International Journal of Reconfigurable and Embedded Systems
Vol. 7, No. 2, July 2018, pp. 124~130
ISSN: 2089-4864, DOI: 10.11591/ijres.v7.i2.pp124-130

A Novel Face Recognition Algorithm Using Gabor-based KPCA

Umasankar Ch[1], D. Naresh Kumar[2], Md. Abdul Rawoof[3], D. Khalandar Basha[4], Mr. N. Madhu[5]
[1, 2, 3]MLR Institute of Technology, Hyderabad, India
[4]Institute of Aeronautical E9ngineering, Hyderabad, India
[5]Vardhaman College of Engineering, Shamshabad, Hyderabad, India

Article Info

Article history:

Received Apr 13, 2018
Revised Jun 14, 20118
Accepted Jun 27, 2018

Keywords:

DKPCA
FER
Gabor
KPCA

ABSTRACT

The Gabor wavelets are used to extract facial features, and then a doubly nonlinear mapping kernel PCA (DKPCA) is proposed to perform feature transformation and face recognition. The conventional kernel PCA nonlinearly maps an input image into a high-dimensional feature space in order to make the mapped features linearly separable. However, this method does not consider the structural characteristics of the face images, and it is difficult to determine which nonlinear mapping is more effective for face recognition. In this work, a new method of nonlinear mapping, which is performed in the original feature space, is defined. The proposed nonlinear mapping not only considers the statistical properties of the input features, but also adopts an Eigen mask to emphasize those important facial feature points The proposed algorithm is evaluated based on the Yale database, the AR database, the ORL database and the YaleB database.

Corresponding Author:

Umasankar Ch,
MLR Institute of Technology,
Hyderabad, India.
Email: sankarch.4u@gmail.com

1. INTRODUCTION

Human face recognition has attracted significant attentions because of its wide range of applications, such as criminal identification, credit card verification, security system etc. In this project, a novel Gabor-based kernel principal component analysis (PCA) with doubly nonlinear mapping is proposed for human face recognition [1]. Human face recognition has engaged remarkable attentions because of its extensive range of applications, such as criminal identification, credit card verification, security system, scene surveillance, entertainments, etc. Among these applications, face recognition techniques are applicable on various source formats ranging from static, controlled format photographs to uncontrolled video sequences which have been developed in different conditions [2]. Therefore, a practical face recognition technique needs to be vigorous to the image variations generated by the illumination conditions, facial expressions, poses or perspectives [3]. However, “the variations between the images of the same face due to illumination and viewing direction are almost always larger than the image variations due to a change in face identity,” and so 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 the training images are under even illumination and a neutral facial expression Machine recognition of faces has several applications, ranging from static matching of controlled photographs as in mug shots matching and credit card verification to surveillance video images. Such applications have different constraints in terms of complexity of processing requirements and thus present a wide range of different technical challenges. Over the last 20 years researchers in psychophysics, neural sciences and engineering, image processing, analysis and computer vision have investigated a number of issues related to face recognition by humans and machines [4]-[7].

Ongoing research activities have been given a renewed emphasis over the last five years. Existing techniques and systems have been tested on different sets of images of varying complexities. But very little synergism exists between studies in psychophysics and the engineering literature. Most importantly, there exist no evaluation or benchmarking studies using large databases with the image quality that arises in commercial and law enforcement applications The provision of the problem includes segmentation of faces from cluttered sense removal of features from the face region, identification, and matching. The common face recognition task thus created is a primary issue in problems such as electronic line up and browsing through a database of faces. Face recognition is one of the challenging tasks. Most existing face recognition methods encounter difficulties in the case of large variation, especially when only one upright frontal image available for each person and the training images are under even illumination and neutral facial expression. Most of the recognition techniques are based on statistical approach. And these techniques need more images of a person with different poses and different illumination conditions for better recognition accuracy. Practically it not possible. It needs to develop a face recognition system which requires only one image of a person for training of the system and can be implemented practically. Here Gabor wavelet kernels along with principal component analysis used for extraction of facial features and recognition. Gabor wavelet kernels have response similar to that of the human visual cortex (first few layers of brain cells).These captures salient visual properties such as spatial localization, orientation selectivity, and spatial frequency. That is using these kernels local features of face image are obtained.

Since Gabor wave lets and PCA are used together, the recognition accuracy can be greatly improved. During the training phase it is enough to use a single face image for the training of the system. Hence the recognition system is robust and is easy to implement partially. Face recognition involves computer recognition of personal identity based on geometric or statistical features derived from face images. Even though humans can detect and identify faces in a scene with little or no effort, building an automated system that accomplishes such objectives is, however very challenging. The challenges are even more profound when one considers the large variations in the visual stimulus due to illumination conditions, viewing directions or poses, facial expression, aging, and disguises such as facial hair, glasses or cosmetics. The enormity of the problem has involved hundreds of scientists in interdisciplinary research but the ultimate solution remains elusive.

2. BACKGROUND

Recently, the application of the Karhunen-Loeve (KL) extension for the presentation and recognition of faces has generated renewed interest. The KL extension has been designed for image compression for more or less 30 years its use in pattern recognition. Their applications have also been recorded for quite some time. Computational complexity was one of the reasons why KL methods, even though optimal, did not find favor with image compression researchers. Sirovich and Kirby revisit the problem of KL depiction of images (cropped faces). Once the eigenvectors (referred to as “Eigen pictures”) are acquired, any image in the ensemble can be approximately rebuilt using a weighted combination of Eigen pictures. By using an increasing number of Eigen pictures, one gets a better approximation to the given image The singular value decomposition (SVD) of a matrix is utilized to reproduce the features from the pattern. SVD can be observed as a deterministic counterpart of the KL transform. The singular values (SV’s) of an image are very secure and constitute the algebraic attributes of the image, being intrinsic but not necessarily visible. It can be Proven their stability and invariance to proportional variance of image intensity in the optimal discriminate vector space, to transposition, rotation, translation, and reflection which are important properties of the SV feature vector. Linear subspace analysis, which considers a feature space as a linear combination of a set of bases, has been widely used in face recognition applications. This is mainly due to its effectiveness and computational efficiency for feature extraction and representation. Different criteria will produce different bases and, consequently, the transformed subspace will also have different properties. Principal component analysis (PCA) is the most popular technique; it generates a set of orthogonal bases that 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. Because only the second-order dependencies in the PCA coefficients are eliminated, PCA cannot capture even the simplest invariance unless this information is explicitly provided in the training data. Independent component analysis (ICA) can be considered a generalization of PCA, which aims to find some independent bases by methods sensitive to high-order statistics. However, reported that ICA gives the same, sometimes even a little worse, recognition accuracy as PCA. Linear discriminate analysis (LDA) 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 PCA can outperform LDA when the training set is small, and the former is less sensitive to different training sets Locality preserving projections (LPP) 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. Kernalized PCA method performs better generalization when the training set is non-linearly separable and by performing a non-linear mapping, the algorithm is found to be suitable for current approach as the technique works well with single face image per person. By using the Cover's theorem, nonlinearly separable patterns in an input space will get into linearly separable with an excessive probability if the input space is modified nonlinearly to a high-dimensional feature space. This plotting is usually achieved through a kernel function and, corresponding to the methods used for recognition in the high-dimensional feature space, we have a set of kernel-based methods, such as the kernel PCA (KPCA), or the kernel Fisher discriminate analysis (KFDA).The two methods such as KPCA and KFDA are linear in case of high-dimensional feature space, but nonlinear in case of low-dimensional image spac. In other words, these techniques can detect the nonlinear structure of the face images, and encode higher order statistics. While kernel-based methods can control many of the limitations of linear transformation, pointed out that none of these methods clearly considers the structure of the manifold on which the face images possibly reside. However, the kernel functions used are deprived of direct physical meaning, i.e., how and why a kernel function is suitable for a pattern of a human face, and how to obtain a nonlinear structure useful for discrimination means that, besides the conventional kernel function, a new mapping function is also defined and used to highlight those features having higher statistical probabilities and spatial importance for face images. More precise, this new mapping function marks not only the statistical distribution of the Gabor features, but also the spatial information about human faces [8]-[11]. Further nonlinear mapping, the transformed features have a higher discriminating power, and the importance of the features transforms to the spatial importance of the face images.

3. SYSTEM DESIGN

Here is the formula of a complex Gabor function in space domain

$$g\,(x,y)=s(x,y)\;\omega_r\,(x,y)$$

where $s(x, y)$ is a complex sinusoid, known as the **carrier,** and $\omega_r(x, y)$ is a 2-D Gaussian-shaped function, known as the **envelope.**

The complex sinusoid is defined as follows

$$s\,(x,y)=\exp\,(\,(\,j\,(\,2\prod\,(\,u_0\,x+v_0\,y\,)+P\,)\,)$$

Where (u_0, v_0) and P define the spatial frequency and the phase of the sinusoid respectively. We can think of this sinusoid as two separate real functions, conveniently allocated in the real and Imaginary part of a complex functions Figure 1.

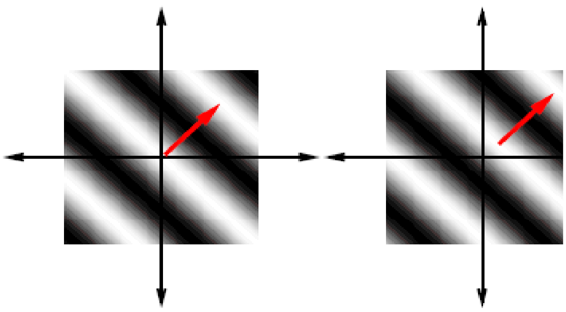

Figure 1. The real and imaginary parts of a complex sinusoid

The images are 128 × 128 pixels.
The parameters are: $u_0 = v_0$=1/80 cycles/pixel, P=0 deg.
The real part and the imaginary part of this sinusoid are

$$\mathrm{Re}(s(x,y))=\cos(2\prod(u_0x+v_0y)+P)$$
$$\mathrm{Im}(s(x,y))=\sin(2\prod(u_0x+v_0y)+P)$$

The parameters u_0 and v_0 define the spatial frequency of the sinusoid in Cartesian Coordinates. This spatial frequency can also be expressed in polar coordinates as magnitude F_0 and direction ω_0:

$$F_0=\sqrt{}u_0^2+v_0^2$$
$$\omega_0=\tan^{-1}(v_0/u_0) \text{ i.e}$$
$$u_0=F_0 \cos \omega_0$$
$$v_0=F_0 \sin \omega_0$$

Using this representation, the complex sinusoid is

$$s=\exp\left(j(2\prod F_0\,(x_0 \cos \omega_0 + y \sin \omega_0)+P)\right)$$

3.1. The Complex Gabor Function
The complex Gabor function is defined by the following parameters;

a. K: this parameter Scales the magnitude of the Gaussian envelope.
b. (a, b): it is responsible for Scaling the two axis of the Gaussian envelope.
c. θ: which will Rotate angle of the Gaussian envelope.
d. (x_0, y_0): determines the Location of the peak of the Gaussian envelope.
e. (u_0, v_0): this parameter gives the spatial frequencies of the sinusoid carrier in Cartesian coordinates. It can also be expressed in polar coordinates as (F_0, ω_0).
f. P: refers to the Phase of the sinusoid carrier.

As mentioned above each complex Gabor consists of two functions in quadrature (out of phase by 90 degrees), appropriately located in the real and imaginary parts of a complex function. Kernel PCA, through the use of kernels, principle components can be computed efficiently in high-dimensional feature spaces that are related to the input space by some nonlinear mapping. Kernel PCA finds principal components which are nonlinearly related to the input space by performing PCA in the space produced by the nonlinear mapping, where the low-dimensional latent structure is, hopefully, easier to discover.

In an experimental face recognition application, three classes of kernel functions have been widely used, which are the polynomial kernels, Gaussian kernels, and sigmoid kernels, [12], respectively.

Polynomial Kernel: $k(Y_i, Y_j) = (Y_i, Y_j)^d$

Gaussian Kernel: $k(Y_i, Y_j) = \exp\left(-\frac{\| Y_i - Y_j \|^2}{2\sigma^2}\right)$

Sigmoid Kernel: $k(Y_i, Y_j) = \tanh\left(k(Y_i.Y_j) + \vartheta\right)$

Where d > 0, k > 0 , and v < 0 the polynomial kernels are extended to include fractional. Power polynomial (FPP) models, i.e. 0 < d <1where a more reliable performance can be achieved.
Pick an appropriate kernel function K (the form of the kernel, plus any parameters).

1) onstruct the Kernel Matrix for the mapped data:

$$K_{ij} \equiv \Phi(\vec{x}_i).\Phi(\vec{x}_j) = K(\vec{x}_i, \vec{x}_j)$$

2) Use this to construct the Covariance Matrix for the centered data:

$$\tilde{K}_{ij} \equiv \tilde{\Phi}(\vec{x}_i).\Phi(\vec{x}_j) = K_{ij} - \frac{1}{N}\sum_{p=1}^{N} K_{ip} - \frac{1}{N}\sum_{q=1}^{N} K_{qj} + \frac{1}{N^2}\sum_{p,q=1}^{N} K_{pq}$$

3) Solve for the set of eigenvectors $\left\{ \quad b^{\alpha}{}_{i} : i = 1 \; to \; N, \alpha = 1 \; to \; M \right\}$ of the matrix $\tilde{K}_{ij}$ which give us our set of basis vectors $\left\{ b^{\alpha} \right\}$ in feature space thus:

$$\left\{ \quad b^{\alpha}{}_{i} : i = 1 \; to \; N, \alpha = 1 \; to \; M \right\}$$

4) The unnormalised KPCA components of a test point $\vec{x}$ are then given by:

$$p^{\alpha}(\vec{x}) \propto b^{\alpha}.\Phi(\vec{x}) \propto \sum_{i=1}^{N} b_{i}^{\alpha} K(\vec{x}, \vec{x}_{i})$$

4. RESULTS AND CONCLUSION

Raining is performed for face images of 12 persons. Here one face image is taken for each person. So training set size=12. Following is the training set. Testing is performed with 96 images. Here each of above person's face images are given as input with different orientations. For each person, 9 face images are given as input. Training set as shown in Figure 2.

Overall accuracy of system is around 89.58% (tested over 96 Images). Finally to test the superiority of the algorithm, images containing animals or any other are given as input. It is found that algorithm is able to discard those images. Following images are given as input (images containing non-human beings). Detection of eigen face (Pass Case) as shown in Figure 3. Tested output mismatch case as shown in Figure 4. Also algorithm is expected to work for any other set of images by tweaking the model parameters. The accuracy in discarding images of nonhuman beings=100% (tested with above a set of images).

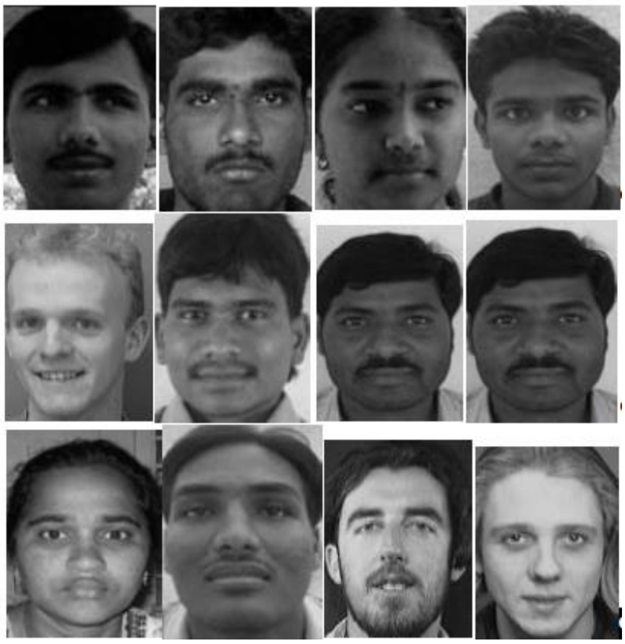

Figure 2 .Training set

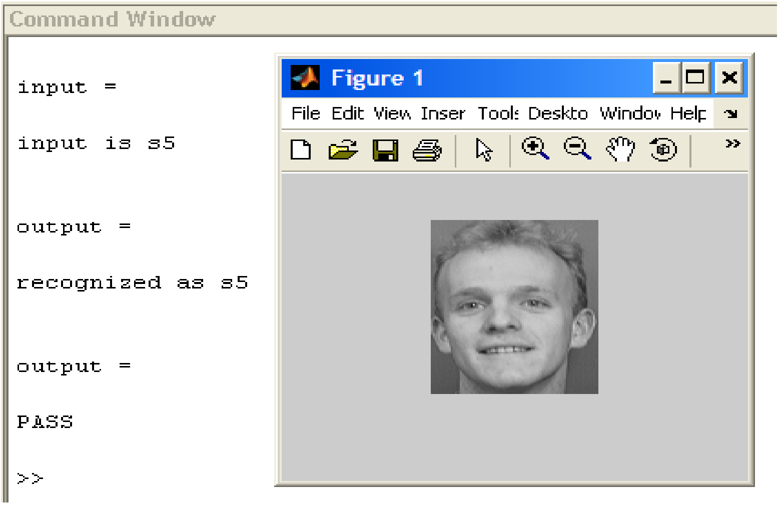

Figure 3. Detection of eigen face (pass case)

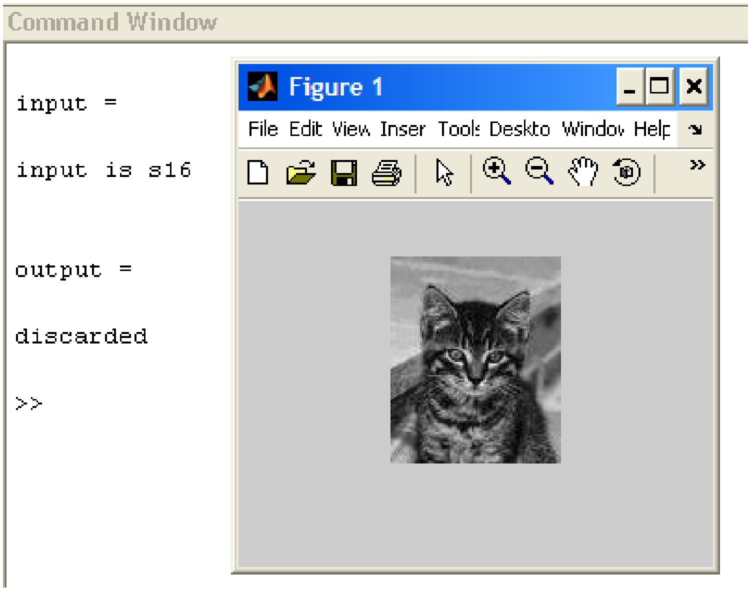

Figure 4. Tested output mismatch case

5. CONCLUSION

This work used a novel doubly nonlinear mapping Gabor-based KPCA for human face recognition. In this approach, the Gabor wavelets are employed to separate facial features, then a doubly nonlinear mapping KPCA is used to perform feature transformation and face recognition. When estimating with the conventional KPCA, an additional nonlinearly mapping is achieved in the original space. This nonlinear mapping not only marks the statistical property of the input features, but also affects an Eigen mask to emphasize those features derived from the important facial feature points. Therefore, after the mappings, the transformed features have a higher discriminant power, and the importance of the features adapts to the spatial importance of the face image. From the results I observe that Gabor based doubly nonlinear kernel PCA method is suited for face recognition and also works well even for different orientations of face, smiling face and laughing face. Also the algorithm is able to discard when non -human being images are given as input to the system.

This approach for Face Recognition process is fast and simple which works well under constrained environment. One of the limitations for this approach is the treatment of face images with glasses. Research needs to be done on this aspect. If drastic changes in poses the recognition accuracy decreases. It is more useful if the Face Recognition system is developed which is completely pose invariant.

ACKNOWLEDGMENT

The authors would like to thank the anonymous reviewers for their comments which were very helpful in improving the quality and presentation of this paper.

REFERENCES

[1] Z. Pan, G. Healey, M. Prasad, and B. Tromberg, “Face recognition in hyperspectral images,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 25, no. 12, pp. 1552–1560, Dec. 2003.
[2] V. Blanz and T. Vetter, “Face recognition based on fitting a 3D morphable model,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 25, no. 9, pp. 1063–1074, Sep. 2003.
[3] A. Fulton and J. C. Bartlett, “Young and old faces in young and old heads: The factor of age in face recognition,” Psych. Aging, vol. 6, no. 4, pp. 623–630, 1991.
[4] M. S. Bartlett, J. R. Movellan, and T. J. Sejnowski, “Face recognition by independent component analysis,” IEEE Trans. Neural Netw., vol. 13, no. 6, pp. 1450–1464, Dec 2002.
[5] L. Wiskott, J. M. Fellous, N. Krüger, and C. Malsburg, “Face recognition by elastic bunch graph matching,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 19, no. 7, pp. 775–779, Jul. 1997.
[6] S. H. Lin, S. Y. Kung, and L. J. Lin, “Face recognition/detection by probabilistic decision-based neural network,” IEEE Trans. Neural Netw., vol. 8, no. 1, pp. 114–132, Feb. 1997.
[7] M. Turk and A. Pentland, “Eigenfaces for recognition,” J. Cogn. Neurosci., vol. 3, pp. 71–86, 1991.
[8] A. Lanitis, C. Draganova, and C. Christodoulou, “Comparing different classifiers for automatic age estimation,” IEEE Trans. Syst., Man, Cybern. B, Cybern., vol. 34, no. 1, pp. 621–628, 2004.
[9] A. Lanitis, C. J. Taylor, and T. F. Cootes, “Toward automatic simulation of aging effects on face images,” IEEE Trans. Image Process., vol. 24, no. 4, pp. 442–455, Apr. 2002.
[10] P. J. Phillips, “Matching pursuit filters applied to face identification,” IEEE Trans. Image Process., vol. 7, no. 8, pp. 1150–1164, Aug. 1998
[11] M. Kirby and L. Sirovich, “Application of the KL procedure for the characterization of human faces,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 12, no. 1, pp. 103–108, Jan. 1990.
[12] D. Nandy and J. Ben-Arie, “Shape from recognition: A novel approach for 3-D face shape recovery,” IEEE Trans. Image Process., vol. 10, no. 2, pp. 206–217, Feb. 2001.

BIOGRAPHIES AUTHORS

UmaSankar.Ch, working as an Assistant Professor in ECE Department at MLR institute of Technology, Hyderabad. He completed his Graduation (B.Tech) in ECE from JNTUH in 2009 and Post graduation (M.Tech) from JNTUH in 2011. He is pursuing his research on FPGA implementation of Image Processing applications at VIT University, Chennai.

D Naresh Kumar, working as an Assistant Professor in ECE Department at MLR institute of Technology, Hyderabad. He completed his Graduation (B.Tech) in ECE from JNTUH in 2007 and Post graduation (M.Tech) from JNTUH in 2012.

Md. Abdul Rawoof, working as an Assistant Professor in ECE Department at MLR institute of Technology, Hyderabad. He completed his Graduation (B.Tech) in ECE from JNTUH in 2009 and Post graduation (M.Tech) from JNTUH in 2012. His Area of interest includes Communications and Image Processing applications.