Development of Back Propagation Neural Network Model for Extracting the Feature from a Image Using Curvelet Transform

Mr. Tejas P. Patil[1], Prof. P. P. Narwade[2]
[1]PG Student, [2]Profeser EXTC Department, MGM's collage of Engineering & Technology, Kamothe(Navi mumbai).

ABSTRACT

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. 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 software etc Study of Back Propagation Neural Network algorithm and Curvelet transform algorithm to extract the data from satellite (Segmentation).To implement the Curvelet Transform to extract the Statistical features (mean, standard deviation) that are calculated for each combination of scale and orientation and To extract the features (Land cover, Vegetation, Soil and Water Bodies) of texture Images. Finally, to implement BPNN (Back Propagation Neural Network) algorithm, this provides computationally efficient method for changing the weights.

Keywords

- *Artificial neural network*
- *Back propagation neural network*
- *Curvelet-transform*
- *Granular neural networks*
- *Neural Network Ensemble*
- *Segmentation*

I. INTRODUCTON

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[1],[10]. 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 software etc[1]. In Neural Networks is a field of Artificial Intelligence (AI) it is inspired rom 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, to be a very complicated task for a computer when conventional programming methods are used[1],[11]. 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.

II. 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[1][4]. However, the success of the networks is highly dependent on the performance of the training process.

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[1]-[4]. 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.

2.1 Artificial Neural Network (ANN) Model[4]

2.1.1 Feed Forward Neural Network

In Figure 2.1 feed-forward Ann's allow signals to travel one way only; from input to output. There is no feedback (loops) i.e. the output of any layer does not affect that same layer. Feed forward Ann's tend to be straightforward networks that associate inputs with outputs. They are extensively used in pattern recognition. This type of organization is also referred to as bottom-up or top-down.

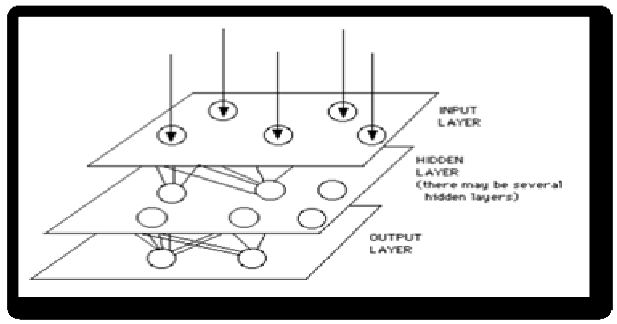


Figure 2.1 : Feed Forward Neural Network

2.1.2 Feed Back Neural Network

Feedback networks can have signals traveling in both directions by introducing loops in the network. Feedback networks are very powerful and can get extremely complicated. Feedback networks are dynamic; their 'state' is changing continuously until they reach an equilibrium point. They remain at the equilibrium point until the input changes and a new equilibrium needs to be found. Feedback architectures are also referred to as interactive or recurrent, although the latter term is often used to denote feedback connections in single-layer organizations as seen in Figure 2.2.

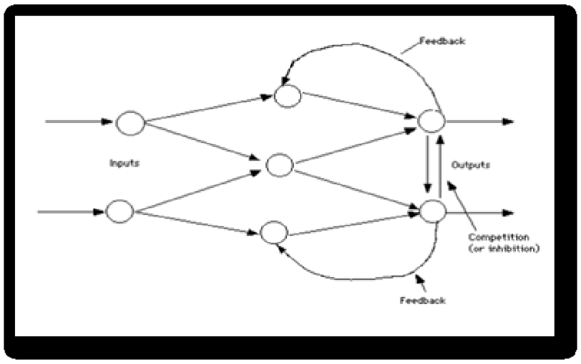


Figure 2.2: Feed Back Neural Network

2.1.3 Perceptrons

The perceptron calculates a weighted sum of inputs and compares it to a threshold. If the sum is higher than the threshold, the output is set to 1, otherwise to -1, depending upon activation function.

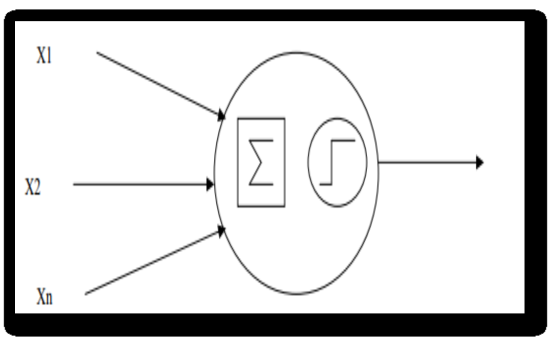


Figure 2.3 : McCulloch-Pitts Neural Network

In the Figure 2.3 McCulloch-Pitts Neural Model all the weights and combined together and summed up and then the summed image is given to Sign Transfer Function.The single layer perceptions could not do some basic pattern recognition operations like determining the parity of a shape or determining whether a shape is connected or not. The Model appropriately training, multilevel perceptions can do these operations.

2.1.4 Transfer Function

The behavior of an ANN (Artificial Neural Network) depends on both the weights and the input-output function (transfer function) that is specified for the units. This function typically falls into one of three categories as seen in Figure 2.4:

To make a neural network that performs some specific task, choose the units that are connected to one another, and set the weights on the connections appropriately. The connections determine whether it is possible for one unit to influence another. The weights specify the strength of the influence. A three-layer network can be taught to perform a particular task by using the following procedure.

The network is presented with training examples, which consist of a pattern of activities for the input units together with the desired pattern of activities for the output units. It is determined how closely the actual output of the network matches the desired output. The weight of each connection can be changed so that the network produces a better approximation of the desired output.

III. BACK PROPAGATION NEURAL NETWORKS

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[4],[9]. 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 3.1 and 3.2 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[7]. 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.

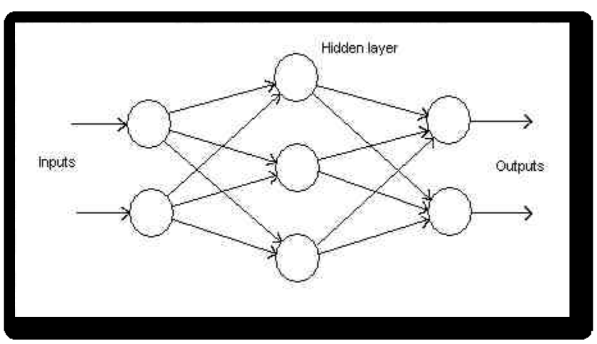


Figure 3.1. A Generalized Network.

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.

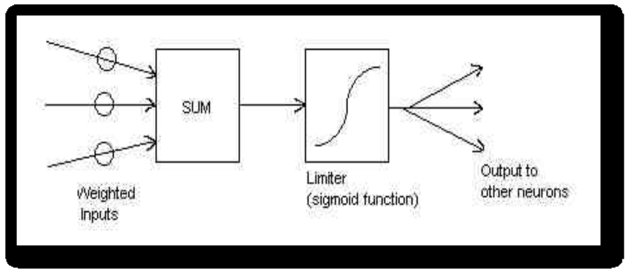


Figure 3.2. The Structure of a Neuron.

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.

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.

3.1. Use of Back Propagation Neural Network Solution

A large amount of input/output data is available, but you're not sure how to relate it to the output. The problem appears to have overwhelming complexity, but there is clearly a solution. It is easy to create a number of examples of the correct behavior. The solution to the problem may change over time, within the bounds of the given input and output parameters.

IV. CURVELET TRANSFORM[3]

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 4.1:

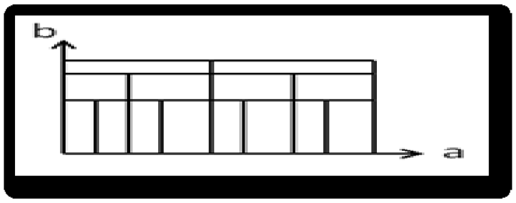


Figure 4.1 : Basics of Wavelet

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 4.2.

4.1 Wavelet approach & Curvelet approach:

Many wavelet coefficients are Less coefficient.

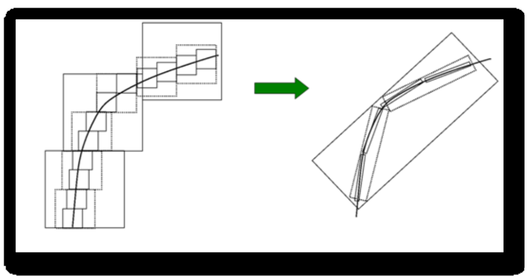


Figure 4.2 Difference between Wavelet approach and Curvelet approach

Table 4.1 gives the discussuion about the points and

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 4.1 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 ture ridge functions in digital images[6]. 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.

maximun frequency of the signal. The CS-based data acquisition depends on its sparsity rather than its bandwidth[6],[8]. CS might have an important impact for designing of measurment device in various engineering fields such as medical magnetic resonance (MRI) imaging and remote sensing.

V. IMPLEMENTATION

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 how the Curvelet transform helps in achieving the accurate Segmented Image which is shown in Figure5.1. Texture features are important in content based image retrieval due to their ability to define the entire image characteristics effectively. Since discrete Curvelet transform has been found to represent the curved edges of images more effectively than wavelet and Gabor filters, it is expected to find the discriminatory texture patterns of an image as well. We describe image representation using wrapping based discrete Curvelet texture features and the use of these features in CBIR process.

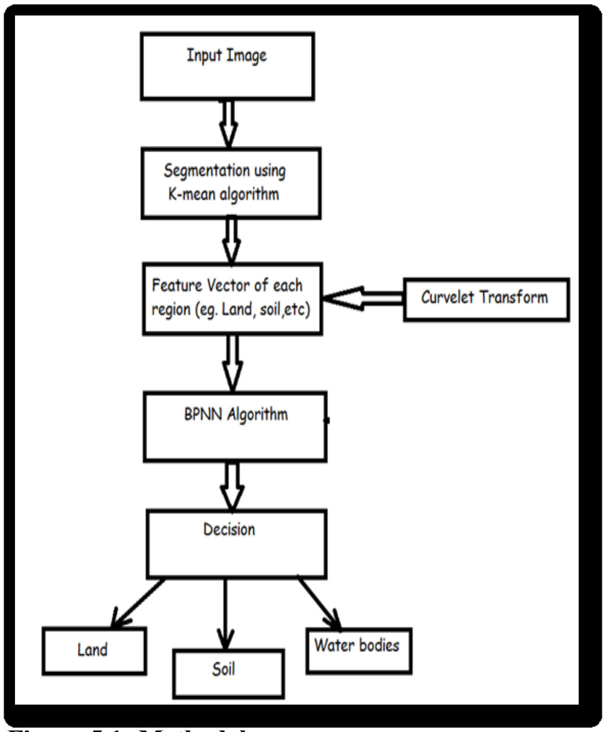


Figure 5.1: Methodology

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.

5.3 Feature Extraction in Curvelet

Texture features are important in content based image retrieval due to their ability to define the entire image characteristics effectively[5],[6]. Since discrete Curvelet transform has been found to represent the curved edges of images more effectively than wavelet and Gabor filters, it is expected to find the discriminatory texture patterns of an image as well. We describe image representation using wrapping based discrete Curvelet texture features and the use of these features in CBIR process. For this purpose, first, we describe the general procedure of Curvelet texture features descriptor generation from spectral domain coefficients. Second, we describe the general image indexing mechanism[12]. Third, we provide the detail information on how the Curvelet texture descriptors are used to index the images in the feature database we use.

5.3.1 Curvelet Transform

Discrete Curvelet transform is applied to an image to obtain its coefficients. These coefficients are then used to form the texture descriptor of that image.

Curvelet coefficients of a 2-D Cartesian grid $f\,[m,n], 0 \le m < M, 0 \le n < N$ are expressed as:

$$C^D\ (j,l,k_1k_2) = \sum_{\substack{0\le i \le m \\ 0<j<n}} f[m,n]\varphi^D_{j,l,k_1k_2}\,[m,n]$$

(7.1)

Where $\varphi^D_{j,l,k_1k_2}[m,n]$ the Curvelet waveform. This transform generates an array of Curvelet coefficients indexed by their scale *j*, orientation *l* and location parameters(k_1, k_2). Curvelet Transform has same frequency that can be analysed in all direction and with different angles .The range that can be used is : 2^n ; where n=1,2,3………..n which is shown in Figure 5.2

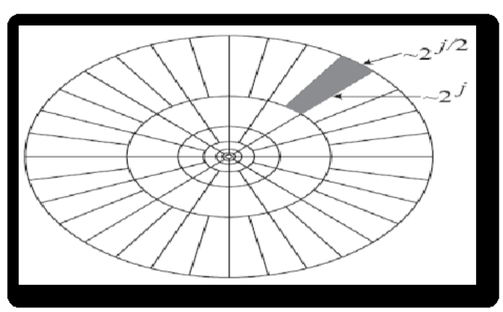


Figure 5.2 Curvelet Transform

Here we use n= 0,4,5,6 so 1, 16, 32, 64 division

5.4 Curvelet Algorithm

[1] First 2D Fast Fourier Transform (FFT) of the image is taken.

[2] 2D Fourier frequency plane is divided into wedges.

[3] The concentric circles decompose an image into multiple scales (used for band passing the image at different scale) and the angular divisions partition into different angles or orientations.

[4] For particular wedge we need to define its scale and angle.Discrete Curvelet transform is implemented using the wrapping based fast discrete Curvelet transform. Basically, Multiresolution discrete Curvelet transform in the spectral domain utilizes the advantages of fast Fourier transform (FFT). During FFT, both the image and the Curvelet at a given scale and orientation are transformed into the Fourier domain. The convolution of the Curvelet with the image in the spatial domain then becomes their product in the Fourier domain[5],[6],[8]. At the end of this computation process, a set of Curvelet coefficients by applying inverse FFT to the spectral product. This set contains Curvelet coefficients in ascending order of the scales and orientations the complete feature extraction process using one single Curvelet is illustrated in Fig. 5.3(a).The wrapping is illustrated in Fig. 5.3(b) and explained as following. As shown in Fig. 5.3(b), in order to do IFFT on the FT wedge, the wedge has to be arranged as a rectangle. The idea is to replicate the wedge on a 2-grid, so a rectangle in the center captures all the components a, b, and c of the wedge.

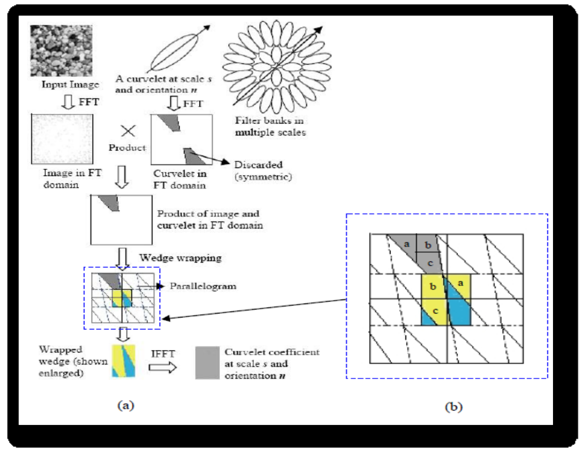
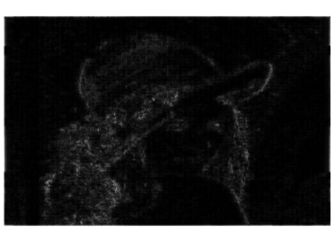
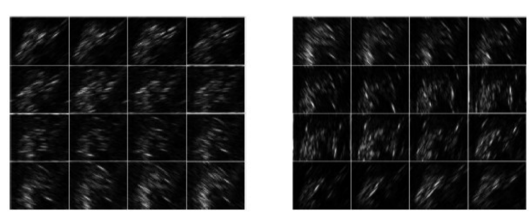


Figure 5.3 : Fast Discrete Curvelet Transform to Generate Curvelet Coefficient

Wedge wrapping is done for all the wedges at each scale in the frequency domain, so we obtain a set of sub bands or wedges at each Curvelet decomposition level. These sub bands are the collection of discrete Curvelet coefficients.To provide an illustration of Curvelet sub bands, we apply fast discrete Curvelet transform to a 512×512 Lena image with 6 decomposition levels using Curvelab-2.1.2 of. The sub bands generated from this image are shown in Fig. 5.4. Lena image has a rich collection of multidirectional edges. From all the sub band images of Lena image shown in Fig. 5.4, we find that the wrapping based discrete Curvelet coefficients capture and represent the edge information more accurately.



a)curvelet subband at scale 6



(b)First 32 Sub bands (Left contains first 16, right contains last 16 sub bands)

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VII. CONCLUSION AND FUTURE SCOPE

7.1 Conclusion

In proposed image classification system a new approach using Curvelet transform and Back propagation Neural Network has been introduced. The correlation coefficient, mean and standard deviation features of the various combinations coefficients produced by Curvelet Transform. A number of Texture images not considered in the work have been analysed 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. The graph of Plot fit and Regression plot gives the difference between the Urban and Rural image in which the Rural image gives better result than the Urban Image in terms of the weight which is confined to the original Fit.

7.2 Future Scope

A new approach for Image Classification with Higher Accracy. There is good potential for Future Development 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 parameter like finding out the depth of water, location of sand, detecting the target for the satellite images for military purpose.

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