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Feature Extraction and Recognition Using Soft Computing Tools

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Abstract— The face is the primary focus of attention in social life playing an important role in conveying identity and emotions. A number of faces can be recognized learned throughout lifespan and identify faces at a glance even after years of separation. This skill is quite robust despite of large variations in visual stimulus due to changing condition, aging and distractions such as beard, glasses or changes in hairstyle. Computers that detect and recognize faces could be applied to a wide variety of tasks including criminal identification, security system, image and film processing, identity verification, tagging purposes and human-computer interaction. Unfortunately, developing a computational model of face detection and recognition is quite difficult because faces are complex, multidimensional and meaningful visual stimuli.

In the present research work, the main aim is to study the techniques of face recognition for image segmentation and image analysis respectively using soft computing approach based on the fuzzy logic and neural network. To extract features from the facial image and to recognize the same by using fuzzy clustering and bunch graph method.

Index Terms— Face recognition, Feature Extraction, Fuzzy Logic , and Neural Network.

1 Introduction

This paper is focused in the process of preprocessing the image, extract the features and recognition of her/his face presents, interesting from the computer point of view. Although a human may solve most of the problems implied and achieve a high degree of adequate recognition since early in life, computer systems have important limitations when confronted with the same problem. The objectives of the research paper is to study various techniques face recognition, To recognize a human face using concept of fuzzy clustering technique of N samples with respect to R representative class and To extract features from the facial image and to recognize the same by using bunch graph method.

2 Related Work

Brunelli and Poggio [4] have implemented two algorithms. One is based on the computation of a set of geometrical features, such as nose width and length, mouth position and chin shape and the other is based on the gray-level template matching. They have reported that the face recognition based on geometrical features gives around 90% correct recognition where as template matching gives perfect recognition. But template matching is very time consuming and cannot handle large database of facial image. On the other hand, the feature based face recognition can handle large database of faces, but gives a result which is less than 100%.

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Krisnamurthy and Ranganath [5] have reported a feature based face recognition system by using the Eigenspaces and wavelet approaches, which gives comparatively good result. Chaddha, et.al [6] have proposed a neural network based technique for recognition of human faces using the outline profile of the end view of the human face. This pattern yields a set of good discriminate features for identification. Here nose point, chin points, forehead point, bridge points, nose bottom points, throat points, upper lip point, mouth of centre lip point, chin curve point or lip bottom point, brow points are extracted and they are trained by using a back propagation neural networks. As a new face is given as the input of the network, it is able to recognize the face. The accuracy of the system is not good, as it is taking only the side face features.

Sinhab [7] has proposed an adaptive neural network based approach , by which the pair of images to be compared should be presented to the neural network as source (input) and target images. The neural network learns about the symmetry between the pair of images by analyzing the examples of associated feature pairs belonging to the source and target images. From such pairs of associated features, the neural network searches out proper locations of target features from the set of ambiguous target features by fuzzy analysis during its learning. If any of target features searched out by the neural network, lies outside the prescribed zone, the training of the neural network is unsuccessful. In case of successful training, the neural network gets adapted with appropriate symmetry relation between the pair of images. When the source image is input to the trained neural network, it gives a processed source image as output which is later superimposed in target image and identity is established.

Zhang and Fulcher reported a face recognition system using Artificial Neural Network Group-based Adaptive Tolerance (GAT) Trees [8]. It is a hierarchical classification, maps on to binary tree structures where each leaf node corresponds to a separate category

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of faces. Decisions are made in descending down the tree, through each intermediate node, as to whether the current input sample belongs to a specific subclass or not. Only N-levels are required in practice to discriminate between a large (2^N) categories.

Robert and Ritter [9] have proposed an artificial neural network method for human face recognition. They have used three neural networks of local linear maps types, which enable a machine to identify the head orientation of a user by learning from examples. One network is used for color segmentation, the second for localization of the face and the third for the final recognition of the head orientation. This technique could not gain importance, because it suffers from mapping problems.

Goudail and et. al [10] have investigated the face recognition method based on the computation of auto-correlation coefficients. The auto correlation coefficients are computationally inexpensive, inherently shift-invariant and robust against changes in facial expression. But it can be further extended by segmentation of module based on template matching. Kondo and Yan [11] have reported a feature based face recognition using Cross correlation.

Wiskott, et. Al [12] has proposed a technique, where faces are represented by labeled graphs based on Gabor Wavelet transform. Image graphs are extracted by an elastic bunch graph matching process and can be compared by a simple similarity function. It is a general method, used for recognizing members of a known class of objects. But it is no way specialized to faces. Later Yeal Adini [13] has improved the method using 2D Garber like function, which can recognize face with respect to the change in illumination condition. Larry [14] has gone a little further and proposed a method to recognize to human facial expression by long image sequence optical flow. Narendra [15] has proposed a transformation technique to extract image regions at all geometric and photometric scales. It is intended as a solution to the problem of multi-scale, integrated edge and region detection or low level image segmentation.

3 Face Recognition Using Fuzzy Clustering Technique

Psychological studies by Gardener H [17] ,reveals that the human being recognizes the face from the selected features of the face such as pattern of the eye, structure of the nose, size of the mouth, shape of the eyebrow, forehead, etc. This human like reasoning is exploited to design a cognitive model for face recognition using fuzzy clustering technique. A large number of the existing clustering techniques without supervision are available for image matching Young, A. N. and H.D E llis Eds [18] andBaron, R.J [19]. Among them nearest mean classification by J.J. Hall and S. N. Srihavi [20], non-arametric clustering Kanade T [21], hierarchical clustering Amit. K [20] and interactive clustering Young, A. N. and H.D E llis Eds [18] are important. The creation of R-dimensional matrix from the facial database images is described as follows:

a) First, the facial image template is partitioned into few distinct segments like eye, nose and mouth. The process is done through a moving window of eye, nose and mouth over the facial image. These selected segments of the face such as eye, nose and mouth are compared with the few representative nodes of eyes, nose and mouth respectively. These representative eyes, noses and mouths are selected based on an intuitive method to cover all the variations of facial features, such a long eye, short eye and normal eye, long nose, flat nose and moderately small nose, long lip mouth, short lip mouth and normal mouth. These representative nodes are the cluster centers of their respective clusters.
b) After comparison with all the representative nodes, the distances of descent of the eye, nose and mouth of a facial image are recorded in a matrix namely fuzzy scatter matrix as shown in Fig. 4.2. During the recognition process, matching of the test face with the entire facial database is not required, but the comparison is done only with 'R' representative nodes, thereby saving the processing time by a factor of (R/N).

3.1 Fuzzy Clustering Technique

The fuzzy clustering is a numeric value (FC) assigned to every possible classification of a collection of samples. Here, the domain of FC is the set of all possible classification of a collection of samples. The range of FC consists of the real numbers classifications. The adapted definition of a cluster is assumed to correspond the extreme values of FC. Thus given the value of FC, any particular classification can be evaluated.

Selection of Representative nodes: The selection of proper representation nodes is the most difficult task in fuzzy clustering technique. No unified theory for choosing the representative node has been developed. Therefore, the heuristic approach has been used in the present research work in selecting the nodes, which cover all the variations of facial features, such a long eye, short eye and normal eye, long nose, flat nose and moderately small nose, long lip mouth, short lip mouth and normal mouth.

The distance of descent of each feature is estimated from the respective representative nodes by the measurement of fuzzy cross correlation derived in the next subsection. The input to the program is a data matrix of front face image of 64X64 pixel size taken either by a CCD camera or scanner.

Distance of Descent: During the matching process the distance is computed for the unknown image, with respect to 'R' representative class. Next, these distances are compared with N samples of n vectors. The minimum distance known as distance of descent is found out from the N samples denoted by

$$\textit{Fuzzy distance of descent} = \max\left(\bigvee_{i=1}^{N} \bigwedge_{j=1}^{R} C_{ij}\right) \tag{4.5}$$

Similarly, the fuzzy distance of descent is found out for each feature. Finally, the image is recognized by a fuzzy If Then rules.

3.2 SIMULATION AND RESULTS

The computational environments to take the facial images are given in Table 4.1. This technique has been tested with Yale database and with personal set of 400 images of 40 classes. But for the demonstration of the algorithm, a smaller database of 15 images from Yale database as shown in Fig. 4.4. The prominent features such as eye, nose and mouth are extracted by the cross-correlation method. Each eye, nose and mouth is compared with the representative eye, nose and mouth of three

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each. In the Simulation, nose of facial image 1, facial image 3, facial image 4 and facial image 12 are taken as reference nose class to include all the varieties of size and shape. Similarly, eyes of facial image 1, facial image 3, facial image 6 and facial image 10 are taken as reference eyes-class and mouths of facial images 3, facial image 4, facial image 9 and facial image 13 are taken as reference mouth-class from Fig. 4.3. These fuzzy scatter matrices are estimated by fuzzy MAX/ MIN operator after getting the fuzzy distance of descent for eye, nose and mouth. During the recognition phase, the face is recognized by a (fuzzy IF ... THEN) rule. For instance any test face has to be matched with the existing data

base, the eye, nose and mouth of the test face is first extracted and the measurement of the distance from the reference classes is found out. This R-dimensional vector is compared with the fuzzy scattered matrix which is given Table 4.2 for Fig.4.3. The R-dimensional vector is also compared with the fuzzy scattered matrix which is given Table 4.3 for Fig.4.4. The distance of the descent is estimated from the N dimensional sample data and the matched image is found out.

Table 3.1: Computational environment

Conditions	Training Images	Test Images
Lighting conditions	Variable	Variable
3D moments	No	No
Expression	Variable	Variable
Distance from camera	Fixed	Fixed
Spectacles	Yes	Yes
Beards	No	No
Mustaches	No	No
Hair style changes	No	No
Background	Variable	Variable

Fig 3.1: Yale database of facial images

Table 3.2: Fuzzy scattered matrix estimated from the distance of the sample classes from the reference nodes using cross-correlation operator

Image Faces	N1	N7	N14	N15	E5	E9	E10	E11	M1	M7	M11	M15
F1	0.0	12.3	9.7	19.4	35.5	16.7	41.5	31.1	0.00	13.3	14.7	18.9
F2	21.3	31.6	22.8	36.3	25.2	12.7	19.6	24.0	18.7	17.4	21.9	20.8
F3	12.3	38.9	13.8	8.5	16.7	6.6	18.1	14.6	4.9	12.6	13.7	20.2
F4	9.7	13.8	9.9	20.4	18.0	9.8	25.3	13.0	13.2	15.9	15.7	18.9
F5	16.4	9.4	20.5	8.1	0.0	22.4	24.7	30.9	39.4	14.6	6.2	15.9
F6	9.2	6.6	13.8	16.1	41.5	18.1	25.8	18.2	12.6	29.5	41.6	9.8
F7	27.2	0.0	29.7	44.1	40.6	22.7	19.5	26.9	12.2	0.00	21.9	16.2
F8	7.6	19.5	9.8	27.1	34.7	15.8	12.9	21.5	41.2	16.9	21.7	29.6
F9	4.8	18.0	12.2	25.8	36.4	0.00	12.0	21.7	14.8	29.8	16.5	30.6
F10	10.5	24.8	10.9	23.9	45.8	14.7	0.0	19.9	17.8	18.9	26.7	15.8
F11	4.1	16.1	9.4	23.5	31.1	14.6	18.2	0.0	12.9	22.7	0.00	29.7
F12	10.3	5.8	15.3	14.2	39.5	18.9	13.8	25.5	21.6	29.6	13.7	6.0
F13	19.4	8.5	20.4	28.7	20.7	5.7	15.8	16.4	13.9	21.7	23.6	9.5
F14	13.8	4.2	0.0	11.4	29.7	8.8	11.6	14.8	29.1	26.5	9.6	45.9
F15	21.2	32.7	26.0	0.0	22.9	6.6	19.3	17.0	11.2	9.8	13.6	0.00

3.3 Results of fuzzy clustering

3.3 DISCUSSION OF RESULTS

Table 3.4 shows the results of fuzzy clustering method which gives the number of recognized face images, the number of unrecognized face images and efficiency of face images. Table 4.5 shows the comparison of acceptance ratio and execution time values for 40, 60,120,160,200 images using principal component analysis (PCA), PCA BPNN (back-propagation neural network) and fuzzy clustering. The comparison shows the fuzzy clustering is better than the PCA and the PCA

No. of Face Image	Successfully Recognized	Face Image Unrecognized	Face Image Efficiency (%)
40	39	1	97
60	56	4	94
120	111	9	92.2
160	144	16	89.7
200	178	22	89

BPNN with respect to blurred images and 5% degree of orientation. The fuzzy clustering takes lesser execution time than

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PCA and PCA BPNN for large set of images as it takes only representative class nodes

Table 3.4 Comparison of acceptance ratio and execution time for Yale database images

Number of images	Acceptance Ratio (%)			Execution Time(Seconds)		
	PCA	PCA with BPNN	FUZZY CLUSTERING	PCA	PCA with BPNN	FUZZY CLUSTERING
40	92.4	96.5	97	38	36	30
60	90.6	94.3	94	46	43	44
120	87.9	92.8	92.2	55	50	54
160	85.7	90.2	89.7	67	58	60
200	83.5	87.1	89	74	67	62

The graphical analysis of acceptance ratio and execution time are shown in Fig 3.2 and Fig 3.3 respectively. The acceptance ratio obtained for fuzzy clustering technique is as good as that of PCA BPNN technique. The acceptance ratio obtained for fuzzy clustering technique is higher than that of PCA technique as shown in Fig.3.2. The reasons are as follows:

1. In case of principal component analysis (PCA) any change in the distance, location or orientation of the input object in relation to the corresponding stored object produces a different pattern. Any distortion of the input object may also produce inaccurate matching.
2. In case of fuzzy clustering techniques, the representative eyes, noses and mouths are selected based on an intuitive method to cover all the variations of facial features.

The fuzzy clustering technique is taking lesser execution time as compared to PCA and PCA BPNN for larger number of images as shown in Fig.4.6. PCA takes more execution time as it works on the principle of template matching. The template matching works well for a standardized set of numbers and is inadequate for complex pattern recognition.

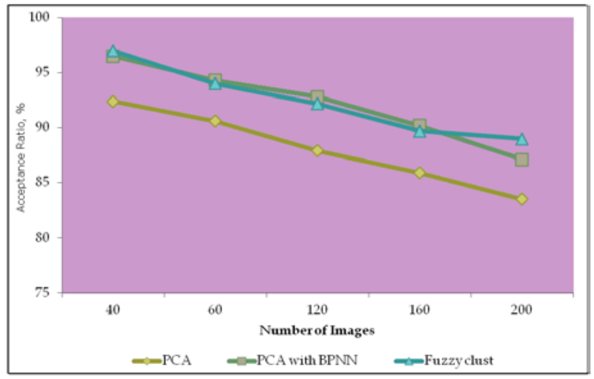

Fig 3.2: Comparison of Acceptance Ratio of fuzzy clustering with PCA and PCABPNN

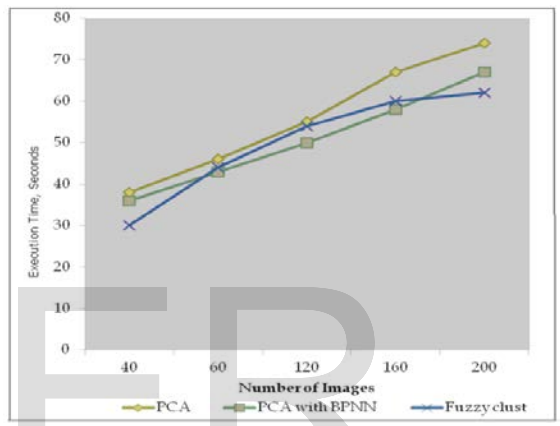

Fig 3.3: Comparison of Execution Time of fuzzy clustering

4 Face Recognition By Bunch Graph Method

One of the most remarkable ability of human vision system is to recognize faces. It is important for several aspects of our social life. There are two distinct techniques applied to recognize the facial images Bernd Jahe [24]. The first technique is based on the template matching from the image database and the second technique emphasis the computation of a set of features taken from the face image. Subsequently, various mathematical parameters, which are to be extracted from facial image such as Eigen vectors, wavelets, and fiducial points, have been utilized for the face recognition. In the present work, the bunch graph is used as the geometric features of the face L. Wiskott [26]. First is face is detected by a frame grabber. The selected locations in the image are often called fiducial points. The fiducial points are selected manually and the vectors are estimated by joining the fiducial points.

The fiducial points are extracted and then the vectors are estimated. After getting the fiducial vectors, the rotation invariable facial images are grouped under a particular class. These faces are being trained with a number of neural networks in the group. Based on the dissimilarity measurement of the facial geometric symmetry, its class is determined and the parameters are fed to that particular adaptive neural network Law T [02]. During the test phase, the fiducial points are extracted

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from the facial image. The vectors and dissimilarity measurements of the face are done in same way as in trained faces. The test face is fed to one or two adaptive neural networks based on the dissimilarity measure. The outputs of individual NN are fed to the AND/OR node to get the nearest matched facial imag.

4.1 FEATURE EXTRACTION BY BUNCH GRAPH METHOD

A bunch graph G represents a face that consists of 'n' nodes connected by E edges. The nodes are located at facial land marks x_n , where n=1,2,….N, called 'fiducial points', i.e. the pupils of the eye, the corner of the mouth, the tip of the nose and bottom of the nose, top and bottom of the ears etc., The edges are labeled with two dimensional distant vectors Δx_e,=x_n-x_m, e=1,2,……E. where edge 'e' connects node n and m. Intuitively selected geometric relationship is used to find out the relative positions of the node points for extracting bunch graph automatically of a face having geometrical relationship.

While considering the features of a face, some constraints are to be used in the process of feature extraction. It is obvious that every face has two eyes, one nose, one mouth, two ears with very similar layouts. This is considered as the first constraint in the feature extraction. The second constraint is the bilateral symmetry of the facial feature. These two constraints are used for selecting a particular neural network.

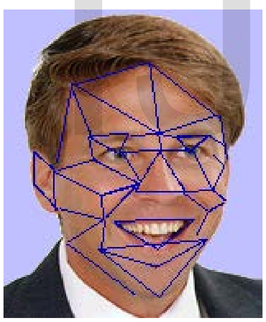

Fig 4.1: Fiducial points such as starting and end points of eyebrow, eye pupil, tip and side points of nose, two end points of mouth and tip of chin etc., and the edges joining these points.

The important features of the face are starting and end-points of eye brow, eye pupil, tip of the nose and bottom points of nose, tip of the lip, two end points of the mouth, tip of the chin, and top point of the forehead as shown in Fig.5.2. Mathematically, it is represented by x_n, n=1, 2, … ,N. Then the face is represented by a face graph consisting of the fiducial points x_n and the edges which are labeled with two dimensional distant vector Δx_e=x_n-x_m, where e=1, 2…E. and edge 'e' connects node n and m of the geometrical structure of the graph. Graphs for different head pose differ in geometry and local features. In order to extract image graphs automatically for new faces, one needs a general representation rather than models of individual faces. The representation should cover a wide range of possible variation in the appearance of faces, such as differently shaped eyes, mouths, or noses, different types of beards, variations due to sex, age and race etc. A representative set of M individual model graphs is generated like a stack-like structure, called a *Bunch Graph*. It is represented by G^{B_m} (m=1… M). Each model graph has the same grid structure and the nodes refer to identical fiducial points. A set of lines referring to one particular fiducial point is called a bunch. An eye bunch, for instance, may include lines from closed and open eyes to cover these local variations. The corresponding bunch graph *B* is then given the same grid structure as the individual graphs, its nodes are labeled with the bunches of lines $J_n^{B_m}$ and its edges are labeled with the averaged distances $\Delta x_e^{B} = \sum_m \Delta x_e^{B_m} / M$. The fiducial points for face images are as follows: Top forehead midpoint, Midpoint of the two eyebrows,Left and right eyebrow starting point, Left and right eyebrow end point, Nose Tip point, Right end of the nose; and so on.

The coordinates of the fiducial points are extracted from the facial image considering lower left corner of the image as the origin. These fiducial points and joining vectors are grouped in a specific orientation class. During the location of fiducial points in a new image of a face, the procedure described below selects the best fitted lines, from the bunch dedicated to each fiducial point.

4.2 GROUP BASED ADAPTIVE NEURAL NETWORK

The face recognition becomes difficult for a shift invariant and rotation invariant faces. When a face is shifted or rotated, the face recognition becomes considerably more difficult. To solve this, a translation-invariant face recognition technique has been developed. For this all shifted and rotated faces in two dimensions has to be included as training examples for the neural network node ,R.J.Shalkoff [27]. There by after training, the ANN group-based node is able to recognize shifted and rotated faces in two dimensions.

A set of adaptive neural networks can be selected in place of single neural network for pattern recognition involving a large number of classes along with noisy input. This has led to use multiple classifiers to improve classification performance. The classification is based on the dissimilarity measurement of the symmetrical parameter of the fiducials points. The choice of an individual classifier is typically ranked on the basis of confidence level. Here it is to be noted that the faces are grouped on the vector of the fiducial points. The ranked classifiers are combined using multiple classifier structure for the translation invariant face recognition. After classification, the bunch graph parameters are passed on to the adaptive neural network [8]. This neural network is trained on geometrical parameters of the facial features grouped on a particular orientation of the face as shown Fig.4.3. The outputs of this neural network are passed on to a AND/OR group operator, which finally gives decision about the face recognition.

4.3 RESULTS AND DISCUSSION

The computational environment is given in Table 4.1. 256 gray levels with an ambient lighting condition are taken for facial recognition.

12 numbers of class images are taken in the experiment as shown in Fig.4.3. Seven images out of ten per class have been taken for training the group based adaptive neural network and three images are kept for testing. The average age of the class is between 18 to 25 years. The central front face, 15^0 left rotated, 15^0 right rotated, 30^0 left rotated, 30^0 right rotated, 45^0 left rotated and 45^0 right rotated training cases have been taken for training the group based adaptive neural networks. For testing the algorithm, the facial images of same persons are taken into consideration. These image templates are then converted into intensity image and the geometrical parameters. The dissimilarity vector is estimated after getting the vectors for facial images. Then it is fed to the appropriate neural network. After the training phase is over; these neural network parameters are used for any test image for recognition.

Table 4.1: Computational environment

Conditions	Training Images	Test Images
Lighting conditions	Fixed	Variable
3D moments	Yes	Yes
Expression	Variable	Variable
Distance from camera	Fixed	Fixed
Spectacles	Yes	Yes
Beards	No	No
Mustaches	No	No
Hair style changes	No	No
Background	Fixed	Fixed

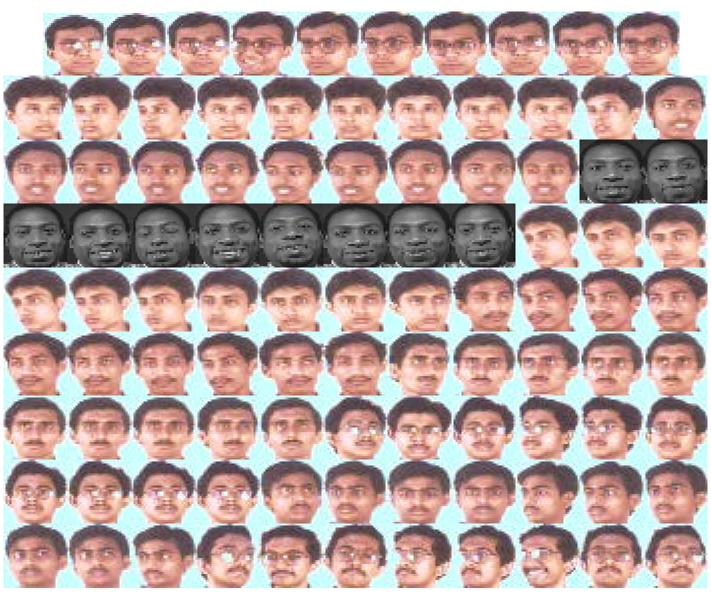

Fig 4.3: Example images used in our experiments

Table4.2 Results of bunch graph

No. of Face Image	Successfully Recognized	Face Image Unrecognized	Face Image Efficiency (%)
15	14	1	96%
50	47	3	94%
100	91	9	91.4%
150	132	18	88%
200	174	26	87%

Table 4.3 Comparison of acceptance ratio for images with degree of orientation using bunch graph and fuzzy clustering method

Images with Degree of orientation	Acceptance Ratio(%) with orientation	
	FUZZY CLUSTERING	BUNCH GRAPH
0	95%	92%
5	89%	94%
15	80%	93%
30	76%	90%

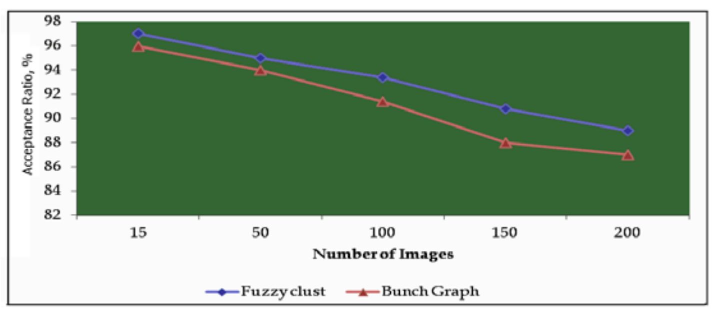

Fig 4.4: Comparison of Acceptance Ratio of bunch graph with fuzzy clustering

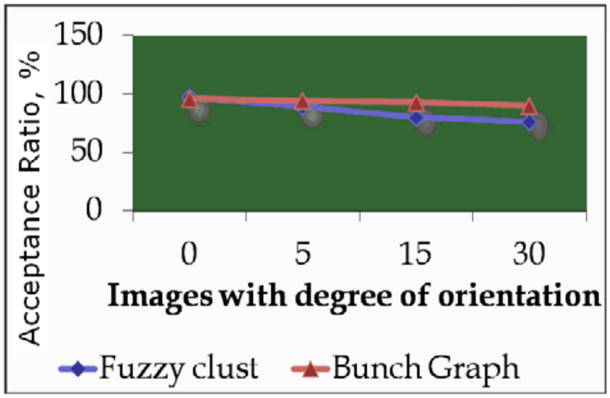

Fig 4.5: Comparison of Acceptance Ratio of bunch graph

The graphical analysis of the images without orientation and with orientation is shown in Fig 4.4 and Fig 4.5 respectively. The acceptance ratio of fuzzy clustering is higher than the bunch graph method when the images are without degree of orientation (zero degree). But the acceptance ratio of the bunch graph method is higher than the fuzzy clustering when the images are oriented at 50, 150 and 300. The reasons are as follows:

In fuzzy clustering, the images should be without orientation as given in computational environment Table 4.1. Fuzzy clustering selects representative nodes of facial features such eyes, nose and mouth of frontal face images. The distance of descent for each feature is estimated from the representative nodes. It is very difficult to select the facial feature if the face is rotated or shifted.

In bunch graph method, the neural networks are being trained on geometrical parameters of the facial features grouped on a particular orientation of the face shifted and rotated. The ANN group-based node is able to recognize shifted and rotated faces.

5. Conclusions

It has been observed that complicated algorithms have not been preferred in the intelligent systems due to the lack of analytical methods, which cannot handle uncertainty and ambiguous information. As a result, soft computing tools have been used in the area of face recognition. The proposed schemes are realized using soft computing tools. Fuzzy clustering technique has been developed to recognize faces. The bunch graph method is developed to extract features and recognizing the face with degree of orientation.

The fuzzy clustering technique recognized faces even if the images are blurred. This technique is proved to be 89% efficient in recognizing the faces without orientation for 200 images. Results of fuzzy clustering compared with PCA and PCA with BPNN techniques, the fuzzy clustering acceptance ratio and execution time is better than PCA and PCABPNN.

The bunch graph method stores individual geometric feature and can be used for classifying the face into a subclass of particular orientation and also for subsequent training of that particular neural network. The face recognition system using bunch graph technique gives 87% of accuracy with a class size of 12 without orientation for 200 images. The fuzzy clustering results are compared with that of the bunch graph, the fuzzy clustering is better than bunch graph when the images are with zero degree of orientation. The percentage of recognition increases with bunch graph method than that of fuzzy clustering technique as degree of orientation increases.

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