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Face Recognition Using Laplacian Faces

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Abstract: **This paper presents Recognition of human faces from abstract features using PCA and Laplacian faces. Abstract features of human are too large and unnecessary features are eliminated through PCA. Efficient and robust results achieved through Laplacian faces.**

Keywords- PCA, Features, Laplacian Faces.

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I. INTRODUCTION

Human Recognition is essential in a wide variety of application Such as access control, security, surveillance, to name a few. The face is an important feature in identifying a person. Human recognition system works on purely abstract form. This presents challenges to the computer vision developers to make a machine intelligent enough to recognize the identity of a person through artificial intelligence techniques. Defining the quantitative features for the faces from the qualitative and abstract features used by human poses great challenge to the developers. Facial shapes and the related geometry will come to the help but the accuracy can be improved through statistical methods.

This paper presents an efficient, robust method to reduce the number of features through statistical tools like PCA and Laplacianfaces. In object recognition, abstract features are quantized for optimistic results. Quantization would be complex if the feature set is too large. For the unwanted features can eliminated through PCA. The accuracy and robustness of results may further be improved through Laplacianfaces.

This paper aims at recognizing the human faces using PCA and Laplacianfaces. The paper is organized is as follows: next section surveys the literature, section-III deals with implementation details of face recognition followed by discussions and results. Section-IV concludes the paper.

II. BACKGROUND

Face recognition involves computer recognition of personal identity based on geometric or statistical features derived from face images. Here the used methods are PCA and Laplacianfaces [1], [2].

2.1 Eigen values and Eigen vectors

If $A:V \rightarrow v$ is a linear operator on some vector space V, v is a non-zero vector in V and λ is a non scalar (possibly zero) such that, A v = λ v then we say that v is an Eigen vector of the operator A, and its associated Eigen value is λ. The scale factor is given the symbol λ and is referred to as an Eigen value. Thus we have, if X is an Eigen vector of $A \in R^{N*N}, AX = \lambda X$. Where λ is scalar multiple Eigen value then the vector Ax is in the same direction as x but scaled by a factor λ. We apply this Eigen value and Eigen vector concept in our paper and find the best matched training image with the test image.

2.2 Principal Component Analysis

In statistics, principal components analysis (PCA) is a technique that can be used to simplify a dataset; more formally it is a transform that chooses a new coordinate system for the data set such that the greatest variance by any projection of the data set comes to lie on the first axis (then called the first principal component), the second greatest variance on the second axis, and so on. PCA can be used for reducing dimensionality in a dataset while retaining those characteristics of the dataset that contribute most to its variance by eliminating the later principal components. PCA aims at

1 Reducing the dimensionality of
The data set.
2 Identifying new meaningful underlying variables.

2.2.1 Finding Principal Components

Principal Component Analysis is traditionally done on a square symmetric covariance
Or correlation matrix obtained from the given m x n data matrix. A covariance matrix is obtained by mean centering the data across the origin and then taking the dot products.

A correlation matrix is obtained by normalizing the covariance matrix. This normalization is required because in statistical data it is very natural to have data spread out over wide ranges. If normalizations were not done, it would be difficult to assess the contributions of various components to the principal component.

Principal components are the Eigen vectors of the square symmetric correlation matrix. The Eigen vector with the maximum Eigen value is the first principal component, the one with next largest Eigen value is the second principal component and so on.

To understand this better, we take an example. Suppose we have data for marks of n students in 2 subjects.

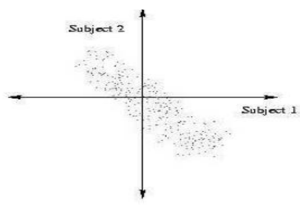

Figure1: Centered Marks of Students in 2 Subjects.

Centering of data is done by subtracting the mean from the data points. It should be noted that although the position of the points in the space has changed, the relationships between them are preserved. Further, even if we rotate the axes, the pattern in the underlying data remains the same.

The Principal Components are just linear combinations of the original axes but they define the directions in which the variability of given data set is maximum. This is useful in case we want to retain some and not all values; the projection of the data points on the first k principal components retains maximum information in the data.

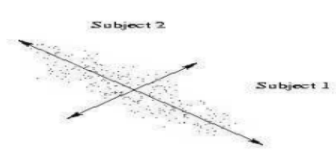

Figure2: Axes rotated to get Principal Components.

2.3 Locality Preserving Projection

Suppose we have a collection of data points of n-dimensional real vectors drawn from an unknown probability distribution. In increasingly many cases of interest in machine learning and data mining, one is confronted with the situation where n is very large. However, there might be reason to suspect that the “intrinsic dimensionality” of the data is much lower. This leads one to consider methods of dimensionality reduction that allow one to represent the data in a lower dimensional space.

We propose a new linear dimensionality reduction algorithm, called **Locality Preserving Projections** (LPP)[4]. Different from principal component analysis which obtains a subspace spanned by the largest Eigen vectors of the global covariance matrix, we show that LPP contains a subspace spanned by the smallest eigenvectors of the local variance matrix. It builds a graph incorporating neighborhood information of the data set. Using the notion of the Laplacian of the graph, we then compute a transformation matrix which maps the data points to a subspace. This linear transformation optimally preserves local neighborhood information in a certain sense [3]. The representation map generated by the algorithm may be viewed as a linear discrete approximation to a continuous map that naturally arises from the geometry of the manifold. The new algorithm is interesting from a number of perspectives.

1. The maps are designed to minimize a different objective criterion from the classical linear techniques.

2. The locality preserving quality of LPP is likely to be of particular use in information.

3. LPP is linear.

4. LPP is defined everywhere.

5. LPP may be conducted in the original space or in the reproducing kernel Hilbert space (RKHS) into which data points are mapped. This gives rise to kernel LPP. As a result of all these features, we expect the LPP based techniques to be a natural alternative to PCA based techniques in exploratory data analysis, information retrieval, and pattern classification applications [5].

2.4 Nearest Neighbor Graph

The **nearest neighbor graph** (**NNG**) for a set of *n* objects *P* in a metric space (e.g., for a set of points in the plane with Euclidean distance) is a directed graph with *P* being its vertex set and with a directed edge from *p* to *q* whenever *q* is a nearest neighbor of *p* (i.e., the distance from *p* to *q* is no larger than from *p* to any other object from *P*).

Let G denote a graph with m nodes. We put an edge between nodes i and j if x_i and x_j are close. There are two variations:

(a) e neighborhoods. Nodes i and j are connected by an edge if where $||x_i-x_j||^2<e$ the norm is the usual Euclidean norm in R^n .

(b) K nearest neighbors. Nodes i and j are connected by an edge if i is among k nearest neighbors of j or j is among k nearest neighbors of i.

III. IMPLEMENTATION:

3.1 Introduction

Many face Recognition techniques have been developed[1],[2]. One of the simpler methods is 'Principal Component Analysis'. PCA is commonly used techniques for dimensionality reduction and PCA does more feature classification. This method will give results with simple logic operations and cost is low. This method will not give 100% results; we could achieve only 80% results. If we want better results, we can move to another method i.e. Laplacian faces. It is discussed in section 3.3.

3.2 PCA

In this method, we consider 'q' images and each image having a size of m*n and convert them into the column matrix i.e. x= [mn*q]. For this calculate the mean and subtract the mean from the original matrix. Then calculate the covariance matrix. For this calculate the Eigen values and Eigen vectors. Calculate the RMS value of difference matrix and find the minimum value i.e. Eigen faces.

Eigen faces method[1] is only applicable for global structure and will give only 80% results and it is simpler method, cost is low. To improve the efficiency laplacianfaces come to use.

3.3 Laplacian faces

It is mainly an appearance-based method. While Eigen faces aims to preserve the global structure, our laplacianfaces method aims to preserve the local structure of the image space. In laplacianfaces, by using locality preserving projections we can able to capture intrinsic face manifold structure. With this method better results can be achieved than Eigen faces method and noise can be eliminated to a greater extent. For face recognition laplacianfaces method is the best method [2].

3.3.1 PCA Projection

We project the image set $\{x_i\}$ into the PCA subspace by removing the smaller principal components. Here we use x to denote the images in the PCA subspace in the following steps. We denote the transformation matrix of PCA by W_{PCA}.

3.3.2 Constructing the nearest-neighbor graph

Let G denote a graph with n nodes. The i^{th} node corresponds to the face image x_i. We put an edge between nodes i and j if x_i and x_j are "close", i.e. x_j is among k nearest neighbors of x_i or x_i is among k nearest neighbors of x_j. The constructed nearest neighbor graph is an approximation of the local manifold structure.

3.3.3 Choosing the weights

The weight matrix S of graph G models the face manifold structure by preserving the local structure.

If node i and j are connected, Put $S_{ij}=e^{-\|X_i-X_j\|/t}$

Otherwise, put $S_{ij}=0$.

S_{ij} is a symmetric matrix and t is a suitable constant.

3.3.4 Eigen map

Compute the eigenvectors and eigenvalues for the generalized Eigen vector problem[6]:

$$W=W_{PCA}W_{LPP}$$

W is the Transformation matrix. This linear mapping best preserves the manifolds estimated intrinsic geometry in a linear sense. The column vectors of W are so called Laplacianfaces.

3.3.5 Algorithm

1. From the image set X_i retain only stronger principal components.

2. For the largest principal components create a nearest-neighbor graph by considering the nodes i.e. S_{ij}.

3. If two nodes are connected put $S_{ij}=e^{-\|X_i-X_j\|/t}$ otherwise $S_{ij}=0$.

4. Compute the Eigen vectors and Eigen values for the generalized eigenvector problem.

5. Calculate the RMS value of difference matrix.

6. Find the minimum values i.e. Laplacian faces.

Many different measures for evaluating the performance of image retrieval systems have been proposed. The measures require a collection images in database and a query image. The common retrieval performance measures – precision and recall are used to evaluate.

1) Precision*:* Precision is the fraction of the images retrieved that are relevant to the users' requirements.

$$Precision = \frac{no\ of\ relevant\ images\ retrived}{total\ no\ of\ images\ retrived}$$

2) Recall: Recall is the fraction of the shapes that are relevant to the query that are successfully retrieved.

$$Recall = \frac{no\ of\ relevant\ images\ retrived}{total\ no\ of\ relevant\ images\ in\ the\ database}$$

The overall performance of our method is measured in terms of Recall rate & Precision. The rigorous experiments are conducted to evaluate the performance. The table 1 shows the results of retrieving images from the database.

Two sets of images are shown below:

o1 o2 o3 o6 o7

a1 a2 a3 a5 a6

METHOD	FIGURE NAME	N=1		N=2		N=3	
		P (%)	R (%)	P (%)	R (%)	P (%)	R (%)
Eigen face	o1	100	100	50	100	33.3	100
	o2	100	100	50	100	33.3	100
	o3	100	100	50	100	33.3	100
	o6	0	0	0	0	0	0
	o7	100	100	50	100	33.3	100
Laplacian	o1	100	100	50	100	33.3	100
	o2	100	100	50	100	33.3	100
	o3	100	100	50	100	33.3	100
	o6	100	100	50	100	33.3	100
	o7	100	100	50	100	33.3	100

TABLE 1
Recall rates(R) & Precision (P) for various query shapes.

IV: CONCLUSION & FUTURE WORK:

This paper used techniques are PCA and Laplacian faces. Using PCA better results could not achieved, achieved using Laplacianfaces with simple operations.

The future scope of this work is to reduce is execution time of the program and it can be made applicable to 3-D images by some other operations and based on facial expression, we can find out the gestures.

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