Face Recognition Using Kernel PrincipalComponent Analysis

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Abstract

Face recognition is attracting much attention in the society of network multimedia information access. Areas such as network security, content indexing and retrieval, and video compression benefits from face recognition technology because people are the center of attention in a lot of video. Network access control via face recognition not only makes hackers virtually impossible to steal one's password, but also increases the user-friendliness in human-computer interaction. The data in face images are distributed in a complex manner due to the variation of light intensity, facial expression and pose. In this paper the Kernel Principal Component Analysis (KPCA) is used to recognize the faces. A Gaussian model of skin segmentation method is applied here to exclude the global features such as beard, eyebrow, moustache, etc. both training and test images are randomly selected from four different data bases to improve the training. The experimental results show that the proposed framework is efficient for recognizing the humanfaces.

Keywords

Face recognition, Kernel principal component analysis, Feature extraction.

I. INTRODUCTION

Humans have always had the innate ability to recognize and distinguish between faces. Face recognition is substantially different from classical pattern recognition problems, such as object recognition. The shapes of the objects are usually different in an object recognition task, while in face recognition one always identifies objects with the same basic shape. This is of utmost difficulty for a face recognition system when one tries to discriminate faces all of which have the same shape with minor texture differences. The face recognition therefore depends heavily on the particular choice of face representation. The aim of feature selection in face representation method is to suppress the variations of face images and simultaneously provide enhanced discriminatory power.

The significant growth of visual information capturing technology has revolutionized the security observations and scientific inquiry, producing significant opportunities and challenges [1][2]. This renewed interest has been powered by advances in computer vision techniques and interest in the design of robust and accurate face recognition systems. The human face provides the information about the identity, sex, race, approximate age, and current mood of an individual. The advanced trends in the image processing provide a clear path to identify the human faces in a considerable manner. The technique presented in this paper reveals the possibilities of biometric applications in security aspects.

In this paper a face recognition technique is proposed. There are a bunch of remarkable findings in face recognition and identification using various techniques and algorithms [3-5] in computations. The focus here is to identify the human faces.

Various statistical models [9][10] are used to discerning skin pixels in a color face image; among them wehave used the Gaussian skin color model [7][8]. There will be no dominant features in the skin segmented face images and these images are used to recognize the faces. KPCA, the powerful extension of PCA used to extract the feature which has been successfully applied in face recognition.

II. SKIN SEGMENATION

There are different skin segmentation algorithms working with different color space like RGB, HSV, HIS, rgb and YCbCr. The threshold value used in these methods decides the success of the model.

The RGB model deals with the illumination conditions of image. And the method required some defined rules of fixing the threshold.

Uniform day light
R>90, G>40,B>20
Max{R,G,B} – min{R,G,B} <15
|R-G|>15, R>G, R>B(1)
Lateral illumination (Flash or any other)
R>220, G> 210, B>170

$$|R - G| \leq 15, B < R, R < G \qquad (2)$$

In the HSV model the segmentation has done through the range value selected for H, the saturation range and V. These parameters used to study the nature of dark colors and the effect of light variation in the image.

$V \geq 40$
0.2 < S < 0.6;

$$0^0 < H < 25^0 \text{ or } 335^0 < H < 360^0 \qquad (3)$$

These thresholds are having a significant role in the segmentation.

The HIS method finds some unchanged color pattern in the skin, intensity, hue and saturation. And we can find the threshold empirically through

$$I_1 = \frac{1}{3}(R + G + B); \quad I_2 = \frac{1}{2}(R - B); \quad I_3 = \frac{1}{4}(2G - R - B)$$
$$I = I_1$$
$$S = \sqrt{I_2^{\,2} + I_3^{\,2}}$$
$$H = \tan^{-1}\left[\frac{I_3}{I_2}\right] \qquad (4)$$

Gomez and Morales [6] produce a constructive induction method for skin detection called rgb model. The normalized coordinates rgb are obtained through the following expressions

$$r = \frac{R}{R + G + B} \qquad g = \frac{G}{R + G + B} \qquad b = \frac{B}{R + G + B} \qquad (5)$$

The YCbCr method tries to exploit the spatial distribution characteristics of human skin color. A skin color map is used to detect the skin pixel from the chrominance components of the image.

Even though they are using a threshold like

$$77 \leq Cb \leq 127 \quad \text{and} \quad 133 \leq Cr \leq 173, \qquad (6)$$

The authors could reach an appraisable result. The work presented in www-cs-students.stanford.edu by Henry Chang and Ulises Robles proves the practical importance of the method.

The low-pass filter [13] derived from about 32000 skin samples is

$$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \qquad (7)$$

The result of skin-color distribution in different people is shown in the figure 1

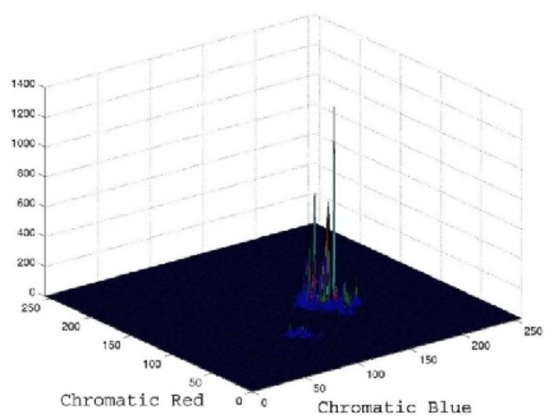

Figure 1: Skin-color distribution in different people

The histogram shows the possibilities of Gaussian model in representing this particular color model.

The Gaussian model N(m,c), where

Mean : $m = E\{x\}$ where $x = (r,b)^T$

Covariance : $C = E\{(x - m)(x - m)^T\}$ (8)

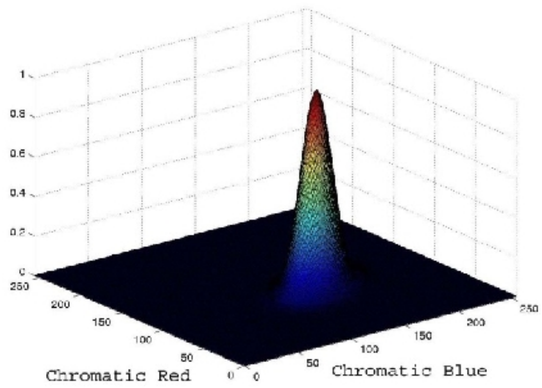

Figure 2: The Gaussian distribution of Skin-color

The Gaussian distribution of the skin color in the experiment data set is given in figure 2. The likelihood of skin pixel can be easily obtained from this Gaussian skin model.

$$\text{Likelihood} = P(r,b) = \exp[-0.5(x - m)^T C^{-1}(x - m)]$$

$$\text{Where}: x = (r,b)^T \qquad (9)$$

The parameters r &b are the chromatic color value of the pixel.

The gray scale image obtained can be converted into binary image by applying an appropriate threshold. This binary face image is used to segment the skin region from a face image.

(a) **(b)**

Figure 3(a): OriginalImage (**b)**: After skin segmentation

A sample color image and its resulting skin-segmented image are shown in Figure 3.

III. FEATURE EXTRACTION

The dimensionality of a face image is extremely high. If we put all face images in a M^2 dimensional space, they will not fully fill the whole space, but will instead only cover a very limited volume. This implies many input components are correlated, and the dimensionality can be significantly reduced.

An excellent Feature Selection method should preserve as much as possible relevant components, and on the other hand, neglects that insignificant information. Even though the Feature Selection is task-dependent, there are someunsupervised strategies which tend to work well in many cases.

A. ***Principal Component Analysis***

Principal component analysis measures the variability of an input component by its variance. PCA works well for Gaussian distribution data, since in this case the eigenvalues of the covariance matrix indeed quantifies the variability of data along their corresponding directions.

Consider a data set of centered N dimensional records X_i, $i = 1,2,3,\ldots M$, that is $X_i \in R^N$ and $\sum_{i=1}^{M} X_i = 0$.

The covariance of the input can be estimated as

$$\sum = \frac{1}{M}\sum_{i=1}^{M} X_i X_i^T \qquad (10)$$

To reduce the dimensionality of input, we can rank the eigenvectors in the order of magnitude of the eigenvalues and choose the first d, d < N, eigenvectors as principal components. In face images, these eigenvectors are called eigenfaces that represent the global feature of the training images.

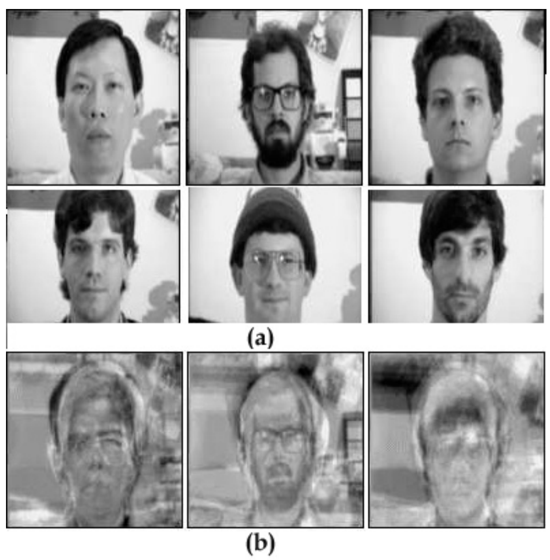

Figure 4: (a) a set of six training face images.
(b) Three eigenfaces with highest eigenvalues, that are derived from (a)

However, when the variations are caused by global factors such as lighting or perspective variations, the performance of PCA will be greatly degraded.

B. ***Kernel Principal Component Analysis (KPCA)***

The Cover's theorem abstracts that the nonlinearly separable patterns in an input space will become linearly separable by transforming the input space into a high dimensional feature space.

A high order statistics of the input variable can be obtained by applying PCA in the high dimensional feature space. This fact leads to the origin of KPCA. It is much difficult to directly compute PCA in the high-dimensional feature space. Computation of dot products of vectors with a high dimension is highly computational expensive. By means of a kernel function it is possible to compute the dot products in the original low-dimensional input space.

Here we would like to present an abstract review of the first KPCA proposed by SchÄolkopf.

The covariance matrix $\sum_\phi$ of a given data set X is

$$\sum_\phi = E[(\phi(x) - E[\phi(x)])(\phi(x) - E[\phi(x)])^T]$$

$$= \frac{1}{N}\sum_{i=1}^{c}\sum_{j=1}^{Ni}(\phi(x_i^j) - m^\phi)(\phi(x_i^j - m^\phi)^T, \qquad (11)$$

Where $m^\phi = \frac{1}{N}\sum_{i=1}^{c}\sum_{j=1}^{Ni}\phi(x_i^j)$ is the mean over all N feature vectors in F.

Since KPCA seeks to find the optimal projection directions in F, onto which all patterns are projected to give the corresponding covariance matrix with maximum trace, the objective function can be denoted by maximizing the following:

$$\text{Jkpca(v)} = v^T \sum_\phi v \qquad (12)$$

It can be proved that the eigenvector v must lie in a space spanned by { $\phi(x_i^j)$ } in F and thus it can be expressed in the form of the following linear expansion:

$$v = \sum_{i=1}^{c}\sum_{j=1}^{N_i} w_i^j \phi(x_i^j) \qquad (13)$$

Substituting (13) into (12), we obtain an equivalent eigenvalue problem as follows:

$$(I - \frac{1}{N}1)K(I - \frac{1}{N}1)^T w = \lambda w, \qquad (14)$$

where I is an N x N identity matrix, 1 is an N x N matrix with all terms being one, $w = (w_1^1,...,w_1^{N_1},...,w_c^1,...,w_c^{N_c})^T$ is the vector of expansion of coefficients of a given eigenvector v, and K is the N x N Gram matrix which can be further defined as

K = (K_{lh})l,h=1,…,c where $K_{lh} = (k_{ij})_{i=1,...,N_l}^{j=1,...,N_h}$ and

$k_{ij} = \left\langle \phi(x_l^i), \phi(x_h^j) \right\rangle$

The solution to (14) can be found by solving for the orthonormal eigenvectors $w_1,\dots,w_m$ corresponding to the m largest eigenvalues¸ $\lambda_1,\dots,\lambda_m$, which are arranged in descending order. Thus, the eigenvectors of can be obtained as Φwi (i = 1,…,m), where

$$\Phi = [\phi(x_1^1),...,\phi(x_1^{N_1}),...,\phi(x_c^1),...,\phi(x_c^{N_c})].$$

Furthermore, the corresponding normalized eigenvectors v_i (i = 1,…,m) can be obtained as $v_i = \frac{1}{\sqrt{\lambda_i}}\Phi w_i$, since

$(\Phi w_i)^T \Phi w_i = \lambda_i$.

With $v_i = \frac{1}{\sqrt{\lambda_i}}\Phi w_i$ (I = 1,…, m) constituting the m orthonormal projection directions in F, any novel input vector x can obtain its low-dimensional feature representation y = (y_1,…,y_m)T in F as:

$$y = (v_1,\ldots, v_m)^T\phi(x), \quad (15)$$

with each KPCA feature y_i (i = 1,…,m) expanded further as

$$y_i = v_i^T\phi(x) = \frac{1}{\sqrt{\lambda_i}} w_i^T\Phi\phi(x)$$

$$= \frac{1}{\sqrt{\lambda_j}} w_i^T [k(x_1^1, x),\ldots, k(x_1^{N_1}, x),\ldots, k(x_c^1, x),\ldots, k(x_c^{N_c}, x)] \quad (16)$$

KPCA is superior to PCA in extracting more powerful features, which are especially essential when recognizing the human faces.

IV. Experimental Results

There are a couple good facial databases available for evaluating the algorithms in face recognition and analysis. In order to give a wide spectrum of face features, we have used four databases for preparing the training and testing images. The database (FERET,ORL, UMIST,and AT&T) that wehave selected has different feature specific parameters like lighting, pose, expressions, age and other global features such as spectacles, beard, etc. As part of experiments wehave selected three sets of different faces from each database. After image preprocessing [12], the face regions of 80×100 pixels are cropped in a generalized resolution by using the facts that all the databases that wehave selected are face centered profiles.

The second phase of our experiment was to segment the skin regions in the training images. This has done using the Gaussian model as explained in the previous sections.

In the third phase, we extracted the kernel eigenfaces of both male and female sets of data separately. The correlation between the projected data sets of mean face of the training images and test images reveals the approximation of the algorithm.

Using KPCA wehave extracted the 10, 20,… principal components from the male and female sets of training images. The Fig. 5 shows the variation of accuracy along different number of principal components used in FERET and UMIST databases. It is quite easy to understand that the rate of accuracy is increasing with increase of principal components, which shows the feature vectors corresponding to large principal components should be stressed with more weights.

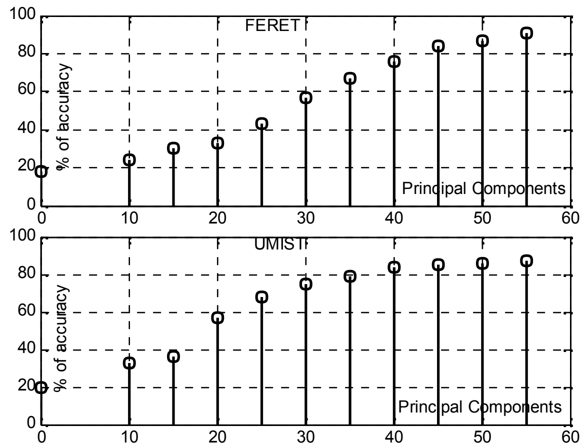

Figure 5: Influence of number principal components and Rate of Recognition

A set of randomly selected face images from different databases is used for testing purpose. An accuracy of 88-94 percentages has obtained in almost all test cases. It is noted that the FERET and AT&T databases shows a consistency in recognition in the last couple of principal components. The following figure shows the recognition rate of both PCA and KPCA in different face databases.

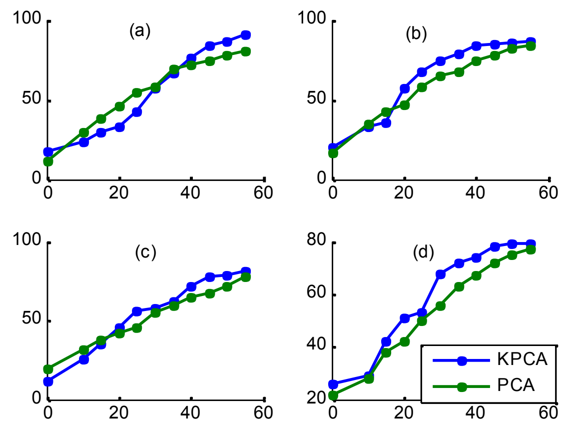

Figure 6: Rate of Recognition in PCA and KPCA methods.

The Experimental results with the test images from (a) FERET database (b) ORL database (c) UMIST database (d) AT&T database

From the results displayed in Table-1 we notice that the KPCA technique gives a comparatively better rate of identification in all databases considering the ordinary PCA.

Table 1: A study of the rate of face recognition in different face databases using PCA and KPCA.

	KPCA	PCA
FERET	91.23	81.58
ORL	87.56	84.19
UMIST	81.98	78.2
AT&T	79.34	77.91

V. CONCLUSION

In this paper, we proposed a KPCA method for face recognition. The experimental results show that the KPCA method is efficient in extracting low level feature of face images which are the most supreme components of face recognition problem. Randomly selected images from four different databases are used as training faces. In almost all databases the KPCA method gives almost 81 - 91 percentage accuracy. The test images taken from the databases show almost consistent result even though it is having different light intensities and face expressions. we hope that this work provides a new effective approach of non-intrusive biometric recognition.

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