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Non-Linear Principal Component Embedding for Face Recognition

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Abstract: A new face recognition method, based on the local non-linear mapping, is proposed in this study. Face images are typically acquired in frontal views and often illuminated by a frontal light source. Unfortunately, recognition performance is found to significantly degrade when the face recognition systems are presented with patterns that go beyond from these controlled conditions. Face images acquired under uncontrolled conditions have been proven to be highly complex and are non-linear in nature; thus, the linear methods fail to capture the non-linear nature of the variations. The proposed method in this study is known as the Non-linear Principal Component Embedding (NPCE) which is aimed to solve the limitation of both linear and non-linear methods by extracting discriminant linear features from highly non-linear features; the method can be viewed as a linear approximation which preserves the local configurations of the nearest neighbours. The NPCE automatically learns the local neighbourhood characteristic and discovers the compact linear subspace which optimally preserves the intrinsic manifold structure; a principal component is then carried out onto low dimensional embedding with reference to the variance of the data. To validate the proposed method, Carnegie Mellon University Pose, Illumination and Expression (CMU-PIE) database was used. Experiments conducted in this research revealed the efficiency of the proposed method in face recognition as follows: (1) extract discriminant linear features from highly non-linear features based on the local mapping and (2) Runtime speed is improved as face feature values are reduced in the embedding space. The proposed method achieves a better recognition performance in the comparison with both the linear and non-linear methods.

Key words: Face recognition, biometrics, manifold learning, principal comment, feature extraction

INTRODUCTION

The state-of-the-art face recognition systems are found to yield satisfactory performance under controlled conditions, i.e., where face images are typically acquired in frontal views and often illuminated by the frontal light source. Unfortunately, recognition performance is found to significantly degrade when the face recognition systems are presented with patterns which go beyond these controlled conditions. Some examples of unconstrained conditions include illumination, pose variations, etc. In particular, variations in face images have been proven to be highly complex and non-linear in nature. Linear subspace analysis has been extensively applied to face recognition. A successful face recognition methodology is largely dependent on particular choice of features used by the classifier. Although, linear methods are easy to understand and are very simple to implement, the linearity assumption does not hold in many real-world scenarios. A disadvantage of the linear techniques is that they fail to capture the characteristics of the non-linear appearance manifold. This is due to the fact that the linear methods extract features only from the input space without considering the non-linear information between the components of the input data. However, non-linear mapping can often be approximated using a linear mapping in a local region. This has motivated the design of the non-linear mapping methods in this study. The history of the non-linear mapping is long; it can be traced back to non-linear mapping (Sammon, 1969). Over time, different techniques have been proposed such as the projection pursuit (Friedman and Tukey, 1974), the projection pursuit regression (Friedman and Stuetzle, 1981), self-organizing maps or SOM, principal curve and its extensions (Hastie and Stuetzle, 1989; Kégl *et al*., 2000; Smola *et al*., 2001; Tibshirani, 1992), auto-encoder neural networks (Baldi and Hornik, 1989; DeMers and Cottrell, 1993) and generative topographic maps or GTM (Bishop *et al*., 1998). A comparison of some of these methods can be found by Mao and Jain (1995). Recently, a new line of the non-linear mapping algorithms was proposed based on the notion of manifold learning. Given a data set which is assumed to be lying approximately on the manifold in a high dimensional space, dimensionality reduction can be achieved by constructing a mapping which respects

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certain properties of the manifold. Manifold learning has been demonstrated in different applications including face pose detection (Hadid *et al*., 2002; Li *et al*., 2001), high dimensional data discrimnant analysis (Bouveyron *et al*., 2007), face recognition (Yang, 2002; Zhang and Wang, 2004), analysis of facial expressions (Chang *et al*., 2004; Elgammal and Lee, 2004), human motion data interpretation (Jenkins and Mataric, 2004), gait analysis (Elgammal and Lee, 2004a, b), visualization of fibre traces (Brun *et al*., 2003), wood texture analysis (Niskanen and Silvn, 2003) and kernel fractiona l-step discriminant analysis (KFDA) for the non-linear feature extraction and dimensionality reduction by Guang *et al*. (2006). Recently, Li *et al*. (2008) proposed the non-linear DCT discriminant feature which analyzes the non-linear discriminabilities of the DCT frequency bands and selects appropriate bands. Nevertheless, these methods still lack discriminant features representation, based on the local structure of data which is very important for recognition when variations of face images are present. Therefore, the aim of this study to device local non-linear discriminant feature representations which are reliable and have more discriminative power face recognition.

MATERIALS AND METHODS

Pre-processing: Face pre-processing and normalization is a significant part of the face recognition systems. Changes in lighting conditions have been found to dramatically decrease the performance of face recognition. Therefore, all images have been pre-processed to obtain a representation of the face which is invariant to illumination, while keeping the information necessary to allow a discriminative recognition of the subjects. Gaussian kernel has been used to estimate the local mean and standard deviation of images to correct non-uniform illumination. The local normalization is computed as follows:

$$g(x, y) = \frac{f(x, y) - m_f(x, y)}{\sigma_f(x, y)} \quad (1)$$

where, f(x,y) is the original image, while m is an estimation of the local mean of f and s is an estimation of the local SD. Figure 1 below illustrates the block diagram of the developed method.

The NPCE algorithm: This method finds reconstruction weight by capturing the intrinsic geometry of the neighbourhood. The NPCE creates a locally linear mapping from the high dimensional coordinates to the low dimensional embedding as shown in Fig. 2.

Compute the average weight which represents every face data by its neighbours.

$$\varphi(w) = \| x_i - \sum_{j=1}^{K} w_{ij} x_{ij} \| \qquad x_{ij} \in X \in R^N \quad (2)$$

where, x_i refers the ith unknown sample and x_{ij} is the corresponding training sample according to the K-values (the nearest neighbours).

Compute the low-dimensional embedding D, the following cost function is minimized:

$$\Phi(D) = \sum_{i=1}^{N} \| D_i - \sum_{j=1}^{K} W_{ij} D_j \|^2 \quad (3)$$

where, N is the number of training and K is the number of the nearest neighbours.

Then, the principal component of the training is calculated as follows:

$$\begin{aligned} \Phi_i &= x_i - \bar{x} \\ C &= \frac{1}{M} \sum_{n=1}^{M} \Phi_n \Phi_n^T \end{aligned} \quad (4)$$

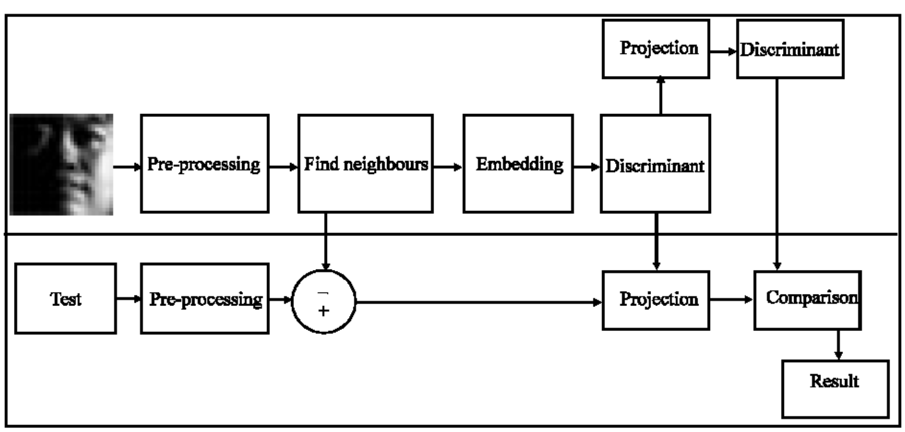

Fig. 1: Block diagram of the NPCE

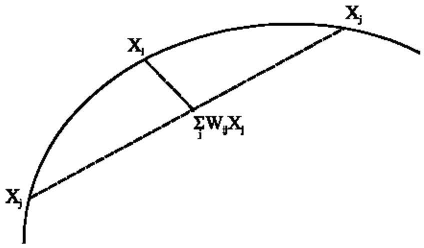

Fig. 2: Reconstruction weights

where, $\bar{x}$ is the mean and C is the covariance matrix; $\{P_1, P_2, \ldots, P_N\}$ are the eigenvectors of C. The eigenvectors then play a role which projects a vector in the low-dimensional face subspace into discriminatory feature space that can be formulated as follows:

$$Q = D \times P \quad Q \in R^{d'}, D \in R^{d} \tag{5}$$

Once, the weighted values of each neighbour sample of the unknown sample are obtained, the mapping formulate can be seen as follows:

$$q_i^{'} = \sum_{i=1}^{K} W_{ij} q_{ij} \tag{6}$$

where, q_{ij} is the closely training sample and the neighbour indices are the same as that of the sample in the original high dimensional space and $q_i^{'}$ is the corresponding one of the unknown samples in the discriminant space.

RESULTS AND DISCUSSION

CMU-PIE database: This is one of the largest datasets developed to investigate the affect of pose, illumination and expression. It contains images of 68 people; each under 13 different poses, 43 different illumination conditions and 4 different expressions (Sim *et al*., 2002). In the experiments conducted in this study, 6 out of 13 poses were selected for each person. Out of 43 illumination configurations, 21 were selected to typically span the set of variations and these covered the left to the right profile.

Non-linear Principal Component Embedding (NPCE): In this set of experiments, the Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) are two powerful tools used for dimensionality reduction and feature extraction in most of pattern recognition applications; these tools were used to assess the efficiency of the method proposed in this study. Figure 3 shows that the dimensions used for testing the NPCE

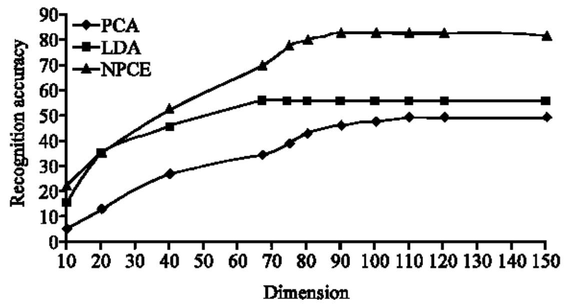

Fig. 3: The recognition rates of the PCA, LDA and NPCE

Table 1: The average error rates (%) of the PCA, LDA, NPCE, across ten tests and four dimensions

Methods	Average error rate (%)
PCA	60.75
LDA	48.15
NPCE	17.13

range (between 10 and 150) and the proposed method was found to significantly outperform the PCA and LDA. More experiments were conducted on the reduced selected dimensions (65, 75, 90 and 110) to assess the performance of the NPCE. For this, good recognition rates were obtained; the recognition rates of 49.66, 55.9 and 82.87% were obtained by the PCA, LDA and NPCE, with feature dimensions of 110, 67 and 100, respectively. As for the LDA, the maximum feature dimension cannot be more than 67, which is C-1 (number of classes-1).

Table 1 shows the average recognition error rates across ten tests and four dimensions (65, 75, 90 and 110). From these results, the NPCE was found to achieve the lowest error rate, as compared to the standard linear methods of PCA and LDA.

Figure 4 shows the results when the NPCE was used, as compared to the KPCA and LDA (Jian *et al*., 2005), as well as the Generalized Discriminant Analysis (GDA) (Baudat and Anouar, 2000). The method was shown to achieve 82.87% accuracy and had significantly outperformed the KPCA plus LDA and GDA; the later methods achieved the maximum accuracy of 77.22 and 79.92%, respectively.

The proposed method was developed to learn embedding in the non-linear manifold based on the k-nearest neighbour method and preserve the local geometry of the original high-dimensional data in a low-dimensional space as good as possible. In addition to these, the NPCE was found to minimize the reconstruction error of the neighbour weights for every data point in the low-dimensional space. The training sets are projected into the intrinsic low-dimensional space to improve their classification ability and runtime speed, while the principal components are projected into the low-dimensional embedding, with reference to the variance of the data, as given in Eq. 5. As a result, the maximum feature dimension

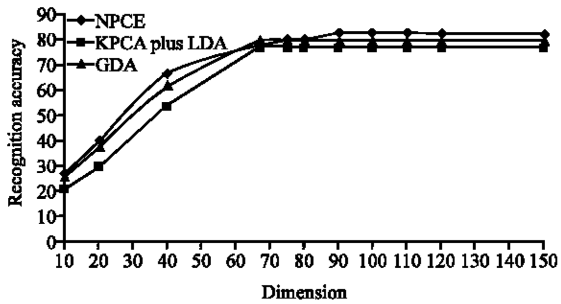

Fig. 4: The recognition rate of the KPCA plus LDA, GDA and NPCE

can be more than C-1 (number of classes-1). Therefore, this is considered as a solution to Small Sample Size (SSS) problem, where the size of sample is always smaller than the dimension of sample. In addition, the performance of the proposed method is compared with several different state-of-the-art non-linear methods. Based on the results presented in Table 1 and Fig. 4, the feature representations are proven to have more discriminative power, while the NPCE achieves a better recognition performance as compared to the linear and non-linear methods.

CONCLUSION

A new Non-linear Principal Component Embedding (NPCE) for face recognition has been introduced and proposed in this research. The proposed method is based on the local non-linear discriminant representation, which is particularly robust against the SSS problem as compared to the traditional one used in LDA. NPCE utilize a novel discriminant principal component to estimate the face feature values in the reduced embedding space. At the same time, the proposed methods have been found to perform an implicit reduction over the whole set of features, as shown by the results derived from the experiments. Therefore, the researchers regard this as significant due to the fact that the runtime speed is as important as the actual recognition rate, i.e., if only a subset of the features is used. The experiments conducted in this study clearly reveal that the proposed method is superior to the state-of-the art methods. Thus, the future study will concentrate on achieving continuous improvement for the devised method and extending it so as to incorporate more local features of the subjects.

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