Feature Extraction Technique for Neural Network Based Pattern Recognition

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***Abstract*— In this work, an attempt is made to extract minimum number of features to represent the pattern used as inputs for Feed Forward Back Propagation Neural Network (FFBPNN). The binary image of a pattern stored in the frame is partitioned into square regions. A feature from each region is computed by the density and co-ordinate distance of 1^s pixels. The neural network is trained with the extracted features and Root Mean Square Error (RMSE) obtained in the training process is used as performance indicator to stop the FFBPNN learning. Tested the proposed feature extraction and classification algorithms on the handwritten numeral database and found very good classification recognition rate.**

Keywords- Feed Forward Back Propagation Neural Network; Feature extraction; Off-Line handwritten numeral recognition

I. INTRODUCTION

The Off-line handwritten recognition has been the intensive research due to its numerous commercial applications like; office document processing, sorting and processing of bank cheques, sorting and reading of postal address, forms reading and street number recognition. From past five decades, proposed various techniques for off-line handwritten recognition based on the feature extraction, feature selection and classification methods. The performance of these plays an important role in the recognition and classification process.

The feature extraction is one of the important preprocessing steps in pattern recognition. It extracts a set of descriptors, various characteristic attributes, the relevant information associated to form a representation of input pattern [1-4]. The features extracted for representation in pattern recognition must satisfy the following requirements. Firstly, intra-class variance must be small, which means that features derived from different samples of the same class should be close. Secondly, the inter-class separation should be large, i.e., features derived from samples of different classes should differ significantly. Furthermore, features should be independent of the size, orientation, and location of the pattern [5]. The statistical, global transformation and series expansion, and geometrical and topological techniques are the commonly used feature extraction methods in handwritten character or document representation [6, 7].

Due to the variation involved in the writing styles, off-line handwritten recognition is a difficult task and is generally addressed in the feature extraction. The document image representation by the statistical distribution of points takes care of style variations to some extent. Although the reconstruction of the original image is not possible in this type of representation, it is used for reducing the dimension of the feature set providing high speed and low complexity. The zoning technique of statistical method is extensively used for feature extraction in Indian language handwritten numeral recognition [8]. In this technique, the scanned images of numerals are transformed to a binary form and then divided into a number of overlapping and non-overlapping zones. Using the density of 1^s in each zone of binary image is once again transformed into features. A set of features such extracted to represent the original character image from the binary image is called the feature vector. The feature vectors extracted from the character should have maximum variation in the interclass and as minimum as possible in the intra-class.

For off-line handwritten recognition, many researchers proposed different feature extraction and classification techniques. Hanumandlu and Murthy [9] extracted the features using the zoning technique for handwritten numeral recognition. They divided each character image into 24 zones and by considering the bottom left corner as the absolute origin, the coordinate vector distance of 1^s pixel. A normalized feature of each zone is computed by dividing the sum distances of all 1^s pixels present with the total number of pixels in that zone. The recognition is carried out by modifying the exponential membership functions fitted to the fuzzy sets. These fuzzy sets are derived from features consisting of normalized distances obtained using the zone approach. They reported that the overall recognition rate was found to be 95% for Hindi and 98.4% for English numerals. Suresh and Arumugam [10], Jou and Lee [11] proposed an recognition technique for handwritten numeral recognition. They preprocessed handwritten characters (numerals), segmented into primitives, and labeled using fuzzy logic. The unknown handwritten numerals string is a match with the membership value for classification. Jou and Lee reported a recognition rate between 87.33% and 88.72% on National Institute of Standards and Technology (NIST) handwritten numerals special database19.

Rajashekaradhya and Ranjan [12] reported an efficient zone based feature extraction algorithm for handwritten numeral recognition of four popular south Indian scripts. They divided the binary image of a character into 50 zones and extracted two features from each zone. Nearest neighbor and Feed forward back propagation neural network classifiers are used for subsequent classification and recognition purpose. They obtained 99 %, 99%, 96% and 95 % recognition rate for Kannada, Telugu, Tamil and Malayalam numerals respectively. Desai [13] partitioned Gujarati digits into horizontal, vertical, and two diagonals profiles for feature extraction and digits recognition. They used multi layered feed forward neural network for the classification and achieved approximately 82% of success rate. Kocera and Cevikb [14] also used feed forward back propagated multi layered perceptron neural networks to classify the digitized characters. They fixed license plate region in the dimension of 220×50 pixels and average absolute deviation formula to extract features. Liu and Suen[15] presents handwritten Bangla and Farsi numeral recognition on binary and gray-scale images. They take the gradient direction histogram feature for recognition and experimented on three databases, ISI Bangla numerals, CENPARMI and IFHCDB Farsi numerals and achieved highest recognition of 99.40%,99.19%, and 99.73% respectively.

Mahmoud [3] proposed optical off-line handwritten Arabic (Indian) numerals. The angle, distance, horizontal, and vertical-span features are extracted. They experimented with different number of features and used Hidden Markov Models (HMM) and nearest neighbor classifier for training and testing. The best results were achieved with 120-feature vector representing a digit. They reported that the achieved average recognition rates of 97.99% and 94.35% from the HMM and the nearest neighbor classifiers respectively.

Vamvakas et al [16] presents a methodology for off-line handwritten character recognition. They proposed a new feature extraction technique based on recursive subdivisions of the character image and the resulting each iteration sub-images have approximately equal numbers of foreground pixels. Feature extraction is followed by a two-stage classification scheme based on the level of granularity of the feature extraction method. They reported an accuracy of 94.73% on CEDAR and 99.03% on MNIST character database. Blumenstein et al [17] proposed feature extraction technique for the recognition of segmented/cursive characters. The modified direction feature (MDF) extraction technique build upon the direction feature (DF) technique that extracts direction information from the structure of character contours. They extended this principal and the direction information is integrated with a technique for detecting transitions between background and foreground pixels in the character image. The proposed feature technique is tested on neural network based classifier and reported the recognition accuracy of above 89% with the CEDAR characters dataset.

S. Lu et al [18] proposed a system for handwritten Bangla numeral recognition with the directional and density features as the input vector. They expanded two-layer self-organizing map (SOM) to improve the discriminability and achieved satisfactory recognition performance. U. Pala et al [19] computed the features from different angular information obtained from the external and internal contour pixels of the characters for the recognition of multi-sized/multi-oriented characters. The Circular and convex hull rings have been used to divide a character into smaller zones to get zone-wise features for higher recognition results. They combined circular and convex hull features to improve the results and these features are fed to support vector machines (SVM) for recognition. From their experimental results when tested, they obtained recognition of 99.18% on Devnagari and 98.86% on Bangla character.

From the study, it is noted that the number of features extracted to represent the pattern are more. In view of the above, the work proposes FFBPNN classifier for pattern recognition system with less number of input nodes. Inputs to the classifier are features extracted from the pattern by the zoning technique.

II. METHODOLOGY

The Methodology adopted in the proposed pattern recognition system is given in Figure1. The database used in the experimentation was preprocessed, binarized and size normalized images of scanned handwritten numerals. The database in binary form is divided into training and testing data. The training data is used to build the knowledge base and designed the pattern classifier. The testing data is used for the experimentation and the performance is evaluated by the class assigned to unknown sample.

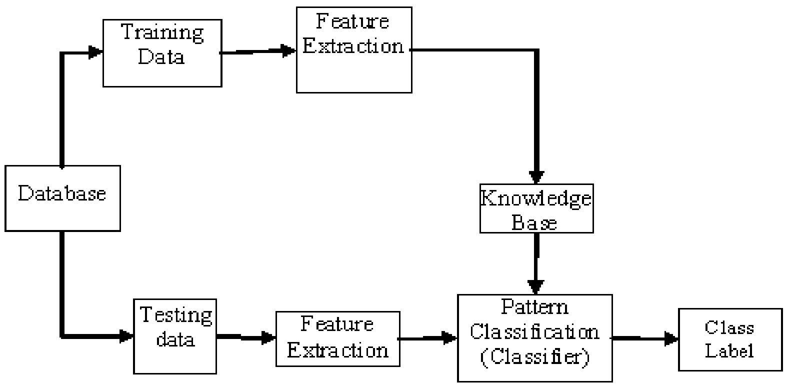

Fig. 1. The proposed pattern recognition system methodology

III Feature extraction

The feature extraction is an important step in pattern recognition and is usually performed on the preprocessed image. The preprocessing includes size normalization, binarization, and thinning steps that are necessary to bring the scanned input images to extract features. The size normalization is required as the size of handwritten character varies from person to person and even time to time with the same person. The handwritten character binarization is done by transforming the black runs into1^s and white portion into 0^s. A set of features are extracted from the binary image further to reduce the size and represent the original image.

A method is proposed to extract features based on the zoning technique. The binary image is fitted in a window of size 15 x 15 and stored in the matrix form (P). Fig. 2(a) shows the size normalized binary image of numeral '3'. The number 103 on top of the left corner of binary image indicates the tenth sample of numeral class 3. The element, i^{th} row j^{th} column of a matrix is denoted as P_{ij} and the value of it is '1' if the black run of character present or otherwise '0' in the cell. The binary image fitted in a matrix is partitioned into nine square regions of size 5x5 as shown in Fig.2 (b) and most of these regions have the portion of 1^s. However, there could be empty regions for some samples and such regions will have zero feature values

a)

```
103:
001111111111000
010000000000010
100000000000001
000000000000001
000000000000010
000000000000100
000011111001000
000010000100000
000000000001100
000000000000110
000000000000010
000000000000100
000000000001000
000000000010000
111111111000000
```

b)

103:

00111	11111	11000
01000	00000	00010
10000	00000	00001
00000	00000	00001
00000	00000	00010
00000	00000	00100
00001	11110	01000
00001	00001	00000
00000	00000	01100
00000	00000	00110
00000	00000	00010
00000	00000	00100
00000	00000	01000
00000	00000	10000
11111	11110	00000

Fig.2. Binary image of numeral 3. a) 10^{th} sample of numeral class 3 fitted in 15x15 size. b) The partitioned binary image numeral class 3.

The different stages involved in feature extraction process are given in the flow diagram as shown in Fig.3. In order to extract the feature, the density of 1^s present in each region are converted into a real number by the two methods and called M_1 and M_2. These feature extraction methods are simple for the implementation. In method M_1, the Feature value of r^{th} region, f_r is computed by the Eq. (1). The total number of 1^s cells in a region is divided by the total number of cells in that region. The shift in 1s position due to writing styles does not affect the feature value. This increases the robustness of feature extraction towards the variations in writing style.

$$f_r = \frac{1}{q_r} \sum C_{ij} \qquad (1)$$

Where, f_r = feature value of r[th] region, q_r = total number of cells in the region *r*,

C_{ij} = Value of (i,j)[th] cell in the region.

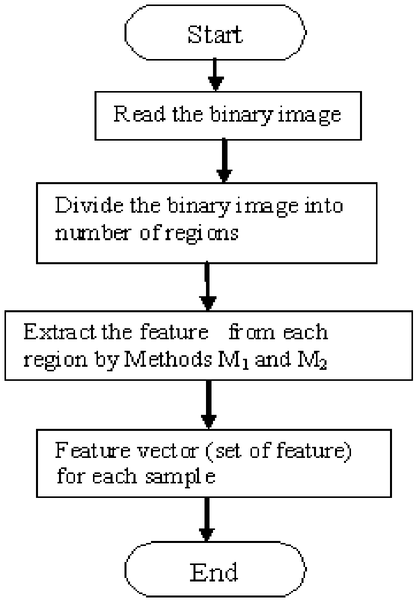

Fig.3 Feature extraction flow diagram

In method M_2, the feature value of a region 'r' is obtained by measuring the co-ordinate distance of cells similar to the technique proposed in [8]. But, the top right corner of a binary image matrix is considered as the reference. The co-ordinate distance of (i,j)[th] cell in the region 'r', d_{ij}^r is computed by the Eq.2.

$$d_{ij}^r = \sqrt{i^2 + j^2} \qquad (2)$$

The normalized feature value of r[th] region is computed by dividing the sum co-ordinate distances of 1s cells from the sum co-ordinate distances of all cells in that region. The feature value of region 'r' is given by the Eq. 3.

$$f_r = \frac{\sum_{c_{ij}=1}^{q_r} d_{ij}^r}{\sum^{q_r} d_{ij}^r} \qquad (3)$$

Where, f_r = feature value of r[th] region, q_r = total number of cells in r[th] region, d_{ij}^r = co-ordinate distance of (i,j)[th] cell, C_{ij} Value of (i,j)[th] cell in the region.

The set of features extracted from each region is called feature vector of a sample. The feature vector of each training and testing sample are extracted by the two feature extraction methods. The feature vectors of training set samples are used to train the FFBPNN and the feature vectors of testing sample are used to find the recognition rate.

IV Training the Neural Network Classifier

The designed multi-layer back propagation neural network (BPNN) classifier consists three layers- input, hidden, and output. It uses the gradient-descent based delta-learning rule. The BPNN is a computationally efficient method for changing the weights to learn a training set of input-output with different activation function and learning rate. Usually, the number of nodes in each layer determines the structure of network. The number of nodes in the input layer is made equal to features extracted to represent the character and these highly influence the performance and complexity of network. The number of nodes in output layer is made equal to the number of classes in the database. The number of nodes in hidden layer is randomly selected by one of the thumb rules, less than twice the input layer and more than the output layer size. So that each output represents a particular numeral class. The designed BPNN has 9-12-10 nodes in input, hidden, and output layer respectively.

The BPNN weight matrixes are randomly initialized and the sigmoid transfer function is used in both the hidden and output layer neurons. Training set input-output pairs of samples are inputted to the neural network one after the other for learning. The neural network is allowed to learn with different learning rate α equal to 0.4, 0.6, and 0.8. The Root Mean Square Error (RMSE) obtained in the neural network learning is the used as performance indicating parameter and to terminate the process. The neural network learning process is stopped when the pre-set performance indicator attains a value 0.0015. At the end of training, the weight matrixes of both hidden and output layers at the end of training are used for classification and recognition.

V. Results and discussions

The proposed algorithms are tested on handwritten numeral database. The database used in the experiment has 440 samples is divided into training and testing each consists of 220 samples. The proposed algorithms were realized in "C" program language. Fig. 4 shows the feature vectors obtained by the methods M_1 and M_2 of training set sample '3' given in Fig.2. The feature values of most the regions are same in both the methods and some features like 9^{th} region feature may differ slightly.

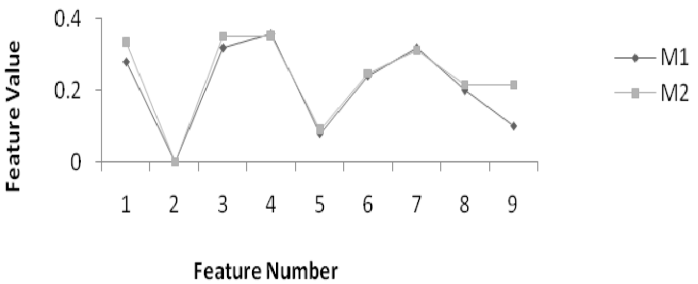

Fig.4. Feature vectors of 10^{th} sample of a numeral class 3 by the methods M_1 and M_2.

From the feature vectors of training samples, it was observed that the intra-class region features have minimum difference. This demonstrates the rigidity towards the variations in writing styles. However, some of the features are slightly differ in intra-class due to extended variations in the position and number of 1^s in a region.

Fig. 5 shows the mean feature vectors of ten (0-9) numeral classes. Fig.5 (a) and (b) shows the mean feature vectors of training samples obtained by M_1 and M_2 respectively. The qualities of extracted features are evaluated by measuring the variation in inter-class feature vectors. It is observed that a region features have maximum variations among the interclass. These features vary in the range 0.0 to 0.3. The feature variation in interclass region values exhibits their discriminating power, distinctiveness, and prominence to represent the individual class. However, in both the methods M_1 and M_2, features f_3 and f_5 have minimum variation among the interclass region.

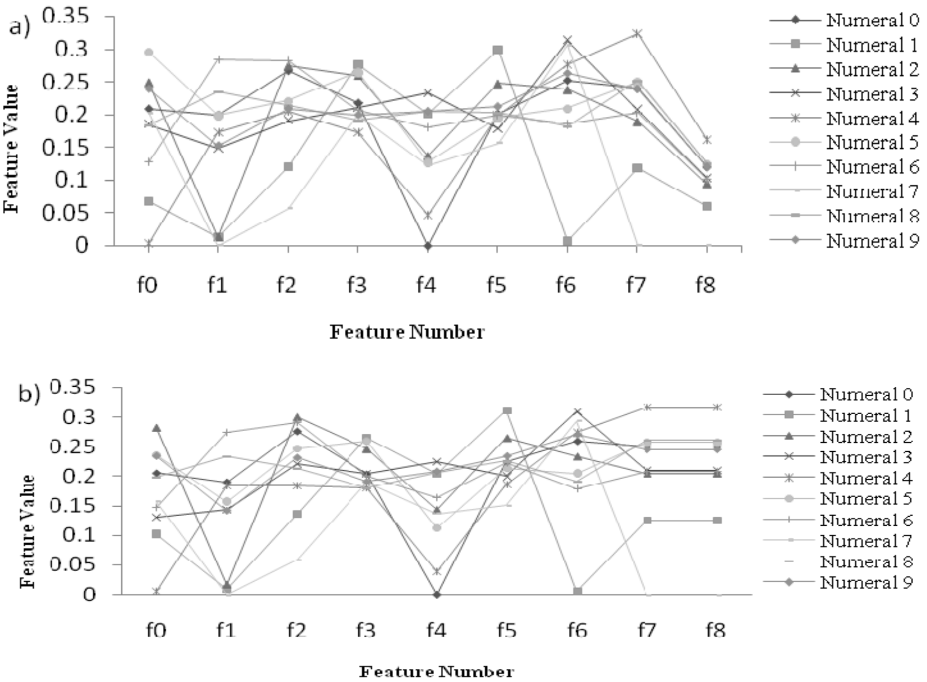

Fig.5. Mean Interclass feature vectors of class numeral '0-9'.
a) Feature extraction method M_1. b) Feature extraction method M_2.

The feature vectors of individual training samples obtained by both the methods and their output pairs are used as input to the neural network separately. The network is allowed to learn with different learning rate with the same performance indicator RMSE equal to 0.0015. The RMSE obtained in the learning process is observed and is represented by the graph. Fig.6.shows the graph of RMSE verses the number of iteration.

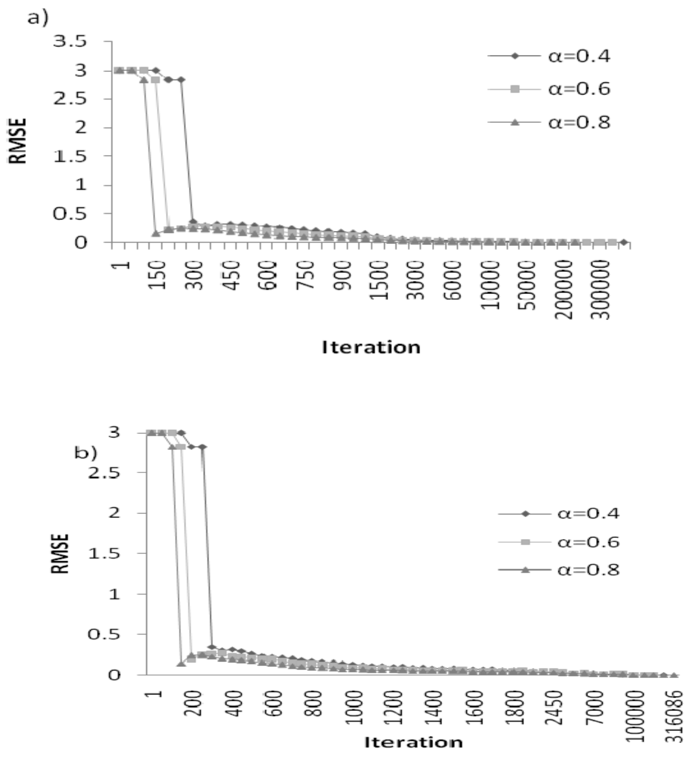

Fig. 6. The Learning process of BPNN. (a) RMSE verses the number of iteration for method M_1.
(b) RMSE verses the number of iteration for method M_2.

In fig.6 (a) and 6 (b), for the different learning rate, α maximum RMSE is same and equal to 3.0. When the value of α is different, the RMSE suddenly fall to 0.15 - 0.35. When it is 0.4, about 300 iterations were taken for both the feature extraction methods by the neural network. When the value of α is increased to 0.6 and 0.8, the number of iteration taken for this fall is less than that of 0.4 and is about 200 and 150 respectively. The total number of iterations took by the two feature extraction methods with different α to attain the preset performance indicator is given in Fig. (7). When α is 0.4, the number of iterations taken by the method M_1 is very large compare to M_2. Similar result is found when the value of α is 0.6, but the difference in number of iteration is less. When α is 0.8 the method M_2 takes more number of iteration and M_1 takes minimum number of iteration. However, the method M_2 takes minimum number of iteration at α equal to 0.6. However, in this work, the system performance is evaluated with all the three learning rates.

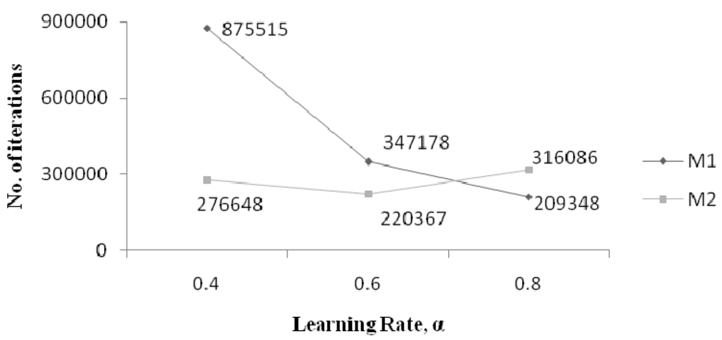

Fig.7. Number of iteration taken by the neural network for learning.

The classification rate is found with the different learning rate and feature extraction method. The feature vectors of a particular class training samples are inputted to the neural network one after the other. An example, the experimentation results of 0^{th} class training samples with the feature extraction method M_1 and learning rate equal to 0.4 is given in Fig.8. It appears that the output -1 has maximum value one and others have minimum value zero. The actual output values of 0^{th} class training samples are given in Fig.9. The output value of node-1 with different α is given is given in Fig.9 (a). The other outputs are given in Fig. 9 (b).

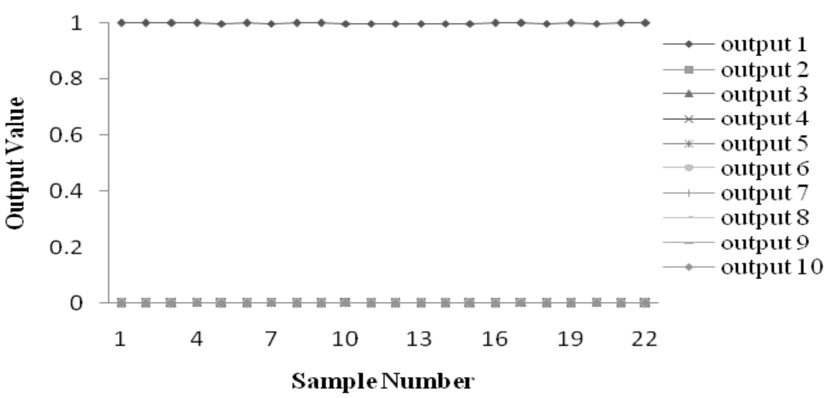

Fig.8. Output of neural network of 0^{th} class training samples.

As seen in the Fig. 9 (a), the output values for 4^{th} and 10^{th} to 17^{th} training samples are different, but these are very close to maximum possible value 1. In Fig 9(b), the values output nodes 2 to10 have different values, but they are close to zero. However, the output of node-1 corresponds to 0^{th} class and they have maximum values, all input samples are assigned to a class “0.”

The Similar results are obtained for each input samples of all other numeral class with different learning rate. When the output of classifier observed, one of the output corresponds to particular class has maximum value. Observing this the input samples is assigned the class of output node having maximum value. The classification rate was 100% for all the numeral classes with different learning rates in both the feature extraction methods M_1 and M_2.

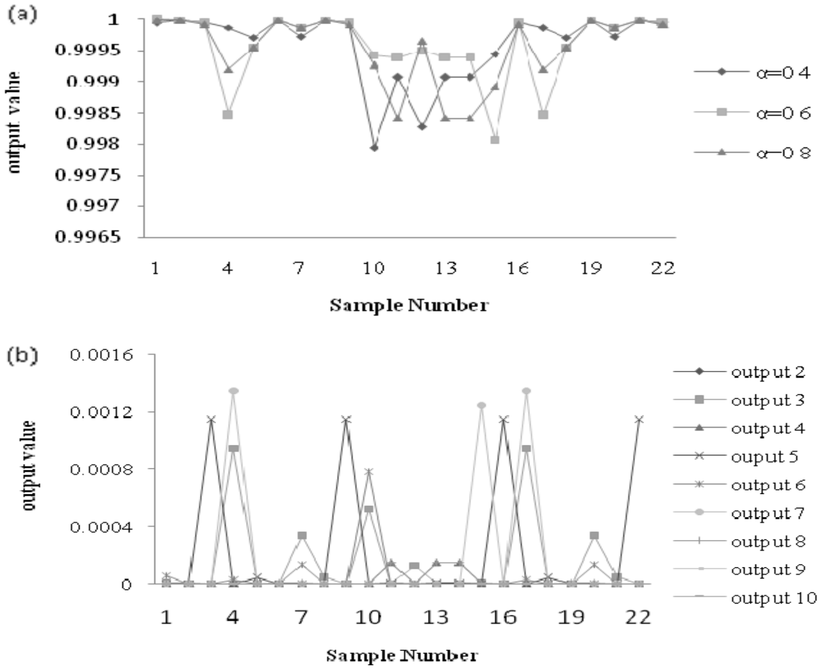

Fig. 9. Neural network output for 0^{th} class training samples. (a) Output-1 with different learning rate 'α'

(b) Output -2 to output-10 with learning rate α=0.4.

On the similar lines, performance is evaluated by the recognition rate on testing data. It consist 22 samples collected from the different individuals having different writing styles and variations in each numeral class. The feature vectors of each testing sample obtained by the methods M_1 and M_2 are fed to the neural network one after the other. All the training samples were recognized correctly images and achieved the overall recognition rate of 100% in both the feature extraction method. Usually, the result of handwritten character recognition depends on the experimental methodology, experimental settings, and the handwriting database. The result obtained in the experimentation is not compared with the literature.

VI. Conclusions

From the experimental results the following conclusions were drawn. The feature vectors obtained by the two techniques have shown nearly similar values. Features have variations among the interclass in each region. This explains their distinctiveness to represent the interclass. The features extracted by the proposed technique are in the range of 0 and 1and can be directly inputted to the BPNN. Only nine features are extracted to represent the character, which in turn reduces the complexity of BPNN. With different learning rate, method M_2 takes less number of iterations for learning than method M_1. However, for higher learning rate method M_1 is better. The classification and recognition rate is 100% with both the methods.

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