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# Comparison of Face Recognition Using Eigen Analysis and Laplacian Analysis

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**Abstract:** The task of facial recognition is discriminating input signals (image Data) into several classes (persons). In this study two algorithms Eigen analysis and Laplacian analysis of face recognition are implemented and compared. These methods differ in the kind of projection method been used and in the similarity matching criterion employed. Eigen analysis uses Eigen Vectors , Principal Component analysis and Weight Vector for the recognition of input facial image. In Lapalacian method Locality Preserving Projections (LPP) are used in which the input face images are mapped into a face subspace for analysis. Different from Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) which effectively see only the Euclidean structure of face space, LPP finds an embedding that preserves local information and obtains a face subspace that best detects the essential face manifold structure. In this study , we compare the Laplacian face approach with Eigen face methods on 25 different face data sets. Experimental results suggest that the Laplacian face approach provides a better representation and achieves lower error rates in face recognition.

**Key words:** Face recognition, Eigen analysis and Laplacian analysis, Principal Component Analysis (PCA), linear discriminant analysis

## INTRODUCTION

Machine recognition of faces from still and video images is emerging as an active research area spanning several disciplines such as image processing, pattern recognition, computer vision and neural networks. In addition, face recognition technology has numerous commercial and law enforcement applications. Although humans seem to recognize faces in cluttered scenes with relative ease, machine recognition is a much more daunting task (Liu and Wechsler, 2000).

The recently developed techniques in face recognition are listed below:

- Appearance based techniques
- Feature based techniques
- Model based techniques

Aim of this study is to recognize a sample face from a set of given faces. The recognition is done by using Eigenface approach [Principal Component Analysis ] and Using Laplacianface approach (Locality Preserving Projections LPP)

## EIGEN BASED FACIAL RECOGNITION

This Eigen analysis uses Principal Component Analysis (PCA) which is a classical linear technique that projects the data along the directions of maximal variance. PCA algorithm finds the eigen faces and its corresponding weight for the images in the dataset. When an input image is given,the algorithm processes it and finds the weight. The image with the minimum distance between them will be shown as the matched image. The will be directly retrieved form the dataset (Navarrete and Ruiz, 2001).

**Principal component analysis:** Principal Component Analysis (PCA) performs dimensionality reduction by projecting the original n-dimensional data onto the $k<<n$ dimensional linear subspace spanned by the leading eigenvectors of the data's covariance matrix. Thus PCA builds a global linear model of the data.

**Weight of images:** Weight of an image specifies, to what degree the specific feature (eigen face) is present in the original image. These weights tell nothing less, as the amount by which the face in question differs from typical faces represented by the eigen faces. Therefore,using this weights one can determine two important things:

- Determine, if the image in question is a face at all. In the case the weights of the image differ too much from the weights of face images (i.e. images, from which we know for sure that they are faces), the image probably is not a face.

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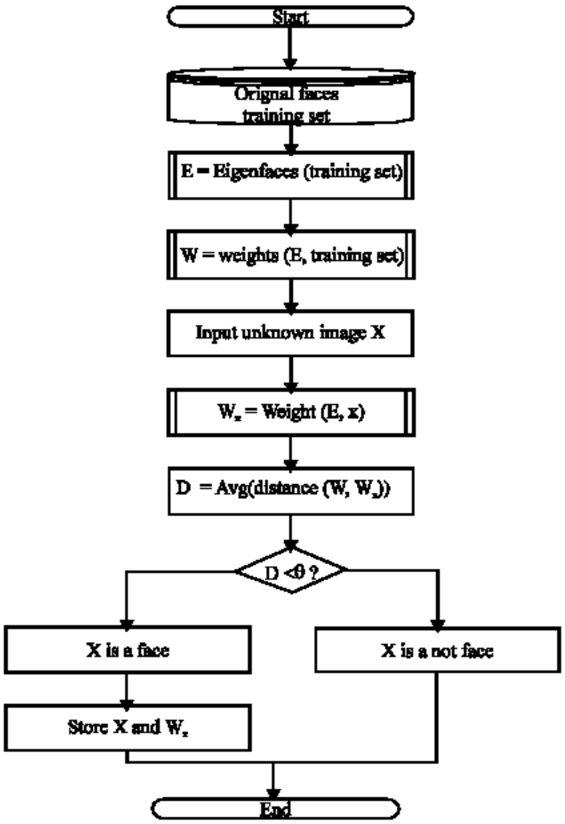


Fig. 1: Flow chart of eigen face based facial recognition

- Similar faces (images) possess similar features (eigenfaces) to similar degrees (weights).If oneextracts weights from all the images available, the images could be grouped to clusters. That is, all images having similar weights are likely to be similar faces.

**Overview of the pca algorithm:** The algorithm for the facial recognition using eigen faces is basically described in the following flowchart (Fig. 1). First, the original images of the training set are transformed into a set of eigen faces. Afterwards, the weights are calculated for each image of the training set and stored in the setω. Upon observing an unknown image X, the weights are calculated for that particular image and stored in the vector ωX. Then, ωX is compared with the weights of images, of which one knows for certain that they are faces. One way to do it would be to regard each weight vector as a point in space and calculate an average distance D between the weight vectors from ωX and the weight vector of the unknown image ωX. If this average distance exceeds some Threshold value è, then the weight vector of the unknown image ωX lies too "far apart" from the weights of the faces.

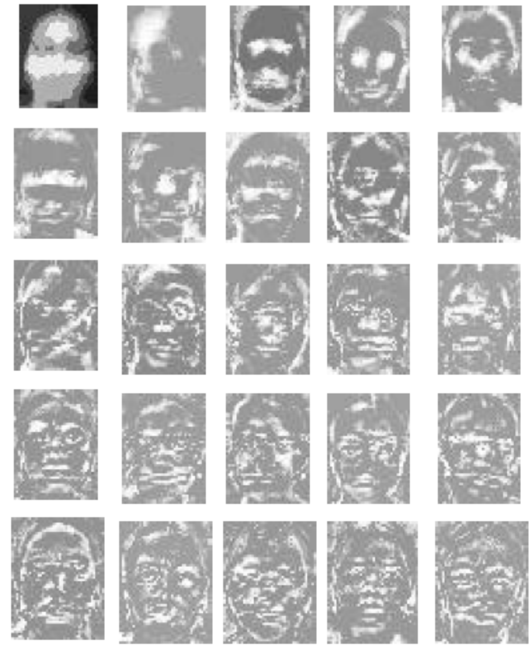

Fig. 2: 1Eigen faces of the given training set

**Calculation of eigen faces with pca:** In this study, the original scheme for determination of the eigenfaces using PCA is as follows

**Step 1:** Prepare the data:

In this step, the number of faces constituting the training set is got as input. Each image is got as a matrix. It is then converted into a single column matrix. All such images are concatenated to form a single matrix (Γi).

**Step 2:** Subtract the mean:

The average matrix Ψ has to be calculated, then subtracted from the original faces (Γi) and the result stored in the variablΦi:

$$\Psi \frac{1}{M}\sum_{n-1}^{M} Tn$$

$$\Phi i = Ti - \Psi$$

**Step 3:** Calculate the covariance matrix:

In the next steps the covariance matrix C is calculated according to

$$C = \frac{1}{M}\sum_{n-1}^{M} \Phi n \Phi_n^T$$

**Step 4:** Calculate the eigenvectors and eigenvalues of the covariance matrix:

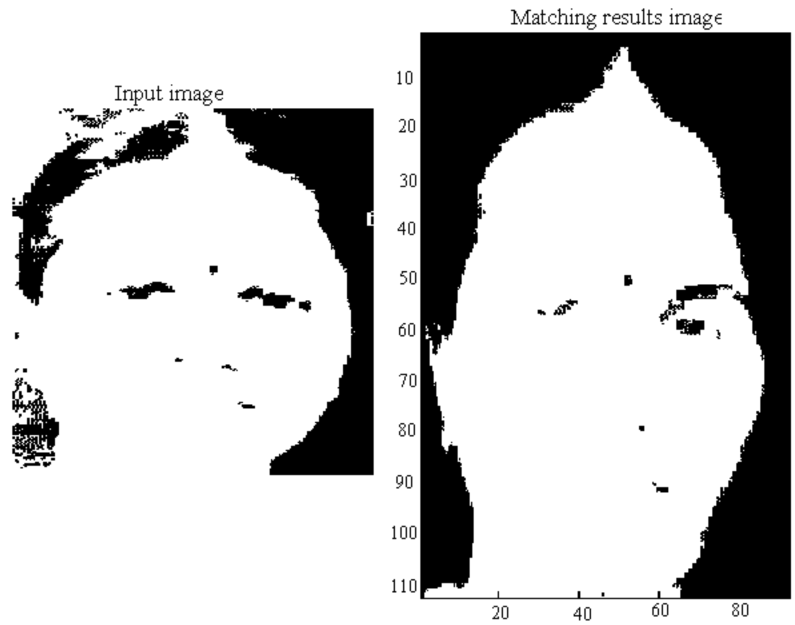


Fig. 3: Matching result image using eigen algorithm

In this step, the eigenvectors (eigenfaces) ui and the corresponding eigenvalues λI should be calculated. The eigenvectors (eigenfaces) must be normalised so that they are unit vectors, i.e. of length (Fig. 2). The description of the exact algorithm for determination of eigenvectors and eigenvalues is omitted here, as it belongs to the standard arsenal of most math programming libraries.

**Step 5:** Select the principal components:

From M eigenvectors (eigenfaces) ui, only MI should be chosen, which have the highest eigen values. The higher the eigen value, the more characteristic features of a face does the particular eigenvector describe. Eigenfaces with low eigenvalues can be omitted, as they explain only a small part of characteristic features of the faces. After MI eigenfaces ui are determined, the "training" phase of the algorithm is finished.

**Step 6:** Classification the faces:

The process of classification of a new (unknown) face Γnew to one of the classes (known faces) proceeds in two steps. First, the new image is transformed into its eigenface components.The resulting weights form the weight vector ΩΓnew

$$\omega k = U_K^T (\Gamma new - \Psi) \; k = 1...M'$$

$$\Omega_{new}^T \omega = [\omega 1 \;\; \omega 2 \; .... \; \omega M']'$$

**Step 7:** Recognition of the image:

The Euclidean distance between two weight vectors d(ΩI ,Ωj ) provides a measure of similarity between the corresponding images i and j. If the Euclidean distance between Γnew and other faces exceeds - on average - some threshold value θ, one can assume that Γnew is no face at all. d(ΩI ,Ωj ) also allows one to construct "clusters" of faces such that similar faces are assigned to one cluster.

## LAPLACIAN BASED FACE RECOGNITION

Locality Preserving Projections (LPP) is a new linear dimensionality reduction algorithm (Fig. 3). It builds a graph incorporating neighborhood information of the data set. Using the notion of the Laplacian of the graph, we compute a transformation matrix which maps the data points to a subspace.

**Introduction:** Many problems in information processing involve some form of dimensionality reduction. Here, we introduce the concept of Locality Preserving Projections (LPP) (He *et al.*, 2005). These are linear projective maps that arise by solving a variational problem that optimally preserves the neighborhood structure of the data set. LPP should be seen as an alternative to Principal Component Analysis (PCA), a classical linear technique that projects the data along the directions of maximal variance. When the high dimensional data lies on a low dimensional manifold embedded in the ambient space, the Locality Preserving Projections are obtained by finding the optimal linear approximations to the eigen functions of the Laplace Beltrami operator Eigenmap or Locally Linear Embedding. on the manifold. As a result, LPP shares many of the data representation properties of non linear techniques such as Laplacian Eigenmap or Locally Linear Embedding.

**Calculation of laplacian faces with LPP:** In this study, the original scheme for determination of the laplacian faces using LPP will be presented.

**Step 1:** Prepare the data

In this step, the faces constituting the training set (Γi) should be prepared for processing.

**Step 2:** Normalize the data

The average matrix **Ψ** has to be calculated, then subtracted from the original faces (Γi) and the result stored in the variable

$$\Psi = \frac{1}{M} \sum_{n-1} \Gamma_n$$

$$S = 1\Sigma_n \sum_{i=1} (x_i - \Psi)^{2\ 1/2}$$

$$\Phi_i = ((\Gamma_i - \psi) * S_{std}/S) + \psi_{std}$$

Where,

Sstd = Universal standard deviation

**Ψ**std = Universal mean

**Step 3:** Calculate the covariance matrix

In the next step the covariance matrix C is calculated according to

$$C = \frac{1}{M} \sum_{n-1}^{M} \Phi n \Phi_n^T$$

This co-varianvce matrix forms the input to the LPP algorithm which is described as follows:

**Step 4:** LPP algorithm:

Locality Preserving Projection

(LPP) is a linear approximation of the nonlinear laplacian eigenmap. The algorithmic procedure is formally stated below:

**Constructing the adjacency graph:** Let G denote a graph with k nodes. We put an edge between nodes i and j if xi and xj are "close". There are two variations:

- Є- neighborhoods, [parameter ЄЄ R] Nodes i and j jare connected by an edge if ||xi - xj||2 < > where the norm is the usual Euclidean norm in Rl.
- n nearest neighbors. [parameter n M N] Nodes i and j connected by an edge if i is among n nearest neighbors of j or j is among n nearest neighbors of i.

**Step 5:** Choosing the weights:

$$W_{ij} = \exp(-\|X_i - X_j\| / t)$$

Here we have two variations for weighting the edges:

- Heat kernel. [parameter t ª R]. If nodes i and j are connected, put
- Simple-minded. [No parameter]. Wij = 1 if and only if vertices iand jare connected by an edge.

**Step 6:** Eigen maps:

Compute the eigenvectors and eigenvalues for the generalized eigenvector problem:

$$XLX^Ta = \lambda XDX^Ta$$

Where D is a diagonal matrix whose entries are column (or row, since W is symmetric) sums of W, Dij = _jWij,.

Then, L = D - W is the Laplacian matrix. The ith column of matrix X is xi.Let a0,a1…. ak-1 be the solutions of Eq. (4), ordered according to their eigenvalues, λ0,λ 1…. λk-1. Thus, the embedding is as follows:

$$yi = A^T xi$$

Where $A = (a_0, a_1 \ldots\ldots a_m)$

**Step 7:** Classification the faces:

The process of classification of a new (unknown) face Γnew to one of the classes (known faces) proceeds in two steps. First, the new image is transformed into its laplacianface components. The resulting weights form the weight vector ΩΓnew. (Santini and Jain, 1999)

**Step 8:** Recognition of the image:

The Euclidean distance between two weight vectors d(ΩI ,Ωj ) provides a measure of similarity between the corresponding images i and j. If the Euclidean distance between Γnew and other faces exceeds - on average - some threshold value θ, one can assume that Γnew is no face at all. d(ΩI, Ωj ) also allows one to construct "clusters" of faces such that similar faces are assigned to one cluster.

**Optimal linear embedding:** The computational complexity of laplacian eigenmap is determined by the size of the data set. If the size is very large, then the nonlinear algorithm is computationally extensive. To overcome these problems, we propose Locality Preserving Projections, which yield linear approximations of laplacian eigenmaps.Thus the alpaca faces are constructed for the images in our data set and is presented here:

**Application of face recogniton:**

- Credit card, Driver's license, Passport and Personal identification
- Mug shots matching
- Bank/store security
- Crowd surveillance
- Expert identification
- Witness face reconstruction
- Electronic Mug Shot Books
- Electronic line-up
- (Graham and Allinson, 1998)

## RESULTS

In this study, the Principle Component Analysis (PCA) andLocality Preserving Projections (LPP) methods in Facial Recognition Technology are analyzed. These methods are Appearance-based Techniques. We have tried to provide a comparative analysis of the above two methods. Though both the methods can be used for face recognition, LPP algorithm produces reduced error rate when compared to PCA algorithm.Hence LPP is more advantageous than PCA.LPP,being linear, is more effective in dimensionality reduction, which is a problem in most other facerecognition techniques developed so far. Thus LPP, being more advantageous over PCA and other algorithms, is widely gaining attention and applicable in many areas. It is mainly used in security systems; it has wide applications in defense systems. There are numerous commercial and law enforcement applications where face recognition can be effectively employed.

**Future development:** In the application areas such as security, defense etc. inclusion of finger print recognition, palm recognition, iris recognition will make the recognition system more effective and highly reliable. Also this would reduce the problem of recognizing the twins. Our project can be used in banks, airports, for recognizing their employees by enhancing the project using web cameras to produce online images of the employees.

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