EFECTIVE IMAGE REPRESENTATION USING PCA AND ICA FOR FACE RECOGNITION

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ABSTRACT

This paper presents principle component analysis (PCA) and independent component analysis (ICA) based two approaches for face recognition. Effective representation of gray scale face images was formed by PCA and ICA components of a given image. Further, efficient and simple image classification was achieved using this effective image representation and cosine similarity technique. Finally, linear discriminant analysis (LDA) was integrated with the two approaches in order to enhance their classification accuracy. The potential of the PCA, ICA, PCA+LDA and ICA+LDA approaches for face recognition were demonstrated using FEI and YALE standard face databases. The results show that the recognition accuracy of LDA integration on PCA and ICA method is significantly higher than the PCA and ICA methods.

***Key words*:** PCA, ICA, LDA, Cosine similarity

1. INTRODUCTION

Face recognition has gained increased interest in recent years due to its potential application on human-computer interaction, security system and entertaining systems. Recognizing a face goes through three major steps, face detection, effective representation and classification. Initially, human faces should be detected among several other objects and different backgrounds then it should be represented in a way that enhances the discriminating feature between different human faces to achieve efficient image classification.

In this paper, we employed principal component analysis (PCA) and independent component analysis (ICA) to represent the images as a combination of set of basis images. Then linear discriminant analysis (LDA) was performed separately on both PCA and ICA representations to transform the images into a new space that enhance the discriminating features among different human faces.

PCA is an unsupervised statistical method for effective image representation that removes the correlation of pixel of similar spatial location among set of images. By choosing the most dominant PCA components, the dimension of the image and noise components can be reduced. Applying PCA to the images leads to representing the images as a combination of set of basis images so that in new PCA representation the coefficients of the images are uncorrelated. Most important features of the images rely on the higher order dependencies among the pixels. However, PCA removes only the second order dependencies. Therefore, a method is needed to remove the higher order dependencies.

ICA is one of the methods that remove higher order dependencies. We employed ICA to the images by considering pixels of an image as a variable and images as sample so that in the new representation, images can be represented as combination of set basis images and the ICA coefficients are independent. Employing ICA directly on the high dimensional image space leads to ineffective image classification. Due to trailing/noise components [1][2]. Therefore, as a preprocessing technique we applied PCA before applying ICA to the images.

2. PRELIMINARIES

For, a given gray scale image with spatial resolution of $m \times n$, each pixel (x, y) contains gray scale intensity of the corresponding pixel. Such $N = mn$ intensity values of each image was represented as column vector with dimension N. Then each such vector generated from image i formed to a new vector $x_i \in \Re^N$ by normalizing each column vector to zero mean and unit variance. Then, data matrix X for all images was constructed by stacking each image vectors in rows.

$$X = [x_1 \quad x_2 \quad . \quad . \quad x_t]^T \qquad (1)$$

Where, t is the number of images and T denotes the matrix transpose. In this way, there were two data matrix for training image (X_{tra}) and test (X_{test}) images were created.

3. PRINCIPLE COMPONENT ANALYSIS (PCA) BASED APPROACH

A gray scale image representation method for face recognition was derived using the PCA technique. Applying PCA to the images leads to representing the images as a combination of set of basis images. This representation removes the correlation of pixel of similar spatial location among each x_i. Following two steps explain the procedure of applying PCA.

Step 1: Singular Value Decomposition (SVD) [3] was applied to the training image matrix X_{tra}. SVD provides a decomposition of the form

$$X_{tra} = U\Sigma V^T \qquad (2)$$

Where, U is an $t \times t$ matrix that contains eigenvectors of $X_{tra}X_{tra}{}^T$, V is a $N \times N$ matrix that contain Eigen vectors of $X_{tra}{}^T X_{tra}$, and Σ is an $t \times N$ diagonal matrix of $\min(t, N)$ ascending ordered singular values. Each singular value is equal to square roots of eigenvalue of eigenvectors in U and V.

Step 2: The dimensionality of the test and training images were reduced from N to K ($K < N$) by considering the most dominant K Eigenvectors that corresponds to K largest Eigenvalues

$$\tilde{X}_{tra} = X_{tra}\tilde{V} \qquad (3)$$

Where, $\tilde{V}$ is matrix that contains K largest Eigenvectors. Each raw of $\tilde{X}_{tra}$ represents the new PCA representation for training images.

Then, multiplying $\tilde{V}$ with the test image will obtain the new image representation $\tilde{X}_{test}$ for the test image in the PCA space.

$$\tilde{X}_{test} = X_{test}\tilde{V} \qquad (4)$$

4. INDEPENENT COMPONENT ANALYSIS (ICA) BASED APPROACH

A gray scale image representation method was derived using an ICA technique [3]. Before applying ICA, PCA approach in section 3 was applied to matrix X in order to reduce the dimension of an image, i.e. x_i, from N to K for the efficient ICA representation. This architecture considered PCA coefficients of the images as the variable and images as the sample. In this method we used the version of ICA that uses Projection pursuit gradient ascent method proposed in [3] to find matrix W from training images such that the columns of Z_{tra} are statistically independent as possible.

$$Z_{tra} = X_{tra}W \qquad (5)$$

Each raw of Z_{tra} represents the new ICA representation for training images.

Then, multiplying W with the test image will obtain the new image representation for the test image in the ICA space.

$$Z_{test} = X_{test}W \qquad (6)$$

5. INTERGRATION OF LINEAR DISCRIMINANT ANALYSIS (LDA)

PCA and ICA produce only the most expressive features that are not suitable for pattern classification. One solution to this problem is to apply LDA [4] to the lower dimensional vector $u \in \Re^K$ (u is a column vector, its elements corresponds to rows of $\tilde{X}_{tra}$ or Z_{tra}) to derive the most discriminant features for pattern recognition. For PCA, the more principle components are used, the better the quality of image reconstruction becomes. The same reasoning, however, does not apply to the LDA. One can actually show that using more principle components can actually lead to decreased classification performance [5]. Next, we briefly review the LDA method and apply it to implement efficient gray face image classification.

Let $\omega_1, \omega_2, .., \omega_L$ denote the classes, and

$M_1, M_2, .., M_L$ and M be the means of the classes and the grand mean, respectively. The within-class and between class scatter matrices Σ_w and Σ_b are defined as follows [4]:

$$\Sigma_w = \sum_{i=1}^{L} P(\omega_i) E\{(u - M_i)(u - M_i)^T \mid \omega_i\} \tag{7}$$

$$\Sigma_b = \sum_{i=1}^{L} P(\omega_i)(M_i - M)(M_i - M)^T \tag{8}$$

Where, $P(\omega_i)$ is a priory probability and $E\{.\}$ denotes the statistical expectation. LDA derives a projection matrix ψ by maximizing the criteria $J = tr(\Sigma_\omega^{-1}\Sigma_b)$ [4]. This criteria is maximized when ψ consists of the eigenvectors of matrix $\Sigma_\omega^{-1}\Sigma_b$ [4].

$$\Sigma_\omega^{-1}\Sigma_b \psi = \psi \nabla \tag{9}$$

Where, ψ, ∇ are the eigenvector and eigenvalue matrices of $\Sigma_\omega^{-1}\Sigma_b$, respectively. The most discriminant features are derived by projecting the vector u into the eigenvectors in ψ

$$v = \psi^T u \tag{10}$$

v Thus contains the most discrimination features for face recognition.

6. EXPERIMENTAL RESULTS

In this section, we used PCA, ICA and PCA+ LDA and ICA+LDA based image representation methods for face recognition. For simplicity cosine similarity measure [6] was used for classification task.

6.1. Experiment on FEI Database

The FEI database [7] contains 720 images of 180 people. Each person has four images with neutral, smile and two different illumination conditions. For simplicity of experiment, all images were aligned by fixing the position of two eyes, and resized to 64x64 pixels. Each image is represented by a 4096-dimensional vector in image face. Sample images are shown in the Figure 1. We used the method similar to the cross-validation to evaluate the performance of three methods. The entire images are separated into 180 classes of individual person. We choose two images in every class to test, the remaining are used to train. Every time the image used to test are different. The experiment should be run 6 times, and so as to most image in database can be test. Under the same setting and the average recognition rates are used as the final recognition accuracy. Figure 2 depict, PCA method obtained maximum accuracy of 37.3% and ICA perform better than PCA with the accuracy 80.9%. Integration of LDA on PCA and ICA achieved high accuracy rate 96.9% and 97.2% respectively.

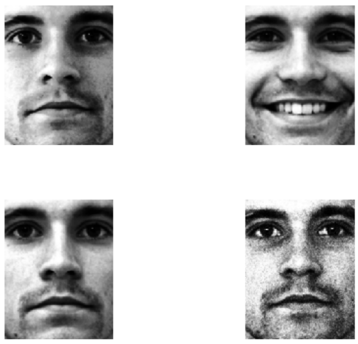

Figure 1: Some example cropped facial images from the FEI database

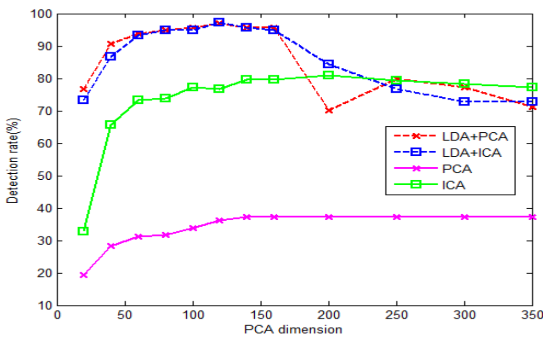

Figure 2: Detection Rate on FEI Database

6.2. Experiment on YALE Database

The YALE database [8] is make up of some image Sequences facial expressions from 15 classes (people). For each class there are 11 images with different facial expression and illumination conditions. Therefore, in experiment, we used 165 images which are treated as static images for both training and testing. Similarly, the images are cropped manually and resized to 64 pixels. Some samples are shown in Figure 3.The entire images are separated into 15 groups of individual person. We randomly choose 2, 4, 6 and 8 images in every group to test, the remaining are used to train. Figure 4 represents the average recognition accuracy of face recognition methods based on PCA, ICA, PCA+LDA and ICA+LDA. PCA and ICA methods perform equally and exhibit the accuracy 46.7% and 47.2% respectively. LDA applied on PCA and ICA space images outperform both PCA and ICA methods with the accuracy 76.2% and 76.6% respectively.

Figure 3: Some example cropped facial images from the YALE database

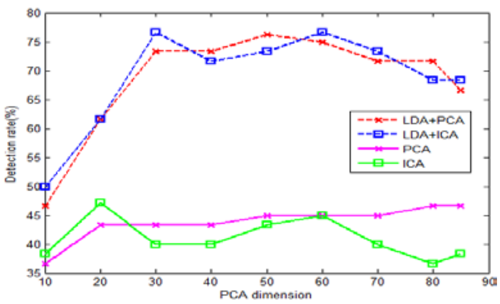

Figure 4: Detection rate on YALE database

7. CONCLUSION

This paper presented a comparative study on four different face recognition methods (PCA, ICA, PCA+LDA and ICA+LDA) that employ cosine similarity measure as a classification method. The performance of the PCA and ICA method was tested separately across FEI and Yale database. For FEI database that contain one neutral, one smiling and two different illumination condition images of a subject, ICA performs better than PCA . However, for Yale database, that contains images of various expression and illumination condition, PCA and ICA performs equally.

The method that apply LDA on PCA and ICA space images outperforms the methods that do the classification on PCA and ICA image space, since it identify the discriminating components of the images.

8. REFERENCES

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