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PERFORMANCE ANALYSIS OF FACE RECOGNITION SYSTEM USING FISHERFACES

Rupali Sunil Salunke[1], Prof. K. N. Pawar [2]
[1]Student, [2]Professsor
[1,2] Department of E&TC
SPPU University, Jalgaon, India

Abstract: Face recognition has been one of the most interesting and important research fields in the past two decades. The reasons come from the need of automatic recognitions and surveillance systems, the interest in human visual system on face recognition, and the design of human-computer interface, etc. These researches involve knowledge and researchers from disciplines such as neuroscience, psychology, computer vision, pattern recognition, image processing, and machine learning, etc. In this paper, we will have a study of most recently methods for face recognition is fisher faces. One of the approach is eigenface, fisher faces and other one is the elastic bunch graph matching. Face recognition issue gained more interest recently due to its various applications and the demand of high security. Some researches with contradicting results were published concerning this issue. This paper is based on popular face recognition projection methods: fisher faces.

***Index Terms* - Fisher faces, Face recognition, Eigan Value.**

I. INTRODUCTION

Humans often use faces to recognize individuals and advancements in computing capability over the past few decades now enable similar recognitions automatically. Early face recognition algorithms used simple geometric models, but the recognition process has now matured into a science of sophisticated mathematical representations and matching processes. Major advancements and initiatives in the past ten to fifteen years have propelled face recognition technology into the spotlight. Face recognition can be used for both verification and identification (open-set and closed-set).

A key problem in computer vision, pattern recognition, and machine learning is to define an appropriate data representation for the task at hand. One way to represent the input data is by finding a subspace which represents most of the data variance. This can be obtained with the use of Principal Components Analysis (PCA). When applied to face images, PCA yields a set of eigen faces. These eigen faces are the eigenvectors associated to the largest eigenvalues of the covariance matrix of the training data. The eigenvectors thus found correspond to the least-squares (LS) solution. This is indeed a powerful way to represent the data because it ensures the data variance is maintained while eliminating unnecessary existing correlations among the original features (dimensions) in the sample vectors.

When the goal is classification rather than representation, the LS solution may not yield the most desirable results. In such cases, one wishes to find a subspace that maps the sample vectors of the same class in a single spot of the feature representation and those of different classes as far apart from each other as possible. The techniques derived to achieve this goal are known as discriminate analysis (DA).

The most known DA is Linear Discriminate Analysis (LDA), which can be derived from an idea suggested by R.A. Fisher in 1936. LDA (Linear Discriminate Analysis) provides the projection that discriminates the data well, and shows a very good performance for face recognition. However, since LDA provides only one transformation matrix over whole data, it is not sufficient to discriminate the complex data consisting of many classes like human faces. When LDA is used to find the subspace representation of a set of face images, the resulting basis vectors defining that space are known as Fisher faces.

The fisher face method of face recognition as described by Belhumeur et al [4] uses both principal component analysis and linear discriminate analysis to produce a subspace projection matrix, similar to that used in the eigen face method. However, the fisherface method is able to take advantage of ewithin- classí information, minimizing variation within each class, yet still maximizing class separation.

Fig. 1: Configuration of general face recognition structure

The main function of face detection step is to determine (1) whether human faces appear in a given image, and (2) where these faces are located at. The expected outputs of this step are patches containing each face in the input image. In order to make further face recognition system more robust and easy to design, face alignment are performed to justify the scales and orientations of these patches. Besides serving as the pre-processing for face recognition, face detection could be used for region-of-interest detection, retargeting, video and image classification, etc.

II. Literature Survey

The Eigenface method is one of the generally used algorithms for face recognition. Karhunen- Loeve is based on the eigen faces technique in which the Principal Component Analysis (PCA) is used. This method is successfully used to perform dimensionality reduction. Principal Component Analysis is used by face recognition and detection. Mathematically, Eigen faces are the principal components divide the face into feature vectors. The feature vector information can be obtained from covariance matrix. These Eigenvectors are used to quantify the variation between multiple faces. The faces are characterized by the linear combination of highest Eigen values. Each face can be considered as a linear combination of the eigen faces. The face can be approximated by using the eigenvectors having the largest eigen values. The best M eigenfaces define an M dimensional space, which is called as the "face space". Principal Component Analysis is also used by L. Sirovich and M. Kirby to efficiently represent pictures of faces. They defined that a face images could be approximately reconstructed using a small collection of weights for each face and a standard face picture. The weights describing each face are obtained by projecting the face image onto the eigen picture [3]. Eigenface is a practical approach for face recognition. Because of the simplicity of its algorithm, implementation of an eigen face recognition system becomes easy. It is efficient in processing time and storage. PCA reduces the dimension size of an image in a short period of time. There is a high correlation between the training data and the recognition data. The accuracy of eigen face depends on many things. As it takes the pixel value as comparison for the projection, the accuracy would decrease with varying light intensity. Preprocessing of image is required to achieve satisfactory result. An advantage of this algorithm is that the eigen faces were invented exactly for those purpose what makes the system very efficient [4].

Fisherfaces is one the most successfully widely used method for face recognition. It is based on appearance method. In 1930 R.A Fisher developed linear/fisher discriminate analysis for face recognition. It shows successful result in the face recognition process. LDA method demonstrated in (Belhumeur et al., 1997; Zhao et al., 1999; Chen et al., 2000; Yu and Yang, 2001; Liu and Wechsler., 2002; Lu et al., 2003a, b; Ye and Li., 2004). All used LDA to find set of basis images which maximizes the ratio of between-class scatter to within-class scatter. The disadvantage of LDA is that within the class the scatter matrix is always single, since the number of pixels in images is larger than the number of images so it can increase detection of error rate if there is a variation in pose and lighting condition within same images. So to overcome this problem many algorithms has been proposed. Because the fisher faces technique uses the advantage of within-class information so it minimizes the variation within class, so the problem with variations in the same images such as lighting variations can be overcome. [2] The fisher face method for face recognition described by Belhumeur et al uses both principal component analysis and linear discriminate analysis, which produce a subspace projection matrix, similar as used in the eigen face method. However, the fisher face method is able to take advantage of within-class information, minimizing variation within each class, yet still maximizing class separation. Like the eigen face construction process, the first step of the fisher face technique is take each (NxM) image array and reshape into a ((N*M)x1) vector. Fisherface is similar to Eigen face but with enhancement of better classification of different classes image. With FLD, one can classify the training set to deal with different people and different facial expression. We have better accuracy in facial expression than Eigen face approach. Besides, Fisher face removes the first three principal components, which are responsible for light intensity changes; it is more invariant to light intensity. [4] The disadvantages of Fisher face are that it is more complex than Eigen face to finding the projection of face space. Calculation of ratio of between-class scatter to within-class scatter requires a lot of processing time. Besides, due to the need of better classification, the dimension of projection in face space is not as compact as Eigen face, results in larger storage of the face and more processing time in recognition. [4]

Face recognition using elastic bunch graph matching is based on recognizing faces by estimating a set of features using a data structure called a bunch graph. Same as for each query image, the landmarks are estimated and located using bunch graph. Then the features are extracted by taking the number of instances of Gabor filters, which is called “face graph”. The matching percentage (MSEBGM) is calculated based on similarity between face graphs of database and query image. In 1999, Elastic Bunch Graph Matching was suggested by Laurenz Wiskott, Jean-Marc Fellous, Norbert Kruger and Christoph von der Malsburg of University of Southern California. This approach is totally different to Eigen face and Fisher face.

III. System Development

3.1 Eigenfaces

The Eigenface is the first method considered as a successful technique of face recognition. The Eigenface method uses Principal Component Analysis (PCA) to linearly project the image space to a low dimensional feature space. The Fisherface method is an enhancement of the Eigenface method that it uses Fisher’s Linear Discriminant Analysis (FLDA or LDA) for the dimensionality reduction. The LDA maximizes the ratio of between-class scatter to that of within-class scatter, therefore, it works better than PCA for purpose of discrimination. The Fisherface is especially useful when facial images have large variations in illumination and facial expression.

Eigenfaces is the name given to a set of eigenvectors when they are used in the computer vision problem of human face recognition.[1] The approach of using eigenfaces for recognition was developed by Sirovich and Kirby (1987) and used by Matthew Turk and Alex Pentland in face classification.[2] The eigenvectors are derived from the covariance matrix of the probability distribution over the high-dimensional vector space of face images. The eigenfaces themselves form a basis set of all images used to construct the covariance matrix. This produces dimension reduction by allowing the smaller set of basis images to represent the original training images. Classification can be achieved by comparing how faces are represented by the basis set. A set of eigenfaces can be generated by performing a mathematical process called principal component analysis (PCA) on a large set of images depicting different human faces. Informally, eigenfaces can be considered a set of "standardized face ingredients", derived from statistical analysis of many pictures of faces. Any human face can be considered to be a combination of these standard faces. For example, one's face might be composed of the average face plus 10% from eigenface 1, 55% from eigenface 2, and even −3% from eigenface 3. Remarkably, it does not take many eigenfaces combined together to achieve a fair approximation of most faces. Also, because a person's face is not recorded by a digital photograph, but instead as just a list of values (one value for each eigenface in the database used), much less space is taken for each person's face. The eigenfaces that are created will appear as light and dark areas that are arranged in a specific pattern. This pattern is how different features of a face are singled out to be evaluated and scored. There will be a pattern to evaluate symmetry, whether there is any style of facial hair, where the hairline is, or an evaluation of the size of the nose or mouth. Other eigenfaces have patterns that are less simple to identify, and the image of the eigenface may look very little like a face. The technique used in creating eigenfaces and using them for recognition is also used outside of face recognition: handwriting recognition, lip reading, voice recognition, sign language/hand gestures interpretation and medical imaging analysis. Therefore, some do not use the term eigenface, but prefer to use 'eigenimage'

3.2 Elastic Bunch Graph Matching

Elastic Bunch Graph Matching is a face recognition algorithm that is distributed with CSU’s Evaluation of Face Recognition Algorithms System. The algorithm is modeled after the Bochum/USC face recognition algorithm used in the FERET evaluation. The algorithm recognizes novel faces by first localizing a set of landmark features and then measuring similarity between these features. Both localization and comparison uses Gabor jets extracted at landmark positions. In localization, jets are extracted from novel images and matched to jets extracted from a set of training/model jets. Similarity between novel images is expressed as function of similarity between localized Gabor jets corresponding to facial landmarks. A study of how accurately a landmark is localized using different displacement estimation methods is presented. The overall performance of the algorithm subject to changes in the number of training/model images, choice of specific wavelet encoding, displacement estimation technique and Gabor jet similarity measure is explored in a series of independent tests. Several findings were particularly striking, including results suggesting that landmark localization is less reliable than might be expected. However, it is also striking that this did not appear to greatly degrade recognition performance.

3.3 Fisherfaces

A key problem in computer vision, pattern recognition and machine learning is to define an appropriate data representation for the task at hand. One way to represent the input data is by finding a subspace which represents most of the data variance. This can be obtained with the use of Principal Components Analysis (PCA). When applied to face images, PCA yields a set of eigenfaces. These eigenfaces are the eigenvectors associated to the largest eigenvalues of the covariance matrix of the training data. The eigenvectors thus found correspond to the least-squares (LS) solution. This is indeed a powerful way to represent the data because it ensures the data variance is maintained while eliminating unnecessary existing correlations among the original features (dimensions) in the sample vectors. When the goal is classification rather than representation, the LS solution may not yield the most desirable results. In such cases, one wishes to find a subspace that maps the sample vectors of the same class in a single spot of the feature representation and those of different classes as far apart from each other as possible. The techniques derived to achieve this goal are known as discriminate analysis (DA). The most known DA is Linear Discriminate Analysis (LDA), which can be derived from an idea suggested by R.A. Fisher in 1936. When LDA is used to find the subspace representation of a set of face images, the resulting basis vectors defining that space are known as Fisherfaces.

3.4 Discriminate Scores

To compute the Fisherfaces, we assume the data in each class is normally distributed. We denote the multivariate Normal distribution as Ni(μi,Σi) , with mean μi and covariance matrix Σi , and its probability density function is

fi(x|μi,Σi) .

In the C class problem, we have Ni(μi,Σi) , with i=1,…,C . Given these Normal distributions and their class prior probabilities Pi , the classification of a test sample x is given by comparing the log-likelihoods of fi(x|μi,Σi)Pi for all i .

That is,

argmin1≤i≤Cdi(x),

where di(x)=(x−μi)TΣ−1i(x−μi)+ln|Σi|−2lnPi are known as the discriminate scores of each class. The discriminate scores thus defined yield the Bayes optimal solution.

The discriminate scores generally result in quadratic classification boundaries between classes. However, for the case where all the covariance matrices are the same, Σi=Σ , ∀ i , the quadratic parts of di cancel out, yielding linear classifiers. These classifiers are called linear discriminant bases. Hence, the name of linear discriminate analysis. The case where all the covariances are identical is known as homoscedastic Normal distributions.

Assume that C=2 and that the classes are homoscedastic Normal. Project the sample feature vectors onto the one-dimensional subspace orthogonal to the classification hyper plane given by the discriminate score. It follows that the number of misclassified samples in the original space of p dimensions and in this subspace of just one dimension are the same. This is easily verifiable. Since the classification boundary is linear, all the samples that where on one side of the space will remain on the same side of the 1-dimensions subspace. This important point was first noted by R.A. Fisher and has allowed us to define the LDA algorithm and fisher faces.

3.5 Computing the Fisherfaces

The theoretical argument given in the preceding section shows how to obtain the Bayes optimal solution for the 2-class homoscedastic case. In general, we will have more than 2-classes. In such a case, we reformulate the above stated problem as that of minimizing within-class differences and maximizing between-class distances. Within class differences can be estimated using the within-class scatter matrix, given by

Sw=∑Cj=1∑nji=1(xij−μj)(xij−μj)T,

Where xij is the ith sample of class j , μj is the mean of class j , and nj the number of samples in class j .Likewise, the between class differences are computed using the between-class scatter matrix,

Sb=∑Cj=1(μj−μ)(μj−μ)T,

Where μ represents the mean of all classes, We now want to find those basis vectors V where Sw is minimized and Sb is maximized, where V is a matrix whose columns vi are the basis vectors defining the subspace. These are given by,

|VTSbV||VTSwV|

The solution to this problem is given by the generalized eigen value decomposition

SbV=SwVΛ,

where V is (as above) the matrix of eigenvectors and Λ is a diagonal matrix of corresponding eigenvalues. The eigenvectors of V associated to non-zero eigenvalues are the Fisherfaces. There is a maximum of C−1 Fisherfaces. This can be readily seen from the definition of Sb . Note that in our definition, Sb is a combination of C feature vectors. Any C vectors define a subspace of C−1 or less dimensions. The equality holds when these vectors are linearly independent from one another. Figure 1 shows the first four Fisherfaces obtained when using the defined algorithm on a set of frontal face image of 100 different subjects. Images were selected to have a neutral expression.

3.6 Fisher face Extensions

Recently, Two-dimensional LDA (2DLDA), a tensor extension of LDA, is proposed. Different from the LDA which requires the input patterns to be converted to one-dimensional vectors, the 2DLDA directly extracts the proper features from image matrices based on Fisher's Linear Discriminate Analysis. Figure shows the system development for face recognition. Figure shows the flow chart and system operational idea.

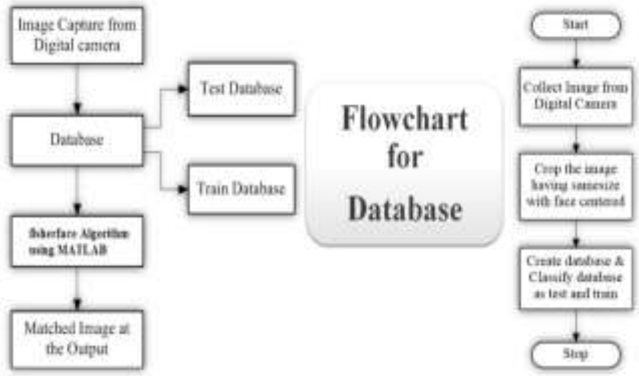

Figure 1. Flowchart and operational theme

IV. Performance Analysis and Result Discussion

Development in this section will be discussed about the results of facial recognition research using fisherface method. In general, face recognition system in this study can be seen in Figure 1. [6].

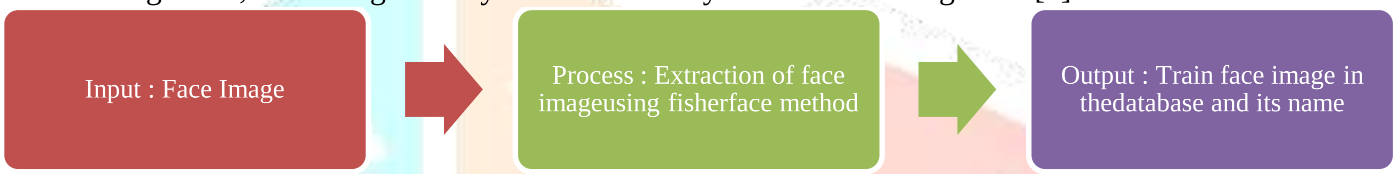

Figure 1. Stages of system process

4.1 Image Data

- Image of the photograph result.

Here is a sample of photos photograph with each individual represented by a minimum of 5 samples of face images with different positions and different expressions

- **Image Data Training**

To know the success of the system created, then the system will be trained in the first with several images as shown in figure above.

- **System Testing**

To determine whether the system is running well made and properly it is necessary to test. The following process

- **Training Process.**

The first stage of system testing is the training stage. This stage aims to generate the weight value of each image of existing training.

- **Image Recognition Process.**

After the training process is successfully done, the next stage is to carry out image recognition process. The goal is how big the system successfully recognize the test image or testing properly. The following is the result of the image recognition process performed by the system.

- ➢ The training image is the same as the testing image
- ➢ The training image is not the same as the testing image.

- **Image recognition results**

The following is an example of the results of facial recognition process with fisherface method can be seen below.

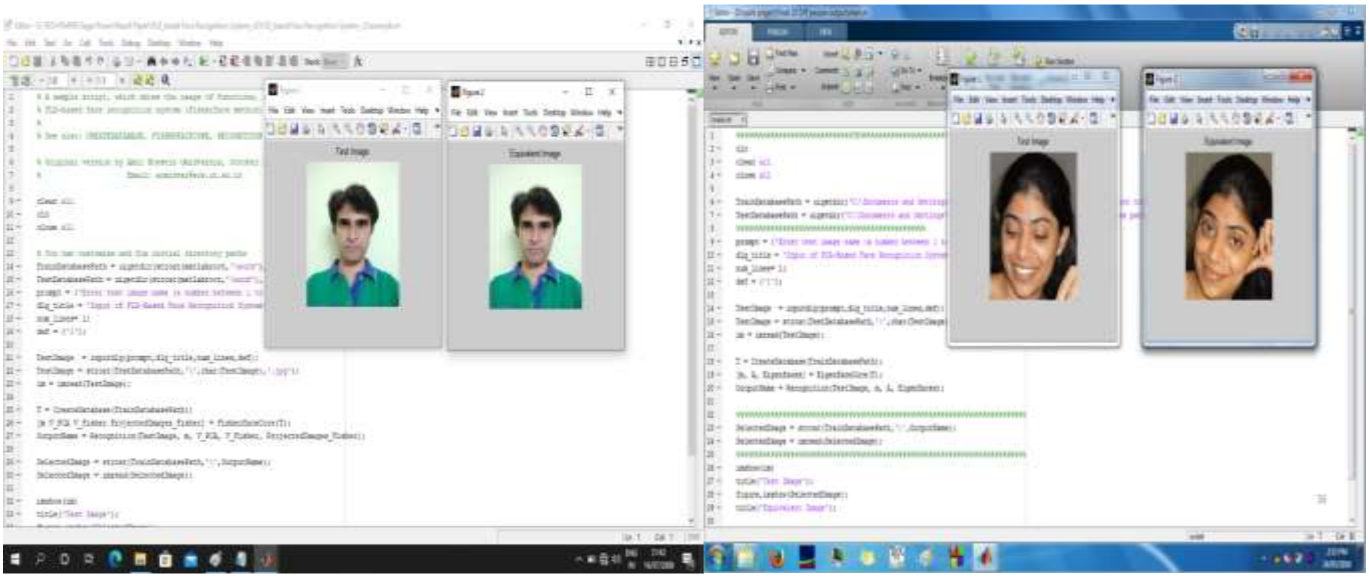

Figure 1. Image recognition result with different data base

System performance is also verified through different test experimentation. The program has been run by different user and recognition has been counted. Computed recognition rate using face database for different set of condition for 10 different subjects face images, with 10 images of each person, is shown in table II. Recognition rate is calculated by using following:

No. of Training images =20 of 10 different person with 2 images of each person.

No. of Test images =40 of 10 different person with 4 images of each person.

Recognition rate = (No. of face images identified /No. of training images)*100

Table 4.1: Percentage Result Calculation

Sr. No.	Method	Total Image Tested	Image Recognized	Image not recognized	Percentage accuracy
1	Fisherface	100	94	6	94%

V. Conclusion

Face recognition system using fisherface methods able to recognize the image of face testing correctly with 100% percentage for the test image the same as the training image and able to recognize the image of face testing correctly with 94.02% when the test image different from the training image. Whereas recognition rate of PP + LBP method was 90% (from review survey) Face recognition with fisherface method not only capable of performing an introduction to the test face images with different color components of the training image and a sketch of the original image. This method is also immune to noise-induced images and the blurring effect on the image. The images that fail in recognition are caused by two factors, namely scaling factors and poses. To overcome the first factor, can be done by using better image scaling, while for the pose problem can be overcome by giving more training images with various poses.

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