Development of Back Propagation Neutral Network Model for Ectracting the Feature from a Satellite Image using Curvelet Transform

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Abstract— New adaptive representation method is proposed to reduce the size of visible satellite images that is present in very high resolution. The development of high resolution remote sensing systems demands new intelligent approaches of acquisition, transmission, and storage of the received data. Such approaches for enormous data volumes look for the aid of data compression. It offers a novel adaptive technique of image representation. This method is based on an inverse pyramidal decomposition of original data and neural networks. Around the basic advantage of the pyramidal decomposition in comparison with the other methods for image compression is the ability to perform Y progressive Z transfer (or storage) for every consecutive decomposition layer. In result, the image could be restored with high compression ratio and gradually improving quality. The image which are processed are .lan (Rural Image), and .bmp (Urban Image) with the size of 454x 477 and 442 x 442 respectively.

Exploring the useful information for the image classification it is noticeable that Artificial Neural Network is a composed method for the Neural Network for Satellite images with additional features for the images and also the Statistical features. But in Haar Transform, it is not continuous and is not differentiable. The transformed image is presented by values of coefficients of the hidden layer of a neural network. They are calculated during the period of training of 3 layer Back Propagation Neural Network (BPNN). The fusion of high-spectral but low spatial resolution multispectral and low spectral but high spatial resolution panchromatic satellite images is a very useful technique in various applications of remote sensing.

Recently, it shows that wavelet-based image fusion method provides high quality of the spectral content of the fused image. The texture image analysis is found within in the range of 86.2- 99.06 % of the performance. To overcome non continuity and non differentiability there is an introduction of a new method based on the Curvelet transform, which represents edges better than wavelets. Since edges play a fundamental role in image understanding, one good way to enhance spatial resolution is to enhance the edges. Curvelet-based image fusion method provides richer information in the spatial and spectral domains simultaneously. The curvelet transform is a very young signal analyzing method with good potential. It is recognized as a milestone on image processing and other applications

Keywords— Curvelet Transform, Back propagation Neural Network, Haar transform, .lan , .bmp , multispectral, Artifical Neural Network.

INTRODUCTION

Image Processing is a technique to enhance raw images received from cameras/sensors placed on satellites, space probes and aircrafts or pictures taken in normal day-today life for various applications. Various techniques have been developed in Image Processing during the last four to five decades. Most of the techniques are developed for enhancing images obtained from unmanned spacecrafts, space probes and military reconnaissance flights. Image Processing systems are becoming popular due to easy availability of powerful personnel computers, large size memory devices, graphics softwares etc. In Neural Networks is a field of Artificial Intelligence (AI) it is inspired from the human brain, find data structures and algorithms for learning and classification of data.

Many tasks that humans perform naturally fast, such as the recognition of a familiar face, proves to be a very complicated task for a computer when conventional programming methods are used. By applying Neural Network techniques a program can learn by examples, and create an internal structure of rules to classify different inputs, such as recognizing images.

ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks are commonly used in pattern classification, function approximation, optimization, pattern matching, machine learning and associative memories. They are currently being an alternative to traditional statistical methods for mining data sets in order to classify data. Artificial Neural Networks are well-established technology for solving prediction and classification problems, using training and testing data to build a model. However, the success of the networks is highly dependent on the performance of the training process and hence the training algorithm. It has training feed-forward neural networks to classify different data sets which are widely used in the machine learning community.

Broad applicable areas of artificial neural networks, pattern recognition is one of the most important applications in such problems: speech synthesis, diagnostic problems, medicine, finance, robotic control, signal processing, computer vision and many other problems that fall under the category of pattern recognition. Among many different neural network classifiers, the multilayer feed-forward networks have been mainly used for solving classification tasks, due to their well-known universal approximation capabilities. The success of neural networks largely depends on their architecture, their training algorithm, and the choice of features used in training.

Artificial neural networks (ANN) are very important tools for solving different kind of problems such as pattern classification, forecasting and regression. However, their design imply a mechanism of error-testing that tests different architectures, transfer functions and the selection of a training algorithm that permits to adjust the synaptic weights of the ANN. This design is very important because the wrong selection of one of these characteristics could provoke that the training algorithm be trapped in a local minimum. Because of this, several met heuristic based methods in order to obtain a good ANN design have been reported.

Neural Networks mimic the pattern of human learning to solve many difficult tasks in the field of applications which include nonlinear regression, classification, pattern recognition and control systems .By configuring virtual neural networks that function like the human brain, computers can perform tasks at greater speeds and with increased flexibility of application. These networks are capable of offering invaluable insights into the vast information stockpiles that are common today. The artificial networks simulate the complex neural network by clustering the artificial neurons. In every neuron system, there must be some input nodes as well as some output nodes. Some of the neurons interface the real world to receive the inputs and some other neurons provide the real world with the outputs of the network. The rest of the neurons are hidden layers whose number depends on the problem to be solved.

LITERATURE SURVEY

Various work has been carried out in Neural Network for various applications .Some deals with the study, analysis and implementation of neural network algorithm in-order to analysis different types of satellite images using ANN technique. Following references were reviewed in order to obtain details on the general concepts of object-based image classification, image processing, segmentation, training of neural networks and corresponding algorithm of this project work: Object-based image classification methods are increasingly being used for classification of land use/cover units from high-resolution satellite images with results closer to human interpretation compared to per-pixel classifiers. The problem of nonlinear separability of classes in a feature space consisting of spectral/spatial/textural features is addressed by kernel-based nonlinear mapping of the feature vectors

[1]. This facilitates use of linear discriminate functions for classification as used in artificial neural networks (ANNs). The most common approach used for building objects is image segmentation, which dates back to the 1970s. In contrast to typical Land sat resolutions, high resolution images support several scales within their images.

[2]. The object-based, multi scale classification and inventory framework provides an effective and flexible way of showing different mixes of human development and forest cover in a hierarchical fashion for human-dominated forest. The wavelet domain features have been intensively used for texture classification and texture segmentation with encouraging results. More of the proposed multi-texture analysis methods are quite successful, but all the applications of the texture analysis so far are limited to gray scale images.

[3]. The wavelet-based feature extraction algorithms have been developed to explore the useful information for the hyper spectral image classification. On the other hand, the idea of using artificial neural network (ANNs) has also proved useful for hyper spectral image classification.

[4]. To combine the advantages of ANNs with wavelet-based feature extraction methods, the wavelet network (WN) has been proposed for data identification and classification. A new approach for image classification is based on the color information, shape

and texture .Use of three RGB (red green blue) bands of a color image in RGB model to extract the describing features. The increased synergy between neural networks (NN) and fuzzy sets has led to the introduction of granular neural networks (GNNs) that operate on granules of information, rather than information itself. The fact that processing is done on a conceptual rather than on a numerical level, combined with the representation of granules using linguistic terms, results in increased interpretability. This is the actual benefit, and not increased accuracy, gained by GNNs.

[5].The constraints used to implement the GNN are such that accuracy degradation should not be surprising. For high dimensional pattern recognition problems, the learning speed of gradient based training algorithms (back-propagation) is generally very slow. Local minimum, improper learning rate and over-fitting are some of the other issues. Extreme learning machine was proposed as a non-iterative learning algorithm for single-hidden layer feed forward neural network (SLFN) to overcome these issues. The input weight and biases are chosen randomly in ELM which makes the classification system of nondeterministic behavior.

BACK PROPAGATION NEURAL NETWORKS

INTRODUCTION

If the human brain is an 'ultimate' neural network, then ideally a device which imitates the brain's functions. However, because of limits in technology, it must settle for a much simpler design. The obvious approach is to design a small electronic device which has a transfer function similar to a biological neuron, and then connect each neuron to many other neurons, using RLC networks to imitate the dendrites, axons, and synapses. This type of electronic model is still rather complex to implement. Further constraints are needed to make the design more manageable. First,change the connectivity between the neurons so that they are in distinct layers, such that each neuron in one layer is connected to every neuron in the next layer. Further,the defined signals flow only in one direction across the network, and can simplify the neuron and synapse design to behave as analog comparators being driven by the other neurons through simple resistors. Therefore building up of a feed forward neural network model that may actually be practical to use.

Referring to figures 1.1 and 1.2 below, the network functions as follows: Each neuron receives a signal from the neurons in the previous layer, and each of those signals is multiplied by a separate weight value. The weighted inputs are summed, and passed through a limiting function which scales the output to a fixed range of values. The output of the limiter is then broadcast to all of the neurons in the next layer. So, to use the network to solve a problem, we apply the input values to the inputs of the first layer, allow the signals to propagate through the network, and read the output values.

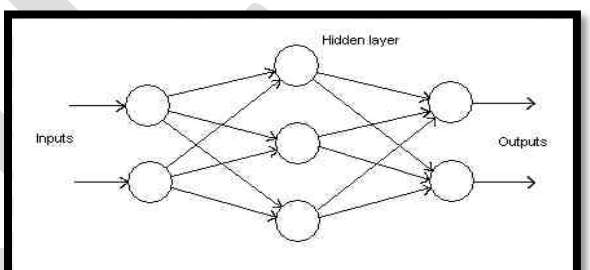

Figure 1.1. A Generalized Network.

Stimulation is applied to the inputs of the first layer, and signals propagate through the middle (hidden) layer(s) to the output layer. Each link between neurons has a unique weighting value.

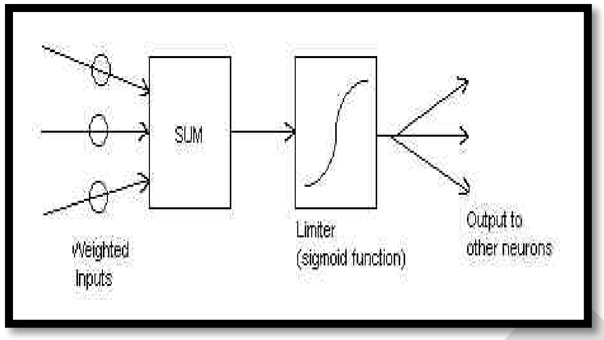

Figure 1.2. The Structure of a Neuron.

Inputs from one or more previous neurons are individually weighted, then summed. The result is non-linearly scaled between 0 and +1, and the output value is passed on to the neurons in the next layer

Since the real uniqueness or 'intelligence' of the network exists in the values of the weights between neurons, we need a method of adjusting the weights to solve a particular problem. For this type of network, the most common learning algorithm is called Back Propagation (BP). A Back Propagation network that is, we must provide a learning set that consists of some input examples and the known-correct output for each case. So, we use these input-output examples to show the network what type of behavior is expected, and the BP algorithm allows the network to adapt.

The Back Propagation learning process works in small iterative steps: one of the example cases is applied to the network, and the network produces some output based on the current state of its synaptic weights (initially, the output will be random). This output is compared to the known-good output, and a mean-squared error signal is calculated. The error value is then propagated backwards through the network, and small changes are made to the weights in each layer. The weight changes are calculated to reduce the error signal for the case in question. The whole process is repeated for each of the example cases, then back to the first case again, and so on. The cycle is repeated until the overall error value drops below some pre-determined threshold. At this point we say that the network has learned the problem "well enough" - the network will never exactly learn the ideal function, but rather it will asymptotically approach the ideal function.

Back propagation is a form of supervised learning for multi-layer nets, also known as the generalized delta rule. Error data at the output layer is "back propagated" to earlier ones, allowing incoming weights to these layers to be updated. It is most often used as training algorithm in current neural network applications. The back propagation algorithm was developed by Paul Werbos in 1974 and rediscovered independently by Rumelhart and Parker. Since its rediscovery, the back propagation algorithm has been widely used as a learning algorithm in feed forward multilayer neural networks.

In general, the difficulty with multilayer Perceptrons is calculating the weights of the hidden layers in an efficient way that result in the least (or zero) output error; the more hidden layers there are, the more difficult it becomes. To update the weights, one must calculate an error. At the output layer this error is easily measured; this is the difference between the actual and desired (target) outputs. At the hidden layers, however, there is no direct observation of the error; hence, some other technique must be used. To calculate an error at the hidden layers that will cause minimization of the output error, as this is the ultimate goal.

The Back Propagation algorithm is an involved mathematical tool; however, execution of the training equations is based on iterative processes, and thus is easily implementable on a computer.

CURVELET TRANSFORM:

Curvelets are a non-adaptive technique for multi-scale object representation. Being an extension of the wavelet concept, they are becoming popular in similar fields, namely in image processing and scientific computing.

Wavelets generalize the Fourier transform by using a basis that represents both location and spatial frequency. For 2D or 3D signals, directional wavelet transforms go further, by using basis functions that are also localized in orientation. A curvelet transform differs from other directional wavelet transforms in that the degree of localisation in orientation varies with scale. In particular, fine-scale basis functions are long ridges; the shape of the basis functions at scale j is 2^{-j} by $2^{-j/2}$ so the fine-scale bases are skinny ridges with a precisely determined orientation.

Curvelets are an appropriate basis for representing images (or other functions) which are smooth apart from singularities along smooth curves, where the curves have bounded curvature, i.e. where objects in the image have a minimum length scale. This property holds for cartoons, geometrical diagrams, and text. As one zooms in on such images, the edges they contain appear increasingly straight. Curvelets take advantage of this property, by defining the higher resolution curvelets to be skinnier the lower resolution curvelets. However, natural images (photographs) do not have this property; they have detail at every scale. Therefore, for natural images, it is preferable to use some sort of directional wavelet transform whose wavelets have the same aspect ratio at every scale.

When the image is of the right type, curvelets provide a representation that is considerably sparser than other wavelet transforms. This can be quantified by considering the best approximation of a geometrical test image that can be represented using only n wavelets, and analysing the approximation error as a function of n. For a Fourier transform, the error decreases only as $O(1/n^{1/2})$. For a wide variety of wavelet transforms, including both directional and non-directional variants, the error decreases as $O(1/n)$. The extra assumption underlying the curvelet transform allows it to achieve $O((log(n))^3/n^2)$.Efficient numerical algorithms exist for computing the curvelet transform of discrete data. The computational cost of a curvelet transform is approximately 10–20 times that of an FFT, and has the same dependence of $O(n^2 log(n))$ for an image of size $n \times n$.

Wavelet transforms are based on small wavelets with limited duration. The translated-version wavelets locate where we concern. Whereas the scaled-version wavelets allow us to analyze the signal in different scale.The wavelet transform provide a multiscale basis as seen in Figure 1.3:

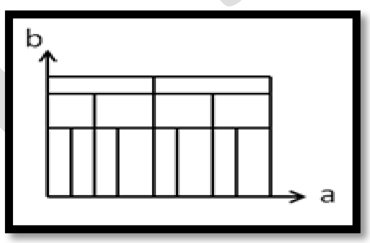

Figure 1.3 : Basics of Wavelet

Althought multiscale can handle point discontinue well,but it is not optimal up to curve. Because the wavelet basis is isotropic, and the curve have direction so it take lot of coefficients to account for edges as shown in figure 1.4.

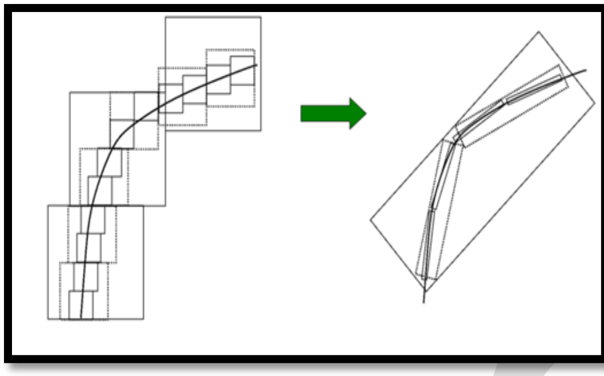

Figure 1.4: Difference between Wavelet approach and Curvelet approach

Point and Curve Discontinuities Discussion	
FT	• A discontinuity point affects all the Fourier coefficients in the domain. Hence the FT doesn't handle points discontinuities well.
Wavelet	• Point: it affects only a limited number of coefficients. Hence the WT handles points discontinuities well. • Curve: Discontinuities across a simple curve affect all the wavelets coefficients on the curve. Hence the WT doesn't handle curves discontinuities well.
Curvelet	• Curvelets are designed to handle curves using only a small number of coefficients. Hence the Curvelet handles curve discontinuities well.

Table 1.1: Point and Curve Discontinuities Discussion of FT, Wavelet and Curvelet

Generation curvelet transform is limited because the geometry of ridgelets is itself unclear, as they are not true ridge functions in digital images. Later, a considerably simpler second-generation curvelet transform based on frequency partition technique was proposed. The second-generation curvelet transform has been shown to be a very efficient tool for many different applications in image processing.

IMPLEMENTATION DETAIL

The methodology includes image acquisition, image segmentation data preprocessing, , Artificial Neural Network training, image classification (using pixel based and object based feature extraction), post classification using accuracy assessment. It also highlights how the Curvelet transform helps in achieving the accurate Segmented Image which is shown in Figure 1.5.

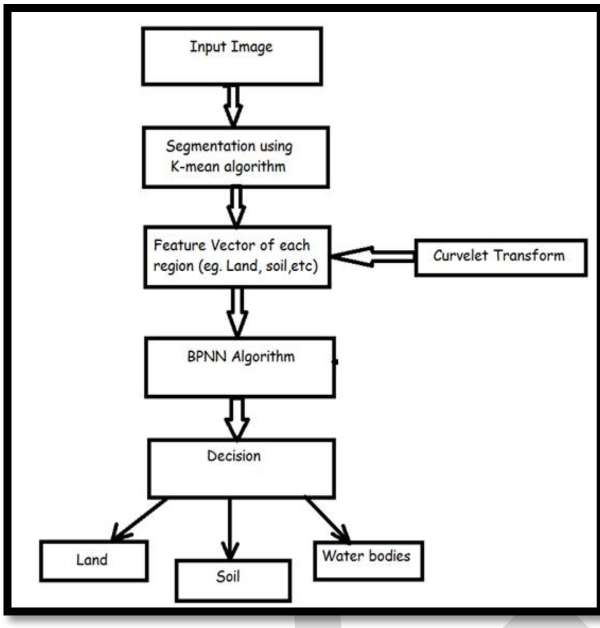

Figure 1.5 : Methodology

Step 1: When the input image is taken it is resized and then segmented using the K-Means algorithm. In K-means algorithm the segmentation is done in 3 planes. And we get the segmented region at the output.
Step 2: Curvelet transform gives the statistical features (Standard deviation and mean value) and better line features and borders and better visual effect.
Step 3:- BPNN Algorithm gives the real identification of the feature with the help on Knowledge Base (Prior Information of the the feature)
Step 4: Decision is made of the image whether the cluster is of Land, Soil or water bodies.

RESULT AND DISCUSSIONS

Lan Satellite Image (Rural Image) : Figure 1.6 shows the original satellite image in the .Lan format. The resolution of the urban image is 454 x 477 pixels.

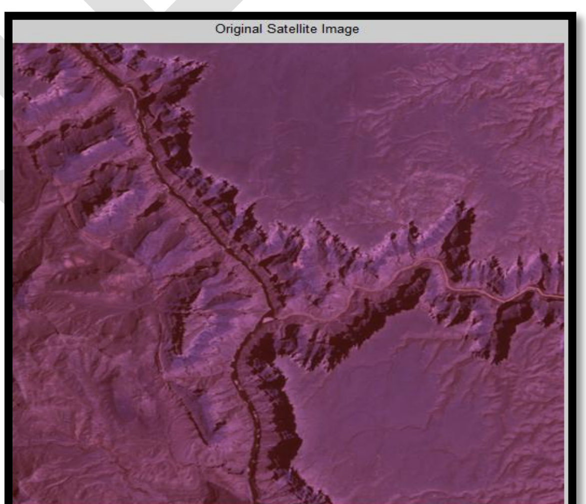

Figure 1.6: Satellite Image in .Lan Format

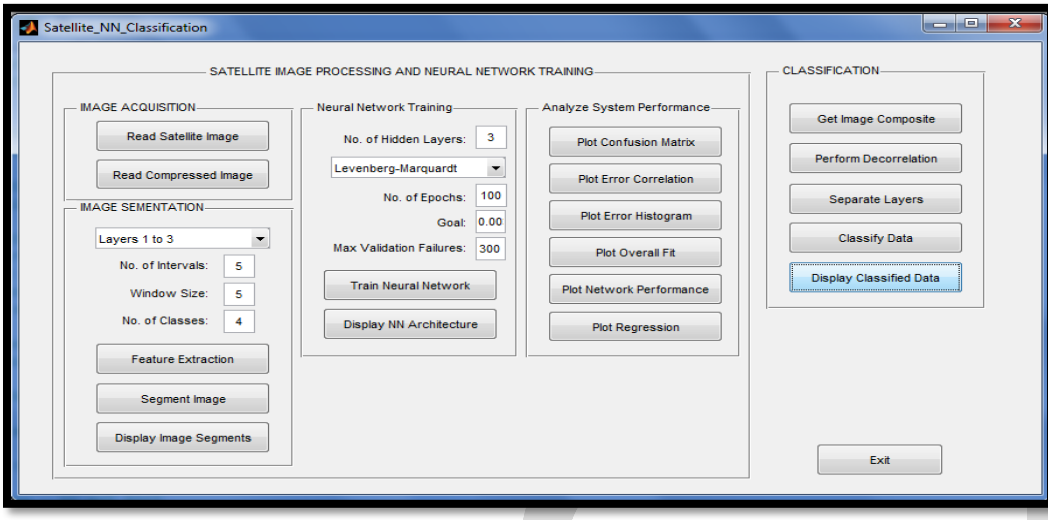

Figure 1.7: GUI Model for Satellite .Lan Image

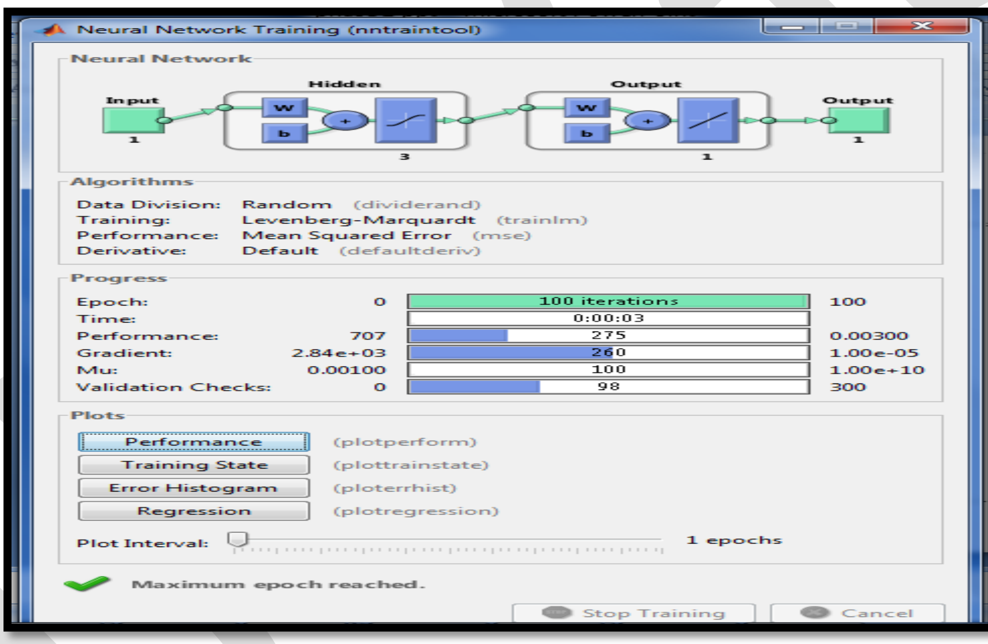

Figure 1.8: Neural Network Training for .Lan Satellite Image

Figure 1.8depicts the training of neural network using LM algorithm for the .Lan Satellite image.

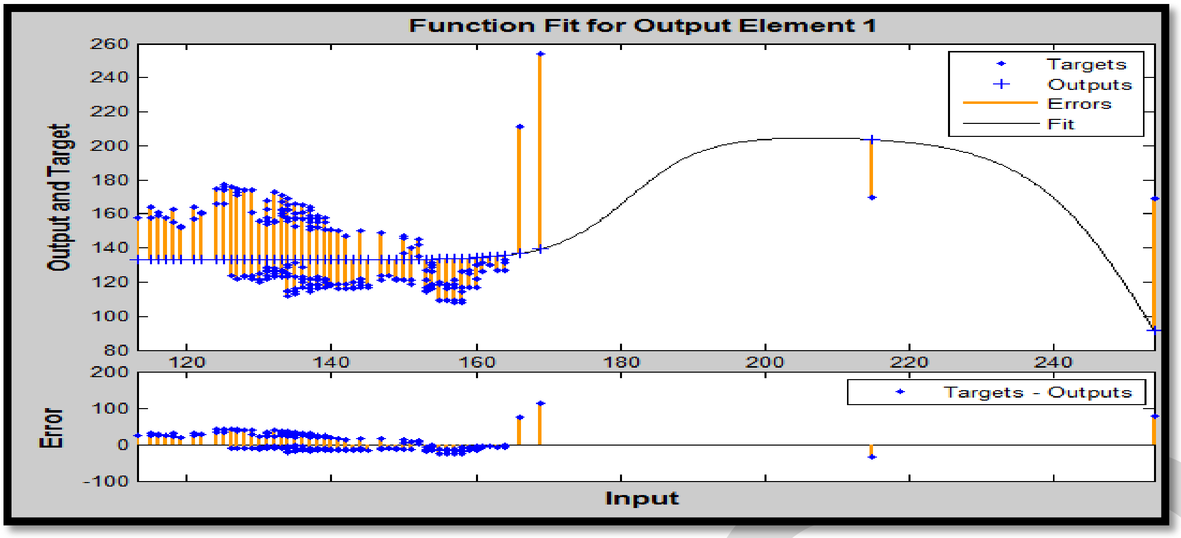

Figure 1.9: Plot fit for the .Lan image.

The fit plot is done for the output and the target. The same is plot for the Error also as shown in figure 1.9

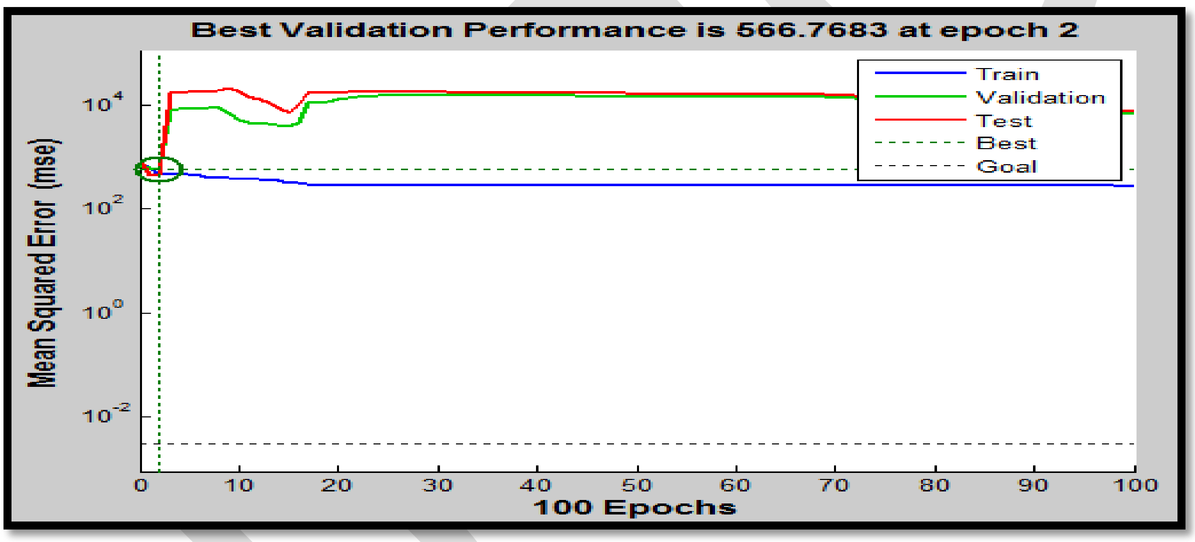

Figure 2.0: Performance plot of the .Lan image.

Figure 2.0 depicts the performance plot of the train, validation, test, best and goal.

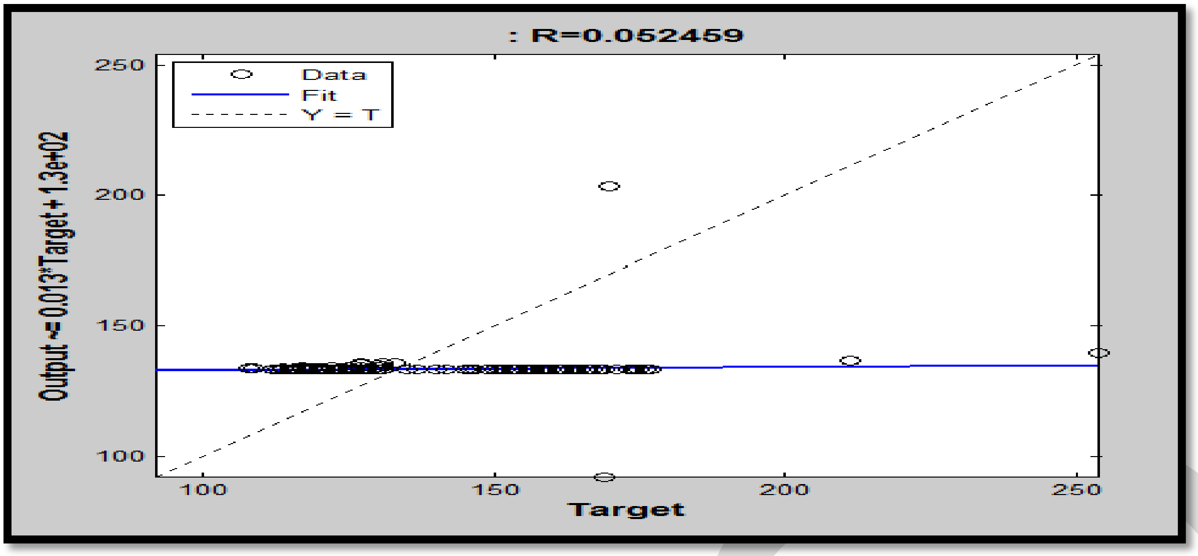

Figure 2.1: Regression plot of the .Lan Satellite image.

The regression R is found to be 0.052459. The regression plot of the output with the target is shown in figure 2.1

CONCLUSION AND FUTURE

Conclusion

In the proposed image classification system we have introduced new approach using Curvelet transform and Back Propagation Neural Network. We used the correlation coefficient, mean and standard deviation features of the various combinations of coefficients produced by the Curvelet transform. A number of texture images not considered in the work have been analyzed in this work and have been found working within the range 86.2- 99.06% of the performance and also the segmented Curves are more towards High accuracy than Haar transform. This work may further be extended by finding out the parameters like finding out the depth of water, location of sand, detecting the target for the satellite images for the military purpose.

Future Scope

A new approach for Image Classification with Higher Accuracy. There Is Good Potential for Future Developments for Development of BPNN Model for Extracting the Feature's from Satellite Image Using Ridgelet Transform Include Integration of The Algorithm with Higher Level Artificial Intelligence and Pattern Recognition Methods for Classification. This work may further be extended by finding out the parameters like finding out the depth of water, location of sand , detecting the target for the satellite images for the military purpose.

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