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# Texture Classification Using a Two-stage Neural Network Approach

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*Abstract*

*In this article, we present a two stage neural network structure which combines the self-organizing map (SOM) and the multilayer perceptron (MLP) for the problem of texture classification. The texture features are extracted using a multichannel approach. These channels comprise of a set of Gabor filters having different sizes, orientations and frequencies to constitute N-dimensional feature vectors. The SOM acts as a clustering mechanism to map these N-dimensional feature vectors onto a 2-dimensional space. This in turn forms the feature space to feed into MLP for training and subsequent classification. It is shown that this mechanism increases the inter-class separation and decreases the intra-class distance in the feature space, hence reduces the classification complexity. Also, the reduction in the dimensionality of the feature space results in reduction of the learning time of the MLP.*

## 1. Introduction:

The problem of texture based segmentation and classification of images is of considerable interest in many image processing applications. Many techniques have been suggested in the past for the purpose of texture analysis [HAR79] and had been attempted by many researchers in different contexts [BER70][WES76]. Recently the artificial neural network based approaches were used in the different phases of texture analysis[ARI90][CHE92]. In contrast to the traditional techniques, neural network based methods have the following advantages: (1) Any arbitrary functional relationship between the input and output patterns can be captured by the neural network and this relationship need not be known or prescribed explicitly. (2) No assumptions need to be made regarding the statistical distributions underlying the input patterns. (3) Neural networks are fault-tolerant in the sense that even if some of the connections are snapped or some of the processing elements are damaged, the performance of the network will not be affected much.

In this work, we propose a texture classification framework based on a two-stage neural network model comprised of self-organizing map (SOM) and multilayer perceptron(MLP). The texture features are extracted from the image using a bank of Gabor filters. The SOM acts as a clustering mechanism which groups the N-dimensional features from the filter bank into a 2-dimensional feature space. The resulting vectors are fed into the MLP which categorizes them into one of the prelearned texture classes. The proposed scheme is a good example of how different neural network models can be cascaded to reduce the complexity of classification.

## 2. Multichannel feature extraction scheme

Textured images have space-varying local properties which may be invariant over a region of the image. These local variations in the textures can be due to the variations in the features such as the orientation, frequency and size. Thus an appropriate mechanism for proper extraction of these features is essential. In the past, several schemes have been suggested for this purpose. Studies on the biological visual system have shown that the receptive fields in early vision possess such processing capabilities. Recently, several studies on the analysis of textures using Gabor wavelets have appeared [JAI91][BOV90]. The local properties of a texture can be obtained using a set of Gabor filters with appropriately chosen filter orientation, frequency and size. Such systems can be shown to have properties similar to the biological visual system [DEV82].

The general form of the Gabor function is given by,

$$g(x,y,k_x,k_y,\sigma_x,\sigma_y) = A\, e^{-\frac{1}{2}\left[\left(\frac{k\,x}{\sigma_x}\right)^2 + \left(\frac{k\,y}{\sigma_y}\right)^2\right]} . e^{j(k_x x + k_y y)}$$

where, A is a scaling factor and $k = \sqrt{(k_x{}^2 + k_y{}^2)}$ .

The spatial extent of the Gabor function is defined by ($\sigma_x$ , $\sigma_y$). The orientation of the span limited sinusoidal grating is given by $\tan^{-1}$ ( $k_y$ /$k_x$ ) and its frequency is specified along the x and y coordinates by $k_x$ and $k_y$ respectively.

The Gabor filtered output of the image is obtained by a linear convolution of the image with the Gabor function. If $i\,(x\,,y\,)$ is the image, then the filtered image is given by,

$f(x,y) = i(x,y) * g(x,y)$ for a given $k_x$, $k_y$, $\sigma_x$ and $\sigma_y$ .

or in the frequency domain,

$F(u,v) = I(u,v) \,.\, G(u,v)$ where $F$, $I$, $G$ are Fourier transforms of $f$, $i$, $g$ respectively.

Gabor functions possess several desirable properties useful for texture analysis. The smallest time-bandwidth product of the Gaussian function makes the Gabor function to concentrate both in space and space-frequency domain optimally [DAU85]. The textures which are having significantly different spatial frequencies can be encoded into multiple channels each having narrow spatial frequency and orientation. The local information regarding the texture elements is described by the orientations and frequencies of the sinusoidal grating and the global properties are captured by the Gaussian envelope of the Gabor function. Hence the local and global properties of the texture regions can be simultaneously represented by making use of the Gabor filters.

## 3. Secondary feature extraction using SOM

This stage can be viewed as a secondary feature extraction stage which quantizes the feature vectors from the Gabor filter bank to achieve more compact representation, yet with information preserved. The network used is the topology-preserving self-organizing feature map (SOM)[KOH90]. It receives the N-dimensional feature vectors from the multichannel filter bank. The network is trained so as to cluster the input patterns in the output space. The number of clusters will be equal to the number of classes in the input patterns. After training, the feature vector from the Gabor filter bank fed to the SOM makes one of the nodes in the output layer to win. The normalized coordinates of this winner node forms the 2- dimensional secondary feature vector to train the MLP.

One main advantage of this approach is the reduced dimension of the feature space. Further, it was observed that the interclass separation is more and intraclass separation is less for the secondary feature vectors from SOM than the primary feature vectors from the filter bank. The efficiency and performance of the classification depends on the parameters of the SOM, especially the neighborhood dependency of the winning node and the number of training epochs.

## 4. Classification using multilayer perceptron

We used a two layer feedforward neural network for the purpose of classification receiving inputs from the output layer of SOM. The texture class labels are assumed to be known a priori and hence error backpropagation algorithm [RUM86] is used for the training of the network. During the image segmentation phase, the texture features at each pixel in the imagery is extracted using the filter bank and applied to the SOM. The normalized coordinates of the winner node of the SOM are then fed to the MLP and depending on its output, the pixel is assigned to any one of the classes. If the outputs are not distinguishable or if they are less than a particular threshold, the pixel is labeled as unclassified.

## 5. Results and discussion

The performance of the proposed scheme is analyzed using the image shown in Fig.1. The image is of size 256x256 and contains four different textures. The feature extraction stage consists of a set of Gabor filters having 3 different bandwidths, 3 frequencies and 4 orientations (0, 45, 90 and 135 degrees). Thus the output of this filter bank constitutes a 36-dimensional feature vector representing each pixel in the image. The SOM used for clustering consists of 36 input nodes in the input layer and a 10x10 array of nodes in the output layer . The multilayer perceptron classifier has 2 input nodes, 4 hidden layer nodes and 4 output nodes.

The classification result of the proposed scheme is shown in Fig.2. For comparison of the proposed method, the classified result when the filter bank outputs are directly fed to MLP without SOM interface is shown in Fig. 3. It is clear that the proposed scheme gives better performance. The Tables 1(a) and 1(b) show the distance matrices of the primary feature vectors from filter bank and of the secondary feature vectors from SOM. This shows that the interclass distance is increased and the intraclass distance is decreased, there by reducing the classification complexity. Another important aspect is the time taken for classification - In this scheme, it is only 22 minutes whereas in the case of using only MLP, it is 107 minutes when run on an I860-based workstation. In the experiment, the initial lateral correlation in the output layer of SOM was taken as the size of the output layer itself and was gradually reduced by a factor of 0.99. The MLP is characterized by a learning factor of 0.15 and a momentum factor of 0.30.

## 5. Conclusion

In this paper, we have proposed a texture classification scheme for the classification and segmentation of the textured multispectral imagery based on a two-stage neural network approach. The scheme uses Gabor filters of different bandwidths, orientations, and frequencies for feature extraction. The classifier phase is achieved by the self-organizing map cascaded with a twolayer feedforward neural network trained using the backpropagation algorithm. The performance of the system in segmenting a given textured image was studied and the performance was compared with a system which uses a twolayer network for classification. It is found that the incorporation of secondary feature extraction using SOM improves the performance and also reduces the complexity of the feature extraction and classification stages. Further, the time requirements for the classification based on the proposed scheme is much less than that of the classification using only MLP.

## References


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| | Texture1 | Texture2 | Texture3 | Texture4 |
|---|---|---|---|---|
| Texture1 | 0.3307 | 0.7295 | 1.0000 | 0.6298 |
| Texture2 | 0.7295 | 0.1514 | 0.3483 | 0.3550 |
| Texture3 | 1.0000 | 0.3483 | 0.1405 | 0.5698 |
| Texture4 | 0.6298 | 0.3550 | 0.5698 | 0.1395 |

Table 1(a) : Normalized distance matrix of the primary feature vectors from filter bank

| | Texture1 | Texture2 | Texture3 | Texture4 |
|---|---|---|---|---|
| Texture1 | 0.0019 | 0.7341 | 1.0000 | 0.6813 |
| Texture2 | 0.7341 | 0.1660 | 0.5034 | 0.8187 |
| Texture3 | 1.0000 | 0.5034 | 0.0000 | 0.6828 |
| Texture4 | 0.6813 | 0.8187 | 0.6828 | 0.07900 |

Table 1(b) : Normalized distance matrix of the secondary feature vectors from SOM

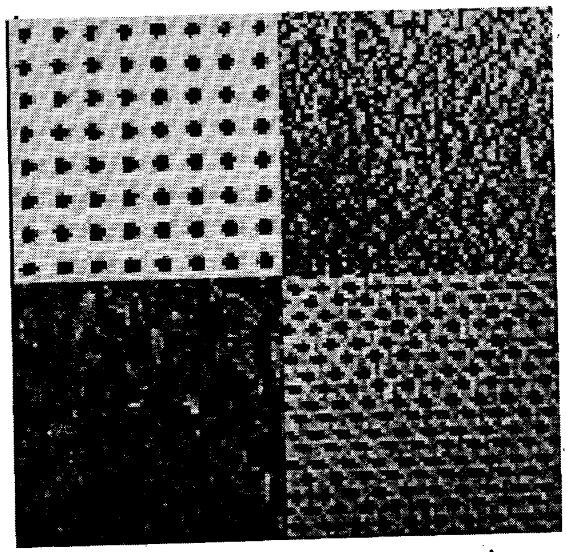

**Fig. 1. The image used for classification experiment.**

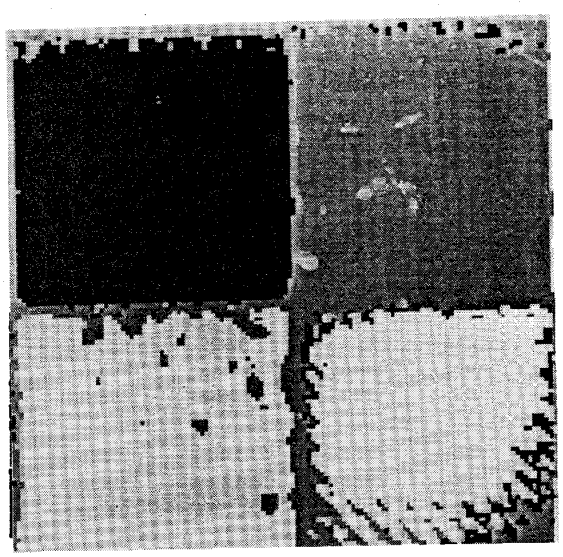

**Fig. 2. Classification result using the proposed scheme.**

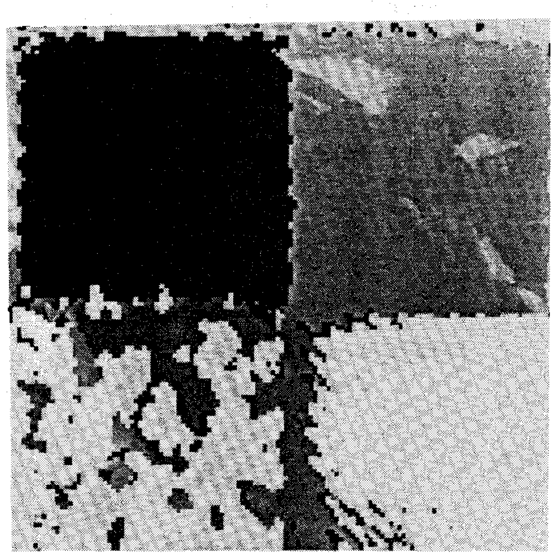

**Fig. 3. Classification result with MLP only**