Face Recognition System Using Non-Linear Doubly Kernel PCA

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Abstract: **The system for face recognition image using non-linear kernel PCA method in case of large variation.**

Keywords: Principal Component Analysis, Independent Component Analysis, Linear Discriminant Analysis, Locality Preserving Projections, Fractional Power Polynomial.

I. INTRODUCTION

Human face recognition has wide range of applications such as criminal identification, credit card verification, security system, scene surveillance, entertainments, etc. Most existing face recognition methods encounter difficulties in the case of large variation, especially when only one upright frontal image is available for each person and training images are under even illumination and a neutral facial expression. In this approach, the Gabor-wavelets are used to extract facial features, then a doubly non-linear mapping kernel -PCA (DKPCA) is proposed to perform feature transformation and face recognition. The method is called as DKPCA because kernel process is applied twice in this method. The conventional Kernel-PCA nonlinearly maps an input image into a high dimension feature space in order to make the mapped features linearly Separable and this method does not consider the structural characteristics of face images. The doubly nonlinear not only consider the statistical property of the input features but also adopts an eigenmask to emphasize important facial feature.

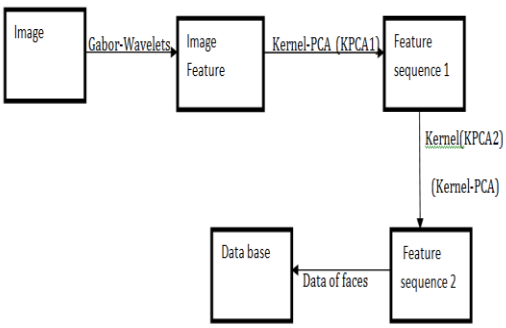

Fig. 1 Training of data of different faces

In this method it has two phases one is training phases and other is testing phase. In the training phase , store the data of different faces in the data base and in the testing phase , compare the data of given person with the data stored in the database in training phase by using different face recognition methods.

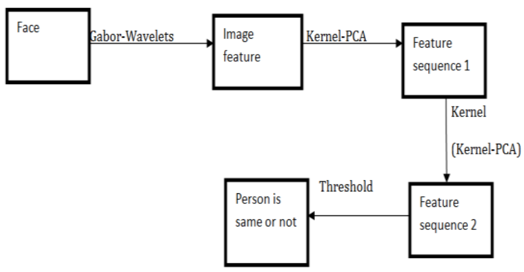

Fig. 2 Testing of data of different faces

II. REVIEW OF LITERATURE

The existing methods of the face recognition is PCA (Principal component analysis) and ICA (Independent component analysis)and LDA(Linear discriminant analysis). In the method of the PCA , decompose the data space into the linear combination of the small collection of bases, which is pair wise orthogonal and which capture the directions of maximum variance in the training data, and the PCA coefficients in the subspace are uncorrelated.PCA can preserve the global structure of the image space, and is optimal in terms of representation and reconstruction. ICA[3] can be considered a generalization of PCA, which aims to find some independent bases by methods sensitive to high-order statistics. However [4]reported that ICA gave the same, sometimes even a little worse, recognition accuracy as PCA. It uses a version of ICA derived from the principle of optimal information transfer through sigmoidal neurons. ICA was performed on face images in the FERET database under two different architectures, one which treated the images as random variables and the pixels as outcomes, and a second which treated the pixels as random variables and the images as outcomes. The first architecture found spatially local basis images for the faces. The second architecture produced a factorial face code. Both ICA representations were superior to representations based on PCA for recognizing faces across days and changes in expression. A classifier that combined the two ICA representations gave the best performance. Linear discriminent analysis (LDA) [4] seeks to find a linear transformation that maximizes the between-class scatter and minimizes the within-class scatter, which preserve the discriminating information and is suitable for recognition. However, this method needs more than one image per person as a training set; furthermore [4] shows that PCA can outperform LDA when the training set is small, and the former is less sensitive to different training sets. Locality preserving projections (LPP) [7] obtains a face subspace that best detects the essential face manifold structure, and preserves the local information about the image space. When the proper dimension of the subspace is selected, the recognition rates using LPP are better than those using PCA or LDA, based on different databases. However, this conclusion is achieved only if multiple training samples for each person are available; otherwise, LPP will give a similar performance level as PCA. PCA method mainly focuses on maintaining the global structure of training images, and is not optimal for discrimination . The performance of PCA degrades significantly compared to the results based on the normal faces. PCA represents faces with their principal components, but the variations between the images of the same face due to illumination are almost always larger than image variations due to change in face identity . Hence, PCA cannot represent and discriminate a face under severely uneven lighting conditions.

III. METHODOLOGY

In this approach, the Gabor-wavelets are used to extract facial features, then a doubly non-linear mapping kernel -PCA (DKPCA) is proposed to perform feature transformation and face recognition.

IV. PLAN OF WORK

The Gabor wavelets exhibit the desirable characteristics of capturing salient visual properties such as spatial localization, orientation selectivity, and spatial frequency .The Gabor wavelets can effectively abstract local and discriminating features, which are useful for texture detection and face recognition .In the spatial domain, a Gabor wavelet is a complex exponential modulated by a Gaussian function, which is defined as

$$\psi_{\omega,\theta}(u,v) = \frac{1}{2\Pi\sigma^2} e^{-(((u\cos\theta+v\sin\theta)^2+(-u\sin\theta+v\cos\theta)^2/2\sigma^2)}.[e^{i(\omega u\cos\theta+\omega v\sin\theta)} - e^{-\omega^2\sigma^2/2}] \quad (1)$$

Given a gray-level image $f(u,v)$, the convolution of $\psi_{\omega,\theta}(u,v)$ and is given as follows:

$$y_{\omega,\theta}(u,v) = f(u,v) * \psi_{\omega,\theta}(u,v) \quad (2)$$

Concatenating the convolution outputs, can produce a one-dimensional Gabor representation of the input image .

$\psi_{\omega,\theta}(u,v)$ is normalized to have zero mean and unit variance; and then the Gabor representations with different and are concatenated to form a high-dimensional vector for face recognition as follows:

$$Y = [Y^T_{\omega_1,\theta_1}, Y^T_{\omega_1,\theta_2}, \ldots, Y^T_{\omega_1,\theta_n}]^T \quad (3)$$

Where l and n are numbers of center frequencies and orientations used for the Gabor wavelets. For a given nonlinear mapping , the input data space can be mapped into a potentially much higher dimensional feature space

$$\Phi : R^N \to F$$
$$Y \to \Phi(Y) \quad (4)$$

Performing PCA in the high-dimensional feature space can obtain high-order statistics of the input variables; that is, also the initial motivation of the KPCA. kernel tricks can be employed to compute the dot products of vectors with a high dimension. kernel tricks compute the dot products in the original low-dimensional input space by means of a kernel function .In a practical face recognition application, three classes of kernel functions have been widely used, which are the polynomial kernels, Gaussian kernels, and sigmoid kernel. Gabor feature vector of an input image can be represented by a N-dimensional vector Y . Y is a concatenation of the Gabor representations. On the one hand, for each $\psi_{\omega,\theta}(u,v)$, can group Nc*Nr the output values together to form a histogram. The nonlinear mapping is devised to emphasize those features that have both higher statistical probabilities and spatial importance

$$\psi : R^N \to R^N$$
$$Y \xrightarrow{E} \psi(Y) \quad (5)$$

Where E is the eigenmask which is used to represent the importance of different facial positions. The eigenmask is a modification of the first eigenface derived from a set of training images. Nonlinear mapping is operated in the original input space, and Y has the same dimension as ψ (Y). In other words, the mapped value is determined by its Gabor representation value and the corresponding eigenmask value .

Suppose that the statistical property of the Gabor representation and the spatial information about faces are complementary to each other, and y and s are independent of each other, ψ can be represented as follows:

$$\psi(y,s) = \psi 1(y). \psi 2(s). \quad (6)$$

This process is equivalent to performing two nonlinear mappings—the first nonlinear mapping is ψ , as shown in (5), and is then followed by the nonlinear mapping as shown in (4)—on an input feature Y to a high-dimensional feature space, and then performing PCA for recognition (certainly, the second mapping Φ is not explicitly processed and all procedures are implemented in the original space, as discussed above). Combining (4) and (5), the doubly nonlinear mapping KPCA defines a nonlinear mapping as follows:

$$\Phi(\psi) : R^N \to R^N \to F$$
$$Y \xrightarrow{E} \psi(Y) \to \Phi(\psi(Y)) \quad (7)$$

PCA is performed in the mapped feature space for recognition.

In this, We will evaluate the performances of the proposed doubly nonlinear mapping KPCA for face recognition based on different face databases.. The face images in the different databases are captured under different conditions, such as varied lighting conditions, facial expressions. To investigate the effect of the different conditions on the face recognition algorithms , the face images in the databases are divided manually into several subclasses according to their different properties . A normal image means that the face image is of frontal view, and under even illumination and with a neutral expression. In these experiments, a face is under even illumination if the azimuth angle and the elevation angle of the lighting are both less than 20 .In each database, one frontal image of each subject with normal illumination and neutral expression is selected as a training sample, and the rest form the testing set. All images the input color images are converted to grayscale ones. To enhance the global contrast of the images and reduce the effect of uneven illuminations, histogram equalization is applied to all the images . This method is to perform an additional nonlinear mapping for the conventional KPCA. In this paper, We select the KPCA with FPP models and evaluate its performance with and without use of the proposed doubly nonlinear mapping for face recognition. To derive the real features of KPCA, We apply only those KPCA eigenvectors that are associated with positive eigen values.

1. Face Recognition Under Normal Conditions: The proposed doubly nonlinear mapping KPCA outperforms all other methods, regardless of which mapping function is used. The method using only $\psi 1$ performs better than that using $\psi 2$ only. This is because the latter applies a fixed eigenmask to all images, while the former transforms the inputs according to their probability distribution.Therefore; the method based on the statistical property of the input is more elastic and suitable for human face recognition. When the statistical characteristic and the spatial information are considered together, i.e. ψ is used as the mapping function, the best performance can be achieved.

2. Face Recognition Under Varying Lighting Conditions: In this part of the experiments, WE select only those images with obviously uneven illuminations as the testing images. The Gabor wavelets can greatly increase the recognition performance based on the different databases. This shows that the Gabor wavelets representations can effectively reduce the effect of varying illumination.

3. Face Recognition With Variations in Facial Expressions and Perspective: The recognition rates of the Gabor wavelets-based methods are even lower than that of the PCA method in some cases. This is because facial expressions are formed from the local distortions of the facial feature points, which will then affect the corresponding local texture and shape properties. In this case, the Gabor representations, which abstract the textural information about the neighborhood of each pixel, are also disturbed by the local distortions caused by changes in facial expression, which results in degradation of the performance. In contrast, PCA maintains the global structure of the input, while discarding the detailed, local information.

4. Face Recognition With Different Databases: In this section, We also show the respective performances of the different face recognition methods based on the different databases without dividing them into sub database. In addition, this method using either $\psi 1$ or $\psi 2$ also outperforms the conventional Gabor-based methods in most of the cases. With these four the recognition rate for the ORL database is always the lowest, the recognition rate for the ORL database is always the lowest, irrespective of which method is used because most of the faces in this database are under perspective variations.

IV. SIGNIFICANCE

The result presented by Xudong Xie and Kin-Man Lam[1]proves that this system performs much better than present available system like PCA etc. Hence it providing significant bench mark under face recognition system applications even working under very unpleasant environments e.g. uneven illumination , varying lighting conditions.

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