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Shallow metal object Detection at X-Band using ANN and Image analysis Techniques

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Abstract: *A robust algorithm has been developed for improving the backscattered signal and recognizing the shape of the shallow buried metallic object using Artificial Neural Network (ANN) and image analysis techniques for remote sensing at X-band. An ANN with image analysis technique based on tangent analysis is proposed to recognize the shape of metallic buried objects and minimize the orientation effect of buried object. The experimental setup has been assembled for detecting the buried metallic objects of any size at different depths in the sand pit. The system uses only one pyramidal horn antenna for transmitting and receiving microwave signals at X-band (10.0GHz). All the data to be processed by this algorithm has been received by moving the transmitter/receiver to different locations at a single frequency in X-band in the far field region. ANN technique has been found to be very efficient. An effective training technique has been used to improve the effectiveness of the algorithm. The retrieved result of shape is in good agreement with original shape.*
Keywords: *Shallow buried objects, image analysis, monostatic scatterometer, ANN, X-band, horn antenna.*

I. Introduction

A lot of researchers from various fields (like archaeology, criminology, military, geophysical exploration, submarine detection etc.) are involved in the detection of buried objects. Microwave radar is known to be the most likely answer to these detection problems except submarine detection where acoustic detection finds maximum use [1–3]. Brunzell [4] describes use of pulse radar for detecting buried object. In subsurface detection, when exploring with X-band of microwave, the nearest target is usually at a distance of about 1meter, maintaining the sanctity of the far field antenna. Hence pulse radar must have extremely high precision in time domain, making it quite expensive. CW radar with low frequency modulation can be used for subsurface detection, keeping system cost low. However CW radar does not provide range information. FM-CW radar is a cheaper alternative to pulse radar, if information about depth of object is needed. Yamaguchi [5–7] described the use of FM-CW radar for detecting human body buried in wet snow pack. Carin [8] described the use of polarimetric synthetic aperture radar (SAR) radar for detecting landmines. All the above mentioned investigation mainly concentrated on detecting buried objects. Considering the problem of detecting landmines with the help of data obtained by radar, there are possibilities of a large number of false alarms due to stones, tree roots etc. A typical war field will usually contain many metal fragments. These objects will interfere with the detection of landmines. Some method is needed which will classify the detected objects. Various image processing techniques have been found extensive use and have increased the confidence in detection of the shape of object, and hence classify them. However these techniques are found to be ineffective when backscattered signal quality is poor (i.e., includes noise with surroundings) [1–8].

Use of neural networks [9] while signal processing the data collected by various remote sensing systems is increasing day by day. Yoshida [10] proposed a pattern classification method for remote sensing data using neural networks on problem of land cover mapping. Tsintikidis [11] demonstrated the potential of neural networks for radiometric sensing of land surface parameters. Bischof [12] demonstrated usefulness of neural networks on problem of multispectral land-sat image classification. The unique ability of human brain to recognize objects under poor observable conditions motivated us to apply neural networks to the problem of recognizing an object buried beneath ground using CW radar. Neural networks offer parallel distributed computing platform that does not need programming like conventional computers. Instead neural networks learn from sample examples and due to generalization property, they are able to correctly solve instances of problems not used during learning. The complexity of the problem increases because of the lossy nature of the medium between air and the dielectric object under consideration.

The precise detection of land mines, unexploded ordnances, plastic pipes etc. are some of the major challenges to the researchers. Since mechanical probing of soil is not possible in every case and is impractical in some of the cases. That’s why the importance of GPR (Ground Penetrating Radar) has greatly increased. But the distance from the object is limitation of GPR. Therefore, it is important to develop some techniques based on remote sensing by which shape of these types of buried object can be recognized with air-borne or space borne sensors. For this purpose, microwave remote sensing can be used as a powerful tool. Therefore, in this paper an attempt has been made to fuse the microwave remote sensing technique with ANN and image analysis techniques to recognize the shape of the buried metallic objects at X-band. It must however be remembered that the complete experiment is a three stage process. In the first stage, an object is detected, in the second stage the image of the object is enhanced and in the third its actual shape is recognised. The details of the detection process have not been covered in this paper. The complete details of the same are given in another paper of the authors published in PIER 2008, titled "Development of a Model for Detection and Estimation of Depth of Shallow Buried Non-Metallic Landmine at Microwave X-band frequency" [13]. In the present paper, image enhancement and shape recognition using ANN is being discussed. For this purpose, monostatic active microwave scatterometer at 10.0GHz was developed and the experiment was carried out for detection of two dimensional buried metallic objects which was buried in various depths (i.e., 0.5 cm to 2.5 cm) in sand pit. A number of datasets have been generated and analyzed by placing the target at different depths in the sand. The major problem in this type of observations is the minimization of clutter i.e., reducing the noise level in backscattered signal. The present work is based on the data processing with ANN to improve signal to clutter ratio as well as the application of image analysis technique to recognize the shape of the 2D metallic object buried in sand. The rest of this paper is organized as following. Section 2 gives the system overview and about its architecture. It provides method used for minimizing noise of the backscattered signals and recognizing shape of any object placed in any orientation in 2D space. Section 3 deals with concluding remarks of the present paper.

II. Methodology

2.1. System Overview and Measurement Procedure:

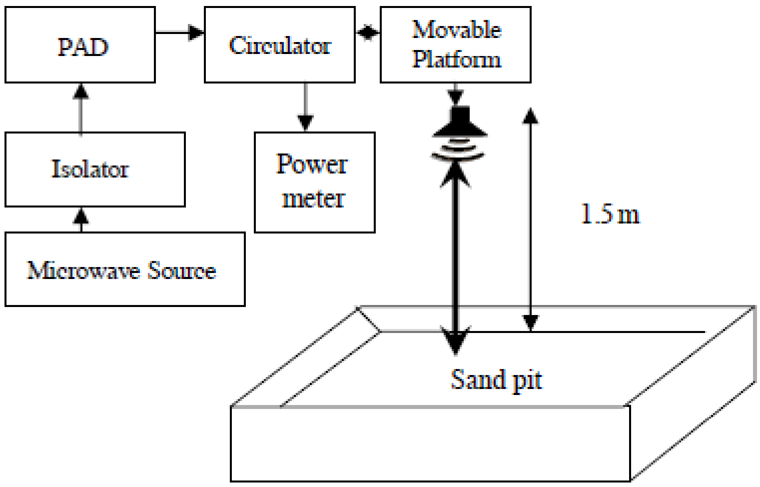


Fig 1. Schematic diagram of monostatic scatterometer.

A monostatic radar (scatterometer) has been used for the detection of buried object as shown in Figure 1 and specifications are given in Table 1. Any radar that measures the scattering or reflective properties of surfaces or volumes is called a scatterometer. Thus a scatterometer may be radar specifically designed for backscattering measurement; or it may be radar designed for other purposes such as imaging or altimetry, but calibrated accurately enough so that scattering measurements with it is possible. Scatterometer may be designed to make measurements at a particular angle, frequency, and polarization. All the observations have been taken at a frequency of 10.0GHz with a plane polarized wave (Horizontal- Horizontal polarization) incident normally on the target. A pyramidal horn antenna has been used as both transmitter and receiver. It has been mounted on a movable platform which can scan the region under investigation in two dimensional spaces in steps of 5 cm. These objects were buried at the center of the sandpit which dimension was 2.0m × 2.0m. The size of the object (Aluminum sheet) was 59.2×59.2 cm2. The same sample was kept at different depths (0.5 cm to 2.5 cm at interval of 0.5 cm) into the sandpit. Every time care was taken to fill-up the sandpit and levels it up and leveling was done by the level profiler. Adequate care is taken every time in filling the sand pit and leveling it up. The surface is assumed smooth at 10.0GHz frequencies and sand was dry with dielectric constant approximately 3.5 during whole experiment. The observations were taken in far field zone. The calibration of the system was checked before and after each scan with a view to ascertain the truthfulness of collected data. The back scattered signals received have been processed to get better image of buried object.

Central Frequency	10.0GHz
Frequency Band Width	0.8GHz
Antenna type	Dual Polarized Pyramidal Horn
Antenna Beam Width	18.5 degree
Antenna Gain	20 dB
Platform Height	1.5m
Cross-pol Isolation	35 dB

TABLE 1: System Parameters

2.2 Image Enhancement:

An ANN (Artificial Neural Network) technique has been used for the processing of signals received. A neural network is network of a number of simple processors with a small amount of local memory. These processors are connected by unidirectional communication channels that carry numerical data. It is like brain as knowledge is acquired by the network through a learning process. It is a parallel distributed network with following features :

A set of processing units.

- An activation state for each unit, which is equivalent to the output of the unit.
- Connection between units. Each connection is defined by a weight *wjk* that determines the effect that the signal of unit *j* has on the unit *k*.
- A propagation rule, which determines the effective input of the unit from its external inputs.
- An activation function, which determines the new level of activation based on the effective input and the current activation.
- An external input (bias, offset) for each unit.
- A method for information gathering (learning rule).
- An environment in which the system can operate.

A neural network has three types of units as shown in Figure 2 [19]:

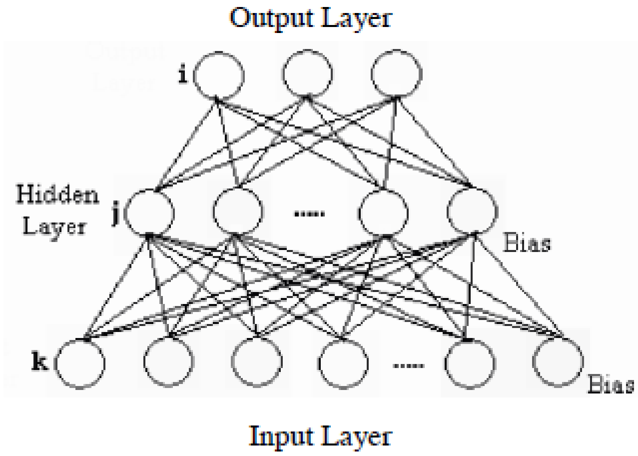


Fig 2. A single-hidden-layer multilayer perceptron neural network

- *Input units*: Receives data from outside of the network.
- *Output units*: Send data out of the network.
- *Hidden units*: Its input and output signals remain within the network.

2.2 Shape Recognition:

Determining the shape of the buried object or the area over which the objects are buried is one of the major challenges to the researchers. Determining shape, dimension, area etc. of the mine fields are urgent requirements for military purposes. It’s usually very tough to get an idea about shape of the buried objects or distribution of pipes when the area to be scanned is very large. The proposed algorithm can automatically identify the approximate shapes of buried objects. The complexity of the proposed algorithm is also less and has been found to be very efficient in determining shapes of the buried objects. The major advantage to this algorithm is that ANN is used which learns through instances. The system has been trained for different shapes by extracting the property of waveform of each object. Each object provides different waveform according to its shape. Another advantage to this system is that the system is not restricted only to the recognition of ordinary shapes like square, rectangular or circular but can be used to recognize any type of shapes. Since each object provides different type of waveform, so a particular type of waveform can be used for recognizing a particular shape. It is clearly observe that the noise is quite reduced in Figure 3.

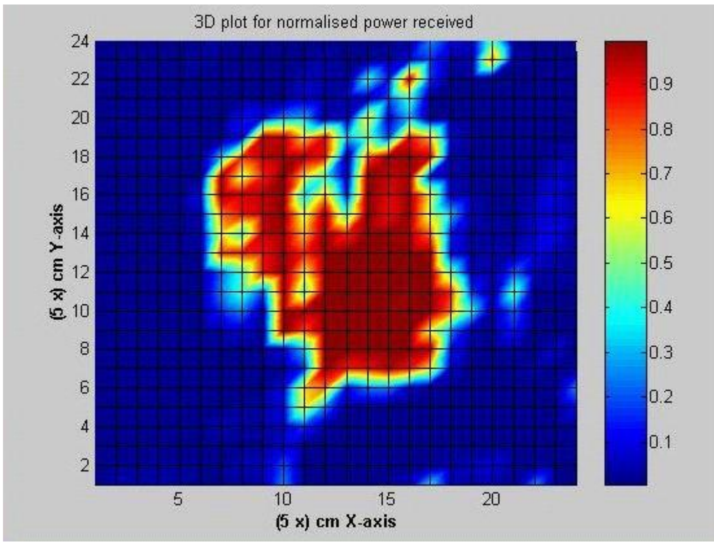


Fig 3. Back scattered signal after processing with ANN technique.

At first all the backscattered signal obtained by scanning the target in 2D space are processed by ANN and then stored in a 2D matrix. To extract the waveform, every element in the rows and then the columns are added. Now a graph may be obtained as the summed value of elements vs. rows and columns. This waveform will provide the identity of the shape of a buried object. This waveform will be fed to the system as input for determining the shape of the object. Since each shape provides different waveform and thus the system can be trained with different waveform for different objects. The accuracy of the system is almost in user's hand. Better is the training data better will be the system. Figure 4 shows the flow chart to detect the shape with ANN and image analysis approaches. Considering some theoretical data with 1 corresponding to the region with object and 0 corresponding to the region without object and with these data, different waveforms for some common shapes are shown in Figures 5(a), (b) and (c).

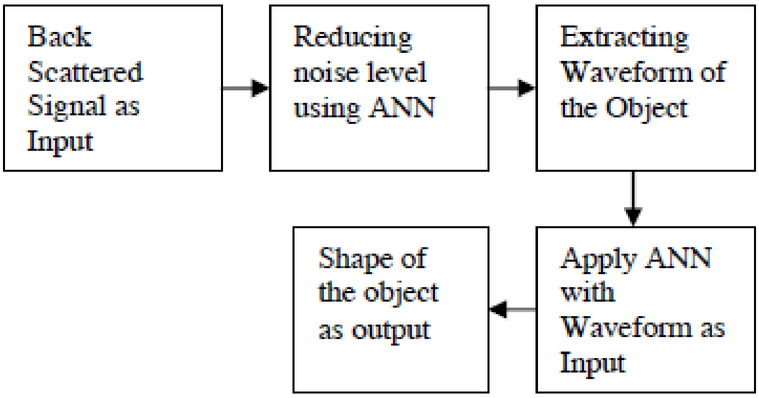


Fig 4. Block diagram of the system for recognizing the shape of the metallic shallow buried object without consideration of orientation effect.

ANN with one hidden layer with two nodes has been used. The number of output nodes depends upon the types of different shapes like square, rectangle etc. to be recognized and the number of input nodes depends on the total number of columns and rows of the matrix of the backscattered signals received by scanning the target. Now the weights obtained after training the system for square and rectangular shapes are as following:

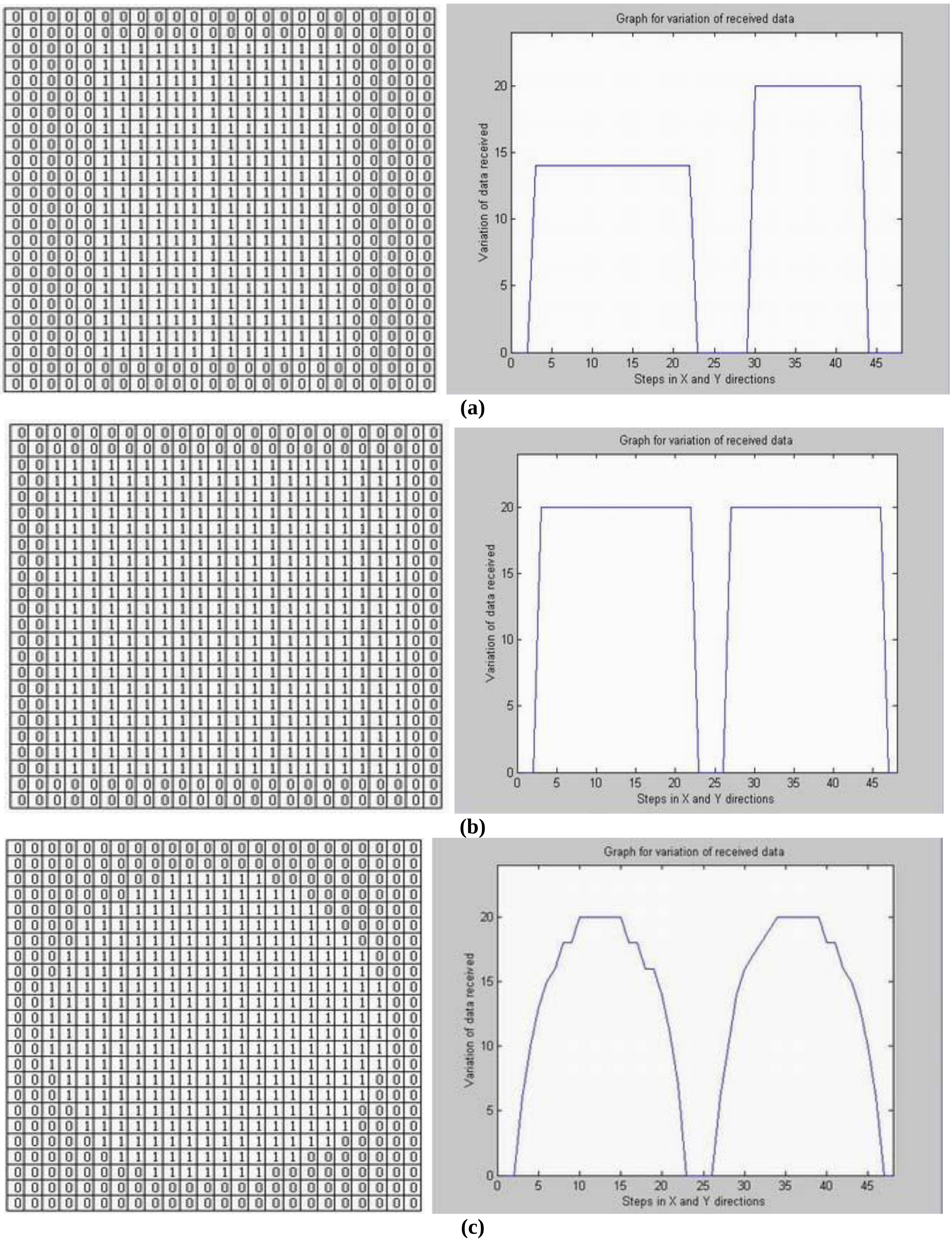


Fig 5. (a) Matrix and corresponding waveform for a rectangular object, (b) Matrix and corresponding waveform for a square object, (c) Matrix and corresponding waveform for a circular object.

The proposed algorithm is shown in Figure 6 and it is giving satisfactory results even after rotating the image.

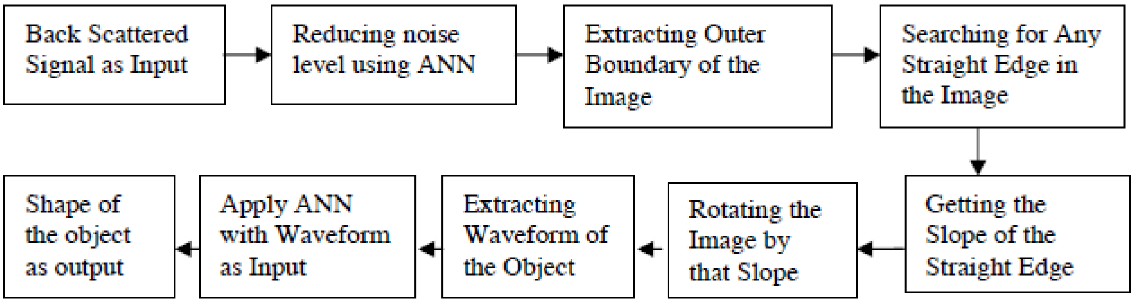
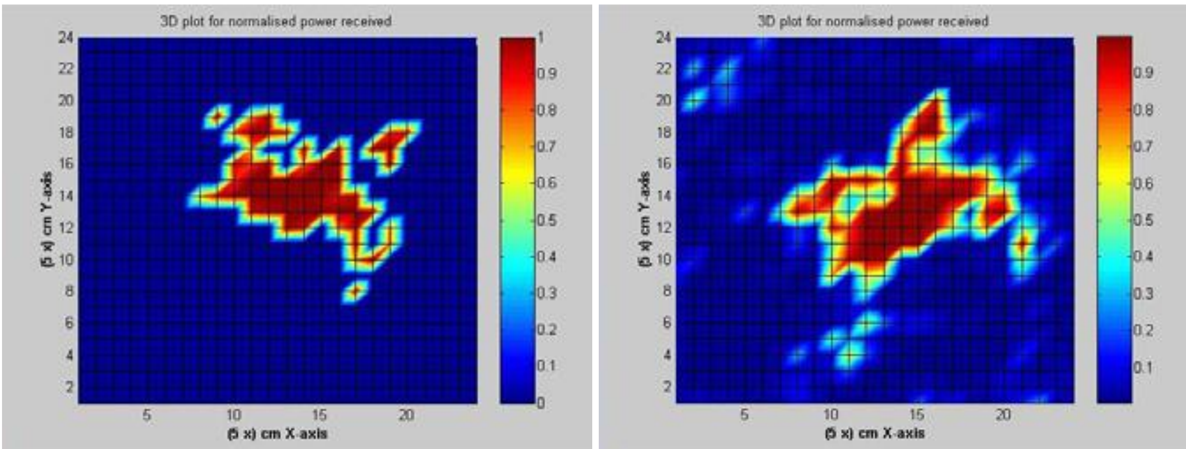


Fig 6. Block diagram of the system recognizing the shape of the buried object when orientation effect has neutralized.

Figure 7(a) shows the image before any rotation and Figure 7(b) shows the image obtained after rotation and both images represent the similar type of shape. A clear shape of the sheet is not visible because of the possibility of errors in the leveling of the sheet or some error in observations but in the program output, it clearly tells about shape i.e., square rectangle or circle.



(a) **(b)**

Fig 7. (a) Enhanced image obtained without rotation, (b) Enhanced image obtained after rotation.

III. Concluding Remarks

The fusion of image analysis techniques with ANN approach have been developed to recognize the shape of shallow buried metallic objects at 10.0GHz which is buried in sand and upper surface is assume smooth at 10.0GHz frequency. The use of lower frequency may provide more accurate information regarding the exactness of the buried objects because attenuation increases with increasing in the frequency. The orientation effect of buried target has been neutralized by proposing tangent calculation technique. A quite good agreement of retrieved shape and real shape has been obtained. The proposed algorithm is useful to any size and maximum shapes of the buried metallic target.

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