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Face Recognition System- A Survey and a New Approach

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Abstract – **Humans often use faces to recognize individuals and advancements in computing capability over the past few decades, these recognition systems are automatic now a days. Previous approaches in this field use simple geometric models, but now changed into a science of sophisticated mathematical representations and matching processes. Major advancements in face recognition took place in the past ten to fifteen years. This paper reviews the existing approaches of face recognition techniques and explanation of our fuzzy clustering based approach. A number of typical appearance and feature based approaches are discussed. Also, some efforts have been put in to develop a new approach in which we use PCA for dimension reduction, the projected feature space is formed using fuzzy c-means clustering algorithm.**

Keywords–**Face recognition, Face recognition techniques, PCA, fuzzy c-means clustering.**

I. INTRODUCTION

Human beings are equipped with the ability of face recognition. It improves over several years of childhood, is significant for several phases of our social life and, together with correlated abilities, such as estimating the appearance of people we interact with, played an important role in the course of evolution.

Face Recognition is something that human beings usually performs with less effort and without much sensible thought, although it seems to be a challenging problem in the field of computer vision, where some 20 years of research is just beginning to yield useful technological solutions. As a biometric technology, automated face recognition has a number of desirable properties that are driving research into practical techniques. The problem of face recognition can be stated as 'identifying an individual from images of the face' and encompasses a number of variations other than the most familiar application of mug shot identification. Facial recognition research and Facial recognition technology is a subfield in a vast field of pattern recognition research and technology. Pattern recognition technology utilized statistical facts to examine and extract patterns from the available data so as to match it with patterns available to us in a database. The data which we use in recognition system is a set of discernible pixel-level patterns because the system does not observe meaningful "faces" as a human would recognize them. Yet, it is important for these schemes to be able to spot a face in a field of vision so that it is only the image pattern of that is processed and analysed.

Research in the field of face recognition ongoing in 1960.s with the original effort of Bledsoe. In the 1960s, the leading semi-automated model for face recognition was introduced which work on the location of the topographies such as nose, mouth, and ears on the pictures and then estimate the distances and ratios to a shared reference point. This fact then matched to stored data in the record. Goldstein, Lesk and Harmon in 1970s refers the use of 21 precise individual symbols such as hair colour, lip thickness, etc. to achieve recognition. But the problem with above mentioned solutions was the huge calculation of the dimensions and locations. But Kanade during 1977 get rid of this problem by developing first fully functional automated face recognition system. The foremost milestone in face recognition introduced in 1988, by Kirby and Sirovich who applied a standard linear algebra method known as principle component analysis.

II. FACE RECOGNITION TECHNIQUES

There are mainly three methods for face recognition:

1. Appearance based methods also known as holistic matching methods:-
   This methods takes the entire facial region as the raw input for processing the recognition system. The initial phase of this face recognition problem is to transform it into a face space analysis problem and then a number of well-known statistical methods are applied to it.
2. Feature based matching methods:-

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In these methods initial phase is to extract the geometry or the appearance of the face local features such as the nose, eyes and mouth. This fact is then fed into a structural classifier.

3. Hybrid methods:-
Hybrid methods use both the appearance and feature based method.

A. Appearance Based Approaches

1. The Eigen face Method

Kirby and Sirvoich first proposed Eigenfaces method for recognition. Encouraged by their work, Turk and Pentland improved this work by implementing Eigenfaces method based on Principal Component Analysis (PCA) for the same goal [1]. PCA is a Karhumen-Loeve transformation. PCA is a recognized linear dimensionality reduction method which determines a set of mutually orthogonal basis functions and uses the leading eigenvectors of the sample covariance matrix to characterize the lower dimensional space as shown in figure 1.

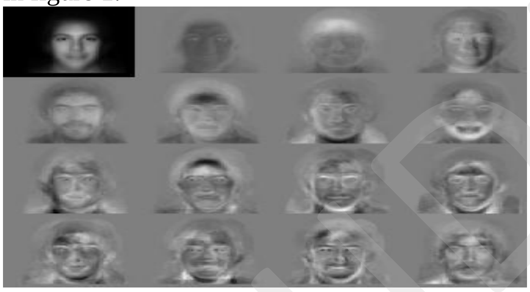

Fig.1. Feature vectors are derived using Eigen faces [2]

Then Moghaddam et al [3] suggested Bayesian PCA method. In this system, the Eigenface Method based on simple subspace-restricted norms are extended to use a probabilistic measure of similarity. Chung et al. [4] in his paper suggested another combined approach for recognition using PCA and Gabor Filters. Their method consists of two phases. Initially to extract facial features he uses Gabor Filter and then use PCA to classify the facial features optimally. Some of the recent PCA-based algorithms discussed as fallow:

Kernel PCA approaches [5] delivers generalisations which take higher order correlations into consideration. This method handles the non-linearity in face recognition and achieve lower error rates.

Symmetrical PCA [6] in which PCA is combined with even-odd decomposition principle. This approach uses the different energy ratios and sensitivities of even/odd symmetrical principal components for feature selection.

Two-dimensional PCA [7] involves framing of a 2-dimensional matrix instead of 1 D vector. Adaptively weighted sub pattern PCA [8] involves the division of the original whole image pattern into sub patterns and then the features are obtained from them. The sorting is done by adaptively computing the contributions of each part. Weighted modular PCA [9] methods involve partitioning the whole face into different modules or sub-regions such as mouth , nose, eyes and forehead and then the weighted sum of errors of all these regions is found to get the final decision.

2. The Fisherface Method

The Fisherface Method is introduced by Belhumeur, 1997 [10], a derivative of Fisher's Linear Discriminant (FLD) which contains linear discriminant analysis (LDA) to obtain the most discriminant features. Similar to eigenface method Fisherface method also use both PCA and LDA to produce a subspace projection matrix. LDA determines a set of projection vectors which form the maximum between-class scatter and minimum within-class scatter matrix simultaneously (Chen et al [11]) and provides lower error rates than Eigen face method. Figure 3 shows the example of six different classes using LDA with large variances within classes, but little variance within classes.

Fig.2.Example of Six Classes Using LDA [2]

Kernel FLD [12] is able to extract the most discriminant features in the feature space, which is same as to extract the most discriminant nonlinear features in the original input space and provides better results than the conventional fisherface which is based on second order statistics of an image-set and does not take into account the higher order statistical dependencies.

Some of the current LDA-based algorithms include [13]:

Direct LDA [14] constructing the image scatter matrix from a normal 2-d image and has the ability to resolve small sample size problem. Further, Dual-space LDA [15] requires the full discriminative information of face space and tries to resolve the

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same problem. Direct-weighted LDA [16] combines the privileges of both direct LDA and weighted pairwise Fisher criteria. Block LDA [17] break down the whole image into blocks and characterizes each block as a row vector. These row vectors for each block form 2D matrices then LDA is applied to these matrices. A methodology to fuse the LDA and PCA [18] representations using two approaches: the K-Nearest Neighbour approach (KNN) and the Nearest Mean approach (NM) was done on the AT&T and the Yale datasets.

3. Frequency Domain Analysis Method

Frequency domain analysis methods transform the image signals from the spatial domain to the frequency domain and analyse the features in frequency domain. Only partial low-frequency components having high energy are selected to signify the image. Dissimilar from PCA and LDA, frequency domain analysis methods are independent of data and do not require training images [19]. Moreover, smart and fast algorithms are available which provides easy implementations and have high computation efficiency.

- Discrete Fourier Transform

Fourier Transform is a frequency domain analytical method. For a 1×N input signal, f (n). Discrete Fourier Transform is defined as

$$F(k) = \int_{n=1}^{N} f(n)e^{-j2\pi(k-1)}\left(\frac{n-1}{N}\right)dt$$

The 2D face image is first converted to 1D vector, f (n) by cascading each column together and transforming them into the frequency domain. Only rare low frequency coefficients are considered since they contain most of the signal's energy.

- Discrete Cosine Transform

Ahmed, Natarajan, and Rao [20] were the first ones to introduce the discrete cosine transform (DCT) in the early seventies. The DCT [21] is basically computed for a cropped version of an input image. This cropped input image holds a face and a small subset of the coefficients which is maintained as a feature vector. DCT performs the transformation of spatial information to decoupled frequency information in the form of DCT coefficients. The DCT for an N × N image can be defined as:

$$C(u,v) = a(u)a(v)\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} z(x,y)\cos\frac{\pi(2x+1)u}{2N}\cos\frac{\pi(2y+1)v}{2N}$$

$$\alpha = \begin{cases}\sqrt{1/N} & u = 0\\ \sqrt{2/N} & u \neq 0\end{cases}$$

$$u, v = 0,1,2 \ldots . N-1$$

The matrix coefficients of an N × N image cover the whole frequency space of image components. The upper left of the matrix covers the DCT coefficients with higher values. DCT changes the face images with high dimension to a subspace with low dimension. The important features of the face such as the lines belonging to hairs and face, the position of eyes, nose and mouth remains in the DCT coefficients.

- Discrete Wavelet Transform

Discrete Wavelet Transform (DWT) [22] represents a signal in terms of wavelets using dilation and translation. The wavelet families Haar, Symelt are used. It can capture localized time frequency information of image and thus motivate its use for feature extraction. The data obtained from the feature extraction is decomposed into different frequency ranges and then the frequency components introduced by intrinsic deformations due to expression or extrinsic factors are isolated into certain sub bands. Wavelet-based methods consider the sub bands that contain the most relevant information to represent the data. As compared to DFT, the DWT is a better space frequency localization.

4. Independent Component Analysis

ICA is a modified form of PCA and is considered to have more representative power than PCA. In ICA a linear transformation is determined to represent a set of random variables as linear combinations of statistically independent source variables.
ICA is used to find the high order statistics present in the image. ICA encodes face images with statistically independent variables. These variables are not essentially associated with the orthogonal axes and looks for direction that are more independent from each other. ICA decorrelates the high-order moments of the input in addition to the second-order moments and its possible use for face recognition has been shown by Bartlett and Sejnowski [23].

5. Support Vector Machines

To develop the classification performance of the PCA and LDA subspace features, support vector machines (SVM) are introduced [24]. SVM

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generally trained through supervised learning. SVM uses a training set of images to calculate the Optimal Separating Hyperplane (OSH), reducing the risk of misclassification among two classes of image in some feature space. Guo et al [25] applied this method for face recognition. He used a binary tree classification system in which a face image is iteratively classified as belonging to one of two classes. A binary tree structure is circulated up until the two classes denote individual subjects and a final classification decision can be made. SVM has been engaged for face recognition by some other researchers and has been shown to return good results.

6. The Laplacian faces approach

Different from PCA and LDA which effectively see only the Euclidean structure of face space and if the face images lie on a nonlinear sub manifold hidden in the image space, then both PCA and LDA fail to discover the underlying structure. The manifold is modelled by a nearest neighbour graph which preserves the local structure of the image space. Locality Preserving Projections (LPP) obtains a face subspace that best detects the essential face manifold structure [26]. Each face image in the image space is mapped to a low dimensional face subspace characterized by a set of feature images. These feature images also known as Laplacianfaces. LPP suffers from a drawback that it does not encode discriminant information, which is important for recognition tasks. Recently, several improved LPP algorithms have been proposed to make use of the label information. Yu et al. [27] Presented a discriminant locality preserving projections (DLPP) algorithm to improve the classification performance of LPP. Null space discriminant locality preserving projections (NDLPP) [28] was proposed to avoid the small sample size problem of DLPP by solving an eigenvalue problem in null space. L. Zhu and S.N. Zhu [29] introduced an orthogonal discriminant locality preserving projections (ODLPP) method based on OLPP. Cai et al. [30] proposed a locality sensitive discriminant analysis (LSDA) method where the data points are mapped into a subspace in which the nearby points with the same label are close to each other while the nearby points with different labels are far apart.

7. Probabilistic Decision Based Neural Network (PDBNN)

Probabilistic Decision Based Neural Network (PDBNN) is proposed by Lin et al [31] comprises of three different modules (a face detector, an eyes localizer and a face recognizer).In this technique only the facial regions of upper are considered.

B. Feature Based Approaches

1. Face Recognition through geometric features

In the initial phase a set of fiducial points are examined in every face and the geometric facts like distances between these points are explored and the image nearest to the query face is nominated. The work in this way was done by Kanade [44] who used the Euclidean distance for correlation between 16 extracted feature vectors constructed on a database of 20 dissimilar people with 2 images per person and achieve a performance rate of 75%. Further, Brunelli and Poggio [32] performs the same on 35 geometric features from a database of 47 different people with 4 images per person as shown in the figure 4 and achieved a performance rate of 95%. Most recently, Cox et al. [33] derived 35 facial features from a database of 685 images and reported a recognition performance of 95% on a database of 685 images with a single image for each individual.

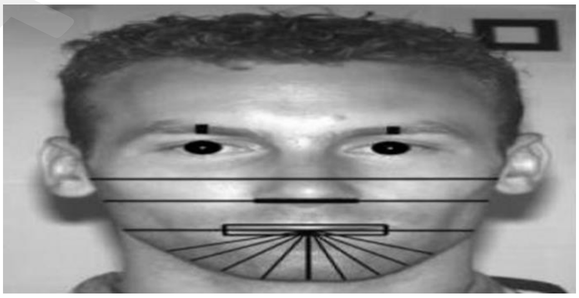

Fig.3.Geometrical feature used by Brunelli and Poggio

2. Elastic Bunch Graph Matching (EBGM)

The real face images have various non-linear characteristics such as differences in illumination, pose expression and show differences in appearance in various scenarios. These variations cannot be considered as the linear analysis. So, Wiskott et al [34] presented a face recognition technique using, “elastic bunch graphs”.

In this method, faces are represented as graphs with nodes positioned at fiducial points. The edges are labelled with 2D distance vectors with each node having a set of 40 complex Gabor wavelet coefficients at different scales and orientations. They are called "jets" and the recognition is based on labelled graphs. A Gabor wavelet transform creates a dynamic link architecture that projects the face onto an elastic grid. The Gabor jet is essentially

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a node on the elastic grid, represented by circles on the given image as shown in the figure 4. These nodes describe the behaviour of image around a given pixel and also represents the frequencies at a specified image pixel. When the image is convolved with a Gabor filter, the output can be used for shape detection and to extract features using image processing. A convolution mergers the functions together and expresses the amount of overlap from functions. The Similarity of the Gabor filter response at each Gabor node is the basis of recognition.

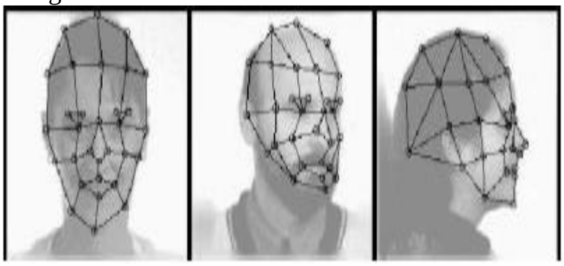

Fig.4. [34] Multiview faces overlaid with labelled graphs

3. Hidden Markov Model (HMM)

The HMM was first presented by Samaira and Young [35]. HMM generally used for images with variations in lighting, facial expression, and orientation and thus has an advantage over the holistic approaches. For treating images using HMM, space sequences are considered. HMM can be explained as a set of finite states with related probability distributions. This method is named as a Hidden Markov Model because the states are not visible, only the result is visible to the external user. This method use pixel strips to cover the forehead, eye, mouth, nose and chin without finding the exact locations of facial features. The face arrangement is observed as a sequence of discrete parts. The order of this system should be maintained for e.g., it should run from top to bottom from forehead, eyes, nose, mouth, and chin as in figure 6. Each of these facial regions is assigned to a state from left to right 1D continuous HMM.

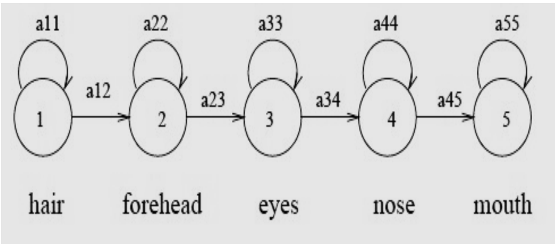

Fig.6: Left to Right HMM for face recognition

4. Convolution Neural Networks

The neural network approaches use a training set of face images in order to create a neural network based classifier. Kohonen was the first who demonstrates the neural network for face reorganization. Since then a number of methods has been projected. Intrator et.al [36] proposed a hybrid or semi supervised method in which they combined unsupervised methods for extracting features and supervised methods for finding features able to reduce classification error. For classification purpose, they considered feed-forward neural networks (FFNN).
Lawrence et.al [37] describes a neural network approach for identification and verification of facial images. He used self-organizing map neural network and Convolutional networks. An unsupervised learning technique based on Self organizing maps (SOM) is used to project the data in a lower dimensional space and a Convolutional Neural Network (CNN) for partial translation and deformation invariance. But both, FFNN and CNN classification methods are not optimal in terms of computational time and complexity.

5. Active Appearance Model (AAM)-2D Morphable Method

Faces are highly variable and deformable objects. Depending on pose, lighting, expression, faces can have different looks in the images. Cootes, Taylor, and Edwards [38] proposed Active Appearance Model which is capable of „explaining‟ the appearance of a face in terms of a compact set of model parameters.
AAM is an integrated statistical model. This technique involves combining a model of shape variation with a model of the appearance variations in a shape normalized frame. AAM is implemented on the basis of a training set having labelled images. The landmark points are marked on each example face at key positions to highlight the main features as shown in figure 5. Model parameters are found to perform matching with the image which minimizes the difference between the image and a synthesized model example projected into the image.

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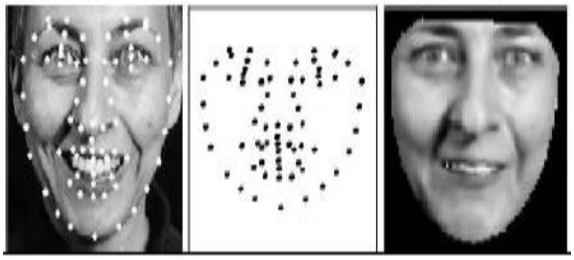

Fig.5. [38] Tanning image is split into shape and shape normalized texture

6. 3D Morphable Model

To handle the facial variations such as pose, illumination etc. it is better to represent the face using the 3 D models. 3D morphable model is a strong, effective and versatile representation of human faces. To make a model, high quality frontal and half profile pictures are taken first of each subject under ambient lighting conditions. These images are then used as input to the analysis by synthesis loop which yields a face model.

Blanz et al. [39] proposed this method based on a 3D morphable face model in which he tries to find an algorithm to recover the parameters like shape and texture from the single image of a face and encodes them in terms of model parameters. The 3D morphable model provides the full 3D correspondence information which allows for automatic extraction of facial components and facial regions

C. Hybrid methods

These methods use both the holistic and feature-based methods to recognize the face and show better results. Some of the hybrid methods include Modular Eigenfaces and Eigenmodules proposed by Pentland et al. [40], which uses both global eigenfaces and local Eigenfeatures and shows much better results than the holistic eigenfaces. Penev and Atick [41], gave a method called Hybrid LFA (Local Feature Analysis). Shape-normalized Flexible appearance technique by Lanitis et al. [42] and Component-based Face region and components by Huang et al. [43] which combines component based recognition and 3D morphable models for face recognition. The major step is to generate 3D face models using 3D morphable model from the three input images of each person in the training. These images are rendered under varying pose and illumination conditions to build a large set of synthetic images which are used to train a component-based face recognition system [43]. A Support Vector Machine (SVM) based recognition system is used which decomposes the face into a set of components that are interconnected by a flexible geometrical model so that it can account for the changes in the head pose leading to changes in the position of the facial components.

However, the major drawback of the component-based system was the need of a large number of training images taken from different viewpoints and under different lighting conditions which is not available in many real world applications. So, to eliminate this drawback 3D morphable models were incorporated.

III. PROPOSED METHODOLOGY

A. Principle Component Analysis

Principal component analysis transforms a set of data obtained from possibly correlated variables into a set of values of uncorrelated variables called principal components. The number of components can be less than or equal to the number of original variables. The first principal component has the highest possible variance, and each of the succeeding components has the highest possible variance under the restriction that it has to be orthogonal to the previous component. We want to find the principal components, in this case eigenvectors of the covariance matrix of facial images.

B. Fuzzy clustering

Fuzzy clustering is a class of algorithms for cluster analysis in which the allocation of data points to clusters is not "hard" (all-or-nothing) but "fuzzy" in the same sense as fuzzy logic. Data clustering is the process of dividing data elements into classes or clusters so that items in the same class are as similar as possible, and items in different classes are as dissimilar as possible. Depending on the nature of the data and the purpose for which clustering is being used, different measures of similarity may be used to place items into classes, where the similarity measure controls how the clusters are formed. Some examples of measures that can be used as in clustering include distance, connectivity, and intensity.

In hard clustering, data is divided into distinct clusters, where each data element belongs to exactly one cluster. In fuzzy clustering (also referred to as soft clustering), data elements can belong to more than one cluster, and associated with each element is a set of membership levels. These indicate the strength of the association between that data element and a particular cluster. Fuzzy clustering is a process of assigning these membership levels, and then

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using them to assign data elements to one or more clusters.

In fuzzy c-means clustering, each point has a degree of belonging to clusters, as in fuzzy logic, rather than belonging completely too just one cluster. Thus, points on the edge of a cluster, may be in the cluster to a lesser degree than points in the center of cluster. An overview and comparison of different fuzzy clustering algorithms is available.

Any point *x* has a set of coefficients giving the degree of being in the k^{th} cluster $w_k(x)$. With fuzzy *c*-means, the centroid of a cluster is the mean of all points, weighted by their degree of belonging to the cluster:

$$c_k = \frac{\sum_x w_k(x)x}{\sum_x w_k(x)}$$

The degree of belonging, $w_k(x)$, is related inversely to the distance from *x* to the cluster center as calculated on the previous pass. It also depends on a parameter *m* that controls how much weight is given to the closest center.

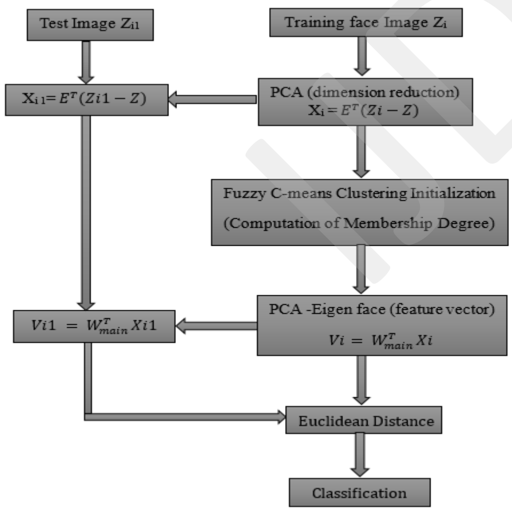

Fig.6. Overview of our propose face recognition system.

Figure. 6 gives an overview of our propose face recognition system. The input consist of image from testing database and there are different images of that person with different expressions and lighting conditions. The system consists of four major blocks: PCA for dimension reduction, fuzzy clustering section for computation of membership function, PCA Eigen face for feature extraction, and Euclidian distance classifier. Section 5 introduces the PCA and FCM approach for face recognition, and we evaluate our proposed approach and the paper ends with a conclusion.

C. Algorithm

Given set of feature vectors transformed by the PCA,

$$X = \{\boldsymbol{x_1}, \boldsymbol{x_2} \ldots \boldsymbol{x_N}\},$$

Partition matrix

$$U = [\mu_{ij}] \quad for\ i = 1, 2 \ldots c\ and\ j = 1, 2, \ldots, N$$

Which satisfies,

$$\sum_{i=1}^{c} \boldsymbol{\mu ij} = 1\ , 0 < \sum_{j=1}^{N} \boldsymbol{\mu ij} < N$$

The Computations of Membership Degrees

- Compute the Euclidean distance matrix between pairs of feature vectors in the training,
- Set diagonal elements of this matrix to infinity,
- Sort the distance matrix in ascending order,
- Collect the class labels of the patterns located in the closest neighbourhood of the pattern,
- Compute the membership grade to class i for *jth* pattern ,

$$\mu ij = \begin{cases} \boldsymbol{0.51 + 0.49\left(\frac{nij}{k}\right)} & \boldsymbol{if\ i = same\ as} \\ & \boldsymbol{the\ label\ of\ the\ jth\ pattern} \\ \boldsymbol{0.49(nij/k)} & \boldsymbol{if\ i \neq same\ as} \\ & \boldsymbol{the\ label\ of\ the\ jth\ pattern} \end{cases}$$

Where, n_{ij} is number of the neighbours of the j^{th} data that belong to i_{th} class.

Procedural Steps

- Results of fuzzy C-means clustering classification are used in computations of mean value and scatter covariance matrices.
- ean vector of each class

$mi = \frac{\sum_{j=1}^{N} \mu ij\ Xj}{\sum_{j=1}^{N} \mu ij}$ The between class and within class fuzzy scatter matrices are respectively,

$$S11 = \sum_{i=1}^{c} Ni(mi - m)(mi - m)^T$$

$$S12 = \sum_{i=1}^{c} \sum_{xk \in Ci} Ni(mi - m)(mi - m)^T = \sum_{i=1}^{c} S12i$$

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- The optimal fuzzy projection W_{main} and feature vector transformed by fuzzy clustering based method are given by

$$Wmain = \arg max_w \frac{|W^T.S11.W|}{|W^T.S11.W|}$$

$$Vi = W_{main}^T Xi = W_{main}^T E^T(Zi - Z)$$

- Fuzzy clustering approach outperform the other methods for the datasets considered.
- Sensitivity variations in illumination and facial expression reduced substantially.
- Fuzzy sets can efficiently manage the vagueness and ambiguity of face images degraded by poor illumination component.

IV. Experimental Results

Fig.7. Pictures from the training base.

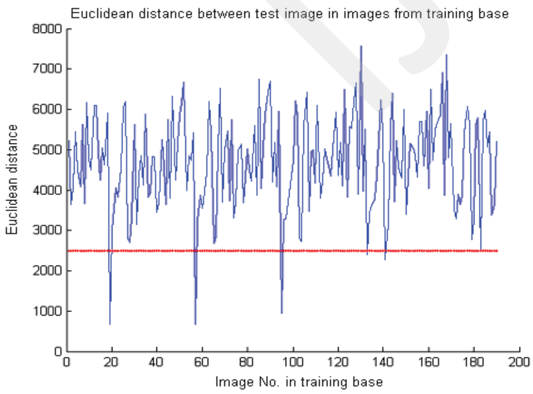

Fig.8.Shows all eigenvalues. Each eigenvalue Corresponds to a single eigenvector and tells us how much images from training bases vary from the mean image in that direction.

Fig.9.An Example of Test image and recognized image from the training database

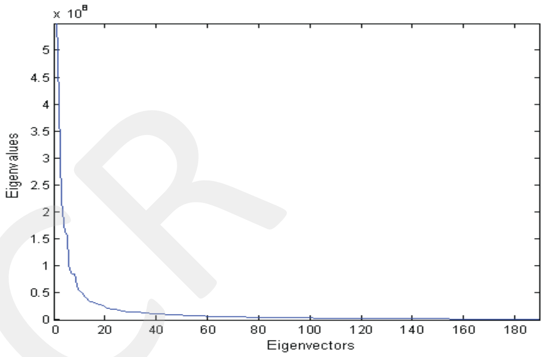

Fig.10.Euclidean distance between the test image and images from the database.

V. Conclusion

Human face detection and recognition have drawn considerable interest and attention from many researchers for decades. It has several applications such as criminal enquiry, authentication in secure system etc. Vigorous research has been conducted in this area for the past four decades and huge progress with encouraging results has been obtained. The aim of this paper is to provide a survey of recent holistic and feature based approaches that complement previous surveys and to develop a new approach.

We proposed fuzzy clustering technique for the face recognition process, along with the use of principal component analysis the experiment shows a result of **98%** with the free environment and the approach is better in case of recognition rate or recognition accuracy as compare with existing approaches.

When frontal images are used, registered person's recognition rate is over 98% (in 310 test images, 4 images are false, and 1 image is rejected). Furthermore, non-registered person's rejected rate of 99% (in 100 test images, 1 image is false) is obtained. The results have demonstrated the promising performance of this algorithm. However, under different perspective variation, the registered

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person's recognition is 74.19% (in 310 images, 16 images are false, and 64 images are rejected)

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