I2D-PCA: An Efficient Subspace Method with Its Application to Palmprint Identification

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Abstract

This paper presents a new method, which is called I2D-PCA (Improved two-dimensional PCA) to improve the performance of 2D-PCA (two-dimension PCA). While keeping the scatter information of "image covariance matrix" in the testing sample space, I2D-PCA is more efficient in dimension reduction and has lower time-complexity. The proposed method is applied to palmprint feature extraction, and the experimental results show the power of it.

Keywords: Principal Component Analysis (PCA), I2D-PCA, 2D-PCA, palmprint identification.

1. Introduction

Subspace analyze is an important tool for feature extraction and dimension reduction [1][7]. By studying the relationship of given samples, subspace methods could find out the low-dimensional feature even without prior knowledge. The most popular method of subspace analyze is PCA (Karhunen-Loève expansion) [8], and PCA-related methods such as LDA, ICA, Kernel PCA and Probabilistic PCA have been studied extensively. 2D-PCA, which is presented by Yang [2][3] recently, is a new approach of linear subspace based on so defined "image covariance matrix". Yang [2][3] argued that 2D-PCA could outperform PCA in covariance matrix estimation, thus achieve higher identification rate and lower computational complexity.

Palmprint identification is a new and hot topic of personal identification. Recent studies [4][5][6] indicate that palmprint is as reliable as fingerprint and has great potential because the failed-to-enroll problem of fingerprint recognition is avoided. Just like face recognition, palmprint identification faces the problem of high dimensionality. Lu [5] extracted palm feature by PCA and constructed the subspace by "eigenpalms", and the experimental result showed that PCA is efficient for palmprint feature extraction.

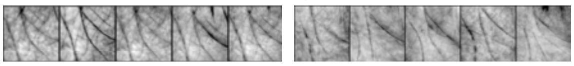
The basic motivation of our study is to find a more efficient representation of palmprint. 2D-PCA is investigated because it outperforms PCA experimentally [2][3]. Though identification rate is improved in our test, we found that feature dimension is still too high after using 2D-PCA to achieve exact estimation. This may degrade the result of recognition. Therefore, a more efficient method I2D-PCA is developed and evaluated.

In 2D-PCA, image covariance matrix is decorrelated (each pixel in its row is decorrelated statistically) to find out the "eigenrows" of the images. However, correlation of columns is neglected. I2D-PCA is well defined in this paper to decorrelate rows as well as columns. Moreover, we prove that this can be implemented by using 2D-PCA. Experimental results of palmprint identification testify that the method is much more efficient than PCA and 2DPCA.

The remainder of this paper is organized as follows: In Section 2, we review PCA and 2D-PCA briefly, and I2D-PCA is defined. Section 3 describes the implementation of I2D-PCA. Experimental results are presented in Section 4 and the conclusion is given in Section 5.

2. Definition of I2D-PCA

Let $\{\mathbf{I}_j\}(j=1,2,\ldots,M)$ to be $m \times n$ (128×128 for our database) palmprint image sequences (Fig.1). We review PCA and 2D-PCA and then define I2D-PCA based on them in this section.



(a) Samples of same class (b) Samples of different classes

Fig.1 Samples of Palmprint Database

2.1. Review of PCA and 2D-PCA

The basic principle of PCA is to maximize the scatter of the features linearly and orthogonally. 2D-PCA follows the rule but changes the feature of the scatter matrix by using 2D data directly.

In PCA, the $m \times n$ image samples $\{\mathbf{I}_j\}$ are used as $mn \times 1$ vectors $\{\mathbf{i}_j\}$. A set of eigenpalms are computed from the eigenvectors of sample covariance matrix $\mathbf{G}$,

$$\mathbf{G} = \frac{1}{M}\sum_{j=1}^{M}(\mathbf{i}_j - \boldsymbol{\mu})(\mathbf{i}_j - \boldsymbol{\mu})^T \tag{1}$$

where $\boldsymbol{\mu}$ is the mean vector of $\{\mathbf{i}_j\}$. The feature space $\mathbf{U}_{pca}$ is spanned by $k(k \leqslant M)$ eigenvectors $\{\mathbf{u}_i\}(I=1,2,\ldots,k)$ of the largest k eigenvalues, and the k-dimensional feature set $\{\mathbf{f}_j\}$ of sample $\{\mathbf{I}_j\}$ are determined as:

$$\mathbf{f}_j = \mathbf{U}_{pca}^T(\mathbf{i}_j - \boldsymbol{\mu}) \quad (j = 1, 2, \cdots, M) \tag{2}$$

Unlike traditional subspace methods, 2D-PCA takes image as 2D matrix instead of 1D vector, which keep the spatial feature of sample space. Yang [2][3] defines "image covariance matrix" $\mathbf{G}_t$ as given in (3) ($\overline{\mathbf{I}}$ is the mean value of the images) and decorrelates it instead of using $\mathbf{G}$.

$$\mathbf{G}_t = \frac{1}{M}\sum_{j=1}^{M}(\mathbf{I}_j - \overline{\mathbf{I}})^T(\mathbf{I}_j - \overline{\mathbf{I}}) \tag{3}$$

In this manner, 2D-PCA does not decorrelate images pixel by pixel, but take each column as a variable and decorrelates them. In other words, 2D-PCA uses "eigenrows" but not "eigenpalms" to construct the subspace. Suppose feature space $\mathbf{U}_{2d\text{-}pca}$ is still spanned by k eigenvectors of largest eigenvalues of $\mathbf{G}_t$, the 2D-PCA feature $\{\mathbf{f}_{j\text{-}2d\text{-}pca}\}$ of $\{\mathbf{I}_j\}$ would be obtained by (4).

$$\mathbf{f}_{j-2d-pca} = \mathbf{I}_j\mathbf{U}_{2d-pca} \tag{4}$$

It should be noticed that $\mathbf{f}_{j\text{-}2d\text{-}pca}$ is by no means k-dimensional but is $m \times k$-dimensional. That is, 2D-PCA couldn't represent the image efficiently though it may offer higher identification accuracy than PCA.

2.2. I2D-PCA

For a given set of images $\{\mathbf{I}_j\}$, the I2D-PCA feature $\mathbf{F}$ is determined by (5).

$$\mathbf{F = RIC}$$

where

$$\begin{cases} \{\mathbf{c}_1, \mathbf{c}_2, \cdots, \mathbf{c}_p, \mathbf{r}_1, \mathbf{r}_2, \cdots, \mathbf{r}_q\} = \arg\max tr(\mathbf{S}_t) \\ \mathbf{c}_i^T\mathbf{c}_j = 0, i \neq j, i, j = 1, \cdots, p \qquad p < n \\ \mathbf{r}_i\,\mathbf{r}_j^T = 0, i \neq j, i, j = 1, \cdots, q \qquad q < \min(m, p) \end{cases}, \tag{5}$$

$\{\mathbf{r}_j\}$ are rows of the left transform matrix $\mathbf{R}$ and $\{\mathbf{c}_i\}$ are rows of the right transform matrix $\mathbf{C}$. And $\mathbf{S}_t = \varepsilon\,[(\mathbf{F} - \varepsilon\,\mathbf{F})(\mathbf{F} - \varepsilon\,\mathbf{F})^T]$ is the feature scatter matrix.

In our method, the basic principle is to maximize $\mathbf{S}_t$ as 2D-PCA does. However, two transform matrixes are needed to implement it. And, the feature dimensionality is $p \times q$ after transformation (5), which makes it more efficient than 2D-PCA.

3. Implementation of I2D-PCA

3.1. Algorithm Implementation

The main idea of I2D-PCA is: after decorrelating columns of the images by 2D-PCA, decorrelates rows of the results to find the final feature. Definition of I2D-PCA (5) can be transformed into (6).

$$\mathbf{F = RIC = (R(IC)) = ((IC)}^T\mathbf{R}^T)^T \tag{6}$$

That is, I2D-PCA can be implemented by using 2D-PCA twice:

- *Step 1.* Obtain 2D-PCA transform matrix $\mathbf{C}$ and feature $\mathbf{F}_1 = \mathbf{IC}$ of each image;
- *Step 2.* Transpose $\{\mathbf{F}_1\}$ into $\{\mathbf{F}_1^T\}$;
- *Step 3.* Using 2D-PCA for the second time and get $\mathbf{F}^T = \mathbf{F}_1^T\mathbf{R}^T$, acquire $\mathbf{F}$ as the I2D-PCA feature.

It is essential to prove that the method could preserve the scatter information of the 2D-PCA features after another time of dimension reduction.

Let $\mathbf{S}_{t1}$ to be covariance matrix (that is, the scatter matrix) of $\mathbf{F}_1$:

$$\begin{aligned} \mathbf{S}_{t1} &= \varepsilon[(\mathbf{F}_1 - \overline{\mathbf{F}}_1)^T(\mathbf{F}_1 - \overline{\mathbf{F}}_1)] = \mathbf{C}^T\varepsilon[(\mathbf{I} - \overline{\mathbf{I}})^T(\mathbf{I} - \overline{\mathbf{I}})]\mathbf{C} \\ &= \varepsilon[(\mathbf{F}_1^T - \overline{\mathbf{F}}_1^T)(\mathbf{F}_1^T - \overline{\mathbf{F}}_1^T)^T] \end{aligned}, \tag{7}$$

then the scatter matrix of $\mathbf{F}$ would be:

$$\begin{aligned} \mathbf{S}_t &= \varepsilon[(\mathbf{F} - \overline{\mathbf{F}})(\mathbf{F} - \overline{\mathbf{F}})^T] \\ &= \varepsilon[(\mathbf{F}_1^T\mathbf{R}^T - \overline{\mathbf{F}}_1^T\mathbf{R}^T)^T(\mathbf{F}_1^T\mathbf{R}^T - \overline{\mathbf{F}}_1^T\mathbf{R}^T)] \\ &= \mathbf{R}\varepsilon[(\mathbf{F}_1^T - \overline{\mathbf{F}}_1^T)^T(\mathbf{F}_1^T - \overline{\mathbf{F}}_1^T)]\mathbf{R}^T \end{aligned}. \tag{8}$$

Let $\mathrm{S}' = \varepsilon\,[(\mathbf{F}_1^T - \overline{\mathbf{F}}_1^T)^T(\mathbf{F}_1^T - \overline{\mathbf{F}}_1^T)]$, It is evident that:

$$tr(\mathbf{S}_{t1}) = tr(\mathbf{S}') \geq tr(\mathbf{S}_t). \tag{9}$$

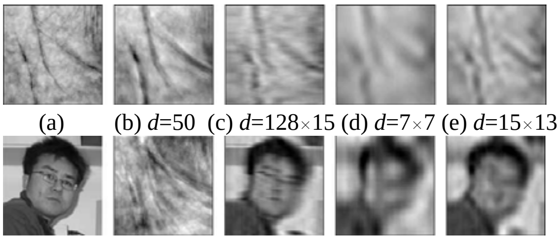
Thus we prove that I2D-PCA can keep the data scatter unchanged when $p=q$ (this indicates $tr(\mathbf{S}_{t1}) = tr(\mathbf{S}_t)$. And $p>q$ would decline the diversity but obtain lower-dimensional features. However, our experiments testify that q should be set to a little lower than p. This may result from the correlation between rows and columns of the image), which means I2D-PCA outperform 2D-PCA in dimension reduction.

3.2. Image Reconstruction

Since transform matrix $\mathbf{R}$ and $\mathbf{C}$ are composed of orthonormal vectors, the reconstruction of original images can be viewed as inverse operation of the transform (5):

$$\tilde{\mathbf{I}} = \mathbf{R}^T\mathbf{F}\mathbf{C}^T. \tag{10}$$

Fig.2 compares the reconstruction results of PCA, 2D-PCA and I2D-PCA. It is evident that 2D-PCA and I2D-PCA have better generalization ability than PCA does, PCA cannot describe a "not class" sample as shown in (g). Furthermore, 2D-PCA cannot represent the original sample efficiently; the dimensionality is too high (we set the dimension to 128×15 here because highest recognition rate is reached under it) for a "feature". It is difficult to use classification methods like density estimation [9] without being affected by dimension curse. I2D-PCA could represent arbitrary image while the feature dimension even less than PCA, which indicates the generalization ability and effectiveness of it.



(a) (b) d=50 (c) d=128×15 (d) d=7×7 (e) d=15×13

(f) (g) d=50 (h) d=128×15 (i) d=7×7 (j) d=15×13

Fig. 2 Reconstruct untrained palmprint image (a) and arbitrary image (f) using PCA ((b),(g)), 2D-PCA ((c),(h)) and I2D-PCA ((d),(e),(i),(j)). Feature dimensionality is denoted as "d" for each image.

4. Experiments and discussions

4.1. Experiment setup

The experimental database is consisted of 1,971 right-hand images from 98 individuals. To evaluate the stability of palmprint features, each individual's hand-image is collected 2~5 times in a period of 3 month. A special digital-camera-based device is designed to capture the images. The original resolution of hand-images is 1792×1200. We take the ROIs (region of interest) out and unify their size to 128×128. After histogram equalization and noise canceling of the ROIs, the palmprint database is set up.

The hold-out rule is employed to evaluate the classification error. Palmprint database is divided into two non-overlapping sets: training set and testing set. The training set is made up of 490 palmprint (5 palmprints from each of unique individual) samples, while the remainder 1481 images make up of the testing set (6-20 samples for each person).

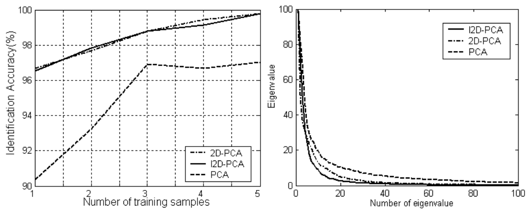
All the experiments are carried out using Matlab 6.2/ PIV 2.6G/ 256 RAM.

4.2. Identification test

Without loss of generality, Euclidean distance measure and nearest neighbor classifier (11) is used to find out the result of identification. Suppose $\mathbf{F}_i$ is the I2D-PCA feature of given testing sample $\mathbf{I}_i$; $\mathbf{M}_j$ is the center vector of the jth class of palmprint features in the training set. The classifier would assign the sample to its corresponding class W_j ($\mathbf{I} \in W_j$) if $d(\mathbf{F},\mathbf{M}_i)$ is minimum in the W classes.

$$d(\mathbf{F}_i, \mathbf{M}_j) = \sum_{x=1}^{p}\sum_{y=1}^{q}(\mathbf{F}_i(x,y) - \mathbf{M}_j(x,y))^2$$
$$d(\mathbf{F}, \mathbf{M}_i) = \min_j d(\mathbf{F}, \mathbf{M}_j) \qquad j = 1, 2, \cdots, W \tag{11}$$

Fig. 3(a) shows the identification results using different number of training samples for PCA, 2D-PCA and I2D-PCA. It is noticeable that 2D-PCA and I2D-PCA would enhance accuracy of performance. Up to 99.72% testing samples are classified correctly using either 2D-PCA or I2D-PCA when 5 samples are trained respectively. When training sample is not sufficient (hard to avoid in biometrics especially), the accuracy of 2D-PCA and I2D-PCA is more than 5% higher than PCA.



(a) Identification accuracy (b) Magnitude of eigenvalues

Fig. 3. Performance of PCA, 2D-PCA and I2D-PCA

Each point in Fig. 3(a) is the best performance under certain feature dimension. PCA is tested using dimension 20~70 with the step of 10, while 50 is the best using 5 training samples. 2D-PCA is tested using 128×5~128×25 (step 128×5), while 128×15 is most appropriate. The dimension for I2D-PCA is 15×13 in

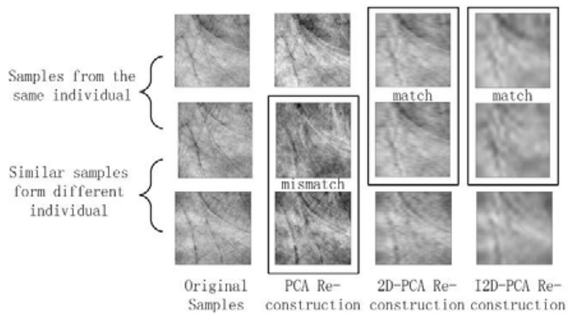


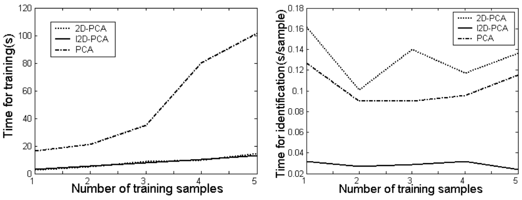
Fig. 4. Matching palmprints using PCA/ 2D-PCA/ I2D-PCA

the range of 5 × 5~25 × 25. Fig. 3(b) shows the distribution of eigenvalues of I2D-PCA. The energy is more centered in I2D-PCA than that of 2D-PCA and PCA, which indicates I2D-PCA is more efficient in dimension reduction.

Another experiment is designed in order to demonstrate the advantage of 2D-PCA and I2D-PCA. A testing sample that have been misclassified by PCA but classified correctly by 2D-PCA and I2D-PCA is picked out, and the corresponding features are reconstructed in Fig. 4. The figure suggests two advantages of 2D-PCA based methods: first, they are not sensitive to shading effect that is fatal to PCA; second, they are more texture-like and describe an untrained sample better (PCA reconstructs trained sample subtly but lack of generality).

4.3. Effectiveness of I2D-PCA

Though both 2D-PCA and I2D-PCA can bring about higher accuracy, I2D-PCA is much more efficient in dimension reduction and has lower system response time.



(a) Time cost for training (b) Time cost for recognition

Fig. 5. Effectiveness of I2D-PCA in complexity

Fig. 5 compares computational complexity of three methods. Time for training is mainly cost by covariance matrix decomposition and feature vector/matrix generation, which make PCA work slower. Though SVD could turn a 16384×16384 matrix decomposition problem into analyzing a $M \times M$ (M is 490 for 5 samples for each class) matrix for PCA, the complexity rises dramatically with the increasing of number of training samples. However, training using 2D-PCA and I2D-PCA is efficient by decomposing 128×128 image covariance matrix. Actually, the "step 3" for I2D-PCA deal with $p \times p$ (which is 15×15 in our test) matrix, which does not affect the complexity as shown in Fig. 5(a). It is clear

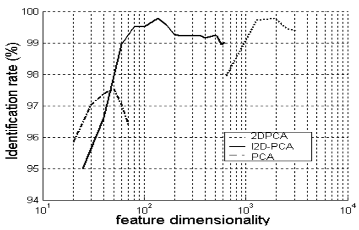


Fig. 6. Effectiveness of I2D-PCA in dimension reduction

that I2D-PCA is more ready to application for it could make each match in 0.04s.

As illustrated in Fig.6, the most significant improvement of I2D-PCA is its ability of dimension reduction. Though 2D-PCA have the identical best identification rate as I2D-PCA, the feature dimension is hard to find for 2D-PCA because the curve is sharp, and the step for searching is at least 128 for the palmprint image, while the step for I2D-PCA is arbitrary. As a result, I2D-PCA needs only about 1/10 dimensionality as 2D-PCA does.

5. Conclusion

In this paper, an efficient subspace method I2D-PCA is developed based on 2D-PCA. The basic idea of it is to decorrelate columns as well as rows statistically for a given image set. The subspace could be implemented by using 2D-PCA twice while keeping the feature scatter unchanged. The supposed method is evaluated by palmprint identification. The experiments testify that I2D-PCA outperforms 2D-PCA and PCA, and demonstrate the effectiveness of it.

6. Acknowledgments

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