CHAPTER 4

MULTI-NEURAL NETWORK (SOM-BPN) CLASSIFIER

4.1 INTRODUCTION

In the previous chapter the HNN classifier is suggested and tested with synthetic and real world data sets. The HNN classifier which when used for recognizing the handwritten Tamil characters resulted in only 80% of classification accuracy. The reason for this low classification accuracy is due to the fact that Tamil characters are having common substructures and thus the extracted features of the characters are highly overlapping. In order to reduce the complexity of the overlapping features, the Tamil characters can be divided into a number of groups. Each group is having a common substructure. For example in Figure 4.1 four different groups of Tamil characters are shown. The common substructure for the group (a) characters is "&". In general a flexible recognition system must be able to recognize an object regardless of its orientation, size and location in the field of view. In order to achieve this the extracted features should have invariancy properties to scale, translation and rotation. In practical recognition applications the invariancy to scale, translation and orientation are usually achieved by a two stage process. Based on the above said analysis in this chapter a Multi-Neural network (SOM-BPN) classifier is suggested for pattern classification. Grouping of similar substructure characters into groups by visual examination is tedious process. To overcome this problem a self-organizing map (SOM) network is employed in the first stage of the multi-neural network classifier. The SOM network is capable of forming its own groups or clusters of the training data based on the common features associated with them. The training process in SOM
Figure 4.1 An example for grouping of Tamil characters having common substructure.
attempts to reflect the range of class types found in training data. The backpropagation network is cascaded with SOM network to form the complete classifier system. The BPN generalizes by detecting features of input pattern that have been learnt to be significant. Only representative set of patterns have to be taught to the BPN and its generalization properties allow similar inputs to be classified well. Two set of features :(i) Walsh co-efficients and (ii) moment invariants are extracted from handwritten Tamil character images. The Walsh co-efficients (Huang and Chung 1987) form the feature set to train the SOM network and the groups are self-organized by it. There are as many individual BPNs in the next stage as the number of groups formed by the SOM network. These individual BPNs are trained with moment invariant features (Khotanzad and Lu 1990) of the characters in the respective groups. In the testing phase, the SOM network gives the group classification using Walsh co-efficients. The BPN attached to this group recognizes the individual character correctly using the moment invariant features. The classifier performance is tested with handwritten Tamil character images written by different persons. This classifier is writer independent. The performance of the Multi-Neural network classifier is compared with (i) Single Layer Neural Network and (ii) Hierarchical Neural Network classifiers. From the experimental results it is found that the classification accuracy of the proposed classifier is better than the MLP and HNN classifiers though the training time is marginally high.

The rest of the chapter is organized as follows. The next section discusses how to extract the Walsh coefficients and moment invariant features of the character images. The proposed SOM-BPN classifier and its learning procedure are discussed in section 4.3. The validity of the Multi-Neural network classifier is presented in section 4.4. Section 4.5 reports the experimental results on a data set consisting of 54 handwritten Tamil character images. The conclusion of this chapter is given in section 4.6.
4.2 WALSH CO-EFFICIENTS AND MOMENT INVARIANT FEATURES

Handwritten Tamil characters with common substructures are grouped together by extracting features using Walsh Transform (Huang and Chung 1987) because they are stable under changes in size, position and orientation of the characters. The fifty four Tamil characters shown in Figure 4.2 form the data set for the experiments. The Walsh coefficients of these characters with different size, position and orientation are extracted. Then these features are used to train the SOM network to form the groups. Each group is formed such that the characters in a group have similar substructures. The Walsh coefficients which when used with SOM network to form groups, resulted groups with common substructures in a better way than using moment invariants. Hence Walsh coefficients are employed to train the SOM network. This shows that the Walsh transform is a simple and reliable method of forming groups with similar substructures. The simplest possible technique of feature extraction using Walsh Transform is described below: The Walsh functions $WAL(n,\theta)$, $-1/2 < \theta \leq 1/2$, are defined recursively as follows:

\[
WAL(0,\theta) = \begin{cases} 
1 & \text{if } -1/2 < \theta \leq 1/2 \\
0 & \text{otherwise} 
\end{cases}
\]

\[
WAL(2j+q,\theta) = (-1)^{\lfloor \theta \rfloor + q} [WAL(j,2(\theta+1/4)) + (-1)^{\lfloor \theta \rfloor} WAL(j,2(\theta-1/4))]
\]

for $q = 0$ or $1$ and $j = 1,2,..n$.

And if $\theta$ is not in $(-1/2,1/2)$, then $WAL(j,\theta) = 0$. The ordering of Walsh functions is the sequence ordering: $WAL(0,\theta)$, $WAL(1,\theta)$, $WAL(2,\theta)$, $WAL(3,\theta)$,.. The input image is represented by $N \times N$ matrix $x_{ij}$, $i=1,...N$; $j=1,...N$ and the origin of the co-ordinate system be translated to the centre of the image. The
Figure 4.2 The data set consist of fifty four Tamil Characters.
Walsh coefficients are determined at N equal intervals from -1/2 to +1/2. when N is odd and N equal to 2k + 1 then the equally spaced points are given as: -1/2, -(k-1)/2k, -(k-2)/2k,..., 0, 1/2k,...,(k-1)/2k, 1/2.

When N is even and N equal to 2k, then the N equally spaced points are given as: -(2k-1)/4k, -(2k-3)/4k,...,-3/4k, -1/4k, 3/4k,...,(2k-1)/4k.

The two dimensional Walsh transform is defined in equation (4.2).

\[ C_{mn} = \frac{1}{N^2} \sum_{\nu=0}^{N-1} \sum_{\mu=0}^{N-1} X_{\nu,WAL}(m,i) WAL(n,i) \]  

(4.2)

where \( C_{mn} \) is called Walsh co-efficients and \( m = 0,...,N-1; n = 0,...,N-1 \). Walsh coefficients for higher sequences are not realistic for handwritten Tamil character and hence it is truncated for those \( C_{mn} \)'s with \( m > 6 \) and \( n > 6 \). The Walsh co-efficients obtained for the character image "Mir" is given below.

The Walsh co-efficient Matrix 6 x 6 for the character "Mir".

\[
\begin{bmatrix}
-0.68 & 0.68 & 0.12 & -0.12 & 0.09 & 0.09 \\
0.68 & -0.68 & -0.12 & 0.12 & 0.09 & -0.09 \\
-0.26 & 0.26 & 0.05 & -0.05 & 0.05 & -0.05 \\
0.26 & -0.26 & -0.05 & 0.05 & -0.05 & 0.05 \\
-0.08 & 0.08 & -0.01 & 0.01 & -0.01 & 0.01 \\
0.08 & -0.08 & 0.01 & -0.01 & 0.01 & -0.01
\end{bmatrix}
\]

The moment invariants are set of non-linear functions which are invariant to translation, scale and orientation and are defined on geometrical moments of the image. They were first introduced by Hu (1962). Dudani et al (1977) have successfully applied them to aircraft identification. Khotanzad and Hung (1987) utilized them in texture classification. Later Khotanzad and Lu (1990) utilized them for classification of printed
alphabets using neural networks. The analytical equations to calculate the set of nonlinear functions $\phi_1$ to $\phi_6$ which are invariant to scale, translation and rotation are given in Appendix 1.

4.3 THE MULTI-NEURAL NETWORK (SOM-BPN) CLASSIFIER

The neural network topology suggested here is the SOM network cascaded with BPN network. The SOM network consists of nodes arranged in a two dimensional array of size 3 X 3. The SOM network is capable of forming its own groups or clusters of training data based on the common features associated with them. The training process in SOM attempts to reflect the range of class types found in training data. In addition to this the SOM network is able to discover the number of classes the map must eventually identify and where they should lie in relation to each other on the map, based on the large difference, interclass features. The above mentioned property of the SOM network is effectively utilized to form different groups among the handwritten Tamil character images. The characters in each group thus formed have good intraclass features and large variations in the interclass features. The BPN is a feedforward network with one input layer, one output layer and one or two hidden layers. The BPN network used here is a three layer network. Each node in the layer is connected to all the nodes in the next layer. Training is equivalent to finding proper weights for all the connections such that a desired output is generated for a corresponding input. The BPN is trained with moment invariant features of the characters in the data set. The training algorithm computes the output and discrepancy between actual and desired output. Then it backpropagates this error signal level by level to the inputs and updating the weights in such a way to minimize the error. The proposed classifier (SOM-BPN) organization is shown in Figure 4.3.
Figure 4.3  The Multi-Neural network (SOM-BPN) classifier.
4.4 VALIDITY OF THE MULTI-NEURAL NETWORK CLASSIFIER

To validate the Multi-Neural network, the data set $D_n$ of $N$ pattern samples is divided into two subsets, one is small number set $D_s$ consisting of $K$ pattern samples and the other is large number set $D_l$, where $K << N$. This is logically represented as follows:

$$D_s \cup D_l = D_n$$
$$D_s \cap D_l = \emptyset$$

This partition is called as N-K dichotomy. $D_s$ in each dichotomy is used to train and $D_l$ to determine the accuracy of the Multi-Neural network classifier. The number of possible combinations of N-K dichotomies are

$$\frac{N!}{(N-K)!*K!}$$ (4.3)

In the first experiment 10 set of character images (10 X 54 = 540) are used for training and the remaining two sets (2 X 54 = 108) of images are used for testing. Totally 66 experiments are conducted and for each experiment the classification accuracy has been determined. The experimental results for the first five experiments are tabulated in Table 4.1. In the Table 4.1 the classification accuracies for the five BPNs corresponding to the five groups of characters formed by SOM network are presented. From the experimental results it is observed that the Multi-Neural network classifier has given consistent classification accuracy. The average classification accuracy obtained is 90.73%.

4.5 EXPERIMENTATION

An important parameter to be determined in any classifier is the error. To obtain the error measure the available data set is divided into two sets; one for training and one for testing. A total of 54 handwritten Tamil
Table 4.1

The classification accuracy of the various BPNs in the SOM-BPN classifier for different training sets

<table>
<thead>
<tr>
<th>Training set No.</th>
<th>Classification accuracy (%)</th>
<th>Average (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BPN-1</td>
<td>BPN-2</td>
</tr>
<tr>
<td>1</td>
<td>91.6</td>
<td>89.8</td>
</tr>
<tr>
<td>2</td>
<td>92.0</td>
<td>92.5</td>
</tr>
<tr>
<td>3</td>
<td>87.5</td>
<td>93.0</td>
</tr>
<tr>
<td>4</td>
<td>89.9</td>
<td>89.8</td>
</tr>
<tr>
<td>5</td>
<td>90.3</td>
<td>91.6</td>
</tr>
</tbody>
</table>
character images of size 25 X 25 are considered here as shown in Figure 4.2. Twelve images for each character with different scale, translation and rotation form the data set. As an example twelve character images of "ffi" are shown in Figure 4.4. The noisy images with respective signal to noise ratios of 50 db, 30 db, 15 db and 8 db are constructed from noiseless set. This is done by randomly selecting some of the 625 pixels of a noiseless binary image and reversing their values from 0 to 1 or vice versa. The random pixel selection is done according to a uniform probability distribution between 1 and 625. Referring to the images given in Figure 4.4 first six images are used for training and the remaining six are used for testing. The estimation of the error rate is obtained by finding the ratio of the number of misclassified test samples to the total number of tested samples. In the experiments the classifier is trained with noiseless images and tested with and without noise images. The SOM network is trained with Walsh co-efficients of the training set images. Figure 4.5 shows the character groups organized by SOM network after 2000 epochs of training. The BPN network is trained with moment invariant features. Figure 4.6 shows the performance of the classifier for noiseless character images when the number of the hidden nodes are varied. For noiseless case the classification accuracy of SOM-BPN classifier has reached a maximum of ninety percent when more than fifteen hidden layer nodes are used. The classification accuracies of single layer neural network classifier and HNN classifier are fifty four and seventy four percent respectively and are indicated in the form of legends in the Figure 4.6.

The performance of this classifier has also been tested with various size and style of characters written by different writers. It is found that the classifier has higher classification accuracy compared to the single layer neural network and hierarchical neural network classifiers. The network is also capable of recognizing the characters independent of size and styles. Besides this the network is capable of accommodating few new characters by supervised fine tuning of the SOM network and revising the weights of
Figure 4.4 The 12 Scaled, Translated and rotated images of the character "5" in the data set.
Figure 4.5 The character groups organized by the SOM network after training (2000 epochs).
Figure 4.6 The classification accuracy of the SOM-BPN classifier for noiseless case.
the BPN by training. The performance of (i) Single Layer Neural network classifier, (ii) Hierarchical neural network classifier and (iii) the Multi-Neural network (SOM-BPN) classifier are studied using 54 handwritten Tamil character images. The time taken for training and the classification accuracy of these three classifiers for varied number of samples for each character are shown in Table 4.2. It is evident from the experimental results that the accuracy of the proposed classifier is better than the above classifiers though the training time is slightly higher than the classifier using hierarchical approach. From the Table 4.2 it is observed that performance of the three classifiers has changed very little when the number of training samples per character is increased from 6 to 12. The Multi-Neural network classifier is trained with noise free handwritten characters images and tested with noisy characters. The performance of the Multi-Neural network for handwritten character images with respective signal to noise ratios of 50 db, 30 db and 15 db are shown in Figures 4.7 to 4.9. Experiments are also conducted with Single Layer Neural Network classifier and Hierarchical Neural Network classifier using noisy characters. The classification accuracies obtained in these experiments are also indicated in the form of legends in the Figures 4.7 to 4.9. In all these experiments SOM-BPN classifier has performed better than the other two classifiers when tested with character images of various levels of noise. It is inferred from the graphs that SOM-BPN classifier gives better classification accuracy when the number of hidden layer nodes used is in the range of 15 to 30. Use of more than 30 hidden layer nodes is not altered the performance of SOM-BPN classifier significantly. In the experiments with noiseless character images, 500 passes over the training set are used to train the BPN. The effect of varying the number of passes is shown in Figure 4.10 for 20 hidden nodes. This analysis is quite useful to stop automatically the training when it reaches a preset maximum classification accuracy. It is possible to test the recognition accuracy of the training samples at certain intervals during training and stop when it becomes sufficiently high.
Table 4.2

The performance of the classifiers for varied number of samples per character

<table>
<thead>
<tr>
<th>No. of Samples per character</th>
<th>Single layer neural network classifier</th>
<th>Hierarchical neural network classifier</th>
<th>SOM-BPN classifier</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Training time (secs)</td>
<td>Recognition rate (%)</td>
<td>Training time (secs)</td>
</tr>
<tr>
<td>4</td>
<td>3402</td>
<td>48.6</td>
<td>1981</td>
</tr>
<tr>
<td>6</td>
<td>3892</td>
<td>54.3</td>
<td>2209</td>
</tr>
<tr>
<td>8</td>
<td>4205</td>
<td>54.17</td>
<td>2380</td>
</tr>
<tr>
<td>10</td>
<td>5016</td>
<td>55.0</td>
<td>2592</td>
</tr>
<tr>
<td>12</td>
<td>5763</td>
<td>54.94</td>
<td>3012</td>
</tr>
</tbody>
</table>
Figure 4.7 The classification accuracy of the SOM-BPN classifier for SNR = 50db.

Figure 4.8 The classification accuracy of SOM-BPN classifier for 30 db noise level.
The classification accuracy of SOM-BPN classifier for 15 db noise level.

The classification accuracy of SOM-BPN classifier as a function of the number of passes.
4.6 CONCLUSION

The Multi-Neural network (SOM-BPN) classifier has performed better than the other two classifiers: (i) Single Layer Neural network classifier and (ii) Hierarchical neural network classifier. The performance of the classifier changed very little when the number of training samples per character is increased from 6 to 12. The classifier is tested with data set having 54 handwritten noiseless and noisy Tamil character images and it can also accommodate more characters. The Multi-Neural network (SOM-BPN) classifier performance is better with noiseless as well as noisy character images than the single layer neural network classifier and HNN classifier. The moment invariant features seems to be sensitive to noise and degrade the performance of the classifiers. However the Multi-Neural network classifier for the noisy character images is better than the other two classifiers. The recognition rate obtained with the Multi-Neural network classifier for noise free case is only about 91%. The reason for this is that even after using two-stage Multi-Neural network with groups of common substructure characters, the overlapping features are not completely separable in the feature space and the recognition rate close to 100% could not be obtained. Hence Fuzzy concepts can be incorporated into the neural networks to classify handwritten Tamil characters when features are overlapping. In the next chapter a fuzzy supervised feedforward neural approach and its learning algorithm are suggested and it gives classification accuracies as high as ninety eight percent.