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Face Recognition Based on Uncorrelated Multilinear PCA Plus Classical LDA

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Abstract

Subspace learning is an important direction in computer vision research. In this paper, a new method of face recognition based on uncorrelated multilinear principal component analysis (UMPCA) and linear discriminant analysis (LDA) is proposed. First, instead of transforming matrices into vectors for principal component analysis (PCA), UMPCA seeks a tensor-to-vector projection that captures most of the variation in the original tensorial input while producing uncorrelated features through successive variance maximization. A subset of features is extracted and the classical LDA is then applied to find the best subspaces. Finally, the comprehensive experiments are provided on AT&T databases and the experiment results show its superiority through the comparison with other PCA plus LDA based algorithms.

Keywords: *Tensor object, uncorrelated multilinear principal analysis, linear discriminant analysis, feature extraction*

1. Introduction

There is a growing interest in subspace learning techniques for face recognition. However, the excessive dimension of the data space often brings the algorithms into the curse of dimensionality dilemma. Dimensionality reduction is commonly used to transform a high-dimensional data set into a low-dimensional subspace while retaining most of the underlying structure in the data [1]. Many face recognition techniques have been developed over the past few decades and two of the most successful and well-studied techniques for this purpose are Principal Component Analysis (PCA) [2] and Linear Discriminant Analysis (LDA) [3]. It has been applied in many scientific fields for dimension reduction and compact data representation. When the data are tensor objects, traditional analysis generates a design matrix by vectorizing each of the tensor objects into a long vector [4]. This usually produces a large number of variables, resulting in high computation and memory demand. Besides the implementation issues, it is well understood that reshaping breaks the natural structure and correlation in the original data. Therefore, a dimensionality reduction algorithm operating directly on a tensor object rather than its vectorized version is needed.

Therefore, some researchers and experts seek multidimensional methods that works well in facing with high order data without vectorizing them, such as $(2D)^2$PCA [5] and $(2D)^2$LDA [6]. $(2D)^{2PCA}$ and $(2D)^{2LDA}$ have been both shown effective in dealing with 2nd-order data, such as image classification and face recognition. However, the two methods are limited in 2D data, so when facing higher order data as video data, they

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will no longer obtain better results. Recently, there are many developments in the analysis of high order Data. Yan *et al*. [7] propose Multilinear Discriminant Analysis (MDA) algorithm and a novel approach called k-mode optimization to iteratively solve the optimization function. Lu *et al*. [8] propose a new multilinear principal component analysis (MPCA) formulation that operating directly on the original tensor data in their tensorial representation. Like conventional principal component analysis, the proposed MPCA seeks low-dimensional multilinear projections of tensor objects that capture the maximal data variation and had been successfully applied in real world analysis and its performance has been verified by simulations. In reference [9], a method that utilized the MDA after MPCA algorithm has been proposed in which both of those algorithms work with tensor objects that can give us better results. Beyond the multilinear research mentioned above, uncorrelated multilinear algorithm has been proposed during the recent years. That uncorrelated multilinear extensions of PCA takes an important property of PCA into account that PCA derives uncorrelated features. Uncorrelated features are highly desirable in many recognition tasks since they contain minimum redundancy and ensure linear independence among features [10]. The proposed novel uncorrelated multilinear principal component analysis (UMPCA) for unsupervised tensor object dimensionality reduction (feature extraction) based on the tensor-to-vector projection (TVP) [11] and it follows the classical PCA derivation of successive variance maximization. During the TVP, a $P \times 1$ vector can be captured that consists of P projections from a tensor to a scalar. In this paper we use UMPCA algorithm for tensor object feature extraction, and then the $P \times 1$ vector will be the inputs of classical LDA to perform better results. Due to using the LDA after applying the UMPCA, we can get lower dimensionality dilemma and better correct recognition rate.

The rest of this paper is organized as follows: Section 2 introduces the basic notion of multilinear projection for dimensionality reduction. In section 3, the algorithm of UMPCA and classical LDA is summarized and discussed in details. Moreover, a UMPCA plus LDA based tensor object recognition is organized for application of face recognition. Section 4 lists experiments on face recognition and compares performance against state-of-the-art algorithm. Finally, we conclude the paper with future work discussions.

2. Tensor Fundamentals

Following the notation in [12], we denote vectors by lowercase boldface letters, e.g., **x**; matrices by uppercase boldface, *e.g.*, **U**; and tensors by calligraphic letters, e.g., $\mathcal{A}$. Tensor is a generalization of vector and matrix. Vectors are first-order tensors, and matrices are second-order tensors. An Nth-order tensor is denoted as $\mathcal{A} \in \mathbb{R}^{I_1 \times I_2 \times \cdots \times I_N}$. It is addressed by N indices i_n, and each i_n addresses the n-mode of $\mathcal{A}$. The n-mode product of a tensor $\mathcal{A}$ by a matrix $\mathbf{U} \in \mathbb{R}^{J_n \times I_n}$, denoted by $\mathcal{A} \times_n \mathbf{U}$, is a tensor with entries:

$$(\mathcal{A} \times_\mathrm{n} \mathrm{U})(\mathrm{i}_1, \cdots, \mathrm{i}_{\mathrm{n}-1}, \mathrm{j}_\mathrm{n}, \mathrm{i}_{\mathrm{n}+1}, \cdots, \mathrm{i}_\mathrm{N}) = \sum_{\mathrm{i}_\mathrm{n}} \mathcal{A}(\mathrm{i}_1, \mathrm{i}_2, \cdots, \mathrm{i}_\mathrm{N}) \cdot \mathrm{U}(\mathrm{j}_\mathrm{n}, \mathrm{i}_\mathrm{n}) \quad (1)$$

The scalar product of two tensors $\mathcal{A}, \mathcal{B} \in \mathbb{R}^{\mathrm{I}_1 \times \mathrm{I}_2 \times \cdots \times \mathrm{I}_\mathrm{N}}$ is defined as

$$\langle \mathcal{A}, \mathcal{B} \rangle = \sum_{\mathrm{i}_1} \cdots \sum_{\mathrm{i}_\mathrm{N}} \mathcal{A}(\mathrm{i}_1, \mathrm{i}_2, \cdots, \mathrm{i}_\mathrm{N}) \cdot \mathcal{B}(\mathrm{i}_1, \mathrm{i}_2, \cdots, \mathrm{i}_\mathrm{N}) \quad (2)$$

Unfolding $\mathcal{A}$ along the n-mode is defined as $\mathcal{A}_{(\mathrm{n})} \in \mathbb{R}^{\mathrm{I}_\mathrm{n} \times (\mathrm{I}_1 \times \cdots \times \mathrm{I}_{\mathrm{n}-1} \times \mathrm{I}_{\mathrm{n}+1} \times \cdots \times \mathrm{I}_\mathrm{N})}$.The column vectors of $\mathcal{A}_{(\mathrm{n})}$ are the n-mode vectors of $\mathcal{A}$. The Frobenius norm of $\mathcal{A}$ is defined as

$$\|\mathcal{A}\| = \sqrt{\langle \mathcal{A}, \mathcal{A} \rangle} = \left\|\mathcal{A}_{(n)}\right\|_F = \sqrt{\sum_{i_1=1}^{I_1} \sum_{i_2=1}^{I_2} \cdots \sum_{i_N=1}^{I_N} a_{i_1 i_2 \cdots i_N}^2} \quad (3)$$

So the distance between tensors $\mathcal{A}$ and $\mathcal{B}$ of the same dimensions is defined asdist$(\mathcal{A}, \mathcal{B}) = \|\mathcal{A} - \mathcal{B}\|$.

2.2. Tensor-to-Vector Projection

The classification of tensor objects in this paper is determined through a multilinear projection from a tensor space to a vector space, called the tensor-to-vector projection. The projection is a generalized version of the projection framework firstly introduced in [11]. The TVP projects a tensor to a vector and it can be viewed as multiple projections from a tensor to a scalar. A tensor $\mathcal{X} \in \mathbb{R}^{I_1 \times I_2 \times \cdots \times I_N}$ is projected to a point y through N unit projection vectors $\left\{u^{(1)^T}, u^{(2)^T}, \cdots, u^{(N)^T}\right\}$ as

$$y = \mathcal{X} \times_1 u^{(1)^T} \times_2 u^{(2)^T} \times \cdots \times_N u^{(N)^T} \quad , \quad \left\|u^{(n)}\right\| = 1 \quad \text{for} \quad n = 1, \cdots, N. \quad (4)$$

Which can also be written as the following inner product

$$y = \langle \mathcal{X}, u^{(1)} \circ u^{(2)} \circ \cdots \circ u^{(N)} \rangle \quad (5)$$

Such a multilinear projection, named an elementary multilinear projection (EMP), comprised of one unit projection vector per mode.

The TVP from a tensor object $\mathcal{X}$ to a vector $y \in \mathbb{R}^P$ in a *P*-dimensional vector space consist of *P* EMPs, which can be written as

$$y = \mathcal{X} \times_{n=1}^{N} \left\{u_P^{(n)^T}, n = 1, \cdots, N\right\}_{p=1}^{P} \quad (6)$$

Where the *p*th component of *y* is obtained from the *p*th EMP as

$$y(p) = \mathcal{X} \times_1 u_p^{(1)^T} \times_2 u_p^{(2)^T} \times \cdots \times_N u_p^{(N)^T} \quad (7)$$

Figure 1 shows the TVP of a tensor object $\mathcal{X} \in \mathbb{R}^{9 \times 6 \times 3}$ to a $P \times 1$ vector consists of *P* projections from $\mathcal{X}$ to a scalar.

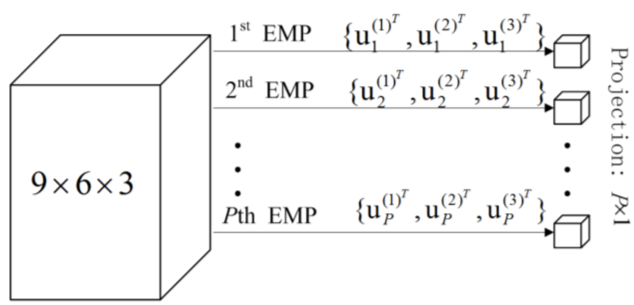


Figure 1. Tensor-to-vector Projection (TVP)

3. Uncorrelated Multilinear Principal Component Analysis and Linear Discriminant Analysis

As a multilinear extension of PCA, UMPCA not only obtains features that maximize the variance captured, but also enforces a zero-correlated constraint, thus extracting uncorrelated features in a similar way to that of the classical PCA [13]. Motivated by Fisherface algorithm, we use UMPCA algorithm for tensor image feature extraction and dimension reduction and then get low dimensionality images which are ready for applying LDA. Finally, we implement the nearest neighbor classifier to classify face images based on its computed LDA features.

3.1. Uncorrelated Multilinear Principal Component Analysis

In this section, UMPCA algorithm is introduced in detail based on the analysis introduced in [14]. The UMPCA objective function is first formulated. Then, the successive variance maximization approach and alternating projection method are adopted to derive uncorrelated features through TVP. The problem to be solved is formally stated as follows.

A set of *M* tensor object samples $\{\mathcal{X}_1, \mathcal{X}_2, \cdots, \mathcal{X}_M\}$ are available for training and each tensor object $\mathcal{X}_m \in \mathbb{R}^{I_1 \times I_2 \times \cdots \times I_N}$ assumes values in the tensor space $\mathbb{R}^{I_1} \otimes \mathbb{R}^{I_2} \cdots \otimes \mathbb{R}^{I_N}$, where I_n is the *n*-mode dimension of the tensor and $\otimes$ denotes the Kronecker product. The objective of the UMPCA is to find a TVP, which consists of *P* EMPs$\left\{u_p^{(n)} \in \mathbb{R}^{I_n \times 1}, n = 1, \cdots, N\right\}_{p=1}^{P}$, mapping from the original space $\mathbb{R}^{I_1} \otimes \mathbb{R}^{I_2} \cdots \otimes \mathbb{R}^{I_N}$ into a vector subspace $\mathbb{R}^P$(with$P < \prod_{n=1}^{N} I_n$)

$$y_m = \mathcal{X}_m \times_{n=1}^{N} \left\{u_p^{(n)^T}, n = 1, \cdots, N\right\}_{p=1}^{P}$$

(8)

The *P* EMPs $\left\{u_p^{(n)^T}, n = 1, \cdots, N\right\}_{p=1}^{P}$ are determined by maximizing the variance captured while producing features with zero correlation. Thus, the objective function for the *P*th EMP is:

$$\left\{u_p^{(n)^T}, n = 1, \cdots, N\right\}_{p=1}^{P} = \arg\max \sum_{m=1}^{M} \left(y_m(p) - \bar{y}_p\right)^2 = S_{T_p}^{y}$$

$$\text{Subject to} \quad u_p^{(n)^T} u_p^{(n)} = 1 \quad \text{and} \quad \frac{g_p^T g_q}{\|g_p\| \|g_q\|} = \delta_{pq} \quad , \quad p,q = 1, \cdots, P$$

(9)

Where δ_{pq} is the Kronecker delta defined as

$$\delta_{pq} = \begin{cases} 1, & \text{if } p = q \\ 0, & \text{otherwise} \end{cases}$$

(10)

To solve the UMPCA problem (9), we follow the successive variance maximization approach. The *P* EMPs $\left\{u_p^{(n)^T}, n = 1, \cdots, N\right\}_{p=1}^{P}$ are sequentially determined in *P* steps, with the *p*th step obtaining the *p*th EMP

Step 1: Determine the first EMP $\left\{u_1^{(n)^T}, n = 1, \cdots, N\right\}_{p=1}^{P}$ by maximizing$S_{T_1}^{y}$.

Step 2: Determine the second EMP $\left\{u_2^{(n)^T}, n = 1, \cdots, N\right\}_{p=1}^{P}$ by maximizing $S_{T_2}^{y}$ subject to the constraint that$g_2^T g_1 = 0$.

Step 3: Determine the third EMP $\left\{u_3^{(n)^T}, n = 1, \cdots, N\right\}_{p=1}^{P}$ by maximizing $S_{T_3}^{y}$ subject to the constraint that $g_3^T g_1 = 0$ and $g_3^T g_2 = 0$.

Step p$(p = 4, \cdots, P)$: Determine the *p*th EMP $\left\{u_p^{(n)^T}, n = 1, \cdots, N\right\}_{p=1}^{P}$ by maximizing $S_{T_p}^{y}$ subject to the constraint that $g_p^T g_q = 0$ for *q*=$1, \cdots, p-1$.

In order to solve for the p^{th} EMP$\left\{u_p^{(n)^T}, n = 1, \cdots, N\right\}$, we need to determine *N* sets of parameters corresponding to *N* projection vectors, $u_p^{(1)}, u_p^{(2)}, \cdots, u_p^{(N)}$, one in each mode.

3.2. Linear Discriminant Analysis

A classical linear discriminant analysis (LDA) is then applied to obtain an UMPCA+LDA approach for recognition, similar to the popular of PCA+LDA. Consider *c* classes existing with *M* samples. The within-class matrix is defined in the form

$$S_W = \sum_m \left(y_m - \bar{y}_{c_m}\right)\left(y_m - \bar{y}_{c_m}\right)^T, \text{ and } \bar{y}_c = \frac{1}{N_c} \sum_m^{c_m = c} y_m$$

(11)

The between-class scatter matrix is defined as

$$S_B = \sum_{c=1}^{C} N_c (\bar{y}_c - \bar{y})(\bar{y}_c - \bar{y})^T, \text{ and } \bar{y} = \frac{1}{M} \sum_m y_m$$

(12)

The optimal projection matrix V is chosen as follows:

$$V_{lda} = \operatorname{argmax} \frac{|V^T S_B V|}{|V^T S_w V|} = [v_1 v_2 \cdots v_M]$$

(10)

Where the $\{v_m, m = 1, \cdots, M\}$ is the set of generalized eigenvectors of S_B and S_W corresponding to the m largest generalized eigenvalues $\{\lambda_m,\ m = 1, \cdots, M\}$: $S_B v_m = \lambda_m S_W v_m$. Thus, the discriminant feature vector z_m is obtained as: $z_m = V_{lda}^T y_m$, and a classifier can then be applied.

4. Experiment Evaluation

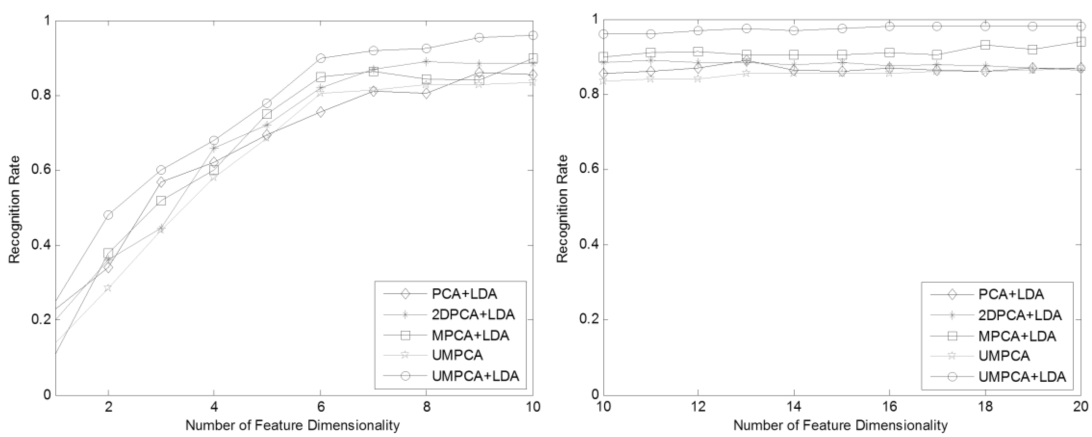
In this section, two standard face databases AT&T [15] and FERET [17] were used to evaluate the effectiveness of our proposed algorithm, UMPCA+LDA, in face recognition accuracy. These algorithms were compared with the popular PCA+LDA, 2DPCA+2DLDA, and the MPCA+LDA [16] algorithm. For experiments, we split the face image records into two data sets: the training set and the testing set and report the best result on different feature dimensions in the LDA step. In all the experiments, the training and the testing data were both transformed into lower dimensional tensors or vectors via the learned subspaces and then the nearest neighbor classifier was applied for final classification with Euclidean distance measure. The performances on the cases with different number of training samples were also evaluated to illustrate their robustness in the small sample size problems.

4.1. The AT&T Database

The gray-level face images from the AT&T database have a resolution of 112×92, and 40 subjects with 10 images each included in the database. Figure 2 shows some sample images from the database. Those images have different characteristics, such as with or without glasses, and with different facial expressions.

Figure 2. Image Examples from the AT&T Database

Different experiments were used to test the different algorithms. The training images are chosen randomly. In the first test, five images per person were used for training. Figure 3 shows the simulation results for the PCA+LDA, 2DPCA+2DLDA, MPCA+LDA, UMPCA and UMPCA+LDA algorithm against P which is the number of feature dimensionality of the subspace. Figure 3(a) plots the correct recognition rates for $\mathrm{P} = 1, \cdots, 10$, and Figure 3(b) plots those for $\mathrm{P} = 10, \cdots, 30$. From the figures, UMPCA+LDA outperforms the other method across all Ps, and also show that for UMPCA, the recognition rate saturates around P=10. This because that the variance captured by UMPCA is considerably lower than those captured by the other methods. Nonetheless, when the variance captured is too low, those corresponding features are no longer descriptive enough to contribute in classification, leading to the saturation [11]. So that in the second experiment, we discuss the test results only for $\mathrm{P} = 1, \cdots, 10$.



(a) (b)

Figure 3. Detailed Face Recognition Results on the Face Database for 5 Training Images per Class

In the second experiment, L samples are randomly selected per class for training and the rest are used for testing. The recognition results for P=1, 3, 6, 9 are listed in Table 1 for L=2, 4, 6, where the best recognition results are shown in bold. From the Table 1, UMPCA+LDA algorithm provides the best recognition accuracy among all other algorithms.

Table 1. Face Recognition Accuracy (%) on the AT&T Database

For various Ls and Ps

L	***P***	1	3	6	9
2	PCA+LDA	8.9	46.8	63.7	72.1
	2DPCA+2DLDA	11.9	53.2	66.6	73.3
	MPCA+LDA	13.7	60.2	71.7	78.7
	UMPCA	12.3	55.9	72.8	80.1
	UMPCA+LDA	**17.4**	**65.7**	**78.6**	**83.6**
4	PCA+LDA	9.8	65.8	74.5	80.2
	2DPCA+2DLDA	13.7	67	75.8	82.5
	MPCA+LDA	13.3	69.5	78.8	84.8
	UMPCA	14.4	59.3	77.5	80.4
	UMPCA+LDA	**15.7**	**70.8**	**82.2**	**88.8**
6	PCA+LDA	10.1	61.3	78.5	84.1
	2DPCA+2DLDA	14.5	72.5	81.9	86
	MPCA+LDA	14.7	73.1	87.6	89.3
	UMPCA	16	62.5	80.5	84.4
	UMPCA+LDA	**18.5**	**76.3**	**85.7**	**92.9**

4.2. The FERET Database

In this section, the performance of the proposed MPCA+GTDA algorithm is tested to compare it with that of other methods on the FERFT database. The facial recognition technology (FERFT) database, which comprises a total of 14126 gray-scale face images acquired from a total of 1199 subjects, is widely used to evaluate the face recognition problem. In this experiment, a subset of a total of 1400 faces from a total of 200 subjects is selected from the FERET database, with seven face images per subject with a resolution of 80×80 pixels. Figure 4 depicts some face images from two subjects in FERET database.

Experiments are carried out with L = 2, 4, 6, and the recognition results are listed in Table 2 for P = 2, 4, 6, 8, where the best recognition results are shown in bold. From Table 2, UMPCA+LDA algorithm provides the best recognition accuracy among all other algorithms.

Figure 4. Sample Images of Two Individual from the FERET Database

Table2. Face Recognition Accuracy (%) on the FERET Database for Various Ls and Ps

L	*P*	2	4	6	8
2	PCA+LDA	11.9	57.8	63.1	74.1
	2DPCA+2DLDA	12.3	55.3	67.6	79.7
	MPCA+LDA	12.2	62.2	79.7	82.8
	UMPCA	12.5	50.9	71.8	80.9
	UMPCA+LDA	**15.4**	**67.7**	**82.6**	**85.3**
4	PCA+LDA	10.8	65	82.9	86.2
	2DPCA+2DLDA	14.7	67.9	87.5	92.5
	MPCA+LDA	13.3	67.1	88.8	90.8
	UMPCA	15.4	58.7	87.5	90.4
	UMPCA+LDA	**16.7**	**73.4**	**90.2**	**93.8**
6	PCA+LDA	11.3	61.3	87.5	93.1
	2DPCA+2DLDA	12.5	72.5	91.9	95
	MPCA+LDA	13.7	73.1	95.6	96.3
	UMPCA	15	62.5	85.6	94.4
	UMPCA+LDA	**17.5**	**79.1**	**93.7**	**98.9**

5. Conclusions

In this paper, we improve the performance of UMPCA+LDA algorithm by optimizing the subspaces dimension and full projection. A UMPCA framework is used to extract uncorrelated discriminative features directly from tensor objects using the tensor-to-vector projection. After that projection, LDA has been applied on a new database for supervised dimensionality reduction. Experiments on face recognition demonstrate that compared with other PCA plus LDA based algorithms including the PCA+LDA, 2DPCA+2DLDA, MPCA+LDA and UMPCA, the UMPCA+LDA achieves the best results and it is particularly effective in low-dimensional spaces. The UMPCA plus LDA algorithm is promising for face recognition and other tensor object recognition, and it can be generalized to the development of other tensor subspace algorithms in the future.

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