ISSN: 2278 – 909X
International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE)
Volume 8, Issue 4, April 2019

Classification of Sonar images using neural network approach

[1]Miss.shraddha vijay Joshi, [2] Assis.Prof.A.B.Kharate,
[1] Student, [2] Assistant Professor
[1,2] Electronic and Telecommunication of HVPM'S College of Engineering and Technology (India)

Abstract— **In this paper a new classification algorithm is proposed for the Classification of five type of Side scan Sonar images. In order to develop algorithm 83 Side scan Sonar images have been considered, With a view to extract features from the Side scan Sonar images after image processing, an algorithm proposes FFT transformed coefficients. The Efficient classifiers based on Multilayer Perceptron (MLP) Neural Network. A separate Cross-Validation dataset is used for proper evaluation of the proposed classification algorithm with respect to important performance measures, such as MSE and classification accuracy. 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 Classify the five type of sonar scan in ocean.**

Index Terms— **Neural solution, MatLab, Microsoft excel, WHT,DCT,FFT Transform technique.**

I. Introduction

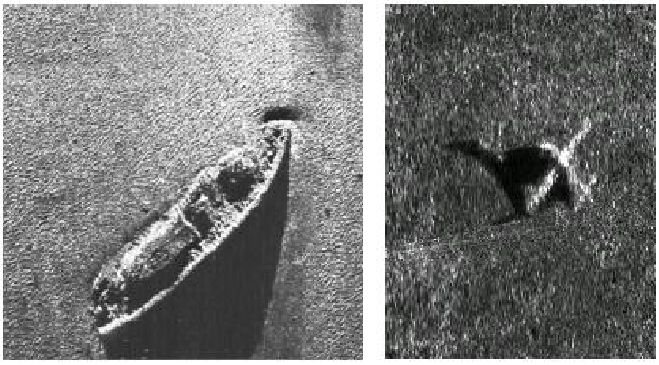
One of the most popular tool for underwater researches is Side Scan Sonars [1],[2],[3]. Side Scan Sonars are used to create an image of sea floor to provide an understanding of the differences in material and texture type of the seabed by using acoustic reflections of pulses.Sometimes, these images cannot 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, scienctists 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 System was developed to simulate human experience by classifying sonar images, if they are human made wreck or natural underwater shapes . Examples of Human-Made wrecks and Natural Shapes can be seen in Figure 1.

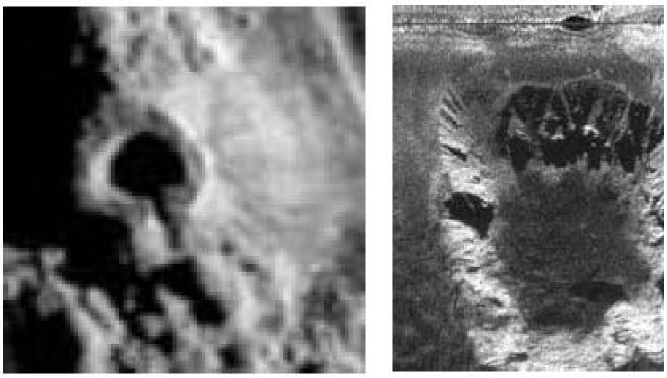
We will take an input Side scan Sonar images and extract the features of images. We will use Artificial Neural Network as our classifier for comparison of Side scan Sonar images. An artificial neural network (ANN), usually called neural network (NN), is a mathematical model or computational model that 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.

ISSN: 2278 – 909X
International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE)
Volume 8, Issue 4, April 2019



(a)



(b)

Figure1 : Sample Test Images (a) Human-Made Wrecks and (b) Natural Underwater Shapes

II. RESEARCH METHODOLOGY

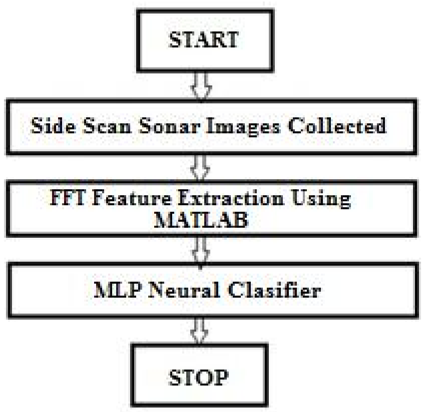


Figure.2 Methodology of work

It is classification of side scan sonar images Using Neural Network Approaches.. Data acquisition for the proposed classifier designed for the classification of side scan sonar images. The most important un correlated features as well as coefficient from the images will be extracted .In order to extract features FFT transformed domain will be used.

2.2Neural Networks

Following Neural Networks are tested:

- **Multilayer perceptron (MLP)**

The most widely recognized neural system demonstrate is the multi layer perceptron (MLP). This sort of neural system is known as a directed system since it requires a coveted yield with the end goal to learn. The objective of this sort of system is to make a model that accurately maps the contribution to the yield utilizing verifiable information with the goal That the model would then be able to be utilized to create the yield when the coveted yield is obscure. A graphical portrayal of a MLP is demonstrated as follows:

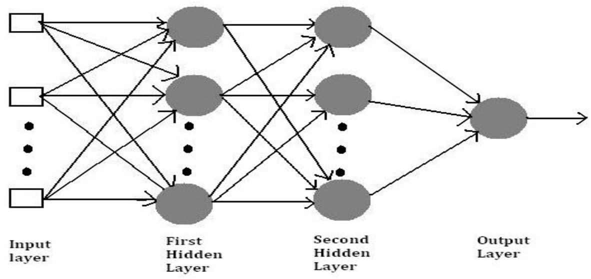


Figure 3: the structure of neural network model mlp.

The MLP and numerous other neural systems pick up utilizing a calculation got back to engendering. With back-proliferation, the info information is over and over displayed to the neural system. With every introduction the yield of the neural system is contrasted with the coveted yield and a mistake is processed. This mistake is then nourished (back-engendered) to the neural system and used to alter the weights to such an extent that the blunder diminishes with every emphasis and the neural model draws nearer and closer to delivering the coveted yield. This procedure is known as "preparing".

2.3Learning Rules used:

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.

Conjugate Gradient

CG is the most prevalent iterative technique for unraveling vast frameworks of direct conditions. CG is successful for frameworks of the shape A=xb-A (1) where x _is an obscure vector, b is a known vector, and A _is a known, square, symmetric, positive-unmistakable (or positive-uncertain) lattice. (Try not to stress in the event that you've overlooked what "positive-distinct" implies; we will survey it.) These frameworks emerge in numerous imperative settings, for example, limited contrast and limited component techniques for fathoming incomplete differential conditions, auxiliary examination, circuit investigation, and math homework.

Created by Widrow and Hoff, the delta govern, additionally called the Least Mean Square (LMS) strategy, is a standout amongst the most usually utilized learning rules. For a given information vector, the yield vector is contrasted with the right answer. In the event that the thing that matters is zero, no learning happens; generally, the weights are changed in accordance with lessen this distinction. The adjustment in weight from ui to uj is given by: dwij = r* ai * ej, where r is the learning rate, ai speaks to the initiation of ui and ej is the distinction between the normal yield and the genuine yield of uj. On the off chance that the arrangement of information designs shape a directly autonomous set then subjective affiliations can be gotten the hang of utilizing the delta run the show.

It has been demonstrated that for systems with direct initiation capacities and with no shrouded units (concealed units are found in systems with in excess of two layers), the blunder squared versus the weight chart is a paraboloid in n-space. Since the proportionality steady is negative, the chart of such a capacity is inward upward and has a base esteem. The vertex of this paraboloid speaks to the point where the mistake is limited. The weight vector relating to this point is then the perfect weight vector..

- ***Quick propagation***

Quick propagation (Quickprop) [1] 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 optimise 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.

- ***Delta by Delta***

Created by Widrow and Hoff, the delta manage, likewise called the Least Mean Square (LMS) technique, is a standout amongst the most regularly utilized learning rules. For a given information vector, the yield vector is contrasted with the right answer. In the event that the thing that matters is zero, no learning happens; generally, the weights are changed in accordance with diminish this distinction. The adjustment in weight from ui to uj is given by: dwij = r* ai * ej, where r is the learning rate, ai speaks to the initiation of ui and ej is the distinction between the normal yield and the genuine yield of uj. In the event that the arrangement of info designs shape a directly free set then discretionary affiliations can be gotten the hang of utilizing the delta run the show.

It has been demonstrated that for systems with direct actuation capacities and with no shrouded units (concealed units are found in systems with in excess of two layers), the blunder squared versus the weight chart is a paraboloid in n-space. Since the proportionality steady is negative, the diagram of such a capacity is inward upward and has a base esteem. The vertex of this paraboloid speaks to the point where the mistake is limited. The weight vector relating to this point is then the perfect weight vector. [10]

III. RESULT

T 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.

The simulation of best classifier along with the confusion matrix is shown below :

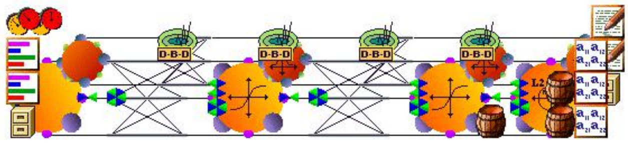


Figure4. The Best Neural network with maximum accuracy (MLP-DBD)

Training Report of the Best Classifier:

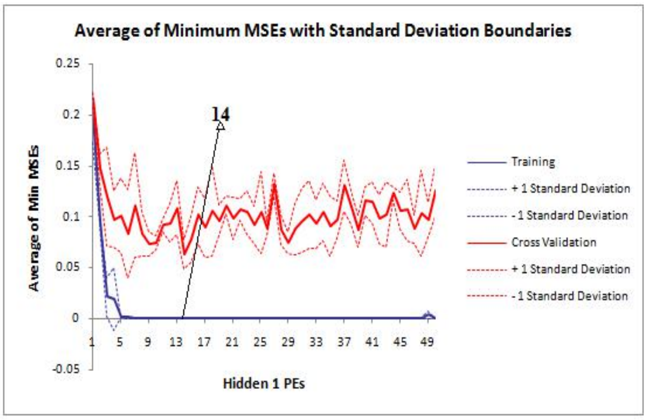


Table 1. Training and cross validation Report of the Best Classifier MLP-DBD

Best Networks	Training	Cross Validation
Hidden 1 PEs	30	14
Run #	1	1
Epoch #	283	122
Minimum MSE	1.25487E-05	0.048455899
Final MSE	0.065089292	0.062114262

Test on Cross validation (CV):

Table 2. Confusion matrix table of Cross validation (CV)

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

Table 3: Performance Measures for cross validation

Performance	NAME(ROCK)	NAME(VOLCANO)	NAME(RIPPLE&SAND)	NAME(SHIP)	NAME(AIRPLANE)
MSE	0.036882344	0.010472041	0.022051877	0.103220692	0.069784316
NMSE	0.373433734	0.106029415	0.127585859	0.597205432	0.314029422
MAE	0.122096281	0.059051699	0.090455911	0.233651181	0.148623817
Min Abs Error	0.002606556	0.00761174	0.003839355	8.91768E-05	0.003318285
Max Abs Error	0.519284323	0.358497372	0.431063713	0.629476599	0.861170553
r	0.827740306	0.979398548	0.941459492	0.7156279	0.837296655
Percent Correct	100	100	100	100	83.33333333

Test on Training:

ISSN: 2278 – 909X
International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE)
Volume 8, Issue 4, April 2019

Table 6: Confusion matrix table of Training

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

Table 7: Performance Measures for training

Performance	NAME(ROCK)	NAME(VOLCANO)	NAME(RIPPLE&SAND)	NAME(SHIP)	NAME(AIRPLANE)
MSE	0.0007593	0.000788512	0.000264437	0.000907315	0.000399266
NMSE	0.013147708	0.009410913	0.001425058	0.004697801	0.001783191
MAE	0.022338146	0.021875387	0.012289394	0.022618563	0.015109414
Min Abs Error	3.35649E-05	0.000250013	0.000157662	0.000414763	6.97031E-05
Max Abs Error	0.051531923	0.052780109	0.045616751	0.060833084	0.053246649
r	0.995032434	0.996426622	0.999359714	0.997999774	0.999142597
Percent Correct	100	100	100	100	100

IV. CONCLUSION

A From the results obtained in FFT domain it concludes that the MLP Neural Network with DBD (delta bar delta) and hidden layer 1 with processing element 14 gives best results of 96.66% in Cross Validation while in training it gives 100% so overall accuracy is 98.33%.

ACKNOWLEDGMENT

We are very grateful to our HVPM College of Engineering and Technology to support and other faculty and associates of ENTC department who are directly & indirectly helped me for these paper.

REFERENCES

[1] Y.Hara, R. G. Atkins, S. H. Yueh, R. T. Shin & J.A. Kong, Application of Neural Networks to Radar Image Classification, *IEEE Trans. Geosci. Remote Sensing*, Vol. 32, 1994, pp.100-109.

2] B. Sekeroglu, Classification of Sonar Images Using Back Propagation Neural Networks, IEEE IGARSS ’04, Alaska 2004.

[3] Lee, J. S., & I. Jurkevich, “Segmentation of SAR images,” IEEE Trans. Geosci. Remote Sensing, Vol. 27, 1989, pp. 674-680.

[4] Mingcui Zhu, Yan Song, Jia Guo, Chen Feng, Guangliang Li, Tianhong Yan6, Bo He,” PCA and Kernel-based Extreme Learning Machine for Side-Scan Sonar Image Classification’,IEEE 2017.

[5] Jason Rhinelander,” Feature Extraction and Target Classification of Side-Scan Sonar Images’, 978-1-5090-4240-1/16/$31.00 ©2016 IEEE.

[6] Marcelo Sperle,Eduardo Negri,” Automatic Classification of Sidescan Sonar Images for Mapping Marine Mineral Resources’, 978-1-4673-7019-6/15/$31.00 ©2015 IEEE.

[7] Cristina Stolojescu-Crisan,Alexandru Isar,” The improvement of the robust exemplar-based inpainting algorithm for SONAR images’, 978-1-4799-7267-8/14/$31.00 ©2014 IEEE.

[8] Olga Lopera,Yves Dupont,” Target classification from HR sonar image’, 978-1-4799-0002-2/13/$31.00 ©2013 IEEE.

[9] Naveen Kumar, Qun Feng Tan, Shrikanth S. Narayanan,” OBJECT CLASSIFICATION IN SIDESCAN SONAR IMAGESWITH SPARSE REPRESENTATION TECHNIQUES’, 978-1-4673-0046-9/12/$26.00 ©2012 IEEE

[10] BORAN SEKEROGLU,” Intelligent Classification of Sonar Images’, Proceedings of the 1st International Conference on Manufacturing Engineering, Quality and Production Systems

[11] Ning Sun and Taebo Shim,” Sonar images classification of seabed physiognomy based on the information fusion methods,’ 978-0-7695-3119-9/08 $25.00 © 2008 IEEE

[12] Arnaud Martin,” Comparative study of information fusion methods for sonar images classification’, 0-7803-9286-81051$20.00 ©2005 IEEE

[13] Boran Sekeroglu,” Classification of Sonar Images Using Back Propagation Neural Network’, 0-7803-8742-2/04/$20.00 (C) 2004 IEEE.