FACE RECOGNITION BY MODIFIED G2DFLD ALGORITHM BY INCORPORATING SPATIAL INFORMATION

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Submitted by

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Declaration of Originality and Compliance of Academic Ethics

I hereby declare that this thesis contains literature survey and original research work by the undersigned candidate, as part of my **Master of Technology in Computer Technology** in the Faculty of Engineering and technology, Jadavpur University during academic session 2018-19.

All information in this document have been obtained and presented in accordance with academic rules and ethical conduct.

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CONTENTS

CHAPTER 1: Introduction

The recognition of human faces are much more about face detection than face recognition. It has been proven that the first step in automatic facial recognition is the accurate detection of human faces in arbitrary scenes, is the most important process involved. When faces can be located exactly in any scene, the recognition step afterwards is not so complicated anymore.

Face recognition systems use computer algorithms to pick out specific, distinctive details about a person's face. These details, such as distance between the eyes or shape of the chin, are then converted into a mathematical representation and compared to data on other faces collected in a face recognition database. The data about a particular face is often called a face template and is distinct from a photograph because it's designed to only include certain details that can be used to distinguish one face from another. Some face recognition systems, instead of positively identifying an unknown person, are designed to calculate a probability match score between the unknown person and specific face templates stored in the database. These systems will offer up several potential matches, ranked in order of likelihood of correct identification, instead of just returning a single result. Face recognition systems vary in their ability to identify people under challenging conditions such as poor lighting, low quality image resolution, and suboptimal angle of view.

1.1 Background And History

Face recognition rises from the moment when the machine started to become more and more intelligent and had to fill in, correct or help the lack of human abilities and senses. Face recognition has always remains a major focus of research because it is people's primary method of person identification. A facial recognition system is a technology capable of identifying a person from a digital image. There are multiple methods in which facial recognition systems work, but in general, they work by comparing selected facial features from given image with faces within a database. Surveys of several face recognition method can be found in [1-4].

Mainly, the process of face recognition is performed in two steps. The first involves feature extraction and selection and, the second is the classification of objects. Later developments introduced varying technologies to the procedure.

Recognition algorithms can be divided into two main approaches, geometric, which looks at distinguishing features, or photometric, which is a statistical approach that distills an image into values and compares the values with templates to eliminate variances. Some classify these algorithms into two broad categories: holistic and feature-based models. The former attempts to recognize the face in its entirety while the feature-based subdivide into components such as according to features and analyze each as well as its spatial location with respect to other features. Popular recognition algorithms include principal component analysis using eigenfaces, linear discriminant analysis, elastic bunch graph matching using the Fisherface algorithm, the hidden Markov model, the multilinear subspace learning using tensor representation, and the neuronal motivated dynamic link matching.

1.2 Literature Survey

In the beginning of the 1970's, face recognition was treated as a 2D pattern recognition problem. The distances between important points where used to recognize known faces, e.g. measuring the distance between the eyes or other important points or measuring different angles of facial components. But it is necessary that the face recognition systems to be fully automatic. Face recognition is such a challenging yet interesting problem that it has attracted researchers who have different backgrounds: psychology, pattern recognition, neural networks, computer vision, and computer graphics. The following methods are used to face recognition. 1. Holistic Matching Methods, 2. Feature-based (structural) Methods, and 3. Hybrid Methods.

1.2.1 Holistic matching method

In holistic approach, the complete face region is taken into account as input data into face catching system. One of the best example of holistic methods are most widely used method for face recognition, Principal Component Analysis, Linear Discriminant Analysis and independent component analysis etc. [5,6].

The first successful demonstration of machine recognition of faces was made by Turk and Pentland in 1991 using eigenfaces. Their approach covers face recognition as a two dimensional recognition problem. The flowchart in Figure 1 illustrates the different stages in an eigenface based recognition system [7-9].

This method of face recognition is a step by step method. many stages are involved in the process. *I*. The first stage is to insert a set of images into a database, these images are names as the training set and this is because they will be used when we compare images and when we create the eigenfaces. *II*. The second stage is to create the eigenfaces. Eigenfaces are made by extracting characteristic features from the faces. The input images are normalized to line up the eyes and mouths. They are then resized so that they have the same size.

Eigenfaces can now be extracted from the image data by using a mathematical tool called Principal Component Analysis (PCA). *III*. When the eigenfaces have been created, each image will be represented as a vector of weights. *IV*. The system is now ready to accept entering queries. *V*. The weight of the incoming unknown image is found and then compared to the weights of those already in the system. If the input image's weight is over a given threshold it is considered to be unidentified. The identification of the input image is done by finding the image in the database whose weights are the closest to the weights of the input image. The image in the database with the closest weight will be returned as a hit to the user of the system.

The FLD method is also widely used which faces a difficulty of “small sample size problem” [10]. To avoid this Er et al. [11] proposed a technique where feature is extracted by PCA first and then resultant features are further processed by FLD method. Then 2D-PCA an improved version of PCA also proposed [12]. Then 2D-FLD method is also proposed with is superior to PCA and 2D-PCA in terms of feature extraction and face recognition. There are also other methods like bayseian [14], neural networks [11,15-19] and SVM based [20-26] that have been proposed. Fisherface methods have been developed further in order to improve the performance [27-32]. The other improvement in holistic matching methods can be found in the literature [33-36].

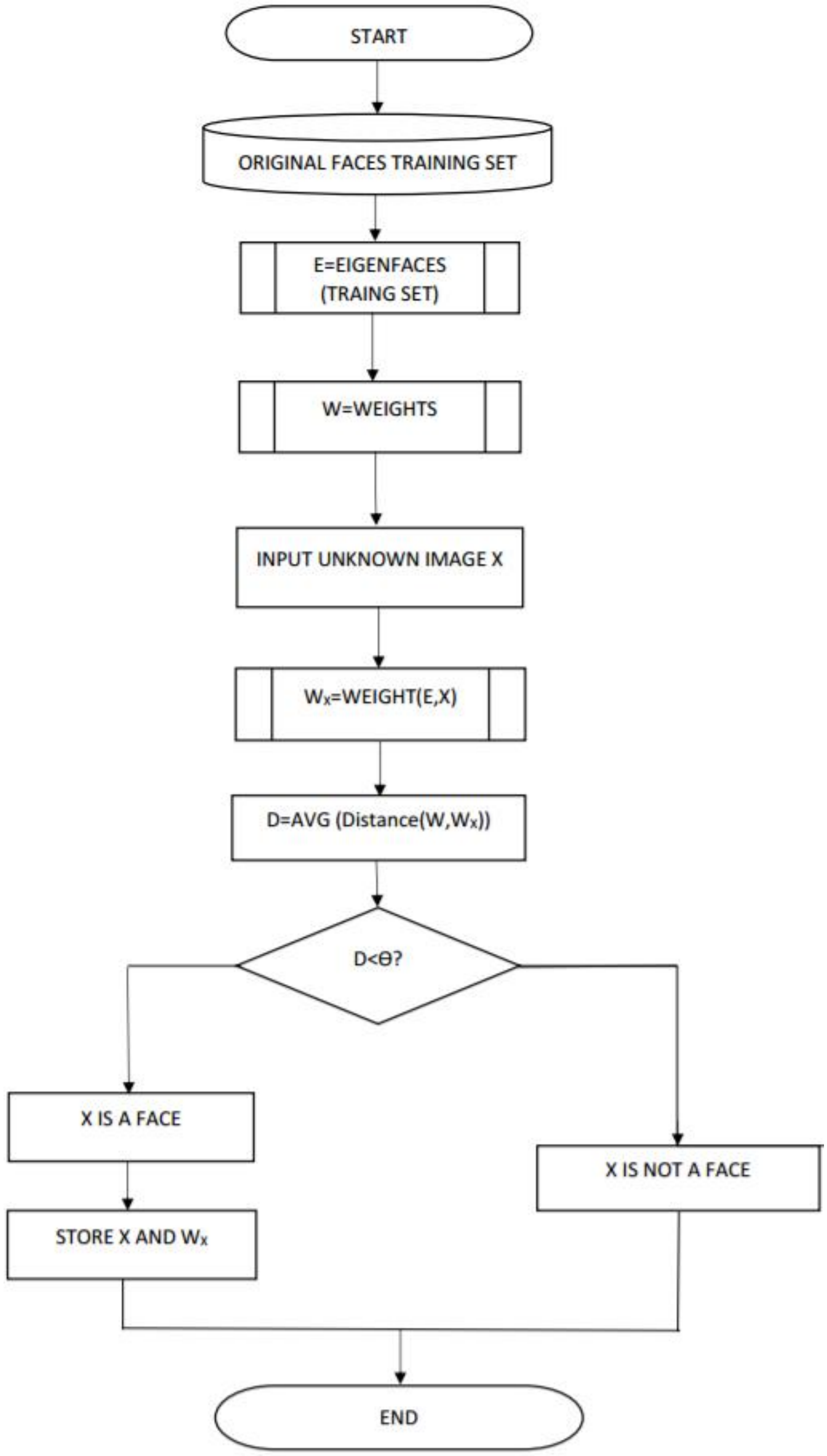

Fig. 1.1. Flow chart of the eigenface-based algorithm.

1.2.2 Feature-based (structural) Methods

In this methods local features such as eyes, nose and mouth are first of all extracted and their locations and local statistics (geometric and/or appearance) are fed into a structural classifier. A big challenge for feature extraction methods is feature "restoration", this is when the system tries to retrieve features that are invisible due to large variations [35-37].

Three different extraction methods:

I. Generic methods based on edges, lines, and curves.

II. Feature-template-based methods.

III. Structural matching methods that take into consideration geometrical Constraints on the features.

The main disadvantage of these methods is that the profile (side-view) images and illumination variations can increase the complexity and time of the approach.

1.2.3 Hybrid Methods

Hybrid face recognition systems use a combination of both holistic and feature extraction methods [38]. Generally 3D Images are used in hybrid methods. The image of a person's face is caught in 3D, allowing the system to note the curves of the eye sockets, for example, or the shapes of the chin or forehead. Even a face in profile would serve because the system uses depth, and an axis of measurement, which gives it enough information to construct a full face. The 3D system usually proceeds thus: Detection, Position, Measurement, Representation and Matching. Detection- Capturing a face either a scanning a photograph or photographing a person's face in real time. Position- Determining the location, size and angle of the head.

Some hybrid methods are modular eigenface method [38], hybrid local feature analysis [39], shape normalized method [40], component based method [41].

In Case the 3D image is to be compared with an existing 3D image, it needs to have no alterations. Typically, however, photos that are put in 2D, and in that case, the 3D image need a few changes. This is tricky, and is one of the biggest challenges in the field today.

1.2.4 Face Recognition Applications & Examples

Face recognition is also useful in human computer interaction, virtual reality, database recovery, multimedia, computer entertainment, information security e.g. operating system, medical records, online banking. Biometric e.g. Personal Identification - Passports, driver licenses, Automated identity verification - border controls, Law enforcement e.g. video surveillances, investigation, Personal Security - driver monitoring system, home video surveillance system.

Face Identification: Face recognition systems identify people by their face images. Face recognition systems establish the presence of an authorized person rather than just checking whether a valid identification (ID) or key is being used or whether the user knows the secret personal identification numbers (Pins) or passwords. The following are example.

To eliminate duplicates in a nationwide voter registration system because there are cases where the same person was assigned more than one identification number. The face recognition system directly compares the face images of the voters and does not use ID numbers to differentiate one from the others. When the top two matched faces are highly similar to the query face image, manual review is required to make sure they are indeed different persons so as to eliminate duplicates.

Access Control: In many of the access control applications, such as office access or computer logon, the size of the group of people that need to be recognized is relatively small. The face pictures are also caught under natural conditions, such as frontal faces and indoor illumination. The face recognition system of this application can achieve high accuracy without much co-operation from user. The following are the example. Face recognition technology is used to monitor continuously who is in front of a computer terminal. It allows the user to leave the terminal without closing files and logging out. When the user leaves for a predetermined time, a screen saver covers up the work and disables the mouse & keyboard. When the user comes back and is recognized, the screen saver clears and the previous session appears as it was left. Any other user who tries to logon without authorization is denied.

Security: Today more than ever, security is a primary concern at airports and for airline staff office and passengers. Airport protection systems that use face recognition technology have been implemented at many airports around the world.

Image database investigations: Searching image databases of licensed drivers, benefit recipients, missing children, immigrants and police bookings.

General identity verification: Electoral registration, banking, electronic commerce, identifying newborns, national IDs, passports, employee IDs.

Surveillance: Like security applications in public places, surveillance by face recognition systems has a low user satisfaction level, if not lower. Free lighting conditions, face orientations and other divisors all make the deployment of face recognition systems for large scale surveillance a challenging task.

Here we have extended the generalized 2DFLD algorithm which maximizes class separability from both the row and column directions simultaneously. Like 2DFLD method, modified G2DFLD method is also based on the original 2D image matrix. In modified G2DFLD method. Unlike 2DFLD method, the principal components extracted from an image matrix by the G2DFLD method are extracted from the neighbouring elements information from the image matrix in order to retrieving the special feature information about the image and the size of the resultant image feature matrix is much smaller using the G-2DFLD method than that of using the 2DFLD method. The experimental results on the AT&T database show that the new modified G-2DFLD scheme gives better results in terms of face recognition.

1.3 Problem statement

The generalized two-dimensional Fisher's linear discriminant method is used for face recognition. The G2DFLD method is an extension of the 2DFLD method for feature extraction. Like 2DFLD method, G2DFLD method is also based on the original 2D image matrix. But 2DFLD method maximizes class separability either from row or column direction and the G2DFLD method maximizes class separability from both the row and column directions simultaneously. To explain these two alternative Fisher's criteria have been defined corresponding to row and column-wise projection directions. Here we have extended the G2DFLD algorithm. Unlike G2DFLD method, the principal components extracted from an image matrix in modified G2DFLD method is a vector of neighbouring elements of the pixel of an image matrix and the pixel itself. Here in order to extract the spatial information, the feature vector from the image matrix, the neighbouring elements information is taken and a smaller size feature matrix is produced. The proposed G2DFLD method was evaluated on popular face recognition databases, the AT&T (formerly ORL) database. The experimental results show that this modified G2DFLD method gives better performance in terms of face recognition.

CHAPTER 2: Modified G2DFLD algorithm using spatial information

2.1 Two dimensional FLD method for feature extraction

The 2DFLD method, which is based on the 2D image matrix, does not need to form a stretched large image vector from the 2D image matrix. The key idea of the algorithm is to project an image matrix X, an $m \times k$ random matrix, onto an optimal projection matrix A of dimension $n \times k$ (k is the number of projection vector and $k <= n$) which results an image feature matrix Y of dimension $m \times k$ by the following linear transformation:

$$Y = XA \tag{2.1}$$

Suppose there are N training images, each one is denoted by $m \times n$ image matrix $\boldsymbol{X_i}$ $(\boldsymbol{i} = \boldsymbol{1}, \boldsymbol{2}, \ldots\ldots, \boldsymbol{N})$. The training images contain C classes or subjects, and the c^{th} class C_c has N_c samples $\boldsymbol{(\sum_{c=1}^{c} N_c = N).}$ Suppose, the mean image of the training samples is denoted by μ and the mean image of the c^{th} class is denoted by μ_c. The between- class and within-class scatter matrices G_b and G_w, respectively are

$$G_b = \sum_{c=1}^{C} N_c (\mu_c - \mu)^T (\mu_c - \mu) \tag{2.2}$$

$$G_w = \sum_{c=1}^{C} \sum_{i \in c}^{N} (X_i - \mu_c)^T (X_i - \mu_c) \tag{2.3}$$

Then the two-dimensional Fisher's criterion $J(Q)$ is represented as follows:

$$J(Q) = \frac{|Q^T G_b Q|}{|Q^T G_w Q|} \tag{2.4}$$

Here Q is the projection matrix.

Here, the size of both the G_b and G_w is $n \times n$ If G_w is a nonsingular matrix, the ratio in (2.4) is maximized when the column vectors of the projection matrix Q, are the eigenvectors of $G_b {G_w}^{-1}$. The optimal projection matrix Q_{opt} is given below:

$$Q_{opt} = argmax|G_b G_w - 1| = [q_1, q_2, \ldots.., q_k] \tag{2.5}$$

Where $\{\boldsymbol{q_i} | \boldsymbol{i} = \mathbf{1}, \mathbf{2}, \ldots. \boldsymbol{k}\}$ is the set of normalized eigenvectors of $G_b {G_w}^{-1}$ corresponding to k largest Eigen values $\{\boldsymbol{\lambda_i} | \boldsymbol{i} = \mathbf{1}, \mathbf{2}, \ldots. \boldsymbol{k}\}$.

Now, each face image $\boldsymbol{X_i}$ $(\boldsymbol{i} = \mathbf{1}, \mathbf{2}, \ldots.., \boldsymbol{N})$ is projected into the optimal projection matrix Q_{opt} to achieve its $(m \times k)$-dimensional 2DFLD-based features Y_i, which is given defined as follows:

$$\overline{Y_i} = \overline{X_i} Q_{opt} \quad i = 1, 2, \ldots, N \tag{2.6}$$

Here $\overline{X_i}$ is mean-subtracted image of X_i and defined as follows:

$$\overline{X_i} = X_i - \mu \tag{2.7}$$

2.2 Generalized two-dimensional FLD (G-2DFLD) method for feature extraction

2.2.1 Key idea and the algorithm

Like 2DFLD method, the generalized two-dimensional FLD (G-2DFLD) method is also based on 2D image matrix. The only difference is, it maximizes class separability from both the row and column directions simultaneously by the following linear transformation:

$$Z = U^T X V \tag{2.8}$$

Where U and V are two projection matrices of dimension $m \times p$ $(p \le m)$ and $n \times q$ $(q \le n)$ respectively. So, our goal is to find the optimal projection directions U and V so that the projected vector in the $(p \times q)$ dimensional space achieve its maximum class separability.

2.2.2 Alternate Fisher's criteria

We have defined two alternative Fisher's criteria $J(U)$ and $J(V)$ corresponding to row and column-wise projection directions as follows:

$$J(U) = \frac{|U^T G_{br} U|}{|U^T G_{wr} U|} \tag{2.9}$$

$$J(V) = \frac{|V^T G_{bc} V|}{|V^T G_{wc} V|} \tag{2.10}$$

Where,

$$G_{br} = \sum_{c=1}^{C} N_c(\mu_c - \mu)(\mu_c - \mu)^T \tag{2.11}$$

$$G_{wr} = \sum_{c=1}^{C} \sum_{i \in c}^{N} (X_i - \mu_c)(X_i - \mu_c)^T \tag{2.12}$$

$$G_{bc} = \sum_{c=1}^{C} N_c(\mu_c - \mu)(\mu_c - \mu)^T \tag{2.13}$$

$$G_{wc} = \sum_{c=1}^{C} \sum_{i \in c}^{N} (X_i - \mu_c)(X_i - \mu_c)^T \tag{2.14}$$

The matrices G_{br}, G_{wr}, G_{bc} and G_{wc}, are defined here as image row between-class scatter matrix, image row within class scatter matrix, image column between-class scatter matrix and image column within class scatter matrix, respectively. It may be noted that size of the scatter matrices G_{br} and G_{wr} is $m \times m$, whereas, for G_{bc} and G_{wc} size is $n \times n$. The sizes of these scatter matrices are much smaller than that of the conventional FLD algorithm, whose scatter matrices are $mn \times mn$ 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 (2.9) and (2.10) are maximized 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 optimal projection (eigenvector) matrices U_{opt} and V_{opt} are given as follows:

$$U_{opt} = argmax|G_{br}G_{wr} - 1| = [u_1, u_2, \ldots\ldots, u_p] \quad (2.15)$$

$$V_{opt} = argmax|G_{bc}G_{wc} - 1| = [v_1, v_2, \ldots\ldots, v_p] \quad (2.16)$$

Where $\{\boldsymbol{u_i} | \boldsymbol{i} = \mathbf{1}, \mathbf{2}, \ldots . \boldsymbol{k}\}$ the set of is normalized eigenvectors of $G_{br}G_{wr}{}^{-1}$ corresponding to p largest eigenvalues $\{\boldsymbol{\lambda_i} | \boldsymbol{i} = \mathbf{1}, \mathbf{2}, \ldots . \boldsymbol{k}\}$ and $\{\boldsymbol{v_i} | \boldsymbol{j} = \mathbf{1}, \mathbf{2}, \ldots . \boldsymbol{k}\}$ is the set of normalized eigenvectors of $G_{bc}G_{wc}{}^{-1}$ corresponding to q largest eigenvalues $\{\boldsymbol{a_i} | \boldsymbol{j} = \mathbf{1}, \mathbf{2}, \ldots . \boldsymbol{k}\}$.

2.2.3 Feature extraction

The optimal projection matrices U_{opt} and $V_{opt}$are used to extract features. For a given image sample X, an image feature is obtained by the following linear projection:

$$Z_{\,ij} = u_i{}^T X v_j, \quad \boldsymbol{i} = \mathbf{1}, \mathbf{2}, \ldots, \boldsymbol{p}; \quad \boldsymbol{j} = \mathbf{1}, \mathbf{2}, \ldots, \boldsymbol{q} \quad (2.17)$$

The $\boldsymbol{Z}_{\,\boldsymbol{ij}}$ $(\boldsymbol{i} = \mathbf{1}, \mathbf{2}, \ldots, \boldsymbol{p}; \quad \boldsymbol{j} = \mathbf{1}, \mathbf{2}, \ldots, \boldsymbol{q})$ is called a principal component of the sample image X. Here, each principal component of the 2DFLD method is a vector, whereas, the principal component of the G-2DFLD method is a scalar. The principal components thus obtained are used to form a G-2DFLD-based image feature matrix Z of dimension $p \times q$ $(p \le m,\ q \le n)$, which is much smaller than the 2DFLD-based image feature matrix Y of dimension $m \times k$ $(k \le n)$. So, in this case an image matrix is reduced considerably in both the row and column directions simultaneously.

2.3 Calculating fisherfaces

Let an image A_i $(i = 1, 2, \ldots, N)$ be a $m \times n$ matrix of intensity values. The dimension of the row and column scatter matrices $G_{br}{G_{wr}}^{-1}$ and $G_{bc}{G_{wc}}^{-1}$ are $m \times m$ and $n \times n$, respectively. Since the eigenvectors these two scatter matrices together define a subspace of the face images, we can combine them linearly to form fisherfaces.

Let $\boldsymbol{U_{opt}} = [\boldsymbol{u_1}, \boldsymbol{u_2}, \ldots, \boldsymbol{u_p}]$ and $\boldsymbol{V_{opt}} = [\boldsymbol{v_1}, \boldsymbol{v_2}, \ldots, \boldsymbol{v_p}]$ are the optimal orthonormal eigenvectors matrices corresponding to the p and q largest eigenvalues of $G_{br}{G_{wr}}^{-1}$ and $G_{bc}{G_{wc}}^{-1}$, respectively. The fisherfaces are generated by linear combination of eigenvectors as follows:

$$I_{ij} = u_i {v_j}^T, \qquad i = 1, 2, \ldots, p; \qquad j = 1, 2, \ldots, q \tag{2.18}$$

2.4 Feature extraction by incorporating spatial information

Any pixel $p(x, y)$ has two vertical and two horizontal neighbors, given by $(x + 1, y), (x - 1, y), (x, y + 1), (x, y - 1)$. This set of pixels are called the 4-neighbors of p, and is denoted by $N_4(p)$. Each of them are at a unit distance from P. The four diagonal neighbors of $p(x, y)$ are given by, $(x + 1, y + 1), (x + 1, y - 1), (x - 1, y + 1), (x - 1\ , y - 1)$. This set is denoted by $N_D(p)$.

The points $N_D(p)$ and $N_4(p)$ are together known as 8-neighbors of the point p, denoted by $N_8(p)$. Some of the points in the N_4, N_D and N_8 may fall outside image when p lies on the border of image.

4-neighbors of a pixel p are its vertical and horizontal neighbors denoted by $N_4(p)$ and 8-neighbors of a pixel p are its vertical horizontal and 4 diagonal neighbors denoted by $N_8(p)$.

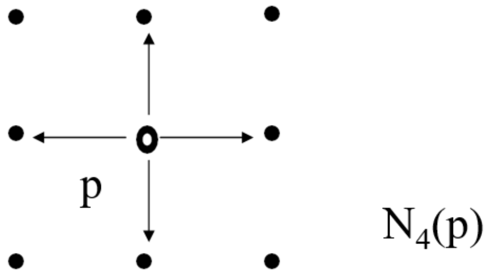

Fig. 2.1 4-neighbors of P

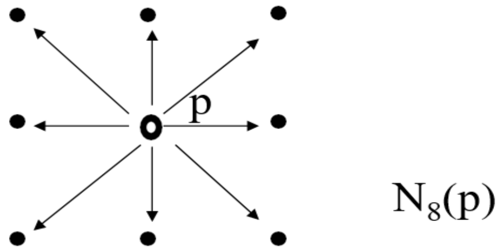

Fig. 2.2 8-neighbors of P

N_8- 8-neighbors (N_4 U N_D)

Two pixels are connected if they are neighbors and their gray levels satisfy some specified criterion of similarity. For example, in a binary image two pixels are connected if they are 4-neighbors and have same value (0/1).

Let V be set of gray levels values used to define adjacency.

• 4-adjacency: Two pixels p and q with values from V are 4- adjacent if q is in the set $N_4\ (p)$.

• 8-adjacency: Two pixels p and q with values from V are 8- adjacent if q is in the set $N_8(p)$.

Let V be the set of gray-level values used to define connectivity; then two pixels p, q that have values from the set V are:

a.4-connected, if q is in the set $N_4\ (p)$.

b.8-connected, if q is in the set $N_8(p)$.

A feature vector is the one containing several different elements (features). The features may be associated to a pixel, a connected component or an object in an image. These characteristics can be viewed as the functions that provide relevant informations. In most cases, these features are used in the treatments related to the classification and pattern recognition.

In the case of segmentation some applications are simply interested in the pixel gray level value as a feature. Here we have taken pixel’s neighbourhood value that are the total 8 neighbours and the pixel itself as an array.

The matrices image row between-class scatter matrix, image row within class scatter matrix, image column between-class scatter matrix and image column within class scatter matrix, respectively are modified as follows.

$$S_{br} = \sum_{c=1}^{C} N_c A_c A_c^T \tag{2.19}$$

Here, A_{cik} and B_{cjk} which are the arrays of 9 pixel values are represented by $[a_{cik}^{(1)}, a_{cik}^{(2)} \dots \dots, a_{cik}^{(9)}]$ and $[b_{cjk}^{(1)}, b_{cjk}^{(2)} \dots \dots, b_{cjk}^{(9)}]$ respectively.

Where,

$$S_{br}(i,j) = \sum_{c=1}^{C} N_c \sum_{k=1}^{m} \frac{1}{9} [(a_{cik}^{(1)} \times b_{cjk}^{(1)}) + \left(a_{cik}^{(2)} \times b_{cjk}^{(2)}\right) \dots \dots + (a_{cik}^{9} \times b_{cjk}^{9})$$

$$S_{br} = \sum_{c=1}^{C} N_c \sum_{k=1}^{m} \frac{1}{9} A_{cik} B_{cjk}^T \tag{2.20}$$

$$S_{wr} = \sum_{c=1}^{C} \sum_{i \in c}^{N} B_c B_c^T \tag{2.21}$$

Here, C_{cik} and D_{cjk} which are the arrays of 9 pixel values are represented by $[c_{cik}^{(1)}, c_{cik}^{(2)} \dots \dots, c_{cik}^{(9)}]$ and $[d_{cjk}^{(1)}, d_{cjk}^{(2)} \dots \dots, d_{cjk}^{(9)}]$ respectively.

Where,

$$S_{wr}(i,j) = \sum_{c=1}^{C} \sum_{i \in c}^{N} \sum_{k=1}^{m} \frac{1}{9} \left[\left(c_{cik}^{(1)} \times d_{cjk}^{(1)}\right) + \left(c_{cik}^{(2)} \times d_{cjk}^{(2)}\right) \dots \dots + (c_{cik}^{9} \times d_{cjk}^{9})\right]$$

$$S_{wr} = \sum_{c=1}^{C} \sum_{i \in c}^{N} \sum_{k=1}^{m} \frac{1}{9} C_{cik} D_{cjk}^T \tag{2.22}$$

$$S_{bc} = \sum_{c=1}^{C} N_c C_c C_c^T \tag{2.23}$$

Here, E_{cik} and F_{cjk} which are the array of 9 pixel values are represented by $[e_{cik}^{(1)}, e_{cik}^{(2)} \dots \dots, e_{cik}^{(9)}]$ and $[f_{cjk}^{(1)}, f_{cjk}^{(2)} \dots \dots, f_{cjk}^{(9)}]$ respectively.

Where,

$$S_{bc}(i,j) = \sum_{c=1}^{C} N_c \sum_{k=1}^{m} \frac{1}{9} [(e_{cik}^{(1)} \times f_{cjk}^{(1)}) + \left(e_{cik}^{(2)} \times f_{cjk}^{(2)}\right) \dots \dots + (e_{cik}^{9} \times f_{cjk}^{9})$$

$$S_{bc} = \sum_{c=1}^{C} N_c \sum_{k=1}^{m} \frac{1}{9} E_{cik} F_{cjk}^T \tag{2.24}$$

$$S_{wc} = \sum_{c=1}^{C} \sum_{i \in c}^{N} D_c D_c^T \tag{2.25}$$

Here, G_{cik} and H_{cjk} which are the array of 9 pixel values are represented by $[g_{cik}^{(1)}, g_{cik}^{(2)} \dots \dots, g_{cik}^{(9)}]$ and $[h_{cjk}^{(1)}, h_{cjk}^{(2)} \dots \dots, h_{cjk}^{(9)}]$ respectively.

Where,

$$S_{wc}(i,j) = \sum_{c=1}^{C} \sum_{i \in c}^{N} \sum_{k=1}^{m} \frac{1}{9} \left[\left(g_{cik}^{(1)} \times h_{cjk}^{(1)}\right) + \left(g_{cik}^{(2)} \times h_{cjk}^{(2)}\right) \dots \dots + (g_{cik}^{9} h_{cjk}^{9})\right]$$

$$S_{wc} = \sum_{c=1}^{C} \sum_{i \in c}^{N} \sum_{k=1}^{m} \frac{1}{9} G_{cik} H_{cjk}^T \tag{2.26}$$

Where m and n is the no of rows and columns. So the feature vector depends on what features are useful for the application. Some people calculate specific characteristics using image processing techniques and computer vision and some others simply use the intensities of the original pixels as features.

It is important to note that, any application implemented to solve a given problem needs the use of analytical tools, these latters require the handling features that may be intrinsic to the image or can be synthesized to establish a knowledge base for the processing algorithm.

CHAPTER 3: Results and Discussions

The AT&T database contains 400 gray-scale images of 40 persons. Each person has 10 gray-scale images, having a resolution of 112*92 pixels. Images of the individuals have been taken by varying light intensity, facial expressions (open/closed eyes, smiling/not smiling) and facial details (glasses/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.

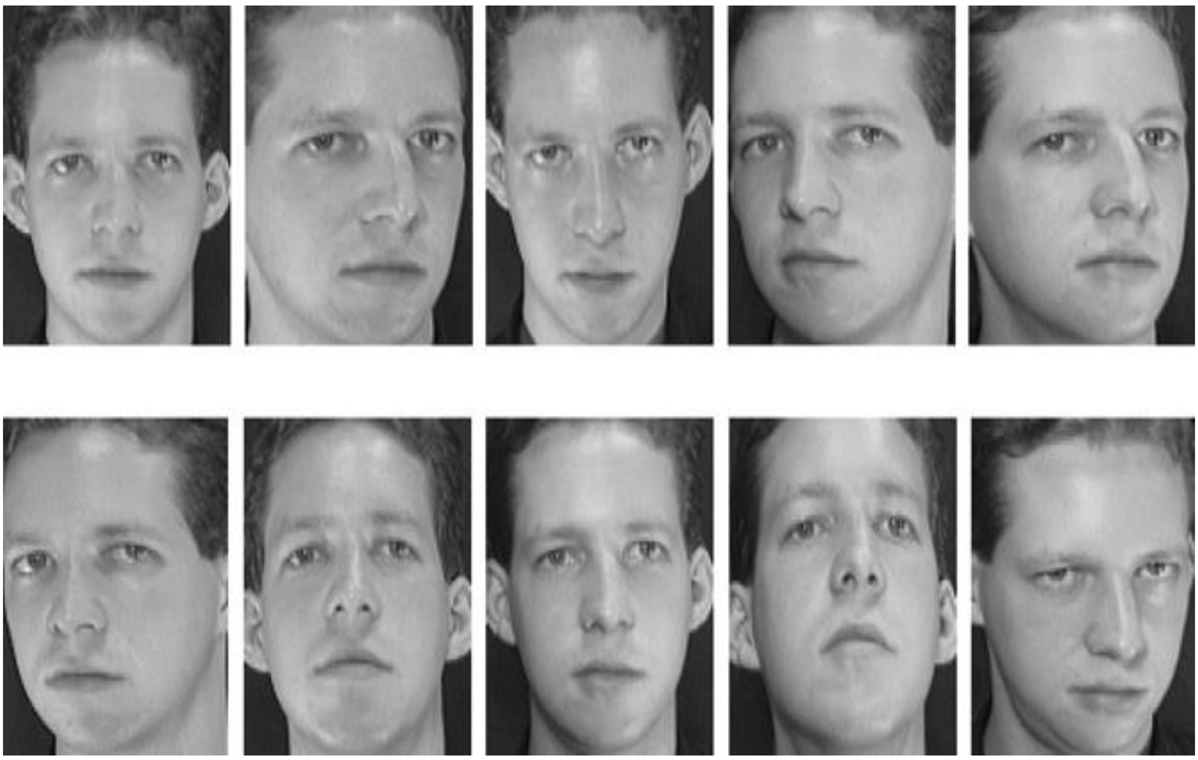

Fig. 3.1. Sample images of a subject from the AT&T database.

3.1 Case 1

In this experiment, *s* images from each subject is randomly selected to form a training set and the remaining images are included in the test set of the images. Here, we choose the value *s* as 5 for the following experiment. There should be no overlap between the training and test images. Experiment is repeated 20 times with different test and training sets in order to reduce the influence of performance on the training and test sets. Several experiments also have been performed by varying the *p* and *q* values. The average recognition rates found from the experiment with varying the values of *p* and *q* are given in the table below. For *s*=5 average recognition rates are measured varying the values of *p* and *q*. best average recognition rate is found to be 98.125% for the dimension ($p\times q$) of the image feature matrix is 14×14. The values of average recognition rates varying the values of *p* and *q* are given in the table 3.1.1. A graph is also plotted by varying the values of *p* and *q* in fig 3.1.1 for *s*=5 average recognition rate is also plotted.

Table 3.1.1. Average recognition rates are plotted by varying the values of *p* and *q*. for *s* = 5.

*p***q*	Average recognition rate
8*8	97.65
10*10	97.8
12*12	97.975
14*14	98.125
16*16	98.075
18*18	98.075
20*20	98.0789

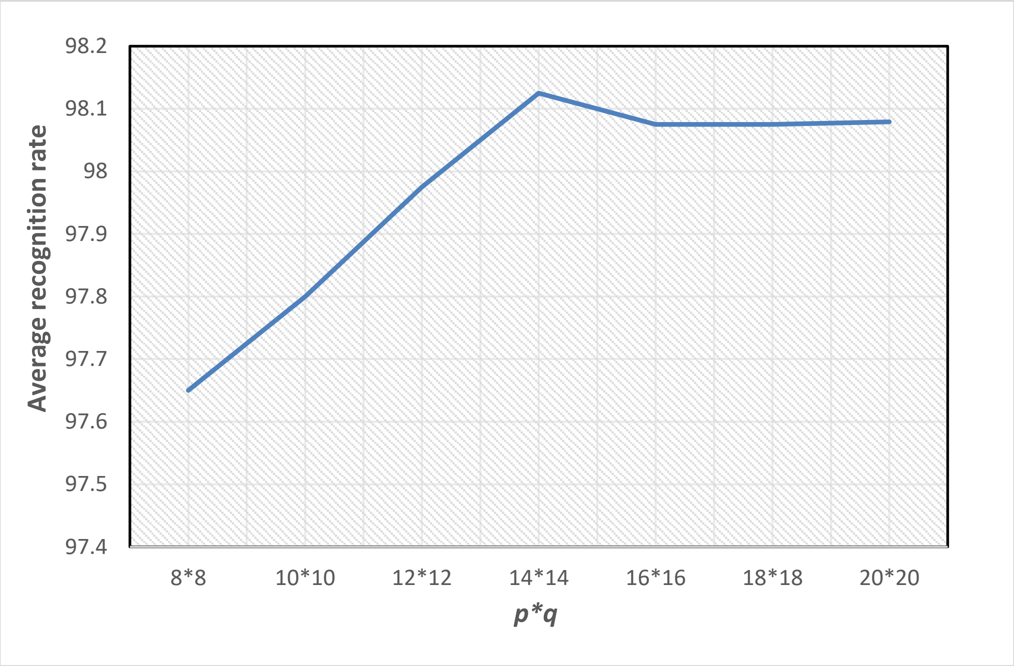

Fig. 3.1.1. Average recognition rates of the G-2DFLD algorithm on the AT&T database for different values of s by varying the values of *p*.

3.2 Case 2

In this experiment, we take *s* images from each subject randomly to form a training set and the test set of the images covers the remaining images. Here, we have chosen the value *s* as 4 for the following experiment. No overlap between the training and test images are allowed. Experiment is repeated 20 times with different test and training sets in order to reduce the influence of performance on the training and test sets. By varying the *p* and *q* values various experiments are done. The average recognition rates found from the experiment with varying the values of *p* and *q* are given in the table below. For *s*=4 average recognition rates are measured varying the values of *p* and *q*. Best average recognition rate that we have got form the experiment is 96.042% for the dimension ($p \times q$) of the image feature matrix is 14×14. The values of average recognition rates varying the values of p and q are given in the table 3.1.2. for *s*=4 average recognition rate is also plotted by varying the values of *p* and *q* in fig 3.1.2.

Table 3.1.2. Average recognition rates are plotted by varying the values of *p* and *q*. For *s* = 4.

*p**q*	Average Recognition Rate
8*8	95.0271
10*10	95.4556
12*12	95.8102
14*14	96.0421
16*16	96.0364
18*18	96.0094
20*20	94.3358

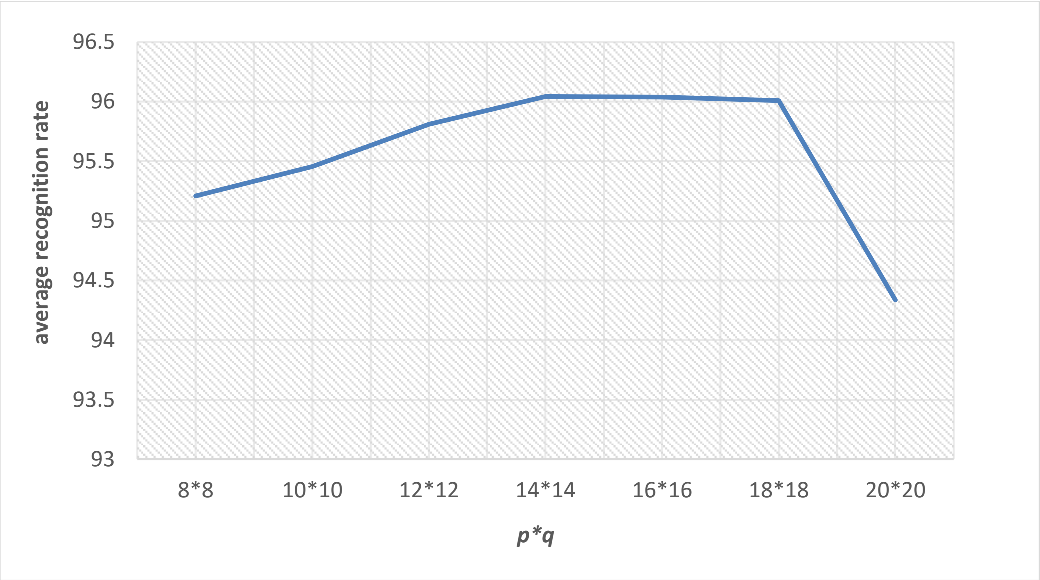

Fig. 3.1.2. Average recognition rates of the G-2DFLD algorithm on the AT&T database for different values of *s* by varying the values of *p*.

3.3 Case 3

In this experiment also, we have taken *s* images from each subject randomly to form a training set and the test set of the images covers the remaining images. We have chosen the value *s* as 4 for the following experiment. No overlap between the training and test images are allowed. Experiment is repeated 20 times with different test and training sets in order to reduce the influence of performance on the training and test sets. By varying the *p* and *q* values various experiments are done. The average recognition rates found from the experiment with varying the values of *p* and *q* are given in the table below. For *s*=3 average recognition rates are measured varying the values of *p* and *q*. Best average recognition rate that we have got form the experiment is 94.08% for the dimension ($p \times q$) of the image feature matrix is 14×14 and 16× 16 both. The values of average recognition rates varying the values of p and q are given in the table 3.1.3. for *s*=3 average recognition rate is also plotted by varying the values of *p* and *q* in fig 3.1.3.

Table 3.1.3. Average recognition rates are plotted by varying the values of *p* and *q*. For *s* = 3.

*p*q*	Average Recognition Rate
8*8	92.72
10*10	93.81
12*12	94.32
14*14	94.08
16*16	94.08
18*18	93.92
20*20	93.67

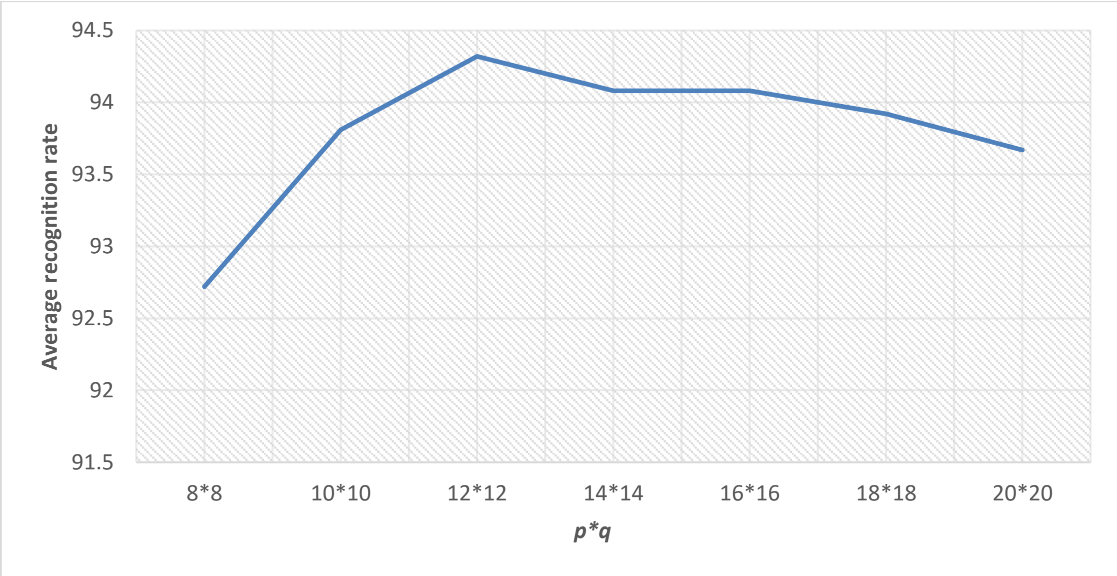

Fig. 3.1.3. Average recognition rates of the G-2DFLD algorithm on the AT&T database for different values of *s* by varying the values of *p*.

CHAPTER 4: Conclusion

We have presented a face recognition system by feature extraction method, modified generalized two-dimensional FLD method, which is based on the original 2D image matrix. The G2DFLD algorithm maximizes class separability from both the row and column directions simultaneously, resulting in smaller image feature matrix. To realize this, we have defined two alternative Fisher's criteria. The principal components extracted from an image matrix from the neighbouring elements of the pixel values by the modified G2DFLD method. Since the size of the scatter matrices in the proposed modified G2DFLD algorithm is much smaller than those in the conventional PCA and FLD schemes, the computational time for feature extraction is much less. Also the image feature matrix generated by the G2DFLD algorithm is much smaller than those of generated by the 2DPCA and 2DFLD algorithms. As a result, the overall time (feature extraction time + recognition time) of G2DFLD algorithm is also much lesser than the 2DPCA and 2DFLD algorithms. Several experiments were done on the AT&T database. The experimental results show that the modified G2DFLD method is more efficient than the other previously used methods, not only in terms of computation times, but also for the task of face recognition.

4.1 Future scope

There are several directions where this work can be extended. Concept of Soft Computing can be used for automatic face recognition system. Using Soft Computing, neural network can be combined with fuzzy logic to enhance the performance of face recognition. Another avenue for research would be to implement other feature extraction technique on the same data set. In future, two or more classifiers can be combined to achieve better results.

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