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Face Recognition Based on Two-dimensional Principal Component Analysis and Kernel Principal Component Analysis

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Abstract: Face recognition has been a very valuable research to pattern recognition and face recognition systems. These years, two-dimensional principal component analysis and kernel principal component analysis have been successfully applied in face recognition systems. However, there is still some space for us to make it better. This study has proposed a novel approach based on Two-dimensional Principal Component Analysis (2DPCA) and Kernel Principal Component Analysis (KPCA) for face recognition. The proposed approach first performs two-dimensional principal component analysis process to project the faces onto the feature pace and then performs kernel principal component analysis on the projected data. And finally, one nearest neighbor classifier based on Euclidean distance is used for recognizing faces. The experiments on ORL face database, Yale face database and FERET face database show that the proposed approach gives a high recognition rate of 100% and outperforms state-of-the-art approaches and demonstrates promising applications.

Key words: Two-dimensional principal component analysis, kernel principal component analysis, face recognition, recognition rate

INTRODUCTION

In recent years, face recognition has got a great deal of attention from the fields of computer view, face recognition systems, pattern recognition and computer vision communities (Zhao *et al*., 2003; Jain *et al*., 2004). And many approaches have been used for face processing and recognizing faces, such as Principal Component Analysis (PCA) (Huo and Song, 2010; Zhang, 2011), Kernel Principal Component Analysis (KPCA) (Xie and Lam, 2006; Wang and Zhang, 2010b) and Two-dimension Principal Component Analysis (2DPCA) (Sun *et al*., 2010; Ying and Liang, 2011).

PCA is widely used in the area of pattern recognition and face processing (Zhao and Yang, 1999; Yang *et al*., 2007; Wang and Li, 2010; Sun *et al*., 2011). It was proposed by Turk and Pentland (1991). However, PCA only use the second order statistical information in data. Thus, it can't perform well in nonlinear cases. So, Smola and Scholkopf (2002) proposed the KPCA algorithm. KPCA is a technique for non-linear feature extraction. It describes the nonlinear correlations among the pixels, so the KPCA is able to capture this important information and obtain better results. Huang and Shao (2004) and Wang and Zhang (2010a) applied the KPCA in face recognition. Lu *et al*. (2005) proposed an efficient kernel discriminant analysis method. The 2DPCA algorithm was proposed by Yang *et al*. (2004). 2DPCA algorithm directly works on two-dimensional matrix which does not need to be transformed into vector and can easily find the feature vector and the feature matrix. It not only can greatly reduce the dimensions of the image but also improve the computational efficiency. These years, many 2DPCA-based algorithms are applied in pattern recognition and face recognition systems and achieved some satisfying effects (Niu *et al*., 2009; Ying and Liang, 2011).

However, the recognition rates of these approaches above-mentioned were not enough for us to make further applications. So, in this study, a novel approach based on 2DPCA-KPCA (TKPCA) was proposed for face recognition. TKPCA approach combines the advantages of 2DPCA and KPCA. It is demonstrated by experiments that the proposed approach has a satisfactory face recognition rate performance and outperforms other approaches.

KERNEL PRINCIPAL COMPONENT ANALYSIS AND TWO-DIMENSIONAL PRINCIPAL COMPONENT ANALYSIS

KPCA: The main idea of KPCA is to map input data into a high-dimensional feature space F and then perform PCA in F. For a given nonlinear mapping, the input data x_k can be mapped to $\phi(x_k)$. This can be expressed as follows:

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$$\phi: R^N \to F,\ x_k \to \phi(x_k),\ k = 1, 2, \ldots, N$$

In the feature space F, we assume:

$$\sum_{k=1}^{N} \phi(x_k) = 0 \tag{1}$$

The covariance matrix is:

$$\overline{C} = \frac{1}{N}\sum_{j=1}^{N} \phi(x_j)\phi(x_j)^T \tag{2}$$

Denote eigenvalues and eigenvectors of the covariance matrix $\overline{C}$ by λ and V, then:

$$\lambda v = \overline{C}v \tag{3}$$

The eigenvectors V can be expressed by a linear combination of $\phi(x_1)..\phi(x_N)$. For some $\alpha_1 \in R^N$, there exists:

$$V = \sum_{i=1}^{N} \alpha_i \phi(x_i) \tag{4}$$

Define a matrix K(M×M):

$$k_{ij} = \phi(x_i)^T \phi(x_j) \tag{5}$$

K is a kernel matrix. Then:

$$K\alpha = N\lambda\alpha \tag{6}$$

Thus, the problem of solving the eigenvector V is transformed to solving the eigenvector α. From Eq. 6, we can obtain a group of nonzero eigenvalues and the corresponding meet the normalization condition:

$$(\alpha^i, \alpha^j) = 1 \quad (j = 1, \ldots, N', N' \le N) \tag{7}$$

According to the Eq. 4, we can get the principal components $V_j = (j = 1, \ldots, N)$ of the feature space. We assume X is the test samples, then the projection of X in $V_j (j = 1, \ldots, N)$ is:

$$(V_j)^T \phi(X) = \sum_{j=1}^{N} \alpha_i^j \phi(X_i)\phi(X) = \sum_{j=1}^{N} \alpha_i^j K(X_i, X) \tag{8}$$

Some kernel functions such as the linear kernel, polynomial kernel and Gaussian kernel have been commonly used in many practical applications of kernel methods.

- Linear kernel:

$$K(x_i, x) = \langle x, xi \rangle \tag{9}$$

- Polynomial kernel:

$$K(x_i, x) = (\langle x, x_i \rangle + c^d),\ d = 12..... \tag{10}$$

- Gaussian kernel:

$$K(x_i, x) = \exp(-q\|-x, x_i\|^2) \tag{11}$$

2DPCA: Let X denotes an n-dimensional column vector and A denotes an m×n image matrix. A is projected onto X by the following linear transformation:

$$Y = AX \tag{12}$$

Thus, we obtain an m-dimension column vector Y which is called the feature vector of the matrix A.

Suppose that there are M training image samples, so the ith sample image can be expressed as matrix $A_i(m \times n)$, i = 1, 2,..., M. Then the average image of all the training samples is denoted by $\overline{A}$:

$$\overline{A} = \frac{1}{M}\sum_{i=1}^{M} A_i \tag{13}$$

Introducing the covariance matrix G_t:

$$G_t = \frac{1}{M}\sum_{i=1}^{M} (A_i - \overline{A})^T (A_i - \overline{A}) \tag{14}$$

The optimal value for the projection matrix $X_{opt.}$ is composed by the d largest eigenvalues, i.e.:

$$X_{opt.} = (X_1, X_2, \ldots, X_d) \tag{15}$$

Let:

$$Y_k = Ax_k,\ k = 1, 2, \ldots, d \tag{16}$$

Then we obtain the feature matrix:

$$B = (Y_1, Y_2, \ldots, Y_d) \tag{17}$$

FACE RECOGNITION USING TKPCA

Suppose that there are N training image samples and N testing image samples, each image can be expressed as $a_{m\times n}$ matrix. Though our proposed approach is the combination of TPCA and KPCA, it is not to add the two approaches together simply. The specific steps are as follows:

- **Training phase:** Different with the traditional 2DPCA, we first define two matrixes to store the training samples, one is a two-dimensional matrix (N, m×n) and another is a three-dimensional matrix (m, n, N). By performing the 2DPCA approach on the two-dimensional matrix, we can calculate the covariance matrix (n, n) of all the training samples. Then to calculate the eigenvalues and eigenvectors, select the L largest eigenvalues and eigenvectors, respectively. And then, we project the three-dimensional matrix onto the 2DPCA feature space (n, L). Thus, we can obtain a new three-dimensional matrix (m, L, N)

In the second stage, we reshape the three-dimensional matrix (m, L, N) and make it a two-dimensional matrix (m×L, N). Then, we consider the transpose of the new two-dimensional matrix as the training data of KPCA. Meanwhile, a polynomial kernel function is selected to be KPCA. Then, we perform the KPCA process to project the training data onto the KPCA feature space.

- **Testing phase:** In this stage, the testing samples are stored in a two-dimensional matrix (N, m×n). We standardize each image of the testing samples and reshape them, then project the reshaped data onto the 2DPCA feature space and reshape them again, respectively. Thus, we get a new two-dimensional matrix (N, m×n) and let the matrix to be the new test data, i.e., the testing samples of KPCA

Unlike the traditional KPCA, in testing phase, we calculate the kernel matrix the same as in the training phase, i.e.:

$$K_{ij} = \phi(t_j)^T\phi(t_j) \tag{18}$$

not:

$$K_{ij} = \phi(t_j)^T\phi(xt_j) \tag{19}$$

Also, a polynomial kernel is used as the kernel function.

The next stage, by performing the KPCA approach, we project the kernel matrix onto the KPCA feature space. And finally, the one nearest neighbor classifier based on Euclidean distance is used for recognizing faces.

EXPERIMENTAL RESULTS

All the experiments were operated on a workstation with Intel(R) Core(TM) 2 Duo CPU (2.93 GHz) in MATLAB (7.10.0) environment. Experiments were performed using TKPCA approach on the ORL database, Yale databases and FERET database. In order to prove the effectiveness of the TKPCA, we also applied the PCA, KPCA and 2DPCA on the three databases to make comparisons with the TKPCA.

Experiments on the ORL face database: Experiments were performed using the first five images of each individual for training and the rest images for testing. Thus, the total number of the training samples and testing samples were both 200. The comparison of CPU time and top recognition rate on ORL database are shown in Table 1.

From Table 1, we can observe that the total CPU time of the PCA, KPCA, 2DPCA and TKPCA is 5.1269, 19.3896, 3.702 and 19.485 sec, respectively. Although, the TKPCA is the combine of 2DPCA and KPCA, its CPU time is just nearly to the CPU time of KPCA. In Table 1, the recognition rate of PCA, KPCA, 2DPCA and TKPCA is 87.5, 89, 90.5 and 100%, respectively. The TKPCA algorithm outperforms the PCA, KPCA and 2DPCA by 12.5, 11 and 9.5%, respectively.

Experiments on the Yale face database: According to the TKPCA algorithm, the experiments were carried out using the first five images of each individual for training and the next five images for testing. Thus, the total number of the training samples and testing samples were both 75. The comparison of CPU time and top recognition rate on Yale database are shown in Table 2.

As can be seen from Table 2, though the total CPU time of TKPCA is 2.7737 sec and higher than the other approaches, it is still less than the sum of the KPCA and 2DPCA. We also can observe that the recognition rate of PCA, KPCA and 2DPCA shows a 4.83, 5 and 2.5% decrease, respectively, when compared to applying on the ORL database. Whereas, the TKPCA still gives the recognition rate of 100%. It outperforms the PCA, KPCA and 2DPCA by 17.33, 16 and 12%, respectively.

Table 1: Comparison of CPU time and top recognition rate of different algorithm on ORL face database

Algorithm	PCA	KPCA	2DPCA	TKPCA
Training time(sec)	4.3238	12.7118	0.6388	10.4528
Testing time(sec)	0.8031	6.6778	3.0632	9.0322
Total time(sec)	5.1269	19.3896	3.702	19.485
Recognition rate (%)	87.5	89	90.5	100.

PCA: Principal component analysis, KPCA: Kernel principal component analysis, 2DPCA: Two-dimensional principal component analysis, TKPCA: Two-dimensional principal component analysis and kernel principal component analysis

Table 2: Comparison of CPU time and top recognition rate of different algorithm on Yale face database

Algorithm	PCA	KPCA	2DPCA	TKPCA
Training time(sec)	0.7631	1.3111	0.5598	1.1759
Testing time(sec)	0.2195	0.5985	0.9881	1.0158
Total time (sec)	0.9826	1.9096	1.5479	2.7737
Recognition rate (%)	82.67	84	88	100

PCA: Principal component analysis, KPCA: Kernel principal component analysis, 2DPCA: Two-dimensional principal component analysis, TKPCA: Two-dimensional principal component analysis and kernel principal component analysis

Table 3: Comparison of CPU time and top recognition rate of different algorithm on FERET face database

Algorithm	PCA	KPCA	2DPCA	TKPCA
Training time	2.1656	2.6431	1.2358	3.6432
Testing time	1.1818	1.3628	1.1654	2.8214
Total time	3.3475	4.0059	2.4489	6.4646
Recognition rate (%)	2.67	2.667	86.7	100

PCA: Principal component analysis, KPCA: Kernel principal component analysis, 2DPCA: Two-dimensional principal component analysis, TKPCA: Two-dimensional principal component analysis and kernel principal component analysis

Experiments on the FERET face database: The last experiment was performed using the FERET database. There were 50 individuals each containing 6 images which were chosen from FERET database. Experiments were performed using the first three images of each individual for training and the rest images for testing. The total number of the training samples and testing samples were both 150. The comparison of CPU time and top recognition rate on FERET database are shown in Table 3.

From Table 3, we can observe that the total CPU time of KPCA and 2DPCA is 4.0059 and 2.4489 sec, respectively. The TKPCA is 6.4646 sec and nearly to the sum of the KPCA and 2DPCA. As can be seen in Table 3, the PCA and KPCA approaches nearly do not work when performing on the FERET database. And the recognition rate of TPCA shows a decrease again. It shows a recognition rate of 86.7%. Whereas, the TKPCA still keeps a recognition rate of 100% and much better than the other three approaches.

The experimental results all above have proved the effectiveness of our proposed approach. And this approach is very easy to implement. Face recognition can not only be used to determine the identity of a person but also can be used to identify criminals. So, this paper promotes the development of information security and provides a better approach for face recognition.

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CONCLUSION

In this study, an approach based on 2DPCA and KPCA has been proposed for face recognition. TKPCA approach combined the advantages of 2DPCA and KPCA, i.e., with not too much CPU time to achieve higher face recognition rate. A polynomial kernel function and the one nearest neighbor classifier based on Euclidean distance have been used for TKPCA face recognition. The experiments on ORL database, Yale database and FERET database have shown that the TKPCA approach gives a high recognition rate of 100% and outperforms the other approaches and demonstrates promising applications in pattern recognition and face recognition systems.

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