Dimensionality Reduction using Different Holistic Techniques in Image Processing

Miss Priyanka Garg[1] A.P Rajiv Dahiya[2] Happy Makkar[3]

ECE,PDM college,Bahadurgarh,india[1,2.] ETE,PDM college,Bahadurgarh,india[3]
Priyanka0713@gmail.com[1]. dahiya_rajiv@yahoo.com[2]. makkar.happy@yahoo.com[3]

Abstract - The face is our primary focus of attention in social intercourse, playing a major role in conveying identity and emotion. Face recognition methods can be classified as feature based methods and subspace methods. Feature-based approaches extract the local features such as the position of the eyes, nose, mouth etc. Subspace method reduces the dimension of the data, while retaining the maximum separation between distinct classes. "Eigen face" and "Fisher face" are the two widely used subspace methods for face recognition. The "Eigen face" approach uses Principal Component Analysis (PCA) for subspace generation, whereas the "Fisher face" approach uses Linear Discriminant Analysis (LDA). PCA provides the accurate representation of the data with minimum reconstruction error and also finds the best axis for projection. The main aim of LDA is to maximize the discrimination between different classes, while minimizing the within class distance. Recognition is performed by projecting a new face image into the subspace spanned by the Eigen faces and then classifying the face by comparing its position in the face space with the positions of known individuals. In this paper, we will discuss Pattern recognition then move on to face recognition techniques using Eigen face Eigen value Decomposition-Principal Component Analysis(EVD-PCA), Singular Value Decomposition-Principal Component Analysis(SVD-PCA), Fisher face Eigen value Decomposition-Linear Discriminant Analysis(EVD-LDA) and Fisher face singular value Decomposition-Linear Discriminant Analysis(SVD-LDA) method where we will add Singular value decomposition (SVD) in comparison to Eigen value decomposition (EVD) to reduce the time complexity and Euclidean distance in face space is proposed.. In this Paper, the final intention is to propose a computational model of face recognition or dimensionality reduction which is fast, reasonably simple and accurate in constrained environments such as office or household.

Keywords - *Face recognition, Holistic approaches, EVD-PCA, SVD-PCA, EVD-LDA and SVD-LDA.*

I. Face Recognition Overview

Face Recognition is an important research problem spanning numerous fields and disciplines. Face recognition methods can be classified as feature based methods and subspace methods. Feature-based approaches extract the local features such as the position of the eyes, nose, mouth etc. Subspace method reduces the dimension of the data, while retaining the maximum separation between distinct classes. "Eigenface" and "Fisherface" [5] are the two widely used subspace methods for face recognition. The "Eigenface" approach uses the linear unsupervised dimensionality re-duction method Principal Component Analysis (PCA) for subspace generation, whereas the "Fisherface" approach uses linear supervised dimensionality reduction method Lin-ear Discriminant Analysis (LDA). PCA finds a projection on a lower dimensional rep-resentation, where along the principal component most of the data variation occurs in an unsupervised manner. PCA provides the accurate representation of the data with minimum reconstruction error and also finds the best axis for projection. The main aim of LDA is to maximize the discrimination between different classes, while minimizing the within class distance. In classification systems, LDA is superior to PCA because, it provides higher class discrimination by using the class information [6] and so, LDA is widely used in face recognition systems. But, when the number of samples per class is small, PCA might outer perform LDA.Different approaches of face recognition for still images can be categorized into three main groups such as Holistic approach, Feature based approach and Hybrid approach. In holistic approach, the whole face region is taken into account as input data into face recognition system. Examples of holistic methods are Eigen faces (most widely used method for face recognition), probabilistic Eigen faces, Fisher faces, support vector machines, nearest feature lines

(NFL) and independent component analysis approaches. They are all based on principal component analysis (PCA) techniques that can be used to simplify a data set into lower dimension while retaining the characteristics of data set. The main advantage of the holistic approaches [7] is that they do not destroy any of the information in the images by concentrating on only limited regions or points of interest. However, as mentioned above, this same property is their greatest drawback, too, since most of these approaches start out with the basic assumption that all the pixels in the image are equally important. Consequently, these techniques are not only computationally expensive but require a high degree of correlation between the test and training images, and do not perform effectively under large variations in pose, scale and illumination, etc.

II. General Procedure

2.1 A face recognition system comprises the following modules shown in Figure 1:

Acquisition Module This is the entry point of the face recognition process. It is the module where the face image under consideration is presented to the system.

Preprocessing Module By means of early vision techniques, face images are normalized and enhanced to improve the recognition performance of the system. The following preprocessing steps can be implemented in a face recognition system:

- Image size Normalization
- Illumination Normalization
- Background Removal
- Translational and Rotational
- Median filter
- High pass filter

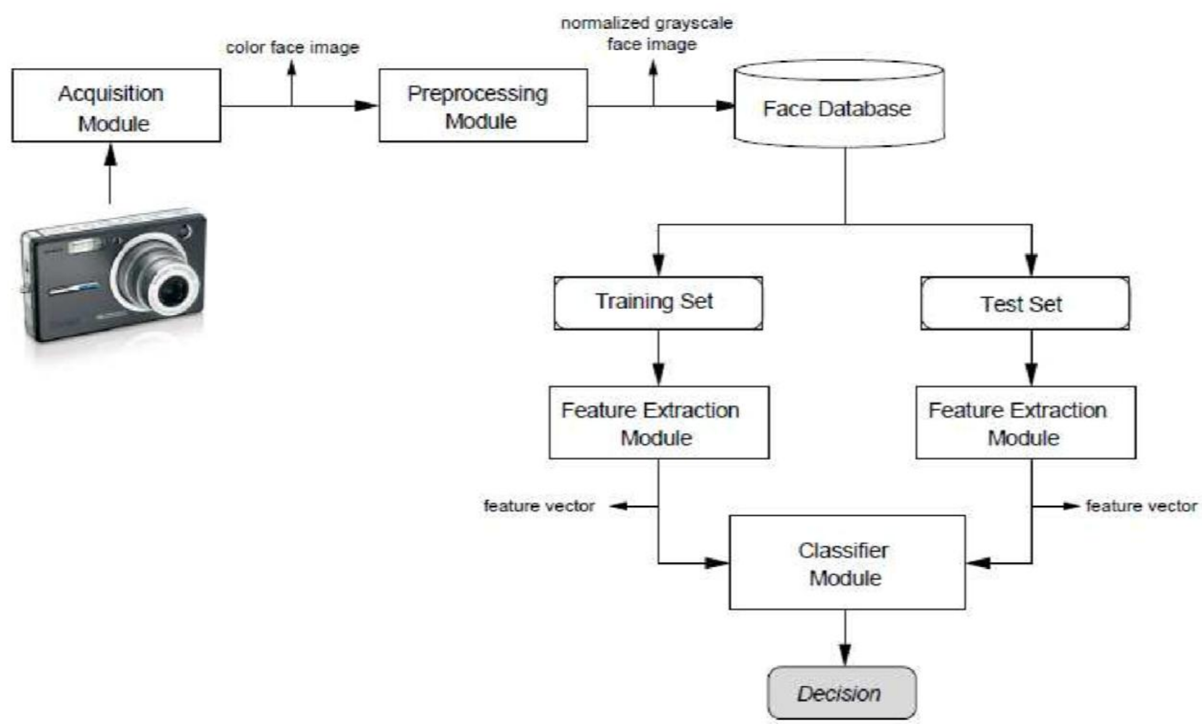


Figure 1: Computational Stages of Face

Recognition System

Feature Extraction Module After performing some pre-processing (if necessary), the normalized face image is presented to the feature extraction module in order to find the key features that are going to be used for classification.

The classification Module In this module, with the help of a pattern classifier, extracted features of the face image is compared with the ones stored in a face library (or face database). After doing this comparison, face image is classified as either known or unknown.

Training set Training sets are used during the "testing phase" of the face recognition process. The feature extraction, and the classification modules adjust their parameters in order to achieve optimum recognition performance by making use of training sets.

2.2 The problem of face recognition can be stated as follows:

- Facial expression change
- Illumination change
- Aging
- Rotation
- Size of the image

III. Holistic Approaches

3.1 Holistic Matching: Eigen faces

One of the best global representation

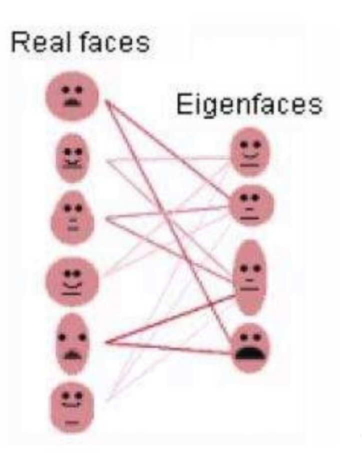


Figure 1: Eigen face matching

1. Find a weighted combination of a small number of transformation vectors that can approximate any face in the face database: Eigen faces.
2. An image can be reduced to a lower dimension: Projection.
3. Run-time performance is very good.
4. Construction: computationally intense, but need to be done infrequently
5. Fair robustness to facial distortions, pose and lighting conditions.
6. Need to rebuild the Eigen space if adding a new person.
7. Start to break down when there are too many classes.
8. Retains unwanted variations due to lighting and facial expression

3.2 Holistic Matching: Fisher Linear Discriminant

1. Eigen faces achieves larger total variance, FLD achieves greater between-class variance, and, consequently, classification is simplified.
2. FLD tries to project away variations in lighting and facial expression while maintaining discriminability.
3. It maximizes the ratio of between-class variance to that of within-class variance
4. Fisher face seeks directions that are efficient for discrimination between the data.

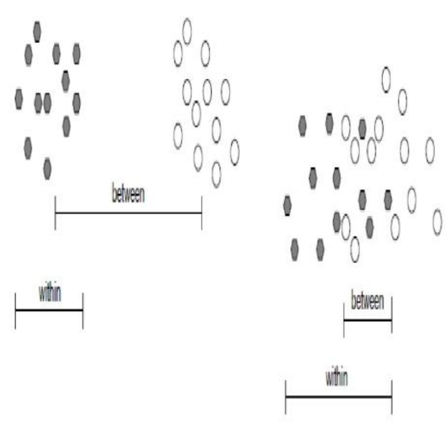


Figure 2: Class Discrimination

IV. Present work

As "Eigen face" approach uses PCA for subspace generation whereas the "Fisher face" approach uses LDA.PCA provides the accurate representation of the data with minimum reconstruction error and also finds the best axis for projection. The main aim of LDA is to maximize the discrimination between different classes, while minimizing the within class distance. In classification systems, LDA is superior to PCA because, it provides higher class discrimination by using the class information [6] and so, LDA is widely used in face recognition systems. But, when the number of samples per class is small, PCA might outer perform LDA.

V. Proposed work

5.1 Based on Eigen value Decomposition-Principle Component Analysis (EVD-PCA):

It is a data reduction technique that is used for image recognition and compression by reducing the redundancy and minimize the noise. PCA is a dimensionality reduction technique based on extracting the desired number of principal components of the multi-dimensional data (eigenvectors). In mathematical terms, we wish to find the principal components of the distribution of faces, or the eigenvectors of the covariance matrix of the set of face images. These eigenvectors can be thought of as a set of features which together characterize the variation between face images. Each image location contributes more or less to each eigenvector, so that we can display the eigenvector as a sort of ghostly face which we call an Eigen face. Each face image in the training set can be represented exactly in terms of a linear combination of the Eigen faces. The number of possible Eigen faces is equal to the number of face images in the training set.

However the faces can also be approximated using only the best Eigen faces - those that have the largest Eigen values, and which therefore account for the most variance within the set of face images. The primary reason for using fewer Eigen faces is computational efficiency. The idea of using Eigen faces was motivated by a technique developed by Sirovich and Kirby [21] for efficiently representing pictures of faces using principal component analysis. They argued that a collection of face images can be approximately reconstructed by storing a small collection of weights for each face and a small set of standard pictures. We didn't care about whether the data set represent feature from one or more classes, i.e., the discrimination power was not taken into consideration while we were talking about PCA.

EVD-PCA Algorithm:

Training

Step 1: Select a training set that includes a number of face images. Let a face image I(x; y) of N2 dimension (N×N) represent as a column vector of N2×1 dimension. A data set of M images can therefore be mapped to a collection of points in this high dimension “face space” as I_1, I_2……….. I_M.

Step 2: Compute the mean of the training set.

Step 3: Eigen Value Decomposition (EVD): Factorize covariance matrix C to compute the Eigen values and Eigenvectors

Step 4: Choose the eigenvectors corresponding to the highest Eigen values by combining these after sorting from higher to lower we get feature or projection vector.

$$v_i = V$$

Step 5: Now we can project the each face in the set into lower dimension and reconstruct it as a Eigen faces.

Testing

Step 1: Each test image is first mean centered by subtracting the mean image.

.Step 2: Then, projected into the same Eigen space defined by *V* .We get the feature vector of the testing image face

Step 3: Now, calculate the Euclidean distance to measure the distance between the projected feature vectors of the test image with projected feature vector of each face image in the training set in "face space".

Step 4: At the last compare the Euclidean distance, and showing the face image which has minimum Euclidean distance.

5.2 Based on Singular Value Decomposition-Principle Component Analysis (SVD-PCA)

The main drawback of PCA with EVD is that the size of the covariance matrix is proportional to the dimensionality of the data points, which makes the computation in feasible and increase the time complexity. So to overcome this EVD replaced by SVD, without affecting its accuracy percentage so much.

Figure 3: Flow Chart for Training

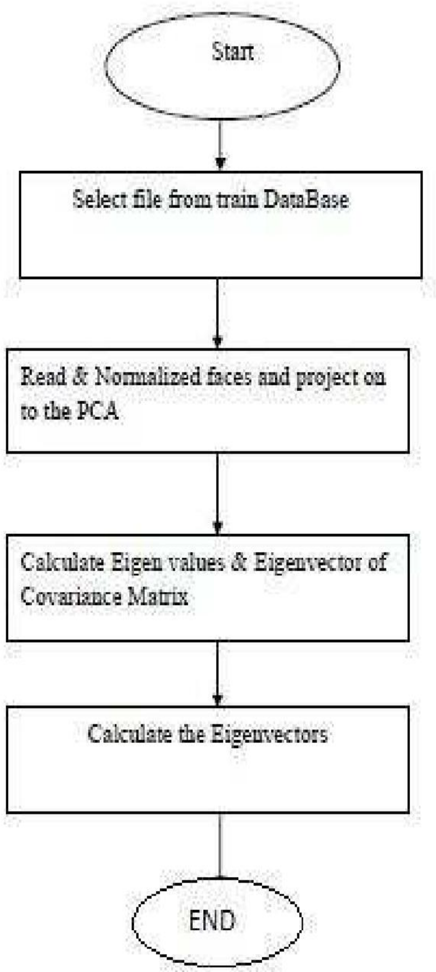
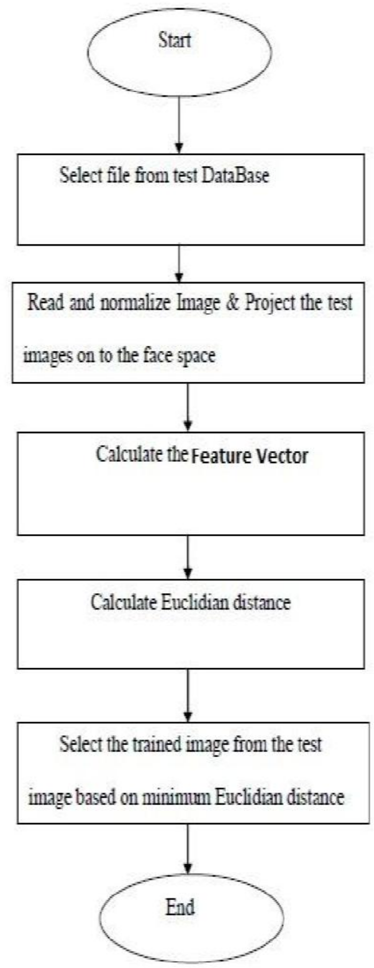


Figure 4: Flow Chart for Testing



SVD-PCA Algorithm to find Feature Vectors (Eigen faces)

These are the following steps:
Input: Select a training set that includes a number of face images
Output: computation is feasible and decrease in time complexity

1. Compute the X^T and X^T X.
2. Determine Eigen values and sort these in the descending order, in the Absolute sense.
3. Construct diagonal matrix S by placing singular values in descending order
4. Use the ordered Eigen values from second step and compute the eigenvectors of $X^T X$
5. Compute U = XV S^{-1} where, X is the normalized training set of the order of M £ N, V is the Eigenvectors of the order of N× N and S is the singularity matrix of the order of M ×N.
6. Apply SVD on X = USV T where the columns of U are the eigenvectors of matrix XX^T, the columns of V are the eigenvectors of $X^T X$ and the diagonals S contains square root of the Eigen values of both XX^T and $X^T X$, which are called the singular values of X.

VI. Simulation

In this section,we will simulate our proposed no. of holistic techniques i.e EVD-PCA,SVD-PCA,EVD-LDA and SVD-LDA. In our experiments, we will use a 1.6 GHz Intel core i5 computer with 4 GB RAM and the MATLAB Version R2010b.

Advantage of modified holistic methods for face recognition

SVD-PCA makes face recognition more accurate and also reduces computation time as compared to other holistic methods(EVD-PCA,,EVD-LDA and SVD-LDA).

VII.Conclusion

In EVD-PCA algorithm, size of the covariance matrix is proportional to the dimensionality of the data points, which makes the computation infeasible for high dimensional data such as faces, due to which time complexity increases.
In SVD-PCA algorithm, as compare to the EVD here we don't need to calculate covariance matrix and for the database of size $m < n$ only the first m columns of V are computed and then S is $m \times m$, V is $n \times m$ and U is $m \times m$. so, In case of SVD-PCA algorithm the identified image is more accurate or same as that of Test image where as in EVD-PCA algorithm identified image is not accurate as that of test image.

LDA One of the supervised linear techniques of the dimensionality reduction in which classes of pattern known a prior. Hence it has a discrimination power but not so accurate as compared to PCA.

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