



An Approach to Classification of Image Using Neural Network & Wavelet Transform

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Abstract—This paper describes a method for classifying different textured images using neural networks and discrete wavelet transform. In this method a multi resolution analysis is applied to textured images to extract a set of intelligible features. These features are very use full for neural network. These extracted features, in the form of DWT coefficient matrices, are used as inputs to four different multilayer perceptron (MLP) Neural Networks and used for classification. Generalization performance is improved when a locally connected, weight-sharing network topology is utilized, thus drastically decreasing the number of free parameters during training. This method takes advantages of the quasi-periodic nature of the textured images. A novel voting network scheme is also employed to achieve a system classification result from the four networks. The efficiency of the algorithm is demonstrated using real-world textured images. The proposed technique was verified using five classes of visually similar textured images, with a successful classification rate above ninety five percentages.

Keywords: Texture classification, Wavelet transforms multilayer perceptron, weight-sharing network, and neural network.

I. INTRODUCTION

An image processing technique is very advance field now days by which different regions of an image are identified based on properties. This process is very important role in many areas such as iris identification, Industrial automation, biomedical image processing, Content Based Image Retrieval and remote sensing application and so on. Texture is use full and important in many areas of image processing, there is no universally accepted definition for the texture. Texture classification has always been one of the most difficult problems in image processing on account of uniformity, regularity, coarseness, and other properties of various texture patterns. An important step in texture classification is feature extraction. However, the first obstacle occurs when the definition of texture arises. There is no universal definition because of the vast array of pattern in natural and artificial textures. This paper focuses on the texture classification based on neural network and wavelet transform. The first step of texture analysis is the identification of proper features that maximize the differentiation of the textures for classification, segmentation and recognition. Features are assumed to be uniform with in regions of interest in the same texture. Since, texture analysis has been a topic of study from so many years. There are various feature extraction and classification techniques that have been proposed and many more available. They can be categorized into four major methods: statistical methods (co-occurrence method), geometrical (Voronoi tessellation features), and model based methods (Markov random fields), and signal processing methods (Gabor filters, wavelet transforms).

More recent methods based on multi-resolution analysis such as wavelet transform have received a lot of attentions.[1]. This method provides a precise and unifying framework for the analysis and characterization of a signal at different scales .It concluded that no texture feature is consistently superior for all images, however, that wavelet transforms are among the best for most images. Another crucial component in texture classification and segmentation is the classifier being used. With years of study, this area has also produced a number of classifiers, such as: nearest neighbor, Fisher linear discriminates, and Bays classifier being the most common. Please refer to [1]. Recently, neural network [4] has emerged as a very successful method for texture classification

The standard discrete wavelet transform (DWT) is a very powerful tool used successfully to solve various problems in signal and image processing. The DWT breaks an image down into four sub-sampled, or images. The results consist of one image that has been high pass in the horizontal and vertical directions (HH), one that has been low passed in the vertical and high passed in the horizontal (LH), one that has been high passed in the vertical and low passed in the horizontal (HL) and last that has been low pass filtered in both directions (LL) Where, H and L mean the high pass and low pass filter, respectively. While HH means that the high pass filter is applied to signals of both directions, represent diagonal features of the image, HL correspond to horizontal structures, LH results vertical information and LL is used for further processing. More explanation to both DWT and Neural Network are given in next Sections 2 and 3 respectively.

The discrete wavelet transform is taken on textured images and used as a preprocessing tool for neural network classifiers. Four different networks are trained at a given resolution level, each with inputs taken from one of the four separable DWT coefficient. To take advantage of the quasi-periodic nature of the textures, a locally-connected, weight-

sharing neural network topology is utilized which extracts local features from the DWT coefficient matrices. A novel voting network scheme is also employed which treats each of the four networks as voting elements and creates a system classification result. Related work includes. The method used in [5] modeled textured images with wavelet packets. Also, an approach described in [6] used the DWT coefficient

II. NEURAL NETWORK AS A CLASSIFIER

From last some years, the artificial intelligence community has undergone a resurgence of interest in the research and development of artificial neural networks. An artificial neural network is an attempt to simulate the manner in which the brain interprets information as determined by the current knowledge of biology, physiology, and psychology. Artificial neural networks behave in much the same manner as biological neural networks, giving many of the same benefits. Artificial neural nets are fault tolerant, exhibit the ability to learn and adapt to new situations, and have the ability to generalize based on a limited set of data. This arises because of the structure which allows neural nets to process information simultaneously, as opposed to the serial nature of traditional digital computers. This parallel nature, inherent in neural networks, achieves the increase in speed by distributing the calculations among many neurons.

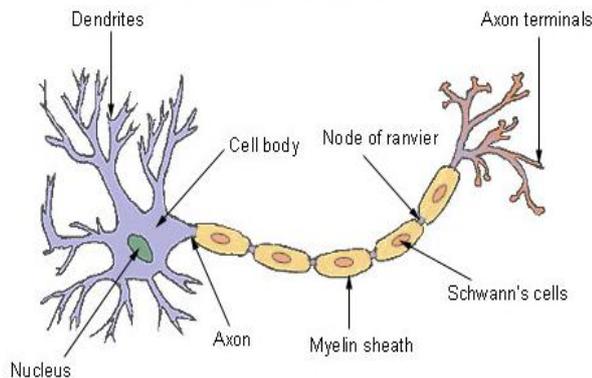


Fig.1: Structure of Basic neuron

The network structure provides a level of fault tolerance, which allows the network to withstand component failures without having the entire network fail. In this topic of seminar, it focuses on a popular feed forward model of neural networks. In this model a set of inputs are applied to the network, and multiplied by a set of connection weights. All of the weighted inputs to the neuron are then summed and an activation function is applied to the summed value. This activation level becomes the neuron's output and can be either an input for other neurons, or an output for the network. Learning in this network is done by adjusting the connection weights based upon training vectors (input and corresponding desired output) This ability is termed associative recall. In pattern recognition, when a particular pattern is noisy or distorted, the network can generalize and choose the closest match. Pattern matching uses continuous input patterns to evoke continuous output patterns. An example is the use of a neural network as a basic controller for a plant.

In this description of feed forward neural network, and a description of the back propagation learning algorithm is given, which is very help full for classification of texture. The basic building block of an artificial neural network is the neuron. The connection weights between neurons are adjusted. The neuron receives inputs o_{pi} from neuron u_i while the network is exposed to input pattern p . Each input is multiplied by a connection weight w_{ij} , where w_{ij} is the connection between neurons u_i and u_j . The connection weights correspond to the strength of the influence of each of the preceding neurons. After the inputs have been multiplied by the connection weights for input pattern p , their values are summed, net_{pj} . Included in the summation is a bias value θ_j to offset the basic level of the input to the activation function, $f(net_{pj})$, which gives the output o_{pj} . Figure shows the structure of the basic neuron.

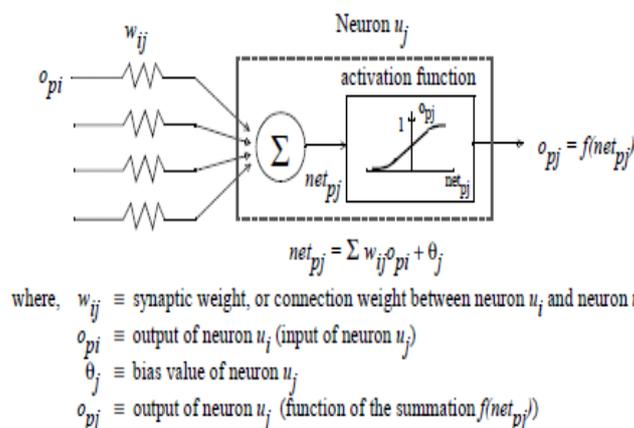


Fig.2. A Basic Neuron with weight.

An artificial neural network is a system of processing elements (PE) interconnected by various synaptic strengths. Recently, they have become popular classification devices for both one-dimensional and two- which use a gradient-descent learning algorithm called back propagation (BP) and topology

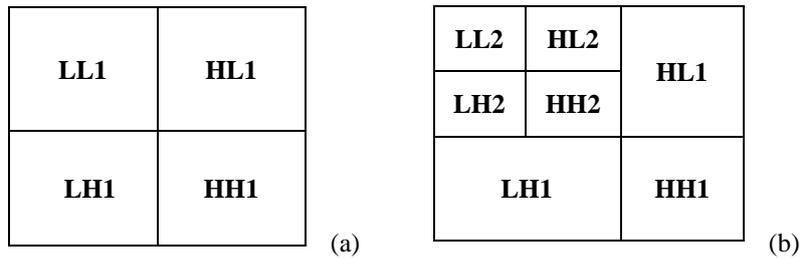


Fig.3: Image Decomposition.(a) One-Level, (b) Two level

called multilayer perceptron (MLP) have been the most dominant structure for classification purposes. Back propagation uses a squared error cost function which expresses the difference between the actual and desired responses of the network.

For a given input vector of x_p the actual outputs of the network are given by u_q , while the desired responses can be given by d_p , for $1 \leq q \leq NL$, where NL is the number of outputs. For each training pattern indexed by p , the cost function is represented. This cost function is minimized using a gradient descent method to update the synaptic weights in the network. These “weights” define the synaptic strengths for each connection between processing elements. The network is updated each iteration and correspondingly “learns” the training patterns. The judging criteria for the network, however, this is the generalization performance on a test set. While a wide variety of methods to improve generalization performance have been adopted, many researchers do agree upon the fact that minimizing the number of free parameters during training (i.e. synaptic weights), through modifications in the network architecture, can greatly improve generalization. One type of “reduced-weight” architecture is called the locally-connected, weight-sharing network as shown in figure 4.

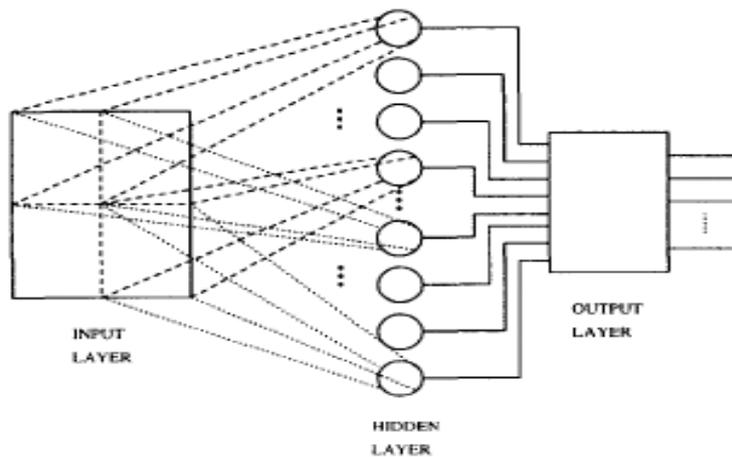


Fig.4: A Locally-Connected, Weight-Sharing Neural Network

III. FEATURE EXTRACTION–DISCRETE WAVELET TRANSFORM

An important step in neural network design is the incorporation of a pre-processing step called feature extraction. The main goal of this process is to derive a set of primitives which amply represent the image. This reduces the dependencies on image characteristics such as brightness, contrast, etc. and creates a much smaller Set of data. A recently proposed feature extraction method is a signal analysis tool called the discrete wavelet transform (DWT). The spatial-frequency information which a DWT contains is ideal for classifying such images as textures. Which can be described as position-frequency phenomena’s DWT contains a sequence of resolution levels. Each level contains more information than the adjacent lower levels.

Because of the orthogonal property of both the scaling function and wavelet, the DWT coefficients from adjacent resolution levels also hold a recursive relationship. It extends the idea to two-dimensional signals or images, this simply means that in order to find the DWT coefficient matrix for an image, that image is filtered and sub sampled by taking every other output for both dimensions. This creates four separable sub matrices at any given resolution level: low-low (LL), LH, HL, and HH. as shown in Fig.5 gives an example of the DWT sample used was taken from Template D34, D16, D65 e in the Brodatz Collection and is shown in Figure. The original image is 300 x 300 pixels scanned at 150 dpi using an HP Scan Jet scanner. The filter coefficients, $h(n)$, by Daubechies also.

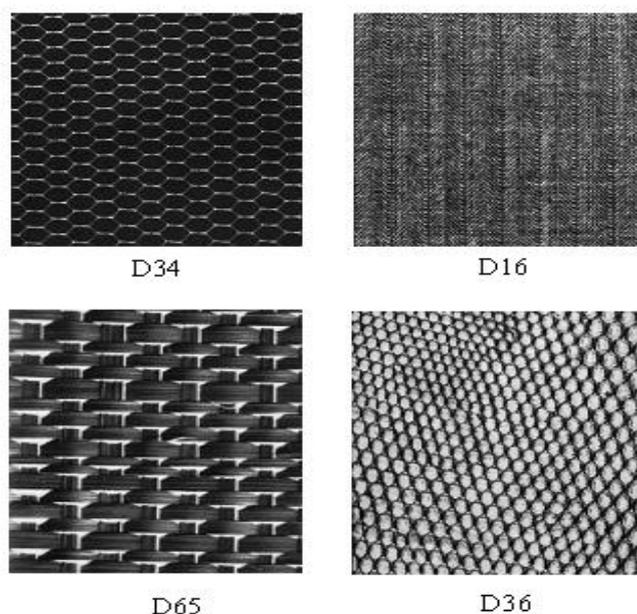


Fig 5: Template Images Used for Creating Test Samples from Brodatz album

IV DWT WITH NEURAL NETWORK

The DWT can be used as a feature extractor preceding a neural network. The DWT coefficient matrix is then a set of features of the original image. Four different networks can be trained at level $j = -1$: LL, LH, HL, and HH, with each network receiving only their respective quadrant from the DWT coefficient matrix as input. Data reduction can be obtained if an even lower resolution level is used. By theory, networks could be trained at any level $j \leq 0$, with a reduction ratio of 4: 1 between adjacent resolution levels. Transferring between resolution levels should not change interpretation of the image. Hence, similar classifications should exist. How does one decide which network is correct in its classification if the system gives four different results, one from each network? Good generalization results can be found if each of the four networks are trained separately at different level of j .

V METHODOLOGY

As shown in figure 6 we can classify image. For implementation apply the steps as per the algorithm. In this method, A multi resolution analysis is applied to textured images to extract a set of intelligible features. These extracted features, in the form of DWT coefficient matrices, are used as inputs to four different multilayer perceptron (MLP) neural networks and classified. Generalization performance is improved when a locally connected, weight-sharing network topology is utilized, thus drastically decreasing the number of free parameters during training. This architecture takes advantage of the quasi-periodic nature of the textured images. A novel voting network scheme is also employed to achieve a system classification result from the four networks.

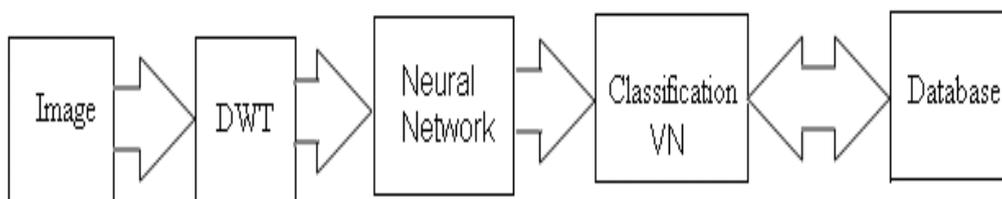


Fig.6: Methodology for classification

VI. CLASSIFICATION USING VOTING NETWORK

It is proposed that a voting network (VN) be used to create a global classification result for the system of four neural networks. Each of the four networks at any given resolution level can be considered a judge or voting element in the system, with a final decision element choosing the system classification result. The vote casted by each network can be looked upon as a form of a membership function for a fuzzy set. This scheme adds an extra level to the hierarchical feature extraction, and hence, improves generalization performance. Figure 7 shows the implementation of such a voting system.

Each of the four neural network blocks are as shown in Figure 7. The four networks are trained separately using therefore different DWT coefficient sub matrices at a resolution level $j \leq 0$. For each training sample, the classification result of the system is the output of the voting network. This, in turn, is a function of the outputs of the four networks. If each neural network has N outputs or classifications, each class can be ranked from 1 to N .

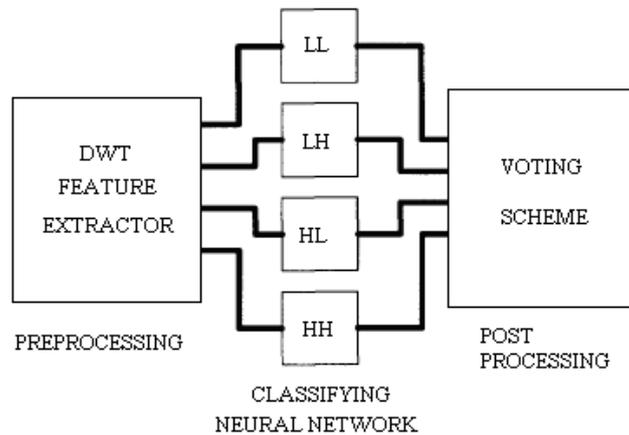


Fig .7: Classification using voting network

Given a particular input to the system, corresponding points can then be awarded to each class depending upon these rankings. An example for such a scoring system is the standard winner take all approach used for an individual neural network. In this scheme, the output with the largest value is considered the winner (i.e. “first place”) or classification result. This scheme determines the winner for a system consisting of a single network.

However, since more than one network is being used in our case, a less stringent approach needs to be found. Examples of point systems for voting networks are shown in Table I. All four voting schemes in Table II award the system classification result to the class with the highest point total. Notice that VN #1 and VN #2 use simple scoring systems which involve all four of the neural networks. VN #3 uses the same scoring system as VN #2, except that the HH network, which continually gave the worst results, was not used. VN #4 also does not use the HH network; however, it adds an extra step by awarding more points for the LL network, which consistently gave the best results. These voting networks are compared in the next section.

TABLE I: Result of Comparison correct classification Rates total Synaptic Weights Network Topology and voting network

Network	Level		Level		Level	
	%	#wts	%	#wts	%	#wts
FC	52.5	24200	84.0	6268	84.0	1668
LC	76.5	6210	87.0	1660	76.0	501
LCWS	71.5	1510	96.5	508	82.0	212
VN1	71.0	---	98.5	---	87.0	---
VN2	71.0	---	99.0	---	89.0	---
VN3	73.0	---	99.0	---	84.5	---
VN4	70	---	99.5	---	81.5	---

TABLE II: Comparison of Four Voting Network Point Systems Used to Classify Four Types of Textured Images

Place	VN #	VN #	VN #	VN # 1 all 4	
	1	1	1	LL	LH,HL
1 st	4	3	3	5	3
2 nd	3	2	2	4	2
3 rd	2	1	1	3	1
4 th	1	0	0	0	0

Thus using voting network scheme we can classify image. Fig. 7 shows actual classification method for the image.

VII CONCLUSION

In this paper, new approach to texture analysis and classification with neural network based on the wavelet transform is given and its good performance on the classification accuracy is demonstrated in the experiments. The discrete wavelet

transform (DWT) was demonstrated to be an excellent feature extraction tool. The use of the DWT coupled with the proper choice of a locally-connected, weight-sharing neural network topology, to give a powerful texture classification scheme. An additional voting network step, which utilizes all of the DWT information at a given resolution level, to improve the generalization performance of the system. The proposed technique was verified using four classes of visually similar textured images, with a successful classification rate above 95%.

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