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# Discrimination of Mine-Like Objects in Infrared Images Using Artificial Neural Network

KEYWORDS: mine like object; infrared; GLCM; back propagation

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**ABSTRACT** *An artificial neural network (ANN) model with a simple architecture containing a single hidden layer is presented to discriminate the mine-like objects from the acquired infrared images. The proposed method consists of preprocessing, segmentation, feature extraction and ANN based classification. Texture features based on gray level co-occurrence matrix (GLCM) are considered as inputs to the neural network classifier. The proposed method is tested on the infrared images acquired from two different soil types namely black cotton soil and sand.The ability of the back propagation neural network in discriminating the mine like objects from the clutters in the infrared images acquired from inhomogeneous soil is discussed. The results are encouraging.*

## 1. Introduction

Landmines kill or maim innocent civilians everyday [1]. The task of detection and clearance of buried landmines in various military applications is highly daunting due to various humanitarian, environmental and economic implications involved. Various automatic target detection and recognition systems used for this problem produce a high false alarm rate due to the various constraints encountered in the real minefield. Nevertheless it still remains an active area of research with different techniques being explored. Dogs and metal detectors are used in most programs for finding the presence of land mines and the exact localization and removal is done by various prodding techniques [2]. Ground Penetrating Radar (GPR) and Infrared (IR) sensor are two of the most widely used sensors in this application. The effectiveness of infrared imaging in locating mine affected areas from an altitude makes it one of the inevitable sensor in sensor fusion techniques. Night vision and noncontact operation with the system are the other advantages of an infrared sensor. Though the performance of an infrared sensor is dependent on a wide range of variables in the atmosphere and the soil [3], effective image processing techniques can be used to improve the performance.

This contribution investigates the recognition ability of the soft computing technique namely the back propagation neural network with a simple architecture in discriminating a landmine from clutter in the acquired infrared images. The gray level co-occurrence matrix (GLCM) based textural features are used as input to the neural network. The paper is organized as follows:. Section 2 discusses the proposed methodology for detection and classification of mine like objects from infrared images. Simulation results are presented in section 4. Section 5 concludes the work.

## 2. The proposed Methodology

The goal of an efficient mine detection system is to achieve a high probability of detection and a low false alarm rate. The process of detection and identification of mine like anomalies from the infrared images involves image processing techniques such as contrast enhancement, filtering, smoothing, segmentation and feature extraction and classification. The flowchart in fig.1 describes the complete processes involved in detection and recognition of mine like objects in the acquired infrared images.

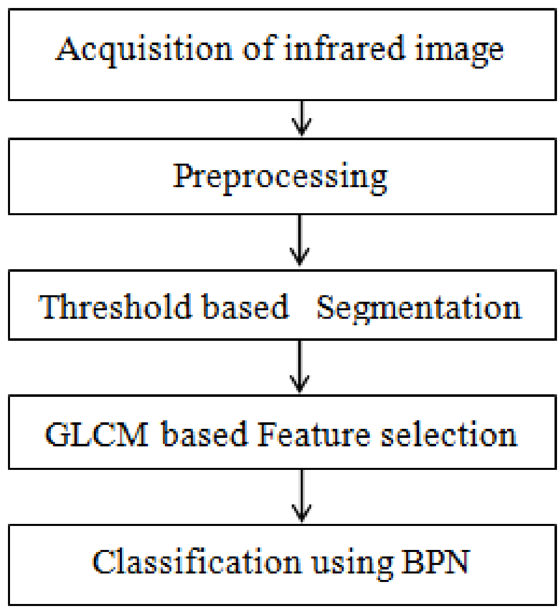


**Fig.1. Overview of the processes involved in recognition of mine like objects**

### 3.1. Preprocessing

The acquired infrared image is converted to gray tone image and it is resized to a standard dimension of 256x256 pixels in order to perform matrix arithmetic during further processing. The two important preprocessing operations which are used to overcome the ambiguity of the target signal in real time image processing such as landmine detection are contrast enhancement and noise removal. The noise effect is degraded and the visual quality of the image is improved in order to carry out further operations. The gray scale image is enhanced using histogram equalization and the enhanced image is filtered using Wiener filter in this application. Wiener filter is effective in tapering off the noisy components especially when the noise and signal are Gaussian distributed in the image [4]. Smoothing is also carried out on the filtered image using an average filter whenever necessary.

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### 3.2. Segmentation

It refers to the process of grouping the homogenous pixels sharing some common attributes such as color, intensity or texture in an image. It separates the regions of interest from the background thus making further analysis easier. Clustering, edge detection and threshold based region growing are the three categories [5] of the various existing image segmentation techniques. In this work, threshold based segmentation is used to isolate the mine like objects present in the infrared images.

### 3.3. Feature Extraction

Once the mine like object is identified in the segmented image, the features of the region of interest are measured and made available for further recognition and classification purpose. Pixel intensity-based features, edge features and texture-based features [6] are generally used in feature selection process. The statistical textural features based on Gray level co-occurrence matrix(GLCM) namely contrast, correlation, energy and homogeneity are measured and used for classification in our work. The probability of the couple pixels at 'θ' direction and 'd' interval is defined by the GLCM matrix[7] as P(i,j|d, θ). By assuming 'θ' as 0° and 'd' as 1 pixel offset, P(i,j|d, θ) is simply expressed as P(i,j).

The statistical textural features extracted from GLCM in this work are as follows:

$$Correlation = \sum_{i=0}^{N}\sum_{j=0}^{N}\frac{(i-\mu_i)(j-\mu_j)P(i,j)}{\sigma_i\sigma_j} \quad Contrast = \sum_{i=0}^{N}\sum_{j=0}^{N}\left|i-j\right|^2 P(i,j)$$

$$Energy = \sum_{i=0}^{N}\sum_{j=0}^{N}P(i,j)^2 \quad Homogenity = \sum_{i=0}^{N}\sum_{j=0}^{N}\frac{P(i,j)}{1+(i-j)} \qquad (1)$$

Where i, j are the spatial coordinates of the probability matrix P (i, j) and N is the gray tone image.

### 3.4. ANN Model for classification

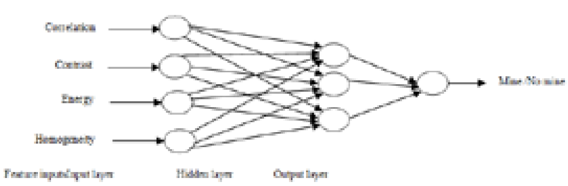
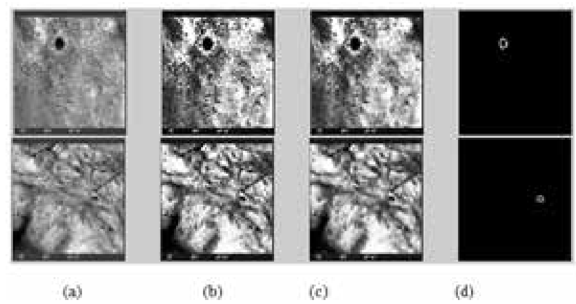



**Fig. 2. Structure of a back propagation neural network with one hidden layer**

Multi-layer back propagation network can be used to recognize patterns when trained with adequate data. A feature based feed-forward three-layer network with four neurons in the input layer, three neurons in the hidden layer and one neuron in the output layer is employed in our work to perform the classification of mine like objects as shown in fig.2. It is a supervised network using a gradient-descent learning algorithm known as back propagation (BP) with a multilayer perceptron (MLP) topology [8]. The weights are initialized randomly between zero and one. A sample feature vector from the training data is fed as input to the network. The values at the output node are calculated. The sigmoid activation function is used to calculate the net output in all the three layers. The error is computed which is the difference between the actual output and the desired output. The values of weights in the weight matrix are updated according to the delta rule till the error becomes minimum. This is repeated for all the training samples until the error becomes minimum or till the completion of enough epochs is reached. The quality metric used in our work is mean square error (MSE). Learning happens as the network is pushed to give desired ouputs, with the gradual change in the connection weights. Then the neural network is tested on the sample images in the test data for its ability to recognize new patterns and associate them with the already defined classes.

### 4. Experimental Results

Various structural and statistical features are measured from the mine like blobs present in the segmented infrared images. Sample images containing a mine like object and a clutter that resembles a mine are shown in fig.3 and their geometrical and textural properties are tabulated in table1.




**(Fig.3. Sample processed infrared images (top row: mine like object and bottom row:**
clutter): (a) original,(b) contrast enhanced,(c) filtered,(d) segmented

**Table 1. Computed geometrical and textural feature values from two sample images**

| Object | Area(pixels) | Circularity Ratio | Mean | Entropy | Contrast | Correlation | Energy | Homogeneity |
|---|---|---|---|---|---|---|---|---|
| Mine like Object | 321 | 0.8473 | 0.0944 | 5.4902 | 0.0013 | 0.7694 | 0.9930 | 0.9993 |
| Clutter | 188 | 0.9840 | 0.0181 | 0.5704 | 0.0086 | 0.8257 | 0.9939 | 0.9990 |

Out of the many features, only the four GLCM based textural features are chosen for training the neural network described above. The network is trained for two classes with the training data. Class 1 is for mine like object and class 2 is for clutter(non-mine).Once trained, the network is tested with the samples from the test data. Fig.4 shows the variation of the quality metric with the number of training epochs. The predetermined MSE value is chosen as 0.000105. The network approached the defined goal only after 673659 iterations.

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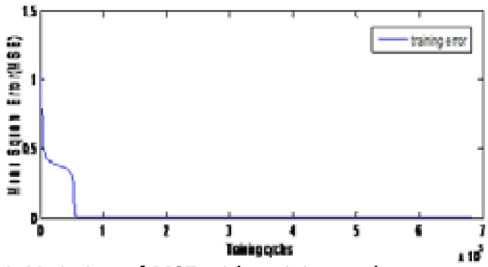

**Fig.4. Variation of MSE with training cycles**

The output of the network for the input features corresponding to a mine like object is identified with '1' and the output corresponding to clutter features is identified with '0'. The desired output (target) and actual output values of the test data are shown in table 2 for nine samples out of which six samples are from the mine like objects and three samples are from the man-made clutter. From the results obtained, it is perceived that the trained neural network has performed successfully on the test data.

**Table 2. BPN outputs for sample test data**

| Sample No | Objects | Desired output | Actual Output (54109 epochs) | Actual Output (673659 epochs) |
|---|---|---|---|---|
| 1 | mine | 1 | 0.8065 | 0.9926 |
| 2 | mine | 1 | 0.8305 | 0.9969 |
| 3 | mine | 1 | 0.6361 | 0.9941 |
| 4 | mine | 1 | 0.2824 | 0.9976 |
| 5 | mine | 1 | 0.6648 | 0.9975 |
| 6 | mine | 1 | 0.9208 | 1.0000 |
| 7 | clutter | 0 | 0.1079 | 0.0031 |
| 8 | clutter | 0 | 0.0053 | 0.0094 |
| 9 | clutter | 0 | 0.0133 | 0.0006 |

The reason for the poor performance of the network for the fourth sample and seventh sample in the test data when the network is trained to learn with 54109 epochs is not known. Nevertheless, the recognition performance is improved when the number of epochs is increased to 673659 with a compromise in time taken for training the network. The simulation was carried out using MATLAB.

## 5. Conclusion

Back propagation neural network with a simple structure consisting of a single hidden layer with three neurons has been modeled and trained for a set of textural features measured from the infrared images acquired from an outdoor test lane. The textural features of the region of interest were computed from the segmented image. Image preprocessing techniques such as enhancement and noise removal were carried out prior to segmentation. The network was trained using the training data that contained both mine like objects and non-mine(clutter)objects. The network learnt to reach the goal only after 673659 epochs. However, the discriminative ability of the network was found to be encouraging when the network was tested with the test data. The performance can be improved by modifying the structure of the network according to the varying size of feature vector and by increasing the number of neurons in the hidden layer.

**REFERENCE**

[1] Bruschini, C. and Gros, B.(1998), "A survey of research on sensor technology for landmine detection", The | Journal of Humanitarian Demining, Issue 2.1. | | [2] Remke L.Van Dam, Jan M.H. Hendrickx, Brian Borchers, Sung-ho Hong, Timothy W.Miller and Russel S.Harmon(2004a), "A controlled outdoor test site for evaluation of soil effects on land mine detection sensors", Detection and Remediation Technologies for Mines and Minelike Targets IX, Vol. 5415, pp. 1335-1344. | | [3] Remke L.van Dam, Brian Borchers, Jan M.H.Hendrickx and Sung-ho Hong(2004b), "Controlled field experiments of wind effects on thermal signatures of buried and surface-laid landmines", Detection and Remediation Technologies for Mines and Minelike Targets IX, Vol. 5415, pp. 648-657. | | [4] Liao, W.J., Chen, D.H. and Baertlein, B.A.(2001), "Algorithms for detection of surface mines in multispectral | IR and visible imagery",Proc.SPIE, Vol. 4394, pp. 310-321. | | [5]Anitha, A., Poonguzhali,S. and Ravindran,G.(2006), "Classification of liver abnormalities in ultrasound image | using neural network by Gabor features" ,Proceedings of the ISCO, pp11-15. | | [6] Monica Subashini, M. ,Sarat Kumar Sahoo(2013), "Brain MR image segmentation for tumor detection using | artificial neural networks", International Journal of Engineering and Technology (IJET), Vol.5, No. 2, pp.925- | 933. | | [7] Fan-Hui Kong(2009), "Image retrieval using both color and texture features", Proceedings of the Eighth | International Conference on Machine Learning and Cybernetics, Baoding, pp.2228-2232. | | [8] ChinkiChandhok, SoniChaturvedi and Khurshid, A.A.(2012), " An approach to image segmentation using K- | means clustering algorithm", International Journal of Information Technology (IJIT), Vol.1,No. 1,pp.11-17. |