Available online at www.sciencedirect.com
SCIENCE DIRECT®

Pattern Recognition Letters 27 (2006) 747–754

Pattern Recognition Letters

www.elsevier.com/locate/patrec

Generating frontal view face image for pose invariant face recognition

Hyung-Soo Lee *, Daijin Kim

Biometrics Engineering Research Center (BERC), Pohang University of Science and Technology, San 31, Hyoja-Dong, Nam-Gu, Pohang 790-784, Republic of Korea

Received 5 April 2005; received in revised form 7 November 2005
Available online 4 January 2006

Communicated by R.P.W. Duin

Abstract

Recognizing human faces is one of the most important areas of research in biometrics. However, drastic change of facial poses is a big challenge for its practical application. This paper proposes generating frontal view face image using linear transformation in feature space for face recognition. We extract features from a posed face image using the kernel PCA. Then, we transform the posed face image into its corresponding frontal face image using the transformation matrix predetermined by learning. Then, the generated frontal face image is identified by three different discrimination methods such as LDA, NDA, or GDA. Experimental results show that the recognition rate with the pose transformation outperforms that without pose transformation greatly.

Keywords: PCA; Kernel PCA; Pose transformation; Discriminant analysis; Pose invariant face recognition

1. Introduction

Recently, the use of biometrics has increased substantially in personal security and/or access control applications. Biometrics is a technology, which is expected to replace traditional authentication methods that are easily stolen, forgotten and duplicated. Fingerprints, face, iris, and voiceprints are commonly used biometric features (Zhang, 2000). Among these features, face provides a more direct, friendly and convenient identification method. It is more acceptable to users compared to other individual identification methods of biometric features. Thus, face recognition plays an important role in biometrics. Many researchers have investigated face recognition. However, face appearance typically varies drastically with changes of facial pose, illumination conditions and so forth. Such variations make the process of face recognition difficult. This paper attempts to overcome pose variation among many difficulties.

Beymer (1994), Biuk and Loncaric (2001), and Huang et al. (2000) divided face images into several subsets according to facial angles and represented each view in a different subspace. Then, they estimated the pose angle of each input facial image and projected the image onto the corresponding subspace. Finally, they classified the face image in the projected subspace. Such a view-based schemes are preferred because it avoids the explicitly establish 3D model from each pose image, which often tends to be a more complicated problem.

In this paper, we propose to generate frontal view face image using linear transformation in feature space for pose invariant face recognition. The method is based on the assumption that the features between posed and frontal images have a certain relation that can be linearly transformed. We justify this assumption by the following. First, as Troje and Bülthoff (1996) demonstrated, human visual system could recognize a human face under varying poses and the recognition rate was increased when the learning and testing views were identical. This is the reason why

* Corresponding author. Fax: +82 54 279 2299.
E-mail addresses: sooz@postech.ac.kr (H.-S. Lee), dkim@postech.ac.kr (D. Kim).

0167-8655/$ - see front matter © 2005 Elsevier B.V. All rights reserved.
doi:10.1016/j.patrec.2005.11.003

we are trying to transform all posed images into their corresponding frontal images and to recognize the transformed frontal images, where we have only frontal images in the gallery. Second, as Vetter and Poggio (1997) described, the human had an ability to recognize a human face under varying poses because they obtained the prior information about how those face images are transformed by learning from other faces through an extensive experience. From this description, if we know the exact principle how the human obtain the prior information, we can use the principle for pose invariant face recognition. Third, the principle of how the human identify the relation between the posed image and the frontal image and what the relation is has been not discovered clearly yet. So, we need to have an assumption to make the pose transformation tractable. We treat the pose transformation as a regression problem by the following. Consider two different posed images where they are represented by their own basis functions. Then, they are represented by two different feature set. We assume that the frontal feature is an independent variable and the other posed feature is a dependent variable. One simple and powerful way of relating these features is to use the regression technique, and we assume that one feature value of the frontal face image can be approximated by a linear combination of all features of the posed face image. This approach is meaningful mathematically and our experimental results validate this assumption well.

Fig. 1 shows an overall process of our proposed pose invariant face recognition method. First, we represent an arbitrary posed face image in feature space using PCA or kernel PCA. Then, we convert the posed face image into its corresponding frontal face image by a predetermined transformation matrix. We compute the transformation matrix between the frontal and posed face images as follows. The frontal face images and the posed face images are represented by the feature vectors based on its respective basis vectors in two different subspaces, respectively. Based on the corresponding features of the frontal and posed face images, we can approximately induce the transformation matrix between two subspaces by applying the multiple regression technique such as a least square estimation. Finally we apply a variety of discriminant analysis methods such as LDA (Etemad and Chellappa, 1997), and NDA (Fukunaga, 1990), GDA (Baudat and Anouar, 2000) to the transformed frontal face image to improve the recognition performance.

This paper is organized as follows. Section 2 explains the subspace representation of a face image. Section 3 describes how to obtain the transformation matrix. Section 4 explains the various discriminant analysis methods such as LDA, NDA, and GDA that are used for feature extraction. Section 5 shows our experimental results of pose invariant face recognition. Finally, a conclusion is drawn.

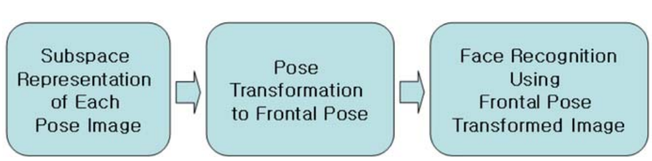

Fig. 1. An overall process of the proposed pose invariant face recognition.

2. Subspace representation

Since a face image has very high-dimensional data, we need to represent the face image in subspace not only for dimension reduction, but also for relevant feature extraction. In this section, we briefly review two methods of subspace representation: PCA and kernel PCA.

2.1. Principal component analysis

From the viewpoint of both the curse of dimensionality and the optimality of the pattern classification, it is desirable to reduce the dimensionality of feature space of the data. In PCA (Hotelling, 1933; Turk and Pentland, 1991; Sirovich and Kirby, 1987), a set of observed n-dimensional data vector $\boldsymbol{X} = \{\boldsymbol{x}_p\}$, $p \in \{1, \ldots, N\}$ is reduced to a set of m-dimensional feature vector $\boldsymbol{S} = \{\boldsymbol{s}_p\}$, $p \in \{1, \ldots, N\}$ by a transformation matrix T as

$$\boldsymbol{s}_p = T^t(\boldsymbol{x}_p - \mathscr{E}[\boldsymbol{x}]), \tag{1}$$

where $m \leqslant n$, $T = (\boldsymbol{w}_1, \ldots, \boldsymbol{w}_m)$ and the vector $\boldsymbol{w}_j$ is the eigenvector which corresponds to the jth largest eigenvalue of the sample covariance matrix $C = \frac{1}{N}\sum_{p=1}^{N}(\boldsymbol{x}_p - \mathscr{E}[\boldsymbol{x}])(\boldsymbol{x}_p - \mathscr{E}[\boldsymbol{x}])^{\mathrm{T}}$, such that $C\boldsymbol{w}_k = \lambda_k \boldsymbol{w}_k$. The m principal axes T are orthonormal axes onto which the retained variance under projection is maximal. One property of PCA is that projection onto the principal subspace minimizes the squared reconstruction error $\sum \|\boldsymbol{x}_p - \hat{\boldsymbol{x}}\|^2$. The optimal linear reconstruction of $\hat{\boldsymbol{x}}$ is given by $\hat{\boldsymbol{x}} = T\boldsymbol{s}_p + \mathscr{E}[\boldsymbol{x}]$, where $\boldsymbol{s}_p = T^t(\boldsymbol{x}_t - \mathscr{E}[\boldsymbol{x}])$, and the orthogonal columns of T span the space of the principal m eigenvectors of C.

2.2. Kernel principal component analysis

Kernel PCA (Schölkopf et al., 1998) computes the principal components in a high-dimensional feature space, which is nonlinearly related to the input space. The basic idea of kernel PCA is that first map the input data x into a high-dimensional feature space F via a nonlinear mapping Φ and then perform a linear PCA in F. We assume that we are dealing with centered data, i.e., $\sum_{i=1}^{N}\Phi(x_i) = 0$, where N is the number of input data. Kernel PCA diagonalizes the covariance matrix of the mapped data $\Phi(x_i)$

$$C = \frac{1}{N}\sum_{i=1}^{N}\Phi(x_i)\cdot\Phi(x_i). \tag{2}$$

To do this, one has to solve the eigenvalue equation $\lambda v = Cv$ for eigenvalues $\lambda \geqslant 0$ and $v \in F\backslash\{0\}$. As $Cv = \frac{1}{N}\sum_{i=1}^{N}(\Phi(x_i)\cdot v)\Phi(x_i)$, all solutions v with $\lambda \neq 0$ lie