Comparing The Performance of Principal Component Analysis and RBF Network for Face Recognition Using Locally Linear Embedding

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Summary
Among the many methods proposed in the literature for face recognition, those relying on face manifold have been explored with great interest in the last few years. In those methods the face images are initially subjected to dimensional reduction and then applied to a classifier. In this paper we have proposed and developed two novel approaches for face recognition to address the challenging task of recognition using a fusion of nonlinear dimensional reduction; Locally Linear Embedding (LLE) integrated with Principal Component Analysis (LLEPCA) and LLE with RBF networks (LLERBF) and then we evaluate and compare their performance. Extensive experiments using the CMU AMP Face EXpression Database and JAFFE databases indicate that the more general model underlying the RBF classifier does not bring any significant improved performance as compared with the Principal Component Analysis approach.

Key words:
Biometrics,Locally Linear Embedding, nonlinear manifold,PCA,RBF.

1. Introduction

Face recognition system from images is of particular interest to researchers owing to its wide scope of potential applications such as identity authentication, access control, and surveillance. It is quite a challenging task to develop a computational model for face recognition due to the fact that faces are complex, multidimensional, and meaningful to visual stimuli.

A lot of research on face recognition, both by computer vision scientists and psychologists have been done over the last decade. From the aspect of computer vision, face recognition can be roughly distinguished into two categories: geometric feature-based approaches and template matching approaches.

In the first category, facial feature values depend on the detection of geometric facial features like eye corners and nostril. However, the first one is time-consuming and complex since it is about modeling a face. The second one assumes an image to be a single or multiple arrays of pixel values. The virtue of the template methods, is the fact that it is not necessary to create representations or models for objects. Most recognition systems using linear method are bound to ignore subtleties of manifolds such as concavities and protrusions, creating a bottleneck for achieving highly accurate recognition. This problem has to be solved before we can make a high performance recognition system. Generally speaking, faces are empirically thought to constitute a highly nonlinear manifold in observational space [7].

We therefore assume that an effective face recognition system should be based on “face manifold”. More so , the full variations among others , lighting condition, expression and orientation, may be viewed as intrinsic variables which generate nonlinear face manifold in observation space.

Despite the fact that there are many impressive results on how to mine the intrinsic invariants of face manifold, manifold learning on face recognition has fewer reports. This may be due to the fact that practical facial data includes a large number of intrinsic invariant and has high curvature both in the observation space and in the embedded space,. Furthermore, the effectiveness of currently manifold learning methods strongly depend s on the selection of neighboring parameters.

Recently, manifold learning has provided an interesting way to discover the intrinsic dimensions of image manifold. However, most of manifold learning methods lack an effective way to model relationships from face manifold into low-dimensional space without dimensional limitations and also have fewer applications on face recognition. For that matter, we shall study two face recognition systems that have LLE stage for dimensional reduction, and computes the embedding space of face images over eigenvectors. The face images represented in this lower dimensional space are the input to a classifier.

2. Problem Statement

For face images, classical dimensional reduction methods among others include PCA [1], Independent Component Analysis (ICA) [2, 3], Linear Discriminate Analysis [4], and Local Feature Analysis (LFA) [5, 6] . The linear methods have their limitations. To start with , they cannot reveal the intrinsic distribution of a given data set. Secondly, if there are changes in pose, facial expression and illumination, the projections may not be appropriate and the corresponding reconstruction error may be much higher. To overcome these problems, we have proposed and compared two new algorithms combining the advantages of linear and nonlinear methods, that is a combination of; a) locally linear embedding and principal component analysis. b) Locally linear embedding and RBF Network. Locally linear embedding (LLE) [7, 8], has got the ability to perform nonlinear dimensional reduction in an unsupervised way. A disadvantage of LLE algorithm is that mapping of test samples is difficult for computation cost of eigen-matrix. Thus our novel approach will manage to overcome this problem.

3. Previous Work on Face Recognition

Earlier face recognition systems were mainly based on geometric facial features and template matching [9,10]. In those works a face was characterized by a set of features such as mouth position, chin shape, nose width and length which are potentially insensitive to illumination conditions. Brunelli et al. [9] compared this approach with a traditional template matching scheme which produced higher recognition rates for the same face database (90% against 100%). Cox, Ghosn and Yianilos [11] proposed a mixture distance technique which achieved the best reported recognition rate among the geometric feature approaches using the same database. Those results were obtained in an experiment where the features were extracted manually. The Principal Component Analysis technique was first suggested for the characterization of human faces by Kirby and Sirovich [12] and later extended by Turk and Pentland [1]. Many refinements to the original idea were further introduced [13,14,15,16]. Several psychologists and neurophysiologists use PCA to model the way the human brain stores, retrieves and recognizes faces . The experiments of Turk and Pentland [1] achieved recognition rates around 96%, 85% and 64% respectively for lighting, orientation and scale variation. Recognition rate around 95% are reported by Pentland and Moghaddam (1994) [13] for a database consisting of 3000 accurate registered and aligned faces. Junping Zhang, Stan Z. Li, and Jue Wang presented a new algorithm which is Manifold Learning and Applications in Recognition [17]. Samaria & Harter presented an approach based on Hidden Markov Models that achieved a recognition rate of 95% for the ORL database at the expense of a high computational overhead. All those works, as well as this one, rely on a preprocessing to detect a face in a scene and to compensate for variation of lighting, position, rotation and scale. The work reported here studies face recognition systems consisting of nonlinear manifold learning technique local linear embedding used for dimensionality reduction and a standard PCA, followed respectively by an Euclidean distance classifier and LLE followed by RBF network classifier. The LLE approach was originally proposed by Roweis, S., Saul, L [7]. In the first step a n-pixel face image is projected onto the embedded space, whose basis is given by the d (d < N) eigenvectors (d+1) which is the embedded space. In the second step the PCA maps the projection of the input image on the face space onto discriminatve features. Based on distance measures Euclidean distance used as classifier for LLEPCA method, and RBF network classifier for LLERBF method.

4. Locally Linear Embedding, Principal Component Analysis And RBF Network.

4.1 Locally Linear Embedding

This is a powerful method for nonlinear mapping. LLE establishes the mapping relation between the observed data and the corresponding low-dimensional one. The local linear embedding algorithm is used to obtain the low-dimensional data Y $(Y \subset R^r)$of the training set X $(X \subset R^N, N>>d)$, Y^* and the optimal eigenvectors obtain by LLE from training data is define as follow:

$$Y^* = \arg\min_Y Y^T (I-W)^T (i-W)Y \qquad (1)$$

The details of LLE algorithm can be referred as to [7].

4.2 Principal component analysis

PCA generates a set of orthonormal basis vectors, known as principal components (PCs), that maximize the scattering of all the projected samples. Let X =[X1 , X2 ,……….,Xn] be the sample set of the original images.

After normalizing a new image set C = [C1 , C2 , ….,Cn] is derived. Each Ci represents a normalized image with dimensionality N, Ci =(Ci1 , Ci2 , …..,Cin)t ,(i= 1,2,…,n) , and the details of PCA algorithm can be referred as to [1].

4.3 The LLERBF Method

Data is first mapped into the intrinsic low-dimensional space base on LLE as in equation 1 and then RBF network classifier is applied.

The RBF classifier is a one hidden layer neural network with several forms of radial basis activation functions. The most common one is the Gaussian function defined by,

$$f_j(y^*) = \exp\frac{\| y^* - \mu_j \|^2}{2\sigma_j^{\,2}} \qquad (2)$$

Where σ_j is the width parameter, μ_j is the vector determining the center of basis function f and y^* is the *n*-dimensional input vector. In an RBF network, a neuron of the hidden layer is activated whenever the input vector is close enough to its center vector. There are several techniques and heuristics for optimizing the basis functions parameters and determining the number of hidden neurons needed to best classification [20]. The second layer of the RBF network, which is the output layer, comprises one neuron to each class. The final classification is given by the output neuron with the greatest output

4.4 The LLEPCA Method

In our proposed novel method, data is first mapped into the intrinsic low-dimensional space based on LLE as in equation 1 and then mapped into the projection space based on PCA. We subtract the unknown samples x_i from the entire embedded space obtain by LLE . Considering the neighbor of unknown samples, the weighted values among unknown data and training data are first calculated.

$$z_i = \| x_i - Y^* \| \qquad (3)$$

Then calculate the average face of the entire weighted values.

$$\Psi = \frac{1}{M}\sum_{i=1}^{M} z_i \qquad (4)$$

After calculating the average, we set up a new group of images Φ , obtained from the difference between each image of the training set and the average features. Thus, each image Φ differs from the average image of the distribution. Each individual distance is calculated by subtracting it from the average image, deriving a new space of images as in the equation below;

$$\Phi_i = z_i - \Psi(i = 1,\ldots,M) \qquad (5)$$

Calculation of the eigenvectors of covariance matrix *C* can then follow. We know that only the eigenvectors with the larger eigenvalues are necessary for face recognition. For that matter , only ($M^{'}<M$) eigenvectors is used . Every image from each class is projected into the “projection space” in the following way:

$$\Omega_i = \bigcup^T (z_i - \Psi), i = 1,\ldots,Nc \qquad (6)$$

Face recognition is performed by extracting the new image submitted for recognition in comparison with images of the classes stored in the database, calculated the same way using the Euclidean distance. Thus, each image submitted for face recognition is projected in the projection space, obtaining the vector Ω in the following way:

$$\Omega = \bigcup^T (\Gamma - \Psi) \qquad (7)$$

For RBF network classifier the input is the output obtains by LLE after subtracting the unknown samples x_i from the entire embedding space.

4.5 Experiment Result

Experiments are carried out to evaluate the face recognition of the proposed LLEPCA and LLERBF in face recognition performance using two face databases, namely the CMU AMP Face EXpression Database [19] and JAFFE database [18]. The CMU AMP Face EXpression Database consists of 75 different images for 13 people with varied poses and expression.

The JAFFE database consist of 213 images of 10 Japanese females, with an almost frontal pose of the head. For our experiments the databases is used for oriental face recognition.

For CMU AMP Face EXpression Database, the 75 images of 13 people are randomly partitioned into two sets, namely , 520 training images and 455 test images without overlapping , and each one containing 64x64=4096 pixels. As for dimensional reduction, the reduction dimensions of training set, are set to be as in table 1,2.

The JAFFE database is partitioned into two sets. 18 images of 10 people are randomly extracted to make 180 training set and the remaining images are the test images.

In our experiments, two parameters (neighbors factor $K^{'}$ and *d* dimension of LLE algorithm need to be predefined first. We set K’ to be 40, 18 respectively for CMU AMP Face EXpression Database and JAFFE database.

The results tabulated in table 1 and illustrated in Fig 1 show the performance of LLEPCA .From Fig 1 and table 1,we can see that LLEPCA algorithm has good recognition result compare to LLERBF Algorithm. Table

2 and Fig2 indicate the performance of the LLERBF method. From the experiments we have found out that the LLE work better when we set *d* to low dimensions. Hence less eigenvectors. PCA and RBF work well if we use more eigenvector (more dimension),.This means we have to select a proper dimension in order to achieve a good recognition rate. For LLEPCA method we found that the dimension *d* of LLE between 50 and 150 is stable if less or more than that dimension. The recognition rate will decrease for CMU AMP Face EXpression Database and for JAFFE Database 70 is the optimum.

For the LLERBF method the good recognition rate achieved when d is set to be 70 for JAFFE Database and between 60 to 150 for CMU AMP Face EXpression Database.

Table 1: Recognition Rate (LLEPCA)

LLE(d)	JAFFE Database	CMU AMP Face Expression DB
40	81.8	84.08
50	87.88	90.33
60	81.8	84.08
70	93.93	90.33
80	87.88	90.33
100	90.9	90.33
150	87.88	90.33
170	69.7	63.7

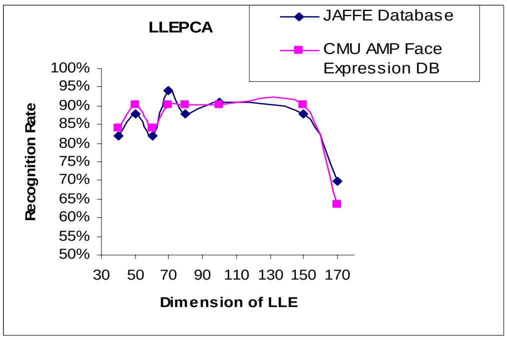

Fig. 1 LLEPCA.

Table 2: Recognition Rate (LLERBF)

LLE(d)	JAFFE Database	CMU AMP Face Expression DB
40	84.84	82.14
50	90.90	83.92
60	87.87	90.33
70	91.00	90.36
80	87.88	90.00
100	90.90	90.36
150	81.81	90.00
170	66.66	71.42

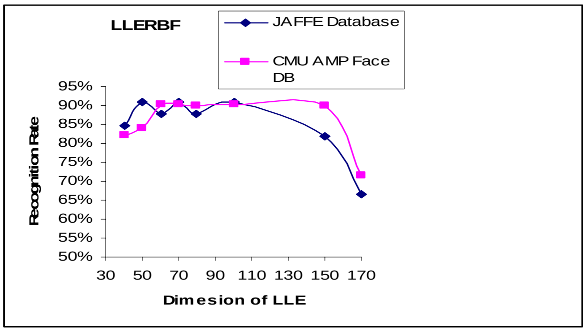

Fig. 2 LLERBF.

3. Discussions

The experiments have been systematically performed. These experiments reveal a number of interesting points:
In all the experiments, the recognition performance increases if the number of K'(LLE) increases until a certain number (which is the number of images per class) then declines downwards.

Embedding space by LLE approach encodes more discriminating information in the low dimensional face subspace by preserving single local coordinate.This is important for classification. An efficient and effective subspace representation of face images should be capable of characterizing the nonlinear Manifold structure. By discovering the face manifold structure, our approach can identify the person with various poses and expressions. The LLE approach appears to be the best at simultaneously handling variation in poses and expressions. The experiments show that there is no significant improvement between LLEPCA and LLERBF.

3. Conclusion

Two face recognition systems were evaluated: The benchmark for two systems was a nonlinear dimensional reduction technique (Locally Linear Embedding). To the best of our knowledge, this is the first devoted work on face recognition that uses this combination for recognition. The Embedding is obtained by LLE that optimally preserves a single global coordinate system of lower dimensionality. Experimental results on the Face Expression database show the effectiveness of our method.

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