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Feature Extraction/Selection and Statistical Classification Technique for Character Recognition

Ashoka H N*
Department of Electrical and Electronics Engineering, University BDT College of Engineering.,Davanagere - 577004, INDIA.

Manjaiah D H
Department of Computer Science
Manglore university,Mangalore, INDIA

Rabindranath Bera
Department of Electronics and Communication Engineering, Sikkim Manipal University, Sikkim INDIA

Abstract*— This paper presents feature extraction, feature selection and statistical classifier for pattern recognition. The binary image of a pattern is partitioned into regions for feature extraction to represent them. The set features are extracted by the density and vector distance one's in each region. The class discriminating power of each region feature is evaluated to select high quality feature. The statistical classifier is developed from the interclass region features. The performance of the classifier is tested on handwritten numeral database and found good classification / recognition rate.

***Keywords*—Feature extraction and selection, statistical classifier, character recognition, Knowledge base.**

I. Introduction

The machine simulation of handwritten character recognition is difficult due to extensive variation like size, shape and fonts. The off-line character recognition is the important area in image processing and pattern recognition fields. The main goal of it is to translate data in documents to machine readable. Many methods have been proposed for character recognition in the 40-50 years of research work. But, human still outperform even the most powerful off-line character recognition system developed so for [1,2]. The off-line character recognition finds application in various fields like reading postal zip code and address reading, automatic inspection and identification, passport number, bank cheque sorting, short hand transcription and form processing.

The performance of character recognition mainly based on the feature extraction algorithm. It is one of the pre-processing steps, extracts relevant information to reduce the dimension and to represent the input pattern. Feature extraction generates a set of descriptors, various attributes and the properties associated with a region or objects and reduce the complexity of classification and recognition system. Different feature extraction methods of character recognition are global transformation and series expansion, statistical and geometrical and topological etc.[3, 4].

Statistical feature extraction includes zoning, projection, crossing and distances method. Out of which zoning technique is extensively used in the handwritten character recognition system [5]. In this method, the image fitted in a particular size is divided into a number of zones and the length black runs or the density of one's in a zone is converted into a feature using different techniques. Hanmandlu and Murthy [6] used zone based feature extraction technique for handwritten Hindi and English numerals. They divide binary image of a character into 24 zones to extract features. The sum of the vector distances of one's cells in each zone is computed from the bottom left corner of a character. The normalized value for each zone is obtained by dividing the sum vector distance of one's cells from the sum vector distance of all cells in the zone. They reported a recognition rate of 98.4% for English numerals.

Rajashekararadhya and Vanaja Ranjan [7] divided the binary image into 50 equal zones and average distances of black pixels are computed as feature. Two features are extracted from each zone and totally 100 features are extracted to represent a character. Further, they divided the binary image into 25 zones and each of 10x10 in size. Average pixel distance of the each column present in the zone is computed vertically. Hence 10 distance features are obtained for zone. This procedure is repeated sequentially for all the zones and in total 250 features is extracted from 25 zones for recognition. They reported a recognition rate of 99 %, 99%, 96% and 95 % for Kannada, Telugu, and Tamil and Malayalam numerals respectively.

In other studies [8], the image is divided into 6 regions of 2x3 sizes and seven multilevel concavity analysis features are extracted from each region. The feature vectors of all six regions are concatenated into a single feature vector with 42 features. Wang et.al [9] proposed Gabor filters based feature extraction technique for Chinese character recognition directly from gray-scale character images.

In the handwritten character recognition, features are created from the knowledge of data. When the prior knowledge of the data is not available to develop feature extractors, Lauer et al [10] introduced a trainable feature extractor as a black box model to give relevant features. Chen et al [11,12] proposed wavelet transform to extract shift-invariant features and contour features. Many other researchers [7,13-14] proposed different feature extraction techniques to reduce the dimensionality of the pattern.

The number of features extracted to represent input pattern is more the complexity of classification and recognition increases. In order to reduce this complexity, feature selection algorithm selects an optimal and an excellent features having salient characteristic necessary for the recognition. Feature selection process reduces the dimensionality of the feature vector and it has two-steps, based on the criterion function followed by the selection of a search strategy [10]. The criterion function finds the suitability of feature over another and the search strategy decides the best possible feature among the number of features.

Feature selection methods are widely categorized as filter methods and wrapper methods. The filter methods evaluate the goodness of features by using the intrinsic characteristics of the training data and are independent of any learning algorithm. The wrapper methods directly use predetermined learning algorithms to evaluate the features. The wrapper methods are computationally more expensive than the filter methods in terms of accuracy. When dealing with huge number of features, filter methods are usually adopted due to their computational efficiency. The basic components in filter methods are the criterion function and the search algorithms. The criterion function is to find the feature ranking based on the separability measures and discriminatory power. Search methods evaluate the individual features according to their goodness and select feature subset [14-17].

In recent times, several authors [18-22] proposed hybrid approach for feature selection taking advantages of both filter and wrapper methods. In the hybrid method, filter method is applied to select a feature from the pool and then the wrapper method is applied to find the optimal subset of features. This makes feature selection faster since the filter method rapidly reduces the effective number of features under consideration. If the cut-off point is set low for a ranked list to select feature in filter method, hybrid method reduce the risk of eliminating good features by the filter methods.

After finding the feature vector for proper representation of input pattern, a classifier is designed using a number of possible approaches. The choice of classifier is a difficult and is often based on the available or best known classifier. In most of the work referred here, number of features extracted to represent a character varies from 25 to 100. As the number of features increases, the complexity classification and recognition system also increases. In view of the above, an attempt is made to extract/select few features to represent the character. To evaluate the performance of proposed feature extraction and selection algorithms novel statistical classifier is designed for the character recognition.

II. METHODOLOGY

The general methodology of character recognition system used in this work is shown in the Fig.1. The numeral database in binary form is divided into training and testing samples. The binary images are partitioned into overlapping and non-overlapping regions, viz horizontal, vertical, rectangles, diagonals and squares for feature extraction. A feature from each region is extracted by the two approaches called A_1 and A_2. The set of features extracted are evaluated and selected only required number of quality features from the large set of features. The KB is build using all the extracted features and only by using the quality features. To classify the unknown samples, their features are matched with the KB using statistical technique.

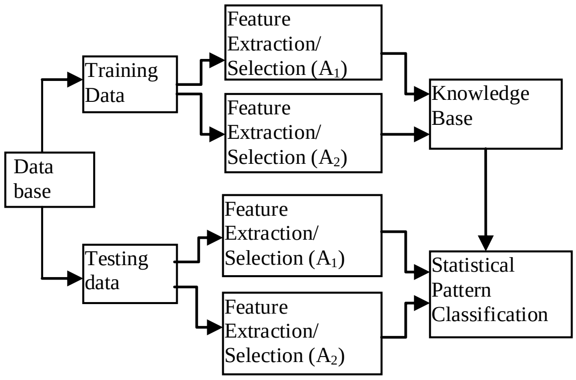

Fig.1.The methodology used in character recognition system

III. FEATURE EXTRACTION/SELECTION

The character images are pre-processed and transformed to a binary form before the feature extraction. The binary images are fitted in a window of size 15 x 15. Fig. 2 shows a binary image one used in the work. Fig. 2(a) shows the size normalized and pre-processed binary image of numeral 4. Fig.2 (b) shows the binary image stored in a matrix (P). The value of matrix elements, P_{ij} is '1'if the portions of black runs pass through the cell or otherwise '0'. The binary image matrix is partitioned into 16 regions to extract one feature from each. Fig.2(c) shows the shape of partitioned regions with their identification number. The shape of regions are so selected that most of these regions for all the classes have the portion of one's. However, there could be empty regions for some samples and such regions will have zero feature values.

A. Feature extraction

Fig.3 shows the flow diagram of the feature extraction algorithm. Feature of a region is computed from the presence of one's in each is transformed to a real number, by the two approaches A_1 and A_2. The set of features (feature vector) such obtained to represent the characters are used to build the knowledge base. The major advantage of these approaches is the simplicity of implementation.

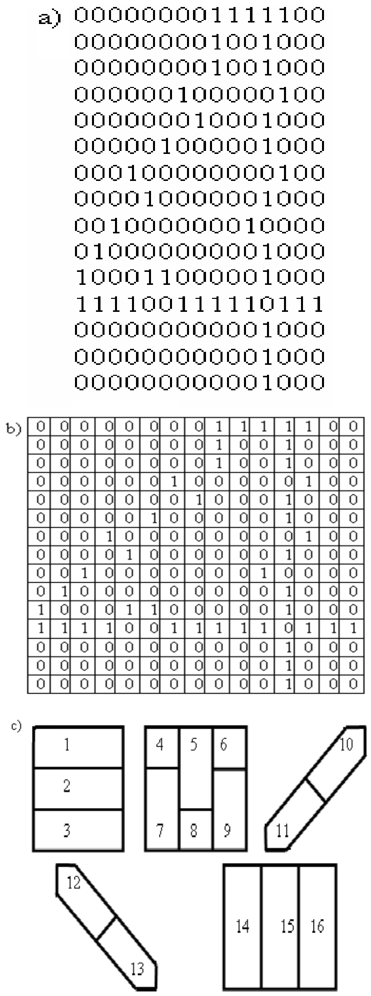

Fig.2 The pre-processed binary image of feature extraction a) Size normalized binary image of a numeral 4. b) Binary image in a matrix c) 16 partitions of binary image.

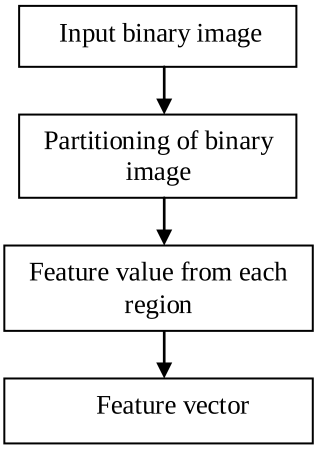

Fig.3. Feature extraction algorithm

In the first approach A_1, a feature computed from the density of one's in a region. The number of one's elements in a region is divided by the total number of elements in that region. A feature value of r^{th} region, f_r is computed by the Eq. (1). In this, the variation of one's position due to writing styles does not change the feature value. This shows the robustness towards variations in the writing styles.

$$f_r = \frac{1}{q_r}\sum_{i=1}^{q_r} p_{ij} \quad j = 1, 2 \ldots\ldots n \qquad (1)$$

where, f_r = feature value of r^{th} region, q_r = total number of cells in the region *r*, P_{ij} = value of cell in i^{th} row j^{th} column of a matrix *p* in the region *r*

In the second approach A_2, the coordinate distance of one's elements of a matrix are measured by considering the top right corner of the matrix as absolute origin (0,0) as the reference point [6]. The coordinate distance of r^{th} region of i^{th} row j^{th} column matrix element, P_{ij} is computed by the Eq.(2). The normalized feature value of r^{th} region is obtained by dividing the sum vector distances of one's elements in a region by the sum vector distances of all the elements in that region and is given in the Eq. (3).

$$d_{ij}^r = \sqrt{i^2 + j^2} \text{ for } d_{ij}^r = 1 \qquad (2)$$

$$f_r = \frac{\sum_{i, P_{ij}=1}^{q_r} d_{ij}^r}{\sum_{i}^{q_r} d_{ij}^r} \qquad (3)$$

where, d_{ij}^r is the r^{th} region coordinate vector distance of i^{th} row j^{th} column of matrix, f_r = r^{th} region feature value, q_r= total number of elements in r^{th} region.

B. Feature Selection

Fig.4 shows the various stages involved in feature selection algorithm. A feature subset from the set of extracted feature is selected in two steps. In the first step, the class discriminating ability of each region is evaluated by computing the variation involved in the mean interclass region features and assigned the feature evaluation index (FEI). The FEI of r^{th} region feature is computed by using Eq.4. and is used to rank the region features.

$$FEI_r = \sum_{i=1}^{C}\sum_{k=i+1}^{C}(f_{ij} - f_{kj}) \quad j=1,2\ldots.n \qquad (4)$$

where, *C* is the number of classes in data base, f_{ij} and f_{kj} are the j^{th} region feature value of i^{th} and k^{th} class. *n* is total number of regions.

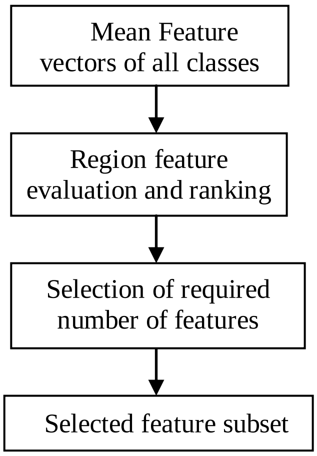

Fig.4. Feature selection Algorithm

In the second step, region features are ranked based on the FEI. The top rank is assigned to a region feature having highest FEI and required numbers of top ranked features are selected from the list.

III. CLASSIFICATION AND RECOGNITION

To recognize the unknown sample, the Knowledge Base (KB) is constructed using mean and standard deviation involved in the training sample interclass region features. The unknown sample features are matched with the reference class features of the KB and the class with which it matches is assigned to a unknown sample.

A. *Classifier design*

The KB is constructed from the statistical information of region features. The mean feature ($\overline{f_r^k}$) and the standard deviation (σ_r^k) of kth class is computed from the training samples using Eq.(5) and (6) respectively.

$$\overline{f_r^k} = \frac{1}{m^k}\sum_{i=1}^{m^k} f_{ri}^k \tag{5}$$

$$\sigma_r^k = \sqrt{\frac{1}{m^k}\sum_{i=1}^{m^k}\left(f_{ri}^k - \overline{f_r^k}\right)^2} \tag{6}$$

for r = 1, 2…………n,
i = 1, 2…………m^k

where, n = total number of regions, m^k = number samples in kth class, f_{ri}^k is the kth class rth feature value of ith sample, $\overline{f_r^k}$ = mean eature value of rth region and σ_r^k = standard deviation of kth class rth region feature.

To allow the variability involved in writing styles, a deviator 'α' is used to fix the feature range. The value of α is found experimentally and at equal to 2, the recognition system gives better classification rate. For each region, minimum and maximum value of a feature range is found by adding and subtracting the product of deviator and standard deviation from the mean feature value. Eq. (7) and (8) were used to find the feature range.

$$f_{r\min}^k = \overline{f_r^k} - \alpha\sigma_r^k \tag{7}$$

$$f_{r\max}^k = \overline{f_r^k} + \alpha\sigma_r^k \tag{8}$$

B. *Recognition scheme*

The similarity measuring technique is proposed to classify the unknown samples. The features of unknown samples are matched with the corresponding region features all the classes. If the region feature falls within the range (minimum and maximum values) of class region KB, feature matching index (FMI) is assigned one. If the feature value does not fall in the reference, FMI is assigned zero. The kth class rth region FMI is computed by the Eq.(9).

$$FMI_r^k = \begin{cases} 1, if\ (f_{r\min}^k \le f_r^k \le f_{r\max}^k) \\ 0, otherwise \end{cases} \tag{9}$$

The FMI assigned to different region features for the individual classes when unknown sample features are matched are added and is given using the Eq.(10).

$$FMI^k = \sum_{j=1}^{n} FMI_r^k \tag{10}$$

The unknown sample is assigned to a class having highest FMI.

IV. RESULTS AND DISCUSSIONS

The handwritten numeral database is used to evaluate the proposed algorithms. The database was pre-processed and in the binary form has 440 representatives samples collected from different standard databases. This database is equally divided into training and testing samples and each has 22 samples in all the10 numeral classes. The proposed algorithms were realized in "C" program language.

The feature vectors, having 16 features are extracted for both the training and testing samples by the two approaches A_1 and A_2 as discussed earlier. Fig. 5 shows the intraclass feature vectors of training samples of numeral class '0'. Fig. 5(a) shows the feature vectors of 22 training samples obtained by the approach A_1 and Fig.5 (b) shows that of approach A_2.The quality of feature is measured by the differences existing in the intraclass and interclass feature values. The quality of region feature is good, if variation is minimum in the intraclass and maximum in the interclass. From the results, observed that the minimum difference in intraclass region features. The feature values are almost same in both the approaches. This is the basic requirement of quality features to have rigidity towards the variations in writing styles. However, some of the feature values differ slightly due to different length of black runs in the regions intraclass of samples. However, the shift in position of black runs does not change the feature value in approach A_1 and it changes the feature value in approach A_2.

Fig. 6 shows the mean feature vectors of 10 numeral classes. The mean feature vector is computed from the 22 training samples. The feature value of different region varies from 0.0 to 0.3 for all the classes. Fig.6 (a) and (b) shows the mean feature vectors obtained by the approaches A_1 and A_2 respectively.

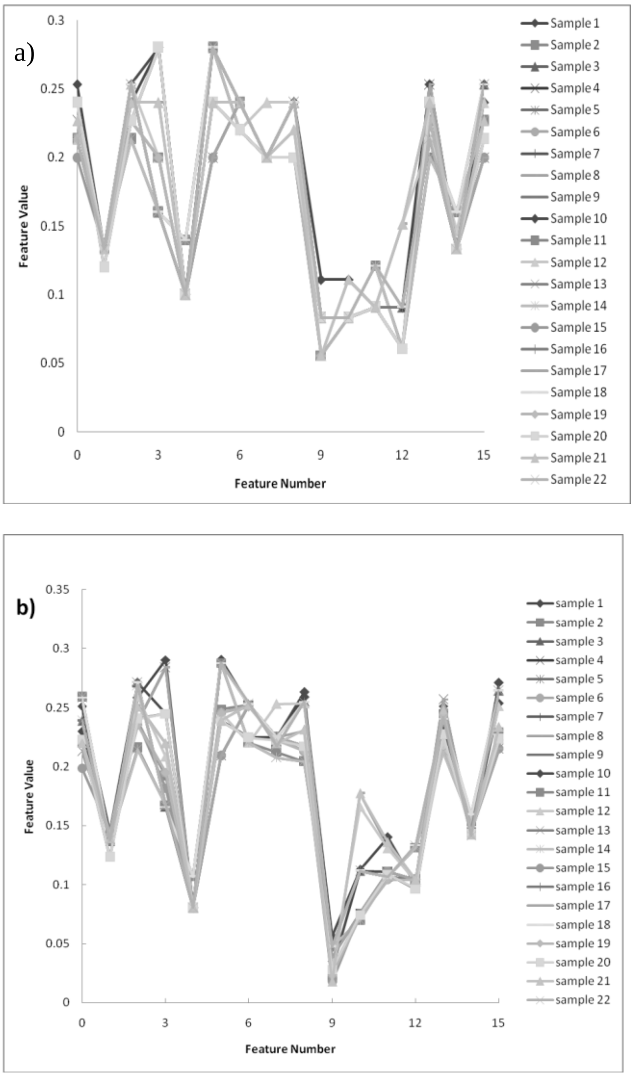

Fig.5 Intraclass feature vectors of training samples of numeral class '0' a) Feature vectors extracted by the approach A_1 and b) Feature vectors extracted by the approach A_2.

The variation in interclass region feature value indicates the quality of features. These features have sufficient variation in both the approaches. This indicates that the extracted features are distinctive, prominent and more powerful to represent a particular sample in class separation. However, some of the features discussed elsewhere have minimum interclass difference and the contribution of these features is modest in class identification.

Table.1 shows FEI value and their ranks assigned to each region feature by the approaches A_1 and A_2. The analysis shows that in approach A_1, feature value of a region 3, f_3 has top ranking and that of region 7, f_7 has least ranking. In approach A_2, f_8 has top ranking and f_{12} has least ranking. Features having low ranking with less discriminative power are eliminated from the extracted feature set.

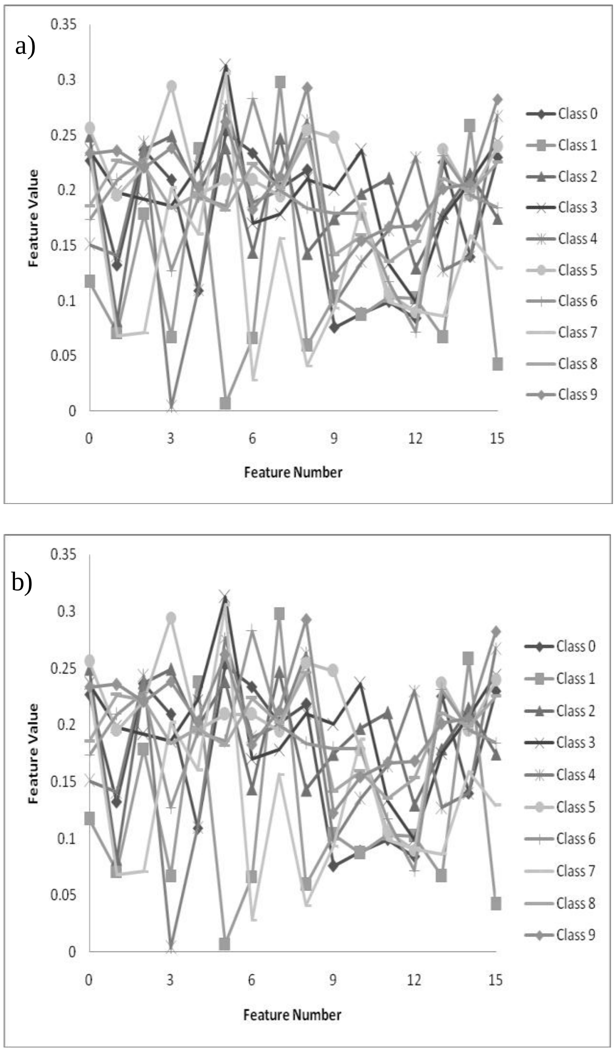

Fig.6. Mean feature vectors of 10 numeral classes a) Mean of feature vectors extracted by approach A_1. b) Mean of feature vectors extracted by approach A_2.

When the cut-off point is set to 12 features, four features having least FEI values are identified from the list of extracted 16 features. Table.2 shows the order of features having least FEI values and low ranking.

Fig. 7 shows the variation in class classification rate of different numerals with the varying value of deviator, α from 0 to 3. It is observed that, the classification rate vary with the value of α.

Table1. FEI values of a features and their ranks

Test sample	No. of Features matched with class (FMI) 0	1	2	3	4	7	5	6	8	9	Class assigned to unknown sample
1	16	6	8	11	10	11	9	7	10	7	0
2	16	6	9	12	8	10	12	8	10	4	0
3	16	6	9	11	10	10	10	8	12	7	0
4	16	6	9	10	8	10	12	6	11	4	0
5	16	6	10	12	10	10	10	9	12	7	0
6	16	6	9	12	8	10	12	8	10	4	0
7	15	6	10	11	9	9	11	7	10	5	0
8	14	6	7	11	12	11	10	8	11	8	0
9	16	6	9	11	10	10	10	8	12	8	0
10	13	5	9	11	8	8	9	7	11	7	0
11	16	6	11	13	10	9	10	9	11	7	0
12	13	6	9	10	12	11	9	8	10	7	0
13	16	6	11	13	10	9	10	9	11	7	0
14	16	7	8	9	12	9	10	9	11	7	0
15	16	6	9	12	8	10	12	8	10	4	0
16	16	6	9	11	10	10	10	8	12	7	0
17	16	6	9	10	8	10	12	6	11	4	0
18	16	6	10	12	10	10	10	9	12	8	0
19	16	6	9	12	8	10	12	8	10	4	0
20	15	6	10	11	9	9	11	7	10	5	0
21	15	6	10	11	9	9	11	7	10	5	0
22	16	6	9	11	10	10	10	8	12	8	0

Table 2. List and order of features having least FEI value and low ranking.

Sl.No.	Feature having least rank: Approach A1	Approach A2	Rank
1	**f_7**	**f_{12}**	**16**
2	**f_{14}**	**f_{14}**	**15**
3	**f_{11}**	**f_7**	**14**
4	**f_4**	**f_0**	**13**

When the α value lies between 0.0 to 1.6, the corresponding standard deviation from the mean is minimum and results in a narrow feature vector range in KB. When the unknown sample feature vector is matched with the narrow feature range, less number of features matches for both the correct class and other classes. These results in more than one class have maximum FMI value and results in misclassification of unknown sample. For the value of α is more than 2.4, the feature range of a KB is widen. When the feature vector of unknown sample matched with the feature range of KB, more number of features matches with the correct class and also with the other classes. But, if the value of α is between 1.6 to 2.4, the classification rate more than 90% for most of the classes. But when the value of α is equal to 2, it is observed that the classification rate is maximum and 100% for all the numeral classes. Hence, the value of *α* is assigned to two and is used in the classifier design and recognition system.

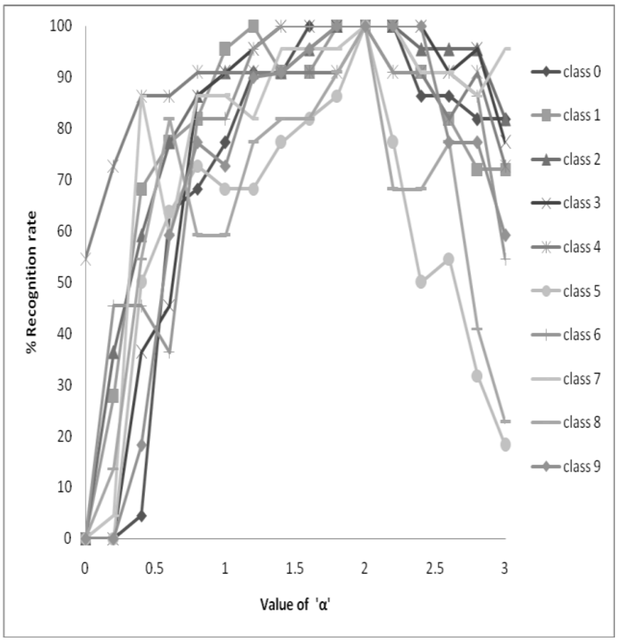

Fig.7 variation in classification rate of different numerals with the varying value of α

Table 3. FMI value and the experimental result of 0th class training samples training samples.

Region/ Feature No.	Feature Rank	Feature Evaluation Index	Feature Rank	Feature Evaluation Index
0	10	2.407272	14	2.113374
1	6	3.490302	6	3.548697
2	12	2.201817	12	2.242220
3	**1**	**4.538181**	3	4.139120
4	13	2.173636	10	2.386720
5	3	4.241818	2	4.147029
6	4	3.985454	5	3.561803
7	16	1.858182	13	2.205792
8	2	4.447273	**1**	**4.501524**
9	11	2.938131	7	3.339897
10	8	2.454545	9	2.568175
11	14	1.882921	11	2.333042
12	9	2.449036	16	1.799582
13	7	3.170908	8	3.328611
14	15	1.863636	15	2.036095
15	5	3.651516	4	3.776415

The classification rates are found with the extracted 16 and selected 12 features for both the approaches A_1 and A_2. Features of training samples were matched with the KB and FMI value of all the numeral classes found for each sample. *Table 3* shows the FMI value and the experimental result of 0^{th} class training samples. All 16 features match with the 0^{th} class for most of the samples. However, for samples 8, 10, 12, etc all the features not matches, but they have maximum FMI value. For all the sample, 0^{th} classes has maximum FMI value and therefore they are classified as numeral '0' Table 4 shows the classification and recognition results of individual numeral class with the extracted 16 features and the selected 12 features by both the approaches A_1 and A_2. The classification rate was 100% for both the approaches. The classification rate reduced to 99.09% with 12 features. To find the recognition rate, feature vector of unknown sample is extracted by both the approach A_1 and A_2 as discussed earlier. Feature vectors are with the reference sample and the recognition rate is 97.27% and 98.18% for the approaches $_{A1}$ and A_2 respectively with 16 features. It is 95.824% and 97.27 % with 12 features respectively for both approaches A_1 and A_2.

Table 4. Classification and recognition rates with the extracted 16 and selected 12 features of both the approach $A_1$and A_2.

Numeral	Classification rate				Recognition rate			
	With 16 features		With 12 features		With 16 features		With 12 features	
	A_1	A_2	A_1	A_2	A_1	A_2	A_1	A_2
0	100	100	100	100	100	100	100	100
1	100	100	100	100	100	100	100	100
2	100	100	100	100	100	100	95.45	95.45
3	100	100	95.45	100	95.45	95.45	95.45	95.45
4	100	100	100	100	100	100	90.09	95.45
5	100	100	95.45	95.45	90.9	95.45	90.9	95.45
6	100	100	100	100	100	100	100	100
7	100	100	100	100	100	100	100	100
8	100	100	100	95.45	95.45	90.9	95.45	90.9
9	100	100	100	100	90.9	100	90.9	100
Over all recognition rate	**100**	**100**	**99.09**	**99.09**	**97.27**	**98.18**	**95.824**	**97.27**

V. CONCLUSION

The experimental results reveals that the features extracted from each region have minimum difference among the intraclass and maximum difference among the interclass. The feature values of regions extracted from two approaches A_1 and A_2 using zoning technique have similar values. However, the evaluated features of a region have different feature ranking. Further, when 12 top ranking features are used for the classifier design and recognition, the different region features are selected. To fix the feature range in a KB, the value of deviator α is found to be optimum at α equal to two. At this value, maximum classification rate is obtained for all the individual numeral classes. The designed statistical classifier with 16 and 12 features have 100% classification rate and good recognition. Hence, the proposed feature extraction, selection and the classifier can be used for character recognition and in general for any pattern recognition system to achieve good classification and recognition rate.

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