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Face Recognition using Independent Component Analysis of Gabor Filter Responses

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Abstract

This paper addresses new face recognition method based on Independent Component Analysis(ICA) and Gabor filter. Our method consists of three parts. The first part is Gabor filtering on predefined fiducial points that could represent robust facial features from original face image. The second part is transforming the facial features into the basis space of ICA, which is able to represent individual facial features optimally. Thus, trained face images are represented as points in the space. In order to identify, test images are also projected into the basis space of ICA from image space and compared to the training images using fisher linear discriminant(FLD) in the space. The basic idea of combining ICA and Gabor filter is to overcome the shortcomings of ICA. When raw images were used as input of ICA, the basis space of ICA cannot reflect the correlation of facial feature well, because original face images have deformation due to in-plane, in-depth rotation and brightness and contrast variation. So, we have overcome these problems using Gabor filter responses as input data. Gabor filter has the robust characteristics in illumination and rotation. Four face recognition method - PCA, Gabor filter response, PCA of Gabor filter response and ICA are used in the recognition experiments. We confirmed the improvement of discrimination ability when the Gabor responses had transferred to the space constructed by the independent components. And, our method has excessive advantage in gallery DB size than recognition method only using Gabor filter responses.

1. Introduction

Face recognition is one of the important research topics and many researchers are trying to achieve successful results, since it has the possibility of many applications, such as security system, human-computer interface and so on[1]. There have been a lot of methods proposed for face recognition. These are divided into two categories: local feature matching method and holistic matching method. The representative method of holistic matching is PCA and ICA[3]. Using these methods, we can construct a space that represent input data with lower dimensional feature vectors. But, PCA and ICA have much restriction in applying to face recognition, because the input face images should be ideally aligned and under well-controlled illumination. In addtion, holistic matching can not describe local variation of face well. On the other hand, Gabor filter, the representative method of local feature matching is effective in description of local feature[4]. So we propose new face recognition method that can overcome the problems of ICA using Gabor filter responses.

2. Independent Component Analysis of Gabor Filter Responses

2.1. Independent Component Analysis

Independent Component Analysis(ICA) is a generalization of principal component analysis(PCA), which decorrelates the higher-order moments of the input. In a task such as face recognition, much of the important information is contained in the high-order statistics of the images. A representational basis in which the high-order statistics are decorrelated may be more powerful for face recognition than one in which only the second order statistics are decorrelated, as in PCA representations. Performing ICA on the N images in the data set separated N statistically independent source images contained in the rows of U. The rows of the matrix W^{-1} contained the linear combination of source images in U that comprise each face image in X. The rows of W^{-1} were chosen as an independent component representation of the face images. An ordering for the ICA representation was provided by the magnitude of the weight vector that extracts each source.

The magnitude of the weight vector for optimally pro-

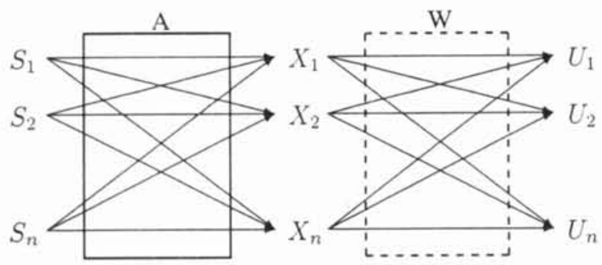


Figure 1. Image Synthesis Model

jecting the source onto the nonlinear transfer function in the ICA algorithm provides a measure of the variance of the original source.

2.2. Gabor Filter Responses

The processing of facial images by Gabor filter is chosen for its biological relevance and technical properties. The Gabor filter kernels are similar shapes as the receptive fields of simple cells in the primary visual cortex. In other words, they are multi-scale and multi-orientation kernels. The response describes a small patch of gray values in an image $I(x)$ around a give pixel $x = (x, y)$. It is defined as a convolution

$$J_i(\vec{x}) = \int I(\vec{x}')\Psi_j(\vec{x} - \vec{x}')d^2\vec{x}' \tag{1}$$

$$\begin{aligned}\Psi_j(\vec{x}) &= \frac{k_j^2}{\sigma^2}\exp(-\frac{k_j^2 x^2}{2\sigma^2}) \\ &\quad \exp[\exp(i\vec{k_j}\vec{x}) - \exp(-\frac{\sigma^2}{2})]\end{aligned} \tag{2}$$

with a family of Gabor filters in the shape of plane waves with wave vectors k_j, restricted by a Gaussian envelope function. We employ a discrete set of 5 different frequencies, index $\nu = 0, \ldots, 4$ and and 8 orientations, index $\mu = 0, \ldots, 7$ with index $j = \mu + 8\nu$. Gabor filter sets provide robustness against varying brightness and contrast in the image.

$$\vec{k}_j = (\frac{k_{jx}}{k_{jy}}) = (\frac{k_\nu \cos\varphi_\mu}{k_\nu \cos\varphi_\mu}), \tag{3}$$

where

$$\begin{aligned}k_\nu &= 2^{-\frac{\nu+2}{2}}\pi, \\ \varphi_\mu &= \mu\frac{\pi}{8}.\end{aligned}$$

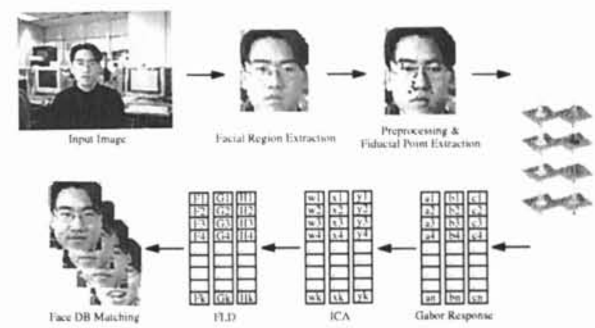


Figure 2. A Block digram of face recognition using ICA of Gabor filter responses

2.3. Independent Component Analysis of Gabor Filter Responses

Independent Component Analysis (ICA) uses face image as input data, then it should be aligned well and should not include some in-plane and in-depth rotation. The face region should be extracted from the original image and the brightness and contrast should be stable, too. Due to these problems, it's difficult to use ICA in real application. So we are trying to overcome these shortcomings by keeping the basic concept that the most distinctive features act as a basis axis in the space. The responses of Gabor filter have some useful characteristics. First, it provides robustness against varying brightness and contrast in the image. Second, the characteristics of the local face area can be represented, so it's more effective than using the original face image directly. We propose a method that uses Gabor filter responses as input of ICA instead of raw face image to overcome the shortcomings mentioned above. Using the Gabor filter responses as input vector, the sensitive reaction due to the rotation and illumination can be reduced. And if we transfer the Gabor filter responses into another space that is based on the basis axis of ICA, the face images can be placed more effectively for classification. To use the Gabor filter response, we should get the magnitude value from the real and imaginary part value. Because the real and imaginary parts are too sensitive in spite of the slight displacement, it cannot be used directly. For example, let the number of fiducial points that can get the Gabor filter responses are N, we can select the 40 magnitude values using (3) and (4) from N points and construct the $N \times 40$ dimensional array. And if we use M gallery images, construct $(N \times 40)$ by M matrix could be constructed and the basis vectors can be calculated from the ensemble matrix AA^T, where the matrix $A = N \times 40$ by M matrix. Then we can select the effective Gabor filter responses and construct the basis space of ICA with the appropriate number of basis vectors. Then the face images for training are projected into the basis space of

ICA and the testing sets are also projected according to the equation (2). The weight values of the projection represent the characteristics of the new face image. To compare the similarity of the values in the basis space of ICA, we used similarity function [2].

$$S_a(J, J') = \frac{\sum_j a_j a_{j'}}{\sqrt{\sum_j {a_j}^2 \sum_j {a_{j'}}^2}} \tag{4}$$

In PCA, euclidean distance measure was used to estimate the similarity [3], but we confirmed that similarity function is more effective in the basis space of ICA.

3. Experiment

To process the face images, we manually located the eyes and then performed geometric normalization with the eye locations fixed and intensity normalization and size normalization. And we used 20 fiducial points that were selected from the relative distance of two eye points. The normalized face image size is chosen to be 128×128. We used two kinds of face dataset : One was SAIT face dataset which was organized by ourselves and composed of 320 images from 40 galleries constructed under various illumination condition. Another was Olivetti face dataset that was composed of 400 images from 40 galleries which was constructed under various depth and plane rotation. Some examples of face dataset are shown in figure 3 and figure 4. SAIT face dataset was composed of 8 face images per a person, so we have constructed 8 sets. To process the experiments, we defined one as training set and the other 7 sets as testing sets in turn. Olivetti face dataset was composed of 10 face images per a person, so we have constructed 10 sets. And as the SAIT face dataset, we defined one as training set and the other 9 sets as testing sets in turn. We've selected 20 fiducial points about one face image, and made 800 dimensional array using 40 magnitude values about each point. Then we constructed 40 by 800 matrix, where the row vector was the data of a testing face image. And we obtained basis vectors from its 40×40 ensemble matrix. To construct the basis space, we selected 40 valid basis vectors and obtained the weight vectors by projecting the training and testing set of face images. To recognize the individuals, we compared the weight vectors using similarity function [4].

3.1. Comparison of PCA, Gabor Filter Response and PCA of Gabor Filter Responses

The experiment results are shown in figure 5. We could confirm the remarkable improvement of recognition rate of 19% compare to PCA in SAIT dataset. It showed that PCA is weak against various illuminations. And figure 5(b) showed the improvement of 11% in Olivetti dataset. Also it showed that pose variation was another drawback of PCA. We confirmed that the recognition rates are similar in spite of the variation of the resolution of face images. It showed that the radical variation of pixel brightness could be an obstacle in PCA.

Figure 3. Face images of SAIT face dataset

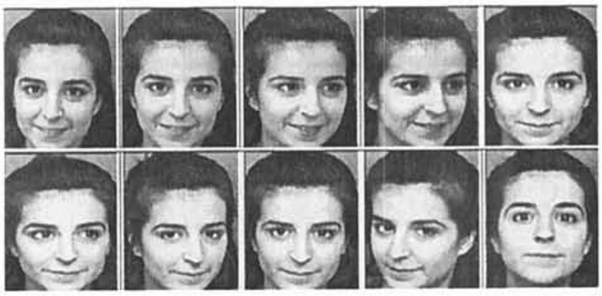
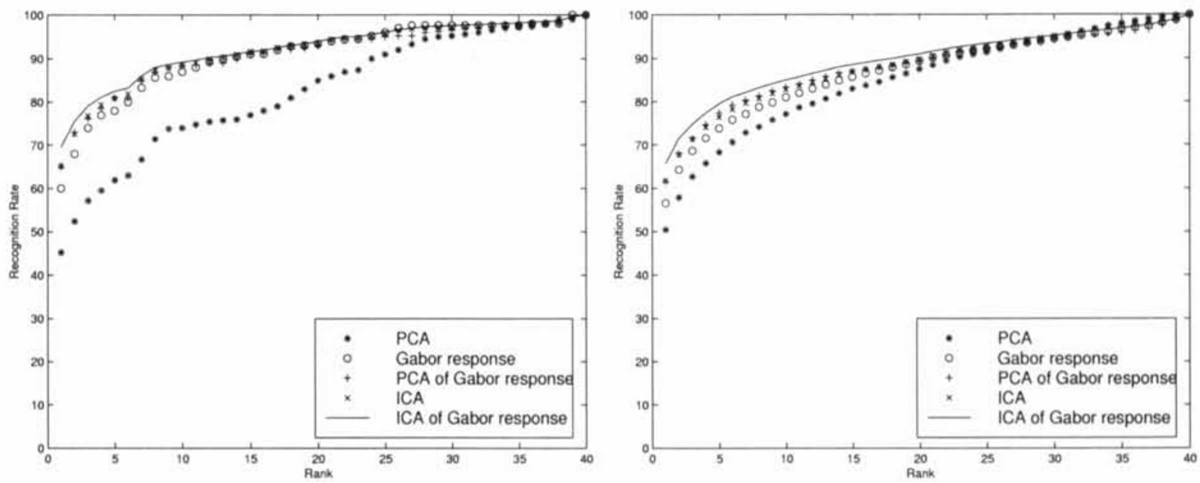


Figure 4. Face images of Olivetti face dataset

And Gabor filter response and suggested method were compared. We could confirm the improvement of recognition rate of 9% and 8.5% in SAIT dataset and Olivetti dataset respectively. Although the improvement of recognition ratio was rather slight, it was a great experimental result considering the reduction of gallery DB size. We could reduce the size of gallery DB to 1/20 times smaller than that of original Gabor filter method.

3.2. Comparison of ICA, PCA of Gabor Filter Response and ICA of Gabor Filter Responses

The experiment results showed that the recognition rate of ICA and PCA of Gabor filter response were very similar. Meanwhile, the recognition ratio of suggested method was higher than other methods as much as 4.5% and 4% in SAIT dataset and Olivetti dataset respectively. It showed that ICA was weak against various illuminations, but the performance of making basis space was more effective than PCA. And the transforming of Gabor filter response to the basis space of ICA was still effective in face recognition compare to original Gabor filter responses and ICA. Simi-



(a) SAIT dataset

(b) Olivetti dataset

Figure 5. Experimental results

lar to the PCA of Gabor filter responses, we could reduce the size of gallery DB to 1/20 times smaller than than that of Gabor filter method.

4. Conclusion

In this paper, we have presented a face recognition system that combines Gabor filter method and ICA. Because face images are too sensitive to illumination and pose variation, we anticipated that the drawback could be overcome by using Gabor filter responses as input of ICA. The experiment result was reasonably acceptable i.e. the space transfer of Gabor filter responses based on independent basis vectors was successful in classification and discrimination. We will study the correlation of Gabor responses due to pose variation in the basis space of ICA and optimal classification method.

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References

[1] R. Chellappa, C. L. Wilson, and S. Sirohey. Human and machine recognition of faces, a survey. *Proc. of the IEEE*, 83:705–750, 1995.

[2] M. Lades, J. C. Vorbruggen, J. Buhmann, J. Lange, C. von der Malsburg, R. P. Wurtz, and W. Konen. Distortion invariant object recognition in the dynamic link architecture. *IEEE transactions on Computers,*, 42(3):300–311, 1993.

[3] M. Turk and A. Pentland. Eigenfaces for recognition. *Journal of Cognitive Neuroscience*, 3:72–86, 1991.

[4] L. Wiskott, J. M. Fellous, N. Kruger, and C. V. der Malsburg. Face recognition by elastic graph matching. *IEEE Trans. on Pattern Recognition and Machine Intelligence*, 19:775–779, 1997.