FUZZY ENTROPY BASED G-2DFLD ALGORITHM FOR FACE RECOGNITION

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MASTER OF COMPUTER APPLICATION

BY

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

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TO WHOME IT MAY CONCERN

I hereby recommend that the project entitled " FUZZY ENTROPY BASED G-2DFLD ALGORITHM FOR FACE RECOGNITION" prepared under my supervision and guidance at Jadavpur University, Kolkata by SK HOJAYFA RAHAMAN (Reg. No:137326 of 2016 - 2017, Class Roll No. 001610503019), may be accepted in partial fulfillment for the degree of Master of Computer Application in the Faculty of Engineering and Technology, Jadavpur University, During the academic year 2018 – 2019. I wish him every success in life.

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DECLARATION OF ORIGINALITY AND COMPLIANCE OF ACADEMIC PROJECT

I hereby declare that this project contains literature survey original research work by the undersigned candidate, as part of his MASTER OF COMPUTER APPLICATION studies. All information in this document have been obtained and presented in accordance with academic rules and conduct. I have fully cited and referenced all material results that are not original to this work.

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<u>CERTIFICATE OF APPROVAL</u>

The foregoing project is hereby accepted as a credible study of an engineering subject carried out and presented in a manner satisfactory to warrant its acceptance as a prerequisite to the degree for which it has been submitted. It is understood that by this approval the undersigned do not necessarily endorse or approve any statement made, option expressed or conclusion drawn therein, but approve the project only for the purpose for which it is submitted.

FINAL EXAMINATION FOR EVALUATION OF PROJECT:

1 ....

2...

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I hereby express my honest and sincere thanks and humble gratitude to my teacher and guide Prof. (Dr.) Jamuna Kanta Sing, Professor of the Department of computer Science & Engineering, Jadavpur University, for his exclusive guidance and entire support in completing and producing this project successfully. I am very much indebted to him for the constant encouragement, and continuous inspiration that he has given to me. The above words are only a token of my deep respect towards him for all he has done to take my project to the present shape.

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CHAPTER 1
INTRODUCTION

1.1. Brief description about face recognition

Face is considered as the most important part of human body. Research shows that even face can speak and it has different words for different emotions. It plays a very crucial role for interacting with people in the society. Face recognition is a biometric software application capable of uniquely identifying or verifying a person by comparing and analyzing patterns based on the person’s facial contours. It is the process of identifying one or more people in images or videos by analyzing and comparing patterns. Algorithms for face recognition typicall extract facial features and compare them to a database to find the best match. It maps an individual’s facial features mathematically and stores the data as faceprint [1].

Face recognition is mostly used for security purposes, deep learning algorithms to compare a live capture or digital image to the store faceprint in order to varify an individual’s identity. It compares the information with a database of known faces to find a match. Accurate face recognition is critical for many security applications. This simple procedure increased the accuracy of an industry standard face-recognition algorithm from 54% to 100%, bringing the robust performance of a familiar human an automated system. It is accurate, if you’re a white Guy. The software is 99% of this time. But the darker skin, the more error arise-up to 35% for images of darker skinned women, according to a new study that breaks fresh ground by measuring how the technology works on people of different races and gender. This technology is improving by leaps and bounds. Some commercial software can now tell the gender of a person in a photograph [2,3].

In 1988, Sirovich and Kirby began applying linear algebra to the problem of face recognition. What became known as the Eigenface approach started as a search for a low-dimensional representation of facial images. Ophthalmologist Frank Burch proposed the concept of using iris patterns as a method to recognize an individual. The first recognition system was developed by woodrow W. Bledsoe under contract to the US Government. This system relied solel on the ability to extract useable feature points. Generally, prices range from $5000 to $10000 per door for a complete system that includes the biometric scanner, a spelized locking system, software integration and installation. Fig.1.1 shows how find the pixel value of any figure [4].

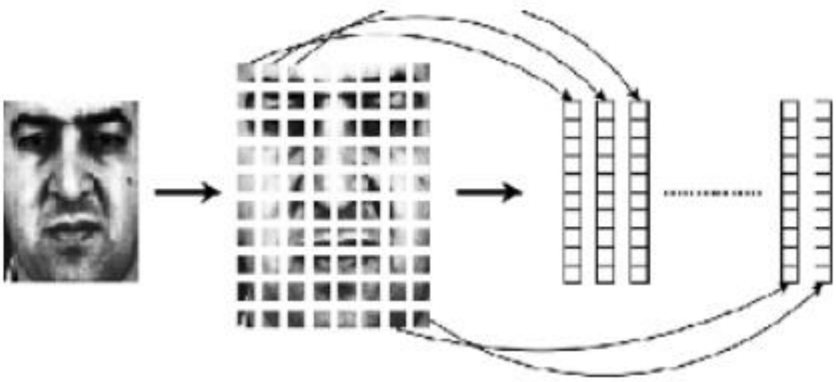

Fig. 1.1. Face represented by a small number of features.

1.2. Review of previous work

On the basis of human psychological studies and behavioural aspects, face recognition procedures are classifed in different categories.

- PRINCIPAL COMPONENT ANALAYSIS (PCA)
- LINEAR DISCRIMINANT ANALAYSIS (LDA)

- TWO-DIMENSIONAl PRINCIPAL COMPONENT ANALYSIS (2DPCA)
- TWO DIMENSIONAL FISHER'S LINEAR DISCRIMINANT (2DFLD)
- GENERALIZED TWO DIMENSIONAL FISHER'S LINEAR DISCRIMINANT (G-2DFLD)

PRINCIPAL COMPONENTS ANALAYSIS (PCA)

Principal components analysis(PCA) is a technique that can be used to simplify a dataset. It is a linear transformation that chosses a new coordinate system for the data. PCA one can tranform each original image of the training set into a corresponding eigenface. If one uses all the eigenfaces extracted from original images, one can reconstruct the original images from the eigenface exactly. The purpose of PCA is to reduce is to reduce the large dimensionality of the face space (observed variables) to the smaller intrinsic dimensionality of feature space (independent variables), which are needed to describe the data economically. This is the case when there is a strong correlation between observed variables [4].

LINEAR DISCRIMINANT ANALAYSIS (LDA)

Look for dimension reduction based on discrimination purpose. The variance among faces in the database may come from distortions such as illumination, facial expression, and pose variation. And sometimes, these variations are larger than variations among standars faces. Here we find a basis for projection that minimize the intra-class variation but preserve the inter-class variation. Rather than expictly modeling this deviation, we linearly project the image into a subspace in a face deviation. It can be used any kind of classification problems [4].

TWO DIMENSIONAL FISHER'S LINEAR DISCRIMINANT (2DFLD)

2DPCA method is a linear subspace method, which is used for feature extraction. The idea behind this method is to find the optimal projection directions, which can maximize the scatter of the transformed images. For the optimal projection directions, eigenvectors corrsponding to the maximum d eigenvalues of the image covariance matrix are used [5]. 2DPCA does not require transforming image matrices into vectors. Thus it reduces the computational complexity of construction of the image covarience matrix and reduces the computation time of the eigen vectors of the covarience matrix. 2DPCA method may fail to emphasize the discrimination between the clusters, no matter how easy the task is, as this is unsupervised techniques.The directions that maximize the scatter of the data might not be as adequate to discriminate between cluster.

GENERALIZED TWO DIMENSIONAL FISHER'S LINEAR DISCRIMINANT (G-2DFLD)

A technique for feature extraction, namely the generalised two-dimensional Fisher's linear discriminant (G-2DFLD) technique and its application for face detection employ multi-class SVM as classifiers (Fig1.2). The G-2DFLD technique was an enlargement of the 2DFLD method for feature extraction. The innovative G-2DFLD method was an enlargement of the G-2DFLD method for feature extraction. The innovative G-2DFLD method was assessed on two well-known face detection databases namely the AT&T (formly ORL) and the UMIST face databases. The test outcomes employing diverse test using different experimental approaches upheld the supremacy of the noval G-2DFLD scheme over the competitors such as the PCA, 2DPCA, FLD and 2DFLD schemes, not only in terms of calculation period, but also for the function of face detection by making use of multi-class SVM as classifiers [6].

Previous attempts to develop facial recognition system include G-2DFLD method and its use for face recognition using multy-class support vector machines as classifier. The G-2DFLD method is extension of the 2DFLD method for feature extraction. Like 2DFLD method, G-2DFLD method is also based on the original 2D image matrix. In this project, a new method of facial recognition system combining Fuzzy Shannon entropy will be introduced [6,7].

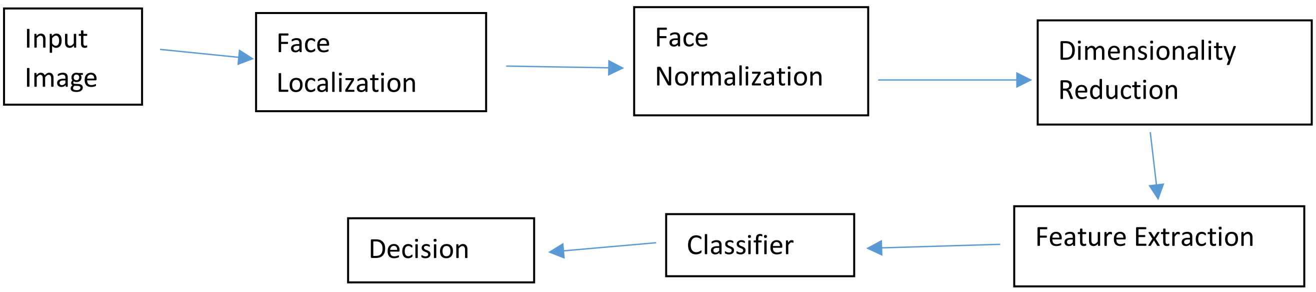

Fig.1.2 Generic face recognition system [7].

Face recognition method can be divided into appearance-based and model-based algorithms. The differential element of these methods is the representation of the face. Appearance-based methods represented a face in terms of several raw intensity images. An image is considered as a high-dimensional vector.

The model-based approach tries to model a human face. The new sample is fitted to the model, and the parameters of the estimated model are used to recognize image. It can be 2D or 3D.

In the Previous work G-2DFLD is based on 2D image matrix. However, unlike 2DFLD method, which maximizes class separability either from row or column direction, the G-2DFLD method method maximizes class separability from both the row and column directions simulyaneously. To realize this, two alternative Fisher's criteria have been defined corresponding to row and column-wise projection directions. Unlike 2DFLD method, the principal components extracted from an image matrix in G-2DFLD method are scalars; yielding much smaller image feature matrix. The experimental results using different experimental strategies show that the G-2DFLD scheme outperformance the PCA, 2DPCA, FLD, and 2DFLD schemes, not only in terms of computation times, but also for the task of face recognition using multi-class support vector machines (SVM) as classifier [8].

1.3. Short description about this work

Face recognition from still image is one of the active research areas. Shanon entropy, which was defined by Shannon, is a method to calculate unpredictability of elements, or contents of input. It shows us the complexity described in 0 to 1 of elements in a number set. Shannon entropy is used Artificial Intelligence, especially in decision trees. Shannon entropy has never been used for facial recognition system. However, in this paper, Shannon entropy will have a significant role in new facial recognition system. Experimental result shows that the Fuzzy entropy based G-2DFLD is better than G-2DFLD and recognition of human faces. Add the entropy in G-2DFLD method we get the maximum recognition value. The algorithm is used to train the RBF neural networks so that the dimension of the search space is drastically reduced in the gradient paradigm. Simulation result conducted on the ORL database show that the system achives excellent performance both in terms of error rates of classification and learning efficiency [9].

CHAPTER 2

Fuzzy entropy based G-2DFLD algorithm

2.1. CLASSIFICATION OF ENTROPY:-

There are different kinds of entropy used in the field of image processing and face recognition.

A. Shannon's Entropy

Shannon's Entropy is a measure of uncertainty used in statistics, probability theory, computer Science, and statistical dynamics [10]. It does a calculation with ratios, which means that even with different size of pictures, It wouldn't get bothered, which leads to higher accuracy on different size of images for facial recognition system. Shannon's entropy H(X) is

$$\mathrm{H(x)}=-\sum_{i=1}^{n} P_i \log_2 P_i(\mathrm{X} = X_1, X_2, X_3, X_4 \ldots.) \tag{2.1}$$

Where P_i is dividing i^{th} number of set X by sum of all numbers in set X, which is probability of the P_i number in set X.

$$P_i = \frac{i^{th}\ element\ of\ X}{sum\ of\ all\ the\ elements\ in\ X} \tag{2.2}$$

B. RENYL ENTROPY

a. Imporant in field of geological survey, ecology and statistics. In case of a measurement of biodiversity, Renyl entropy is a measurement of diversity index.

b. It is also used in XY Spin Chain model, related to Heisenberg's Uncertainty Principle.

c. This entropy is entirely a function of ‘α’ and calculated in such a way that it will be an automorphic function w.r.t to any particular subgroup of an individual modular group.

d. It is a generalization of Shannon entropy, when used in case of enlargement.

This is mathematically represented as-

$$H_\alpha(X)= \frac{1}{1-\alpha}\log\sum_{i=1}^{n} p_i^\alpha \qquad (2.3)$$

Where α >0, $\alpha \neq 1$.

Here, X is a discrete random variable with possible outcomes *1,2,3.......n* and corresponding probabilities p_i=P_r(X=i) for *i=1,2........n.* The logarithm is conventionally taken to be base 2, especiall in the context of information theory where bits are used. If the probabilities p_i=$\frac{1}{n}$ for all *i=1,2.....n*, then all the Renyi entropies of the distribution are equal: $H_\alpha(X) = \ log_n$. In general, for all discrete random variables X, $H_\alpha(X)$ is non-increasing function in α [11,12].

C. HARVRD-CHARVEL ENTROPY

a. Used in Statistical mechanics in Physics [13].

b. It was first used in Bose-Einstein Statistics.

c. Later it was modified by Dracozy.

The mathematical formula for this entropy is given as-

$$H_{hs}P_{m1m2} = \frac{1}{2^{\alpha-1}}\sum_{m1}\sum_{m2}(P_{m1m2})^\alpha - 1 \qquad (2.4)$$

Where α >0, $\alpha \neq 1$.

D. KAPUR ENTROPY

a. The concept of thresholding for image processing is first inserted here [14].

b. To reduce the complexity of entropy function, a new threshold algorithm is introduced, which is mathematically represented as-

$$H_{hs}P_{m1m2} = \left(\frac{\sum_{m1}\sum_{m2} p_{m1,m2}^{\alpha+\beta-1}}{\sum_{m1}\sum_{m2} p_{m1,m2}^{\beta}}\right)(2^{1-\alpha}-1)^{-1} \quad (2.5)$$

Where α >0, $\alpha \neq 1$ and $\beta > 0, \beta \neq 1$.

2.2. Fuzzy entropy based G – 2DFLD

Here three quantities are considered as the entropy factors, G_{ik}, U_{ik} , and P_{ik} , which are mathematically defined here-

$$G_{ik} = \frac{e^{\frac{-||X_k - V_i||^2}{2\sigma^2}}}{\sum_{i=1}^{N} e^{\frac{-||X_k - V_i||^2}{2\sigma^2}}} \quad (2.6)$$

Where *i* is the number of class and *k* is the number of image. The value of G_{ik} is [0,1].

Here, $e^{\frac{-||X_k - V_i||^2}{2\sigma^2}}$ is Gaussian radial basis function, where σ >0.

The normalization value is

$$U_{ik} = \frac{G_{ik}}{\sum_{i=1}^{C} G_{ik}} \quad (2.7)$$

Where *C* is the number of class. Similar manner, the Uik value is [0,1].

$$P_{ik} = -\sum_{i=1}^{C} U_{ik} log U_{ik} \quad (2.8)$$

Now the term P_{ik} is multiplied with all the scatter matrices (image row within-class scatter matrix, image column within-class scatter matrix).

Since those matrices are responsible to find the optimal projection matrices U_{opt} and V_{opt}, hence entropy should be inserted in those matrices and then we have calculate the optimality on the basis of

$G_{br}\, {G_{wr}}^{-1}$ and $G_{bc}\, {G_{wc}}^{-1}$. Whenever tiis term is multiplied, all the values afterwards will change in G-2DFLD method and hence, the feature extraction and fisherface calculation should be done.

2.2.1.Generalized two-dimentional FLD(G-2DFLD) method for feature extraction

The 2DFLD method is based on the 2D image matrix. It does not need from a stretchedlarge vector from the 2D image matrix. The key idea is to project an image matrix X, an m×n random matrix (Fig.2.1). Same as 2DFLD method, the general two- dimensional FLD(G-2DFLD) method is based on 2D image matrix. The difference is , it maximizes class separability from both the row and column directions simultiniously by the following linear transformation:

$$Z = U^{T} XV \tag{2.9}$$

Here *U* is projection matrices of dimension m×p (p ≤ m) (Fig.2.2.),

and *V* is projection matricesof dimension n×q (q≤n) (Fig.2.3). Therefore, we find the optimal projection direction *U* and *V*. So the projected vector in the (p×q) – dimensional space reaches its maximum class separability [1,10,14,15].

Let us consider, *N* number of imagein a training set, where the order of each image is m × n, and total number of class is *C*. The image is define as X_i=*(i=1,2,....N)*, and c^{th} class which contains N_c images.

Here, we get the mean and class-wise mean is μ and μ_c.

$$\text{Where, } \mu=\frac{1}{N}\sum_{i=1}^{N} X_i \tag{2.10}$$

$$\text{and, } \mu_c=\frac{1}{N_c}\sum_{i=1}^{N} X_i \tag{2.11}$$

DIAGRAM

a_{11}	a_{12}	a_{13}	••••••	a_{1n}
a_{21}	a_{22}	a_{23}	•••••••	a_{2n}
••••				
••••				••••••
a_{m1}	a_{m2}	a_{m3}	•••••••••	a_{mn}

Fig.2.1. Two dimensional image X matrix (m×n)

a_{11}	a_{12}	a_{13}	••••••	a_{1p}
a_{21}	a_{22}	a_{23}	•••••••	a_{2p}
••••				•••••
a_{m1}	a_{m2}		••••••	a_{mp}

Fig.2.2. Two dimensional projection matrix U (m×p)

a_{11}	a_{12}		……..	a_{1m}
a_{21}	a_{22}		…….	a_{2m}
……				……
a_{p1}	a_{p2}		…….	a_{pm}

Fig.2.3. Two dimensional U^T matrix (p×m)

a_{11}	a_{12}	a_{13}	……..	a_{1q}
a_{21}	a_{22}	a_{23}	………	a_{2q}
…….				……
a_{n1}	a_{n2}	a_{n3}	……….	a_{nq}

Fig.2.4. Two dimensional projection matrix V (n×q)

Therefore , the transformed matrix Z, which order is (p×q). And get this order of matrix in multiplication rule . The diagram is

a_{11}	a_{12}		…….	a_{1q}
a_{21}	a_{22}			a_{2q}
…….				……
a_{p1}	a_{p2}		…..	a_{pq}

Fig.2.5. Two dimensional Z matrix (p×q)

The mean and class-wise mean calculated by the original matrix X. Therefore the dimension of these two matrices are m×n (Fig.2.6, Fig.2.7).

The diagram are

a_{11}	a_{12}		……..	a_{1n}
a_{21}	a_{22}		………	a_{2n}
…….				……
$a_{a_{m1}}$	a_{m2}		……..	a_{mn}

Fig.2.6. Two dimensional μ matrix (m×n)

a_{11}	a_{12}		…….	a_{1n}
a_{21}	a_{22}		…….	a_{2n}
……				……
a_{m1}	a_{m2}		…….	a_{mn}

Fig.2.7. Two dimensional μ_c matrix (m×n)

2.2.2. Alternative Fisher's criteria

Here we defined two alternative Fisher's criteria J(U) and J(v) corresponding to row and column- wise projection directions as follows:

$$J(U) = \frac{|U^T G_{bc} U|}{|U^T G_{wr} U|} \quad (2.10)$$

$$\text{and } J(V) = \frac{|V^T G_{bc} V|}{|V^T G_{wc} V|} \quad (2.11)$$

where

$$G_{br} = \sum_c^C P_{ik} Nc(\mu_c - \mu)(\mu_c - \mu)^T \quad (2.12)$$

$$G_{wr} = \sum_c^C \sum_{i \epsilon c}^N P_{ik}(X_i - \mu_c)(X_i - \mu_c)^T \quad (2.13)$$

$$G_{bc} = \sum_c^C P_{ik} Nc(\mu_c - \mu)^T (\mu_c - \mu \quad (2.14)$$

$$G_{wc} = \sum_c^C \sum_{i \epsilon c}^N P_{ik} (X_i - \mu_c)^T (X_i - \mu_c) \quad (2.15)$$

Where, G_{br} = image row between-class scatter matrix.

G_{wr} = image row within-class scatter matrix.

G_{bc} = image column between-class scatter matrix.

G_{wc} = image column within-class scatter matrix.

It may be noted that size of the scatter matrices G_{br} and G_{wr} is m×m, whereas for G_{bc} and G_{wc} the size is n×n. The sizes of these scatter matrices are much smaller than that of the conventional FLD algorithm, whose scatter matrices are mn×mn in size. For a square image, m=n and we have $G_{br} = {G_{bc}}^T$ and $G_{wr} = {G_{wc}}^T$ and vice versa.

The ratios in (2.10) and (2.11) are maximum, when the column vectors of the projection matrices U and V are the eigenvectors of $G_{br}\, {G_{wr}}^{-1}$ and $G_{bc}\, {G_{wc}}^{-1}$ respectively.

The dimension of μ and $μ_c$ are m×n, therefore the matrix ($μ_c$- μ) (Fig.2.8.) will also have same dimension. And $(μ_c - μ)^T$ (Fig.2.9.) has opposite dimension. Therefore m×n and n×m are the dimension of ($μ_c$- μ) and $(μ_c - μ)^T$ respectively.

The diagram of these matrix are

a_{11}	a_{12}		....	a_{1n}
a_{21}	a_{22}		......	a_{2n}
.....				....
a_{m1}	a_{m2}		....	a_{mn}

Fig.2.8. Two dimensional ($μ_c$- μ) matrix (m×n)

a_{11}	a_{12}		……..	a_{1m}
a_{21}	a_{22}		……..	a_{2m}
…….				…..
a_{n1}	a_{n2}		……..	a_{nm}

Fig.2.9. Two dimensional $(\mu_c - \mu)^T$ matrix (n×m)

Therefore, we get the dimension of G_{br} (Fig.2.10.) and G_{wr} (Fig.2.11.) are m×m(using the above equation). Similarly we get the dimension G_{bc} (Fig.2.12) and G_{wc} (Fig.2.13) are n×n and n×n respectively.

a_{11}	a_{12}		…….	a_{1m}
a_{21}	a_{22}		…….	a_{2m}
…..				……
a_{m1}	a_{m2}		……	a_{mm}

Fig.2.10. Two dimensional G_{br} matrix(m×m)

a_{11}	a_{12}		....	a_{1m}
a_{21}	a_{22}		......	a_{2m}
....				......
a_{m1}	a_{m2}		....	a_{mm}

Fig.2.11. Two dimensional G_{wr} matrix (m×m)

a_{11}	a_{12}		....	a_{1n}
a_{21}	a_{22}		....	a_{2n}
....				......
a_{n1}	a_{n2}			a_{nn}

Fig.2.12. Two dimensional G_{bc} matrix (n×n)

a_{11}	a_{12}		………	a_{1n}
a_{21}	a_{22}		……..	a_{2n}
…….				…….
a_{n1}	a_{n2}		……..	a_{nn}

Fig.2.13. Two dimensional G_{wc} matrix (n×n)

The optimal projection (eigen vector) matrices U_{opt} and V_{opt} are defined as follows:

$$U_{opt}=argmax_U|G_{br}\, {G_{wr}}^{-1}| \qquad (2.16)$$

$$=[u1,u2,.........,u_p\ ]$$

$$V_{opt}=argmax_V|G_{bc}\, {G_{wc}}^{-1}| \qquad (2.17)$$

$$=[v1,v2,.........,v_q\ ]$$

Where $\{u_i|i=1,2,3,.........p\}$ is the set of eigenvectors of $G_{br}\, {G_{wr}}^{-1}$ corresponding to p largest eigenvalues $\{\lambda_i|i=1,2,3,.........p\}$ and $\{v_j|j=1,2,3,.........q\}$ is the set of normalized eigenvectors of $G_{bc}\, {G_{wc}}^{-1}$ corresponding to q largest eigenvalues $\{\alpha_j|j=1,2,3,.........q\}$ [16,17].

The dimension of U_{opt} (Fig.2.14.) and V_{opt} (Fig.2.15.) are m×p and n×q respectively(calculate by above equation). The diagram are

a_{11}	a_{12}		……	a_{1p}
a_{21}	a_{22}		……	a_{2p}
…..				…..
a_{m1}	a_{m2}		…….	a_{mp}

Fig.2.14. Two dimensional U_{opt} matrix (m×p)

a_{11}	a_{12}		……….	a_{1q}
a_{21}	a_{22}		……	a_{2q}
…….				……
a_{n1}	a_{n2}		…….	a_{nq}

Fig.2.15. Two dimensional V_{opt} matrix (n×q)

2.2.2.1. Feature extraction

Here the optimal projection matrices U_{opt} and V_{opt} are used for feature extraction. For a given image sample X, an image feature is obtained by the following linear projection:

$$Z_{ij} = u_i^T X v_j,\ i=1,2,\ldots\ldots\ldots\ldots p\ ;\ j=1,2,\ldots\ldots\ldots\ldots q\ ; \quad (2.18)$$

$Z_{ij}(i = 1,2,\ldots\ldots\ldots\ldots\ldots \text{p}\ ;\ \text{j} = 1,2,\ldots\ldots\ldots\ldots\ldots \text{q}\ ;)$ *is* called principal component of the sample image X. It defined that each principal component of the 2DFLD method is a vector, where the principal component of the 2DFLD method is a scalar. The Principal component obtain are used to from a G-2DFLD based image feature matrix Z of dimension p×q (p≤m, q≤n), which is much smaller than the 2DFLD – based image feature matrices Y of dimension m×K (K≤n). Therefore ,we get the result in this case an image matrix is reduced considerably in both the row and column directions simultaneously[17,18].

The diagram of $Z_{ij}(p \times q)$ is

a_{11}	a_{12}		••••••••	a_{1q}
a_{21}	a_{22}		••••	a_{2q}
•••••				•••••
a_{p1}	a_{p2}		•••••	a_{pq}

Fig.2.16. Two dimensional Z_{ij} matrix(p×q)

2.2.3. Calculating fisherface

Let us consider an image A_i(i=1,2,...........N) b an m×n matrices of intensity values. Here the dimension of the row and column scatter matrices $G_{br}\, {G_{wr}}^{-1}$ and $G_{bc}\, {G_{wc}}^{-1}$ are m×m and n×n respectively. Since the eigenvectors of these two scatter matrices together define a subspace of the face images, we can combine them linearly to from fisherfaces[9,10].

Let U_{opt} = $[U_1, U_2, U_3 \ldots \ldots .. U_p]$ and V_{opt} = $[V_1, V_2, V_3 \ldots \ldots .. V_p]$ are the optimal orthogonal eigenvectors matrices corresponding to the p and q largest eigen values of $G_{br}\, {G_{wr}}^{-1}$ and $G_{bc}\, {G_{wc}}^{-1}$, respectively. Therefore the fisherfaces are generated by linear combination of eigenvectors as follows:

$$I_{ij} = u_i v_j^T,\ i = 1,2,\ldots\ldots\ldots p; j = 1,2,\ldots\ldots\ldots q \qquad (2.19)$$

2.3. Radial basis Function Neural network

In the RBF network, the hidden layer plays an important role as an interface between the networks and their environment. They are built of locally tuned respective fields called radial basis functions. Generally, a RBF network is feedforward architecture consisting of three layers as shown Fig.2.2. The hidden layer is composed of the respective fields, where nonlinear effect of noncomputing lies, while the output layer is a collection of some linear processing units [19,20].

The output of the hidden layer is given by

$$z_i(X) = \phi\left(\frac{||X - U_i||}{\sigma_i^2}\right), \text{ where } i=1,2,\ldots.k. \qquad (2.20)$$

Where, X is an i dimensional input vector, U_i is a vector with the same dimension X. K is the number of hidden units and $z_i(X)$ is i^{th} RBF unit.

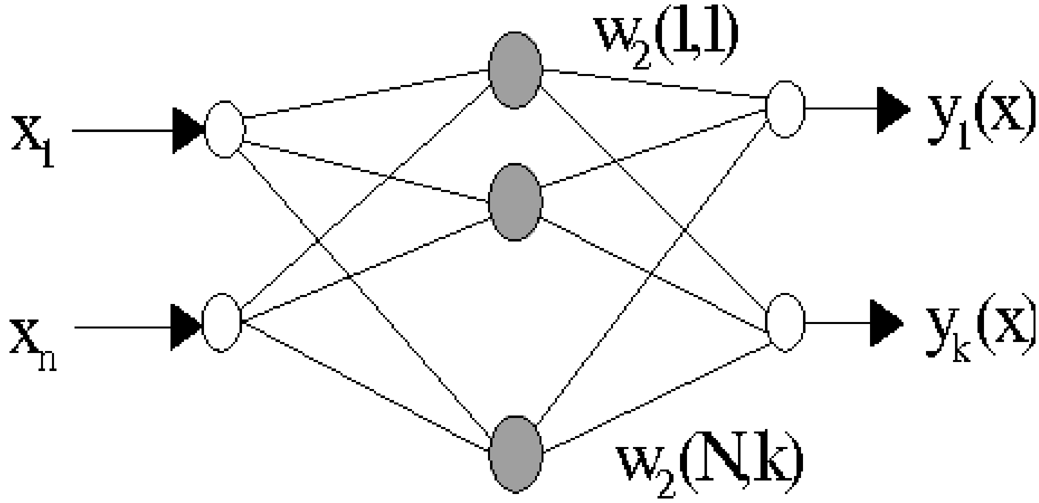

Fig.2.2. RBF neural network [20]

Chapter 3

Experimental results

The result value of the proposed method has been evaluated on the AT&T Laboratories Cambridge database(formely ORL database) [10] and the UMISTface database [9].

We get the value of Recognition rate as the percentage of ratio of the total number of currect recognition by the method to the total number of images in the test set for a single experimental run. Therefore the average recognition rate, R_{avg}, of the defined as follows:

$$R_{avg} = \frac{\sum_{i=1}^{n} n_{cls}^{i}}{l \ x \ n_{tot}} \text{ x } 100 \qquad (3.1)$$

Where *l* is the number of experimental runs

The n_{cls}^{i} is the total number of test face in each run

each one of l values are performed by randomly partitoning the database into two sets; training set and test set [23,24].

3.1.1. Experiments on the AT&T face database

Here the AT&T database contains 400 gray-scale image of 40 persons. Each person has 10 gray-scale images, have a resolution of 112×92 pixels. The local structure features such as eyes, nose, mouth, etc. are extracted from the frontal view images and their distance, locations, angle, etc. are used for recognition [25,26,27,28]. Images of the individuals are taken by varying light intensity, facial expressions(open/closed eyes, smiling/not smiling) and facial details (gasses/no glasses) against a dark homogeneous background, with tilt and rotation up to 20 and scale variation up to 10% . Sample face images of a person are shown in Fig.3.1 Therefore there are huge number of pixels [29,30,31,32].

Fig 3.1. Sample images of a subject from the AT&T database

3.1.2. Randomly partitioning the database

In our expiriment, we randomly chouse s images from each subject to from the training set and the remaining images are included in the test set. These ensure sufficient training and to test the effectiveness of the proposed techniques for different sizes of the training sets. Here we select the value of s as 3 , 4 , 5 , 6 and 7. We cannot overlap between the training and test image. To complete the influence of performance on the training and test sets, for each value of s, these experiment are repeated 20 times with these different training and test sets. Since the number of projection vectors p and q have a considerable impact on the performance of the Fuzzy Entropy based G-2DFLD algorithm , we perform several recognition which varies the values of p and q. For s=3, 4, 5, 6, and 7 the best average recognition rates are found to be 94.34% , 96.62%, 98.125% , 98.78125% , 98.83312% respectively and dimention (p x q) of the corresponding image feature matrices are (16 ×16), (20×20), (18×18), (20 ×20) and (16 ×16) respectively. The average specificty (%) are found to be 99.82%, 99.90%, 99.94%, 99.97%, 99.96% for s=3 , 4 , 5 , 6 and 7 [Tab.3.1.], respectively [33,34,35].

Tab.3.1. Maximum average recognition rate

Training and Test Sets	Maximum Average Recognition rate
Orl_trn_3, Orl_tst_7	94.34%
Orl_trn_4, Orl_tst_6	96.62%
Orl_trn_5 , Orl_tst_5 Orl_tst_5, Orl_trn_5	98.125%
Orl_tst_6, Orl_trn_4	98.78125%
Orl_tst_7, Orl_trn_3	98.83312%

GRAPHICAL REPRESENTATIONS OF THE TOTAL EXPERIMENT:-

In this experiment, we took five scenraios. Let us look through them-

Scenario 1:-

Orl_trn_*3_i (i=1,2...20)* as training set

Orl_tst_7_*i (i=1,2...20)* as test set

Here, we test Orl_trn_3_*i (i=1,2...20*) as training set and Orl_tst_7_*i (i=1,2...20)* as test set, and find the value. Next we calculate the average value on this table [Tab.3.2.] and draw the graph.

The average recognition rate alongwith the feature spaces are given as-

Tab.3.2. best average recognition rates, s=3

P × q	Avg
8 × 8	93.26786
10 × 10	93.44786
12 × 12	93.76786
14 × 14	93.92857
16 × 16	94.34086
18 × 18	94.03571
20 × 20	94.11929

Corresponding to this result, the graphical representation will be like-

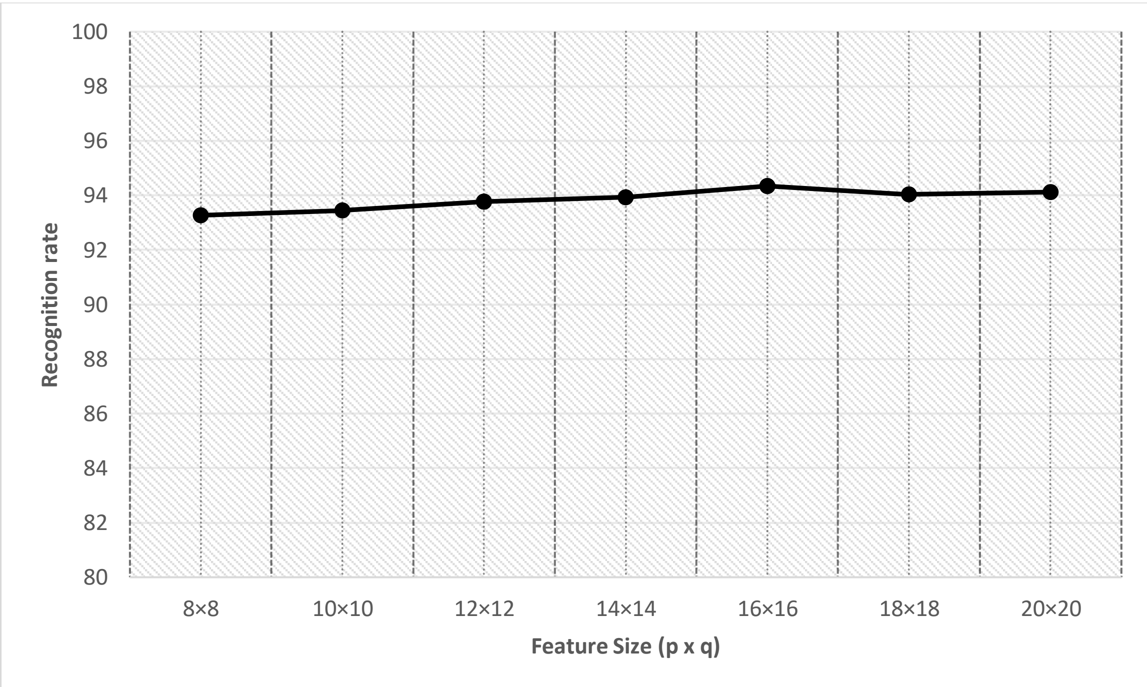

Fig.3.2. Average recognition rates(sensitivity (%)) of G-2DFLD algorithm on the AT&T database s=3 by varying the values of p and q.

Scenario 2:-

Orl_trn_4_*i (i=1,2...20)* as Training set

Orl_tst_6_*i (i=1,2...20)* as Test set

Here, we test Orl_trn_4_*i* (*i=1,2...20*) as training set and Orl_tst_6_*i* (*i=1,2...20)* as test set, and find the value. Next we calculate the average value on this table [Tab.3.3.] and draw the graph.

The average recognition rate alongwith the feature spaces are given as-

Tab.3.3. best average recognition rates, s=4

P × q	avg
8 × 8	95.72756
10 × 10	96.09167
12 × 12	96.125
14 × 14	96.39583
16 × 16	96.45833
18 × 18	96.5625
20 × 20	96.625

Corresponding to this result, the graphical representation will be like-

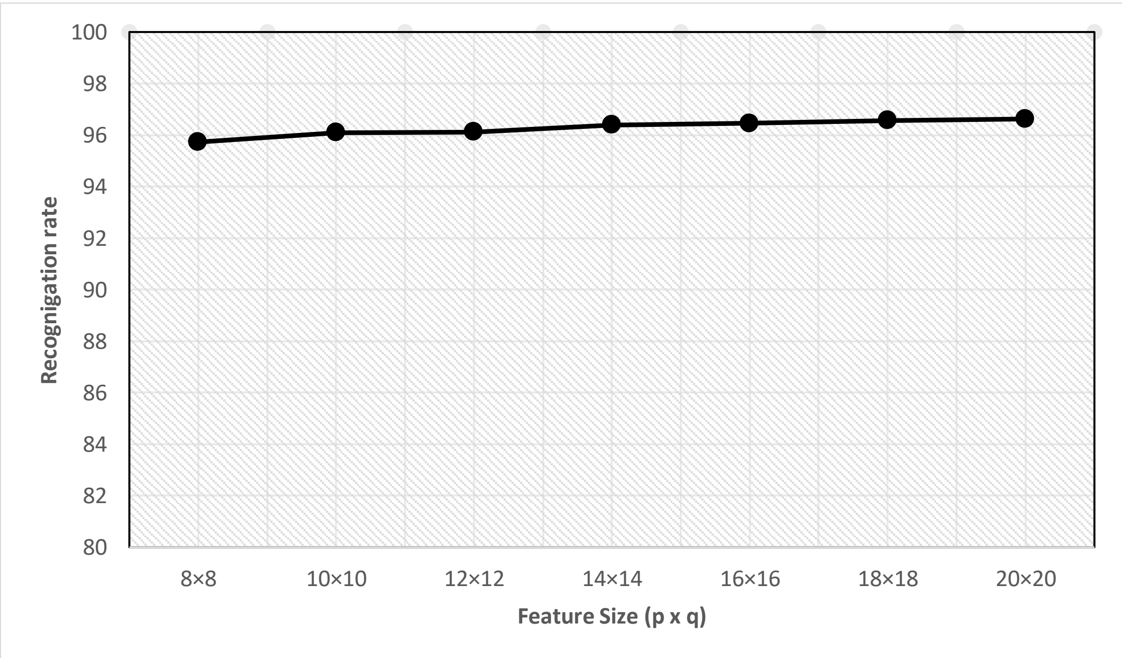

Fig.3.3. Average recognition rates(sensitivity (%)) of G-2DFLD algorithm on the AT&T database s=4 by varying the values of p and q.

Scenario 3:-

Orl_trn_5_*i (i=1,2..10)* as training

Orl_tst_5_*i (i=1,2...10)* as test

Orl_tst_5_*i (i=1,2...10)* as training

Orl_trn_5_*i (i=1,2...10)* as test

Here, we test Orl_trn_5_*i (i=1,2..10)* as training,Orl_tst_5_*i (i=1,2...10)* as test

,Orl_tst_5_*i (i=1,2...10)* as training,Orl_trn_5_*i (i=1,2...10)* as test

and find the value. Next we calculate the average value on this table [Tab.3.4.] and draw the graph.

The average recognition rate alongwith the feature spaces are given as-

Tab.3.4. best average recognition rates, s=5

P × q	avg
8 × 8	97.7
10 × 10	97.825
12 × 12	97.9
14 × 14	98.05
16 × 16	98.1
18 × 18	98.125
20 × 20	98.05

Corresponding to this result, the graphical representation will be like-

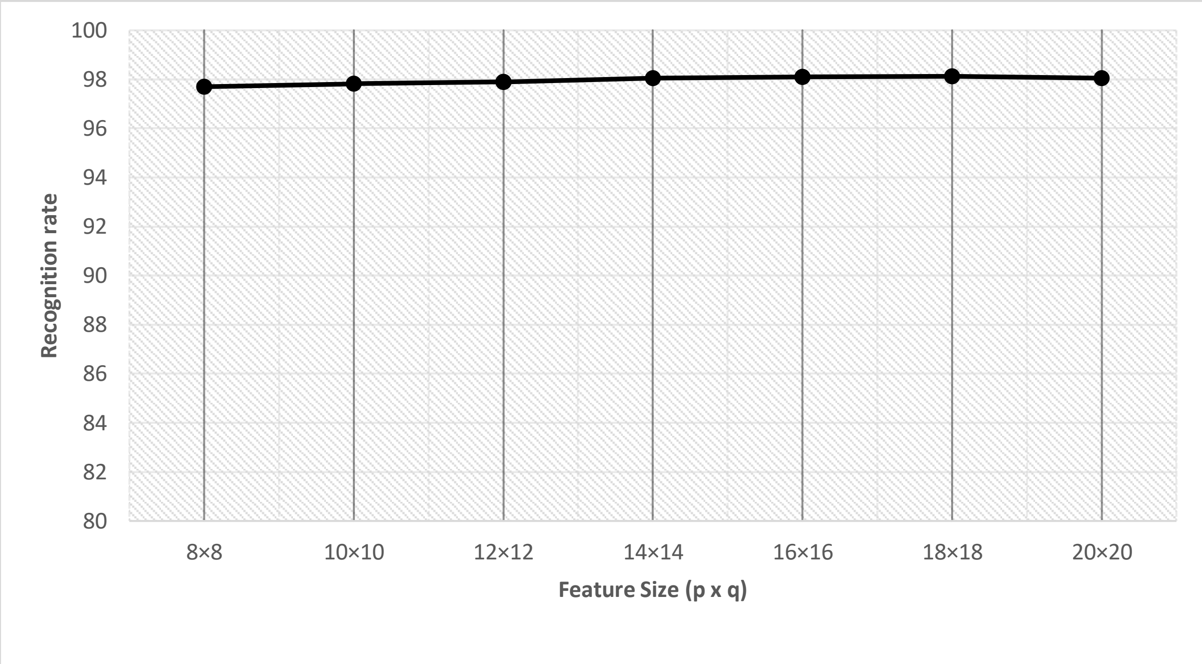

Fig.3.4. Average recognition rates(sensitivity (%)) of G-2DFLD algorithm on the AT&T database s=5 by varying the values of p and q.

Scenario 4:-

Orl_tst_6_*i (i=1,2...20)* as training set

Orl_trn_4_*i (i=1,2,...20)* as test set

Here, we test Orl_trn_6_*i (i*=1,2...20) as training set and Orl_tst_4_*i (i*=1,2...20) as test set, and find the value. Next we calculate the average value on this table [Tab.3.5.] and draw the graph.

The average recognition rate alongwith the feature spaces are given as-

Tab.3.5. best average recognition rates,s=6

P × q	avg
8 × 8	95.72756
10 × 10	96.09167
12 × 12	96.125
14 × 14	96.39583
16 × 16	96.45833
18 × 18	96.5625
20 × 20	96.625

Corresponding to this result, the graphical representation will be like-

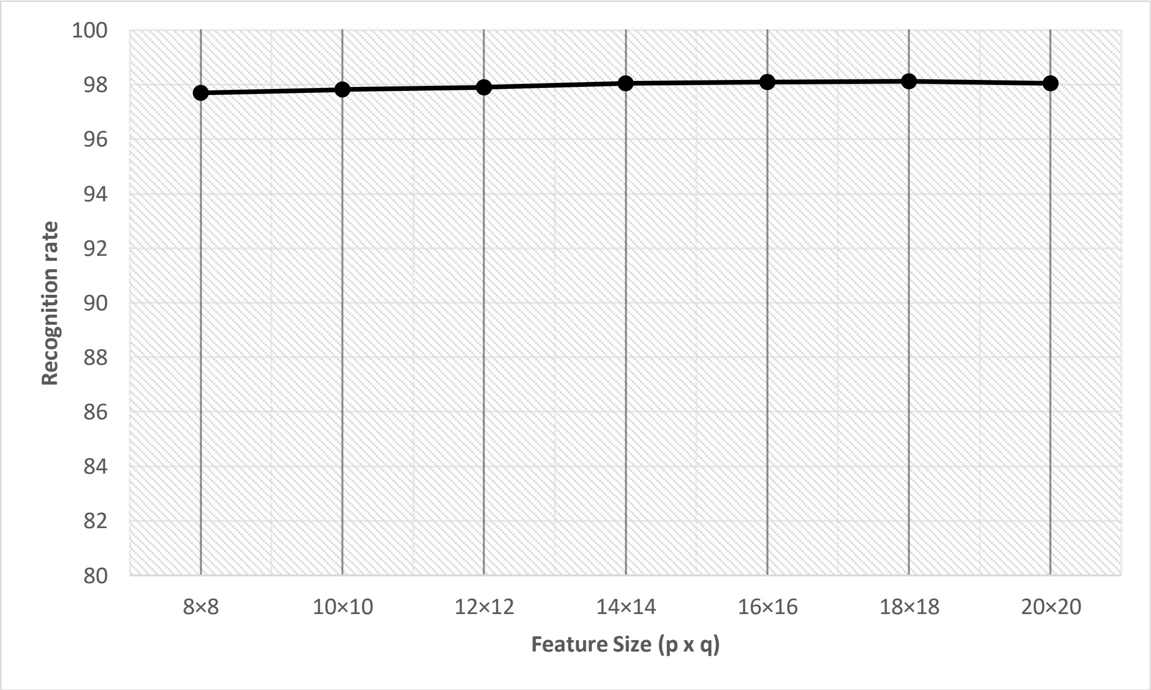

Fig.3.5: Average recognition rates(sensitivity (%)) of G-2DFLD algorithm on the AT&T database s=6 by varying the values of p and q.

Scenario 5:-

Orl_tst_7_*i* (*i*=1,2...20) as Training set

Orl_trn_3_*i* (*i*=1,2...20) as Test Set

Here, we test Orl_trn_7_i (i=1,2...20) as training set and Orl_tst_3_*i (i*=1,2...20) as test set, and find the value. Next we calculate the average value on this table [Tab.3.6.] and draw the graph.

The average recognition rate along with the feature spaces are given as-

Tab.3.6. best average recognition rates, s=5

P × q	avg
8 × 8	98.73332
10 × 10	98.77498
12 × 12	98.66665
14 × 14	98.70811
16 × 16	98.83312
18 × 18	98.74983
20 × 20	98.74981

Corresponding to this result, the graphical representation will be like-

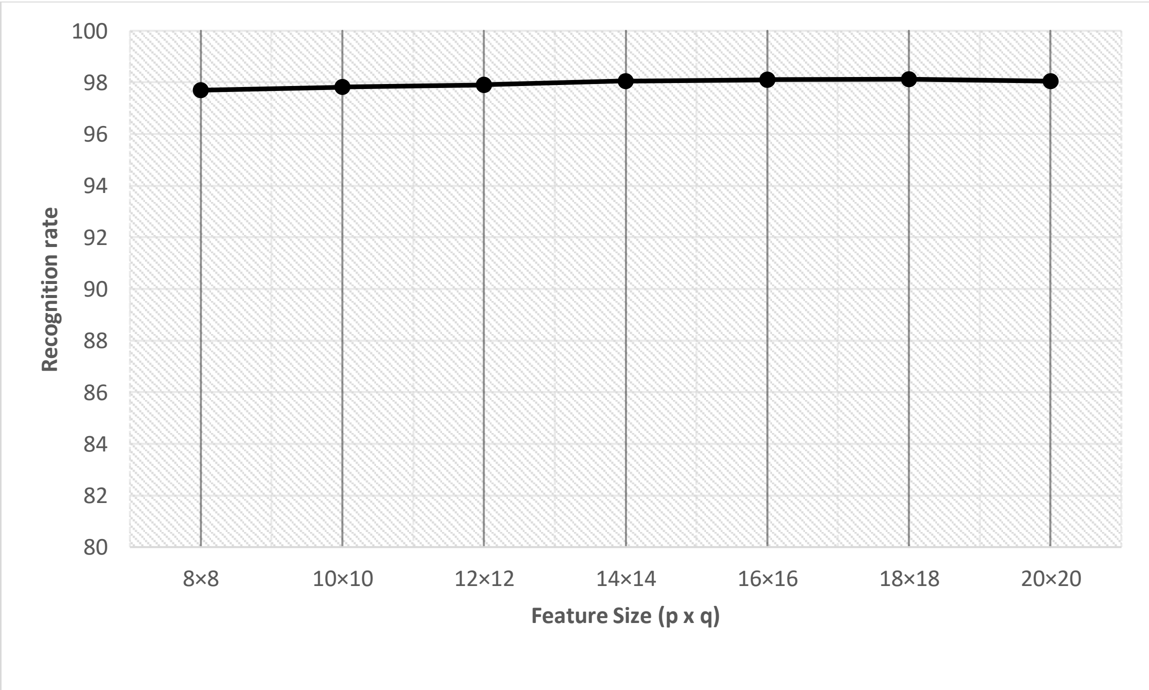

Fig.3.6. Average recognition rates(sensitivity (%)) of G-2DFLD algorithm on the AT&T database s=7 by varying the values of p and q [35].

3.2. COMPARISON IN TERMS OF RECOGNITION RATES OBTAINED FROM DIFFERENT METHODS FROM AT&T FACE DATABASE FOR DIFFERENT VALUES

Tab.3.7. RECOGNITION RATES OBTAINED FROM DIFFERENT METHODS FROM AT&T FACE DATABASE FOR DIFFERENT VALUES [36]

METHOD	AVERAGE RECOGNITION RATE				
	S=3	s=4	s=5	s=6	s=7
WFG-2DFLD β=0.4	93.25(14×14)	96.16(14×14)	98(14×14)	98.91(18×18)	98.82(16×16)
MMSD(β=0.4)	90.23(39)	....	95.89(39)	....	98.72(39)
G-2DFLD	92.82(16×16)	95.94(16v16)	97.98(14×14)	98.72(14×14)	98.42(8×8)
FUZZY FISHERFACE	82.32(39)	88.32(39)	....	......	......
2DFLD	92.30(112×16)	95.08(112×16)	97.5(112×14)	98.26(112×14)	....
G-2DFLD(ASSOCIATED WITH ENTROPY)	94.34(16×16)	96.62(20×20)	98.125(18×18)	98.78(20×20)	98.83(16×16)

Chapter 4

Conclusions

Face recognition systems have become a populer tool for identifying and verifying the identity of users in recent years. In order to complete successfully the recognition process , an initial , Fuzzy entropy based G-2DFLD algorithm must be implemented [37,38,39].

The results of the experiments show that our Fuzzy algorithms give the better results regarding the classification of pixels (between 94% - 96%) improving about 5% in this method.

Therefore our method leads to very accurate face detection and face recognition result.

We are also focusing on working with images where more than one face appears , adapting the face recognition algorithm accordingly.

Tables 3.2, 3.3, 3.4, 3.5 and 3.6 provides the general performance of the face recognition approaches. Here i find the average recognition value. Tab.3.7. shows the performance of recent appearance-based method such as,

WFG-2DFLD, MMSD, G-2DFLD, FUZZY FISHERFACE, G-2DFLD(Associated with entropy) .

G-2DFLD(Associated with entropy) method using SVM classifier enables higher recognition rate as expense of complexity. The normalized recognition rate of these method is around 95%.

The most important step in face recognition is the ability to evaluate existing methods and provide new directions on the basis of evaluations. The image used in the evaluation should be derived from real-time situations, similar to those in which the recognition system is expected to be installed. All the discussions so far have focused on recognition faces from still images [40,41].

CHAPTER 5

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