive examples and extension to robust landmine detection is recommended for future work.

REFERENCES

[1] D Potin, E Duflos, and P Vanheeghe. 2006. Landmines Ground-Penetrating Radar Signal Enhancement by Digital Filtering. IEEE Transactions on Geoscience and Remote Sensing.

[2] Fawzy Abujarad, Abbas Omar. 2006. GPR Data Processing Using the Component-Separation Methods PCA and ICA. Proc. of IST 2006, Minori, Italy. pp. 60-64.

[3] Fawzy Abujarad, Andreas Jostingmeier, A. S. Omar. 2004. Clutter Removal for Landmine using Different Signal Processing Techniques. Proc. of the Tenth International conference on Ground Penetrating Radar, Delft, Netherlands. pp. 697-700.

[4] Andrew Karem and Hichem Frigui. A multiple instance learning approach for landmine detection using ground penetrating radar. Multimedia Research Lab, CECS Dept. University of Louisville, 978-1-4577-1005-6/11/$26.00 ©2011 IEEE.

[5] John Schofield, David Daniels and Paul Hammerton. 2014. A Multiple Migration and Stacking Algorithm Designed for Land Mine Detection. IEEE transactions on geoscience and remote sensing. 52(11).

[6] M. Neyrat, C. Guiffaut and A. Reineix. 2008. Reverse time migration algorithm for detection of buried objects in time domain. In: Proc. IEEE Antennas Propag. Soc. Int. Symp. pp. 1-4.

[7] Wechsler and J, Sklansky. 1975. Automatic detection of rib contour in chest radio graphs. Ph.D. dissertation, Univ. California, Irvine, CA, USA.

[8] L. Collins, P. Gao, S. Tantum, J. Moulton, L. Makowsky, D. Reidy and R. Weaver. 2000. A comparison of statistical signal processing algorithms for detection and identification of low metal mines. Presented at the UXO/Countermine Forum, Anaheim, CA.

[9] J. Groenenboom and A.G. Yarovoy. 2000. Data processing for a landmine detection dedicated GPR. Presented at the Proc. Eighth Int. Conf. Ground Penetrating Radar, GPR2000, Gold Coast, Australia.

[10] W. Al Nuaimy, Y. Huang, M. Nakhkash, M.T.C. Fang, V.T. Nguyenand A. Eriksen. 2000. Automatic detection of buried utilities and solid objects with GPR using neural networks and pattern recognition. J. Appl. Geophysics. 43(2-4): 157-165.

[11] Gyubin Jang, Kang wook Kim, Kwang Hee Ko. 2011. Multi-Feature Based Landmine Identification Using Ground Penetrating Radar. Proc. of APSAR 2011, Seoul, Korea. pp. 1-3.

[12] William N., Thomas C., H.C. So and K.C. Ho. Particle Filtering Based Approach for Landmine Detection Using Ground Penetrating Radar. IEEE Transaction on Geoscience and Remote Sensing. 46(11).

[13] Yixin Chen, Jinbo Bi and James Z. Wang. 2006. Miles: Multiple-instance learning via embedded instance selection. IEEE Trans. on Pattern Analysis and Machine Intelligence. 28(12).

[14] A. Belouchrani, K. Abed Meraim, J.-F. Cardoso, and E. Moulines. 1997. A blind source separation technique based on second order statistics. IEEE Trans. on Signal Processing. 45(2): 434-444.

[15] J. Bobin, Y. Moudden, J-L. Starck and M. Elad. Multichannel morphological component analysis. DAPNIA/SEDI-SAP Laboratoire APC the Computer Science Department.

[16] S. Ebihara. 2003. Blind separation for estimation of near-surface interface by GPR with time-frequency distribution. IEICE Trans. Commun. E86-B(10): 3071-3080.

[17] P. D. Gader, J. M. Keller, and B. Nelson. 2001. Recognition technology for the detection of buried landmines. IEEE Trans. Fuzzy Syst. 9(1): 31-43.

[18] D. Potin, P. Vanheeghe, E. Duflos, and M. Davy. 2006. An abrupt change detection algorithm for buried landmines localization. IEEE Trans. Geoscience. Remote Sens. 44(2): 260-272.

[19] A. Benter, W. Moore, and M. Antolovich. 2011. Focusing ground penetrating radar images with vertical offset filtering. Progress in Electromagnetics Research M. 19: 183-195.

[20] Kovalenko V., A. G. Yaravoy and L. P. Ligthart. 2007. A novel clutter suppression algorithm for landmine detection with GPR. IEEE Trans. on Geoscience and Remote Sensing. 45(11): 3740- 3751.

[21] T Savelyev, L Van Kempen, H Sahli, J Sachs and M Sato. 2007. Investigation of Time Frequencies Features for GPR landmine discrimination. IEEE Trans. on Geoscience and Remote Sensing.