改善された独立成分分析の手法に基づいたロバスト顔認識

[1]韓先花　[1]陳延偉　[2]山田晶彦　[2]藤田日出人
[1]滋賀県草津市野路東１丁目 1-1、立命館大学情報理工学部
[2]三洋電機　研究開発本部 デジタル技術研究所

あらまし　顔認識を実現するためのプログラムでは、統計的パターン認識手法が重要な役割を演じる。その中には、主成分分析（PCA）、独立成分分析（ICA）と**線形判別分析**(LDA)**等**部分空間学習アルゴリズムを用いた顔認識の研究、開発が活発に行われている。LDAは教師付き顔認証のために良い結果を得ることができます、しかし、認識するsubjectsのトレーニング顔はなしあるいは1つしか手入れできないのシステムの応用が制限されます。**そして、PCA による顔画像表現に比べICA による顔画像表現の有効性を議論した。**しかし、顔認証のような次元数が多すぎなパターン認識作業へのICAの適用性は、しばしば若干の問題で苦しみます。その問題の一つは**次元数が膨大となり、計算量が大きくとなる、もう一つは**コンピュータメモリの問題です。本稿では、ICAのこの2**つの問題を扱うために、**独立成分分析の改善されたarchitecture**を提案する。提案されたICA手法は、**顔認識が高速に行われていることができるだけではなく、実験の結果により顔**認識の有効性が確認することができた。**

Robust face recognition based on modified architecture of Independent Component Analysis

[1]Xian-Hua Han, [1]Yen-Wei Chen, [2]Akihiko Yamada and [2]Hideto Fujita
[1]College of Information Science and Engineering, Ritsumeikan University, 525-8577,Japan.
[2]Digital Technology Research Center, SANYO Electric Co., Ltd., Japan.

Abstract A number of current face recognition algorithms use face representations found by statistical subspace learning methods. Therein, Principal Component Analysis(PCA), Independent Component Analysis(ICA) and Linear Discriminant Analysis(LDA) are a high-focused research topic in this field. LDA can get good results for supervised face recognition. However, it is limited for some face recognition system, where no or only one sample face can be obtained for training. In the other hand, ICA can obtain acceptable recognition result. However, the applicability of ICA to high-dimension pattern recognition tasks such as face recognition often suffers some problems. The most important one is real-time problem, another is the computer memory. The mentioned two problems make ICA classifier unsuitable and inapplicable in real system. In this paper, we propose a modified ICA architecture to deal with the two problems. Firstly, we use eigenface method to calculate the eigenvector and eigenvalue for the training samples, and whitening the face images. Finally, the independent coefficients of image factorial code can be obtained by ICA analysis. Experimental results show that the proposed method can not only obtain high-speed but also get acceptable accuracy rate.

1. Introduction

Face recognition (FR) has received more and more attentions with a wide range of applications such as access control, forensic identification and human computer interface. A successful face recognition methodology depends heavily on the particular choice of the features used by the (pattern) classifier [1-3]. Feature selection in pattern recognition involves the derivation of salient features from the raw input data in order to reduce the amount of data used for classification and simultaneously provide enhanced discriminatory power.

Subspace learning technique such as Principle Component Analysis (PCA)[4][5], Independent Component Analysis (ICA)[6] are very hot topic for feature selection and dimensionality reduction. PCA is an eigenvector method designed to model linear variation in high-dimensional data. PCA performs dimensionality reduction by projecting the original n-dimensional data onto the k (<<n)-dimensional linear subspace spanned by the leading eigenvectors of the data's covariance matrix. ICA can be viewed as a generalization of PCA since it concerns not only second-order dependencies but also high-order dependencies between variables. So ICA also can perform dimension reduction and then, obtain the most independent component of input data. It has also been claimed that ICA outperforms PCA for face recognition [7][8]. However, the two conventional used architectures of ICA for face recognition have strict demand on computer time or computer memory. One of the ICA architecture rearranges face image into a row vector, and then perform ICA training. However, the samples of ICA input are so much that it can take a lot of computer time. The other rearranges face image into a column vector, and then the components will increase with the face size. This strategy can not only take a lot of computer time and also need a plenty of computer memory. So in this paper, we proposed a modified ICA method, which can save much of computer time and memory, and at the same time, can obtain acceptable experimental results on FERET face database. Firstly, The face images are considered as random variables and the pixels as outcomes(image basis), and then, do PCA analysis. The PCA components of the above analysis will be an approximation of eigenvector of the matrix (image factorial code), in which the pixels are treated as random variables and the images as outcomes. So based on this relation, the uncorrelated coefficients of image factorial code can be obtained for ICA analysis. Experimental results show that the proposed method can not only obtain high-speed but also get acceptable accuracy rate.

The paper is organized as follows: in the second section, we review ICA architecture for face recognition and introduce the proposed modified ICA algorithm. The experimental results are shown in section 3. The concluding remarks will be given in the final section.

2. Independent component analysis

ICA is a data analysis tool derived from the "source separation" signal processing techniques. The aim of source separation is to recover original signals $\mathbf{S}_i$, from known observations $\mathbf{X}_i$, where each observation is a (unknown) mixture of the original signals. Under the assumption that the original signals $\mathbf{S}_i$ are statistically independent, and under mild conditions on the mixture, it is possible to recover the original signals from the observations. The algorithmic techniques making this task possible are often called ICA, as they factorize the observations as a combination of original sources.

For face recognition, it firstly need to rearrange face images into vector, and the face images **X** can be represented by a linear combination of basis functions as in Eq.(1), where $\mathbf{A}_i$ is the face basis and y_i is the coefficient, which can be used as face features.

$$\mathbf{X} = \sum_{i=0}^{N-1} \mathbf{A}_i y_i = \mathbf{A}_0 y_0 + \mathbf{A}_1 y_1 + \cdots\cdots + \mathbf{A}_{N-1} y_{N-1} \quad (1)$$

Since we must obtain the **A** from sample face **X** alone, Eq. (1) can be viewed as a blind source separation problem, which can be solved by ICA. The goal of ICA is to find a matrix **W**, that results in the estimates of coefficients **y** being statistically as independent as possible over a set of data **X** as shown in Eq. (2)

$$\mathbf{y} = \mathbf{WX} \quad (2)$$

The estimates or independent components **y** may possibly be permuted and rescaled. The **W** corresponds to the inverse matrix of basis face **A**.

Bell & Sejnowski proposed a neural learning algorithm for ICA [9]. The approach is to maximize the joint entropy by stochastic gradient ascent. The updating formula for **W** is:

$$\Delta\mathbf{W} = (\mathbf{I} + g(\mathbf{y})\mathbf{y}^T)\mathbf{W} \quad (3)$$

where $g(\mathbf{y}) = 1 - \frac{2}{1+e^{-\mathbf{y}}}$ is calculated for each component of **y**.

2.1 The ICA architecture 1

The goal in this approach is to find a set of statistically independent basis images. The data matrix **X** is organized so that the images are in rows and the pixels are in columns, and each image has zero mean. In this approach, ICA finds a matrix **W** such that the rows of **U=WX** are as statistically independent as possible. The source images estimated by the rows of **X** are then used as basis images to represent faces. Face image representations consist of the coordinates of these images with respect to the image basis defined by the rows of **U**. These coordinates are contained in the mixing matrix $\mathbf{A}=\mathbf{W}^{-1}$. The procedure of this architecture is as followings:

(1) Calculating the first m eigenvector $\mathbf{V}_m$ of face matrix **X**, and then the first m PC axes(components) of face matrix **X** can be obtained $\mathbf{P}_m= \mathbf{V}_m^T*\mathbf{X}$.

(2) Performing ICA on $\mathbf{P}_m$, obtain the whitening matrix $\mathbf{W}_Z$ and the transformation matrix **W**.

(3) The final ICA transformation matrix $\mathbf{W}_I = \mathbf{W} * \mathbf{W}_Z$ and m ICA components **U**: $\mathbf{U} = \mathbf{W}_I \mathbf{P}_m$ are as the face basis.

(4) The ICA coefficient $\mathbf{B}_m$, which can be used as factors for recognition, can be obtained:

$$\mathbf{X} = \mathbf{V}_m * \mathbf{P}_m = \mathbf{V}_m * \mathbf{W}_I^{-1}\mathbf{U} = \mathbf{B}_m\mathbf{U} \quad (4)$$

2.2 The ICA architecture 2

Architecture 2 uses ICA to find a representation in which the coefficients used to code images are statistically independent, i.e., a factorial face code. Barlow and Atick have discussed advantages of factorial codes for encoding complex objects that are characterized by high-order combinations of features. These include fact that the probability of any combination of features can be obtained from their marginal probabilities.

To achieve this goal, the data matrix **X** is organized so that rows represent different pixels and columns represent different images. The procedure of this architecture is as followings:

(1) Firstly calculating the whitening matrix $\mathbf{W}_Z$ after obtain the eigenvector and eigenvalue of data matrix **X** 's covariance matrix $\mathbf{XX}^T$. Here, we can only retain m larger eigenvalue and their corresponding eigenvector. However this step need a lot of computer memory and calculating time when image size is very

large.

(2)Projecting data matrix $\mathbf{X}$ into the whitening matrix $\mathbf{W}_Z$, and then the whitening coefficients (m by number of face sample) can be obtained.

(3) Performing the core ICA algorithm on whitening coefficients, and obtaining the ICA transformation matrix $\mathbf{W}$.

(4) The final ICA matrix $\mathbf{W}_I = \mathbf{W} * \mathbf{W}_Z$ and then the columns of $\mathbf{A}= \mathbf{W}_I^{-1}$are treated as a set of basis images. The ICA representations (Features) are in columns of $\mathbf{U}= \mathbf{W}_I\mathbf{X}$. Each column of $\mathbf{U}$ contains the coefficients of the basis images in $\mathbf{A}$ for reconstructing each image in $\mathbf{X}$. ICA attempts to make the outputs, $\mathbf{U}$, as independent as possible. Hence, $\mathbf{U}$ is a factorial code for the face images.

2.3 The Proposed architecture (The ICA architecture 3)

The proposed Architecture also uses ICA to find a representation, in which the coefficients used to code images are statistically independent, i.e., a factorial face code. However, we calculate the whitening matrix using eigenface method. This can greatly save computer memory and calculating time, and at the same time, can obtain acceptable results.

The data matrix $\mathbf{X}$ is firstly organized so that the images are in rows and the pixels are in columns, and each column pixels have zero mean. The procedure of the proposed architecture is as the following:

(1) Calculating the first m eigenvectors $\mathbf{V}_m$ and eigenvalues $\mathbf{D}_m$ of face matrix $\mathbf{X}$, and then the first m PC axes(components) of of face matrix $\mathbf{X}$ can be obtained $\mathbf{P}_m = \mathbf{V}_m^T * \mathbf{X}$.

(2) $\mathbf{P}_m$ will be an approximation of the data matrix $\mathbf{X}$, i.e. $\mathbf{P}_m$ are estimation of the first m eigenvector from the face matrix in the ICA architecture 2.

(3) Estimating the whitening matrix $\mathbf{W}_Z$ of the face matrix in the ICA architecture 2 using $\mathbf{P}_m$ and the eigenvalue matrix $\mathbf{D}_m$: $\mathbf{W}_Z = \mathbf{D}_m^{-1/2}\,\mathbf{P}_m$.

(4) Performing the core ICA algorithm on whitening coefficients, and obtaining the ICA transformation matrix $\mathbf{W}$.

(5) The final ICA matrix $\mathbf{W}_I = \mathbf{W} * \mathbf{W}_Z$, and then the columns of $\mathbf{A}= \mathbf{W}_I^{-1}$ are treated as a set of basis images. The ICA representations (Features) are in columns of $\mathbf{U}= \mathbf{W}_I\mathbf{X}$. Each column of $\mathbf{U}$ contains the coefficients of the basis images in $\mathbf{A}$ for reconstructing each image in $\mathbf{X}$. ICA attempts to make the outputs, $\mathbf{U}$, as independent as possible. Hence, $\mathbf{U}$ is a factorial code for the face images.

This architecture calculates the whitening matrix based eigenface method, and at the same time, only has the sample number of training faces when performing core ICA, so it is very fast and can save a lot of computer memory.

3. Experimental Results

In this section, we apply the modified ICA architecture for subspace learning. The used face database is FERET database[10], in which there are 6 face images for each person, and 70 persons. So there are 420 face images altogether in database. In our training procedure, we randomly select 3 face images of each people (210 faces) for subspace learning with the modified ICA. The remainder 210 face images (3 face images of each people) are as the test face images. At the same time, we also normalized the used face images with simple histogram equalization, and eliminate the effect of different illumination. Figure 1 gives the average recognition rate vs. dimension using PCA and the proposed ICA architecture when 210 face images are randomly selected for training faces. Fig. 1(a) is the results when the top 3 recognized faces are considered for calculating accuracy rate (for example, test face belong to the same people with the top 3 recognized faces, the accuracy rate will be 100%, otherwise 67% only 2 of the 3 top face belong to same people with test face, etc.). Fig. 1(b) is the results when different top recognized faces are considered for calculating accuracy rate at fixed dimension 50. Table 1 give the compared calculating time and recognition rate of different ICA architectures when only 50 ICA basis functions are retained. It is obvious that the proposed method can not only greatly reduce the computing time compared with the conventional ICA architecture but also obtain acceptable accuracy rate.

In the next experiment, we validate that the proposed method can also obtain relative good result when no sample faces of test people can be obtained for training. We also use FERET database, but firstly group the database into two parts: one is for training and the others is for logged database and test. Thus, the face images of the former 49 people (294 faces) are used for subspace learning with the modified ICA. The face images of the remainder 20 people(except the final people, where we wonder if they belong to one person) are as database of the face recognition system. We randomly select k (k=3) face images of each person as the logged faces, which can be compared with test faces for recognition. The left face images in recognition database are as the test face for validating the proposed methods. At the same time, we also normalized the used face images with simple histogram equalization, and reveal the effect of different illumination. Figure 2 gives the average recognition rate using PCA and the proposed ICA architecture (without and with normalization) when 3 images are randomly selected for logged faces. It can be seen that our method can obtain acceptable result even for the case the face images of test people can not be obtained for training, which will be a limitation for Linear Discriminant Analysis (LDA).

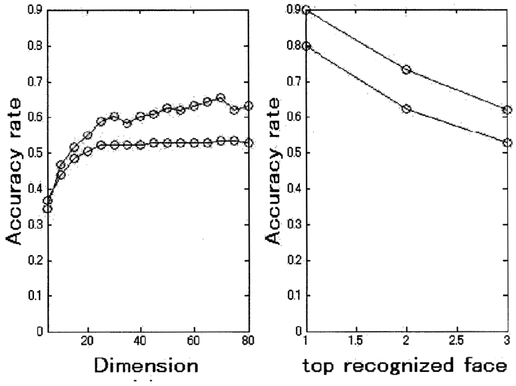

Figure 1 Accuracy (recognition) rate (red line: PCA method; green line: The proposed ICA architecture), (a) recognition rate for top 3 faces Vs. dimension of basis functions; (b)recognition rate for different top faces when dimension is 50.

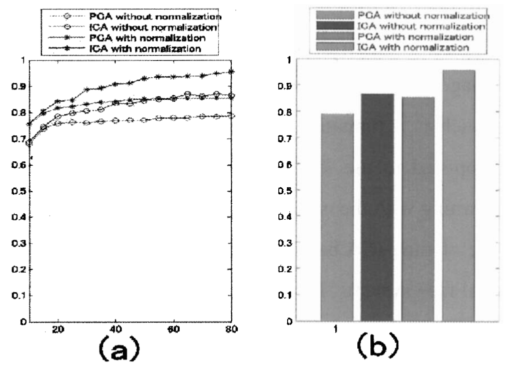

Figure 2 Recognition rate of 3 logged faces and 3 test face for each person, (a) Recognition rate Vs. dimension of basis functions; (b)Recognition rate when dimension is 80.

4. Conclusions

We proposed a modified ICA architecture for face recognition. Firstly, the face images are considered as random variables and the pixels as outcomes (image basis), and then, do PCA analysis. The PCA components of the above analysis will be an approximation of eigenvector of the matrix (image factorial code), in which the pixels are treated as

Table 1 the compared calculating time and recognition rate of different ICA architectures.

	ICA Arch 1	ICA Arch 2	ICA Arch 3
Time of pre-processing step(s)	0.813	141.078	0.813
Time of ICA stem(s)	269.406	27.579	29.954
Total time(s)	270.219	168.657	30.767
Recognition rate(%)	51.30	71.48	71.48

random variables and the images as outcomes. So based on this relation, the uncorrelated coefficients of image factorial code can be obtained for ICA analysis. Experimental result show that the proposed method can not only obtain high-speed and also get acceptable accuracy rate even for the case the face images of test people can not be obtained for training, which is a limitation for LDA. So in this case, we proposed to use known face database for subspace learning with the modified ICA architecture, and then, the off-line ICA basis can be used for recognition of real face systems. Experiment results showed that the proposed ICA architecture can not only greatly reduce the computing time compared with the conventional ICA architecture but also obtain acceptable accuracy rate.

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