CLASSIFICATION OF SONAR IMAGES USING NEURAL NETWORK ALGORITHM

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Abstract : This paper is an approach to improve the performance of intelligent classification and recognition of side scan sonar images. Today side scan sonar systems are the state of art sensor for mine hunting as they need a relatively short time to map large area of sea floor with a relatively high resolution. This paper focuses on sonar images classification and recognition system application developed to simulate human experience in recognition under water shapes by using two Neural Networks, applying four learning rules and three transformation algorithm to each Neural Networks. With a purpose to classify five types of side scan sonar images, 83 side scan sonar images are considered along with separate cross validation dataset. Performance measures such as MSE and classification accuracy boosts result performance.The Average Classification Accuracy of MLP Neural Network comprising of one hidden layers with 14 PE's organized in a typical topology is found to be superior (98.33%) for Training and cross-validation. Finally, optimal algorithm has been developed on the basis of the best classifier performance. The algorithm will provide an effective alternative to traditional method of Side scan Sonar images analysis for classifying the five type of sonar scan sonar images of ocean bed.

***IndexTerms* - Neurosolution, MatLab, Microsoft excel, all five type of Side scan Sonar images.**

I. INTRODUCTION

One of the most popular tool for underwater researches is Side Scan Sonars. Side Scan Sonars are used to create an image of sea floor to provide an understanding of the differences in material and texture type of the seabed by using acoustic reflections of pulses. Sometimes, these images cannot provide an efficient information to researchers and scientists to easily recognize them. They are mostly in grayscale or in two colors, and additional noise, such as depth and water pollution of sea floor decrease the quality and visibility of sonar images. But, in spite of all these disadvantages, scientists are still performing researches and experiments to discover and recognize the depth of the oceans.

However, classification or recognition of the objects that appear in these images is difficult task and needs human experience. But, if we consider the amount of the area that is covered by the oceans, it is more effective to provide automatic intelligent recognition or classification that simulates human experience. Sonar Image Classification and Recognition System was developed to simulate human experience by classifying five types of sonar images namely; Airplane, Ship, Ripples and Sand, Volcano, and Rock as shown in Fig. 1.

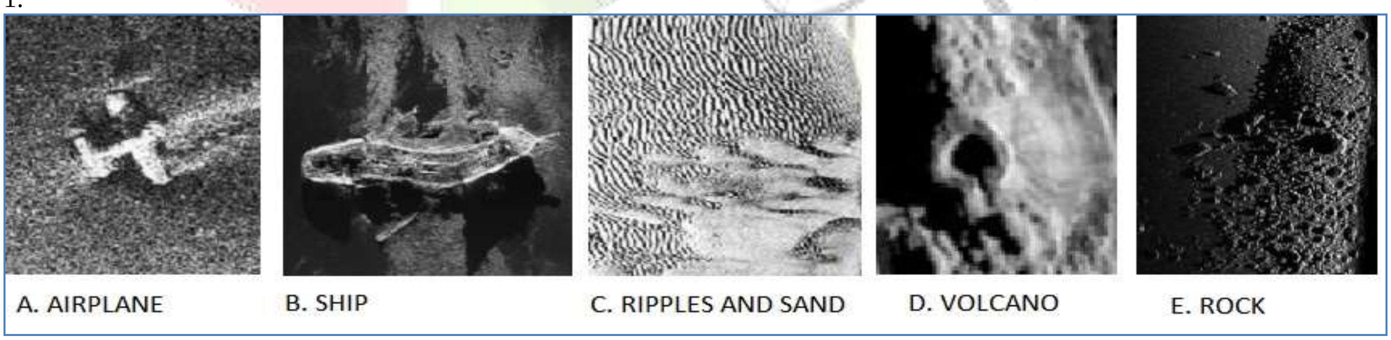

Figure 1

This paper considers 83 side scan sonar images in input database. We will use Artificial Neural Network as our classifier for comparison of Side scan Sonar images. An artificial neural network (ANN), usually called neural network (NN), is a mathematical model or computational model that is inspired by the structure and/or functional aspects of biological neural networks. Depending on the applications, many systems have been proposed to solve or at least to reduce the problems, by making use of image processing, pattern recognition and some automatic classification tools. .

The reliability and the success of these systems are depend on the effectiveness of applied data pre-processing techniques and neural networks which can be used for efficient modelling of human's visual system during the recognition or classification of patterns. Neural networks have an important part in the modelling of human experience and decision making process into computers.

II. Proposed Algorithm

Proposed algorithm has three main phases- Feature extraction of sides can sonar images, Designing and training a network, and Recognition i.e. testing the network. The details are as follows;

2.1 Feature Extraction Of Side Scan Sonar Images

For the proposed classifier design for theclassification ofside scan sonar images, the most important inputs are uncorrelated features as well as coefficient from the images. These coefficients will be extracted using Fast Fourier Transform with the help of MATLAB. This process gives raw sheet of image coefficients which we will then manually tag for further use.

2.2 Designing and Training a Network

Training the Neural Model is process which decreases the error in each iteration of classification to get closer in producing desired response. For designing a classifier following network is tested along with the four learning rules described below. For better classification, from the input image coefficients a separate cross-validation and training datasets are used.

2.2.1 Multilayer perceptron (MLP)

The most common neural network model is the multi-layer perceptron (MLP). This type of neural network is known as a supervised network because it requires a desired output in order to learn. The goal of this type of network is to create a model that correctly maps the input to the output using historical data so that the model can then be used to produce the output when the desired output is unknown.

The MLP neural networks learn using an algorithm called back- propagation. With back-propagation, the input data is repeatedly presented to the neural network. With each presentation the output of the neural network is compared to the desired output and an error is computed. This error is then fed back (back-propagated) to the neural network and used to adjust the weights such that the error decreases with each iteration and the neural model gets closer and closer to producing the desired output.

2.2.2 Learning Rules used;

2.2.2.1 Momentum

Momentum simply adds a fraction m of the previous weight update to the current one. The momentum parameter is used to prevent the system from converging to a local minimum or saddle point. A high momentum parameter can also help to increase the speed of convergence of the system. However, setting the momentum parameter too high can create a risk of overshooting the minimum, which can cause the system to become unstable. A momentum coefficient that is too low cannot reliably avoid local minima, and can also slow down the training of the system.

2.2.2.2 Conjugate Gradient

CG is the most popular iterative method for solving large systems of linear equations. These systems arise in many important settings, such as finite difference and finite element methods for solving partial differential equations, structural analysis, circuit analysis, and math homework.

2.2.2.3 Quick propagation

Quick propagation (Quickprop) is one of the most effective and widely used adaptive learning rules. There is only one global parameter making a significant contribution to the result, the e-parameter. Quick-propagation uses a set of heuristics to optimize Back-propagation, the condition where e is used is when the sign for the current slope and previous slope for the weight is the same.

2.2.2.4 Delta bar Delta

The Delta-Bar-Delta (DBD) attempts to increase the speed of convergence by applying heuristics based upon the previous values of the gradients for inferring the curvature of the local error surface. The delta bar delta paradigm uses a learning method where each weight has its own self-adapting coefficient. It also does not use the momentum factor of the back propagation networks. The remaining operations of the network, such as feed forward recall, are same to the normal back-propagation networks. Delta-Bar-Delta is a heuristic approach in training neural networks, because the past error values can be used to infer future calculated error values.

2.3 Recognition or testing a network

Testing a network is main phase as to see how the trained network recognizes the input images. For getting better result, performance measures such as MSE is used along with the confusion matrix for both types of input- training dataset and cross-validation dataset. The MLP neural network has been simulated for 83 different images of side scan sonar images out of which 63 were used for training purpose and 20 were used for cross validation.

III. Simulation Results

3.1 Computer Simulation

The simulation of best classifier along with the confusion matrix is shown in Fig. 2;

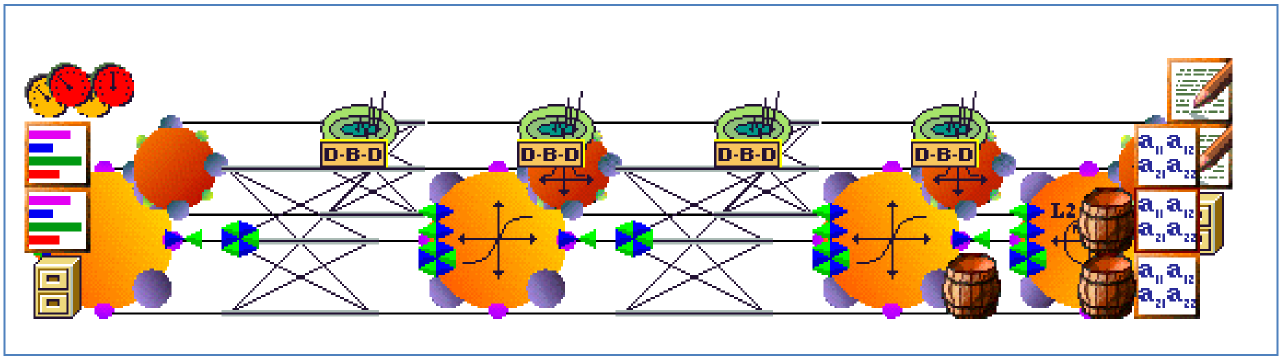

Figure 2

3.2 Results

Table 3.2.1. Confusion matrix on Cross Validation data set

Output / Desired	ROCK	VOLCANO	RIPPLE&SAND	SHIP	AIRPLANE
ROCK	2	0	0	0	0
VOLCANO	0	2	0	0	0
RIPPLE&SAND	0	0	4	0	0
SHIP	0	0	0	4	1
AIRPLANE	0	0	0	0	5

Table 3.2.2. Confusion matrix on Training data set

Output / Desired	ROCK	VOLCANO	RIPPLE&SAND	SHIP	AIRPLANE
ROCK	4	0	0	0	0
VOLCANO	0	6	0	0	0
RIPPLE&SAND	0	0	16	0	0
SHIP	0	0	0	17	0
AIRPLANE	0	0	0	0	22

Table 3.2.3. Accuracy of the network on Cross Validation data set

Performance	ROCK	VOLCANO	RIPPLE&SAND	SHIP	AIRPLANE
MSE	0.04	0.01	0.02	0.10	0.07
NMSE	0.37	0.11	0.13	0.60	0.31
MAE	0.12	0.06	0.09	0.23	0.15
Min Abs Error	0.00	0.01	0.00	0.00	0.00
Max Abs Error	0.52	0.36	0.43	0.63	0.86
R	0.83	0.98	0.94	0.72	0.84
Percent Correct	100.00	100.00	100.00	100.00	83.33

Table 3.2.4. Accuracy of the network on Training data set

Performance	ROCK	VOLCANO	RIPPLE&SAND	SHIP	AIRPLANE
MSE	0.00	0.00	0.00	0.00	0.00
NMSE	0.01	0.01	0.00	0.00	0.00
MAE	0.02	0.02	0.01	0.02	0.02
Min Abs Error	0.00	0.00	0.00	0.00	0.00
Max Abs Error	0.05	0.05	0.05	0.06	0.05
R	1.00	1.00	1.00	1.00	1.00
Percent Correct	100.00	100.00	100.00	100.00	100.00

IV. Conclusion and Future Work

From the results obtained as shown in Table 3.2.1, Table 3.2.2, Table 3.2.3, and Table 3.2.4, it concludes that the MLP Neural Network with DBD (delta bar delta) and hidden layer 1 with processing element 14 gives best results of 100% in training dataset while in Cross Validation it gives 100% for all four except 83.33% for Airplane images, Hence overall result is 98.33%. Future work may include improvising the result with lesser processing elements or using different techniques for classification and recognition.

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