Horizontal and Vertical 2DPCA Based Discriminant Analysis for Face Verification Using the FRGC Version 2 Database

Jian Yang[1,2] and Chengjun Liu[1]

[1] Department of Computer Science,
New Jersey Institute of Technology, Newark, NJ 07102
[2] Department of Computer Science,
Nanjing University of Science and Technology,
Nanjing 210094, P.R. China
{csjyang,chengjun.liu}@njit.edu

Abstract. This paper presents a horizontal and vertical 2D principal component analysis (2DPCA) based discriminant analysis (HVDA) method for face verification. The HVDA method, which derives features by applying 2DPCA horizontally and vertically on the image matrices (2D arrays), achieves high computational efficiency compared with the traditional PCA and/or LDA based methods that operate on high dimensional image vectors (1D arrays). The HVDA method further performs discriminant analysis to enhance the discriminating power of the horizontal and vertical 2DPCA features. Finally, the HVDA method takes advantage of the color information across two color spaces, namely, the YIQ and the YC_bC_r color spaces, to further improve its performance. Experiments using the Face Recognition Grand Challenge (FRGC) version 2 database, which contains 12,776 training images, 16,028 controlled target images, and 8,014 uncontrolled query images, show the effectiveness of the proposed method. In particular, the HVDA method achieves 78.24% face verification rate at 0.1% false accept rate on the most challenging FRGC experiment, i.e., the FRGC Experiment 4 (based on the ROC III curve).

Keywords: Principal Component Analysis (PCA), Biometric Experimentation Environment (BEE), Face Recognition Grand Challenge (FRGC), Fisher Linear Discriminant Analysis (FLD or LDA), feature extraction, face verification, biometrics, color space.

1 Introduction

Principal component analysis (PCA) is a classical technique widely used in pattern recognition. Sirovich and Kirby first applied PCA to represent pictures of human faces [1], and Turk and Pentland further proposed the well-known Eigenfaces method for face recognition [2]. Since then, PCA has become a popular method for face recognition. Due to its simplicity and robustness, PCA was chosen as the baseline algorithm for the Face Recognition Grand Challenge (FRGC) evaluation [10].

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PCA-based techniques usually operate on vectors. That is, before applying PCA, the 2D image matrices should be mapped into pattern vectors by concatenating their columns or rows. The pattern vectors generally lead to a high-dimensional space. For example, an image with a spatial resolution of 128×128 defines a 16, 384-dimensional vector space. In such a high-dimensional vector space, computing the eigenvectors of the covariance matrix is very time-consuming. Although the singular value decomposition (SVD) technique is effective for reducing computation when the training sample size is much smaller than the dimensionality of the images [1, 2], it does not help much when the training sample size becomes large. For example, for the FRGC version 2 database, the number of training images is 12,776. If all these training images are used, PCA has to compute the eigenvectors of a $12{,}776 \times 12{,}776$ matrix. It should be mentioned that the Fisherfaces method [3] also encounters the same problem as PCA does, since the Fisherfaces method requires a PCA step before applying the Fisher linear discriminant analysis (FLD or LDA).

Compared with PCA, the two-dimensional PCA method (2DPCA) [4] is a more straightforward technique for dealing with 2D images (matrices), as 2DPCA works on matrices (2D arrays) rather than on vectors (1D arrays). Therefore, 2DPCA does not transform an image into a vector, but rather, it constructs an *image covariance matrix* directly from the original image matrices. In contrast to the covariance matrix of PCA, the size of the image covariance matrix of 2DPCA is much smaller. For example, if the image size is 128×128, the *image covariance matrix* of 2DPCA is still 128×128, regardless of the training sample size. As a result, 2DPCA has a remarkable computational advantage over PCA.

The original 2DPCA method, which focuses on the columns of images and achieves the optimal image energy compression in horizontal direction, however, overlooks the information that might be contained in the image rows. In this paper, we embed both kinds of image information (in rows and columns) into a discriminant analysis framework for face recognition. Specifically, we first perform the *image-column based* 2DPCA (*horizontal 2DPCA*) and the *image-row based* 2DPCA (*vertical 2DPCA*), and then apply LDA for further feature extraction. The proposed framework is called Horizontal and Vertical 2DPCA based Discriminant Analysis (HVDA).

FRGC is the most comprehensive face recognition efforts so far organized by the US government, which consists of a large amount of face data and a standard evaluation method, known as the Biometric Experimentation Environment (BEE) system [10, 6]. The FRGC version 2 database contains both controlled and uncontrolled high resolution images, and the BEE baseline algorithm reveals that the FRGC Experiment 4 is the most challenging experiment, because it evaluates face verification performance of controlled face images versus uncontrolled face images. As the training set for FRGC version 2 database consists of 12,776 high resolution images, face recognition methods have to deal with high-dimensional images and very large data sets [11]. The proposed HVDA method has the computational advantage over the conventional PCA and/or LDA based methods, such as the Eigenfaces and the Fisherfaces methods, for dealing with high resolution images and large training data sets due to the computational efficiency of 2DPCA.

Recent research in face recognition shows that color information plays an important role in improving face recognition performance [7]. Different color spaces as well as various color configurations within or across color spaces are investigated and assessed using the FERET and the FRGC Version 2 databases. The experimental results reveal that the color configuration YQC_r, where Y and Q color components are from the YIQ color space and C_r is from the YC_bC_r color space, is most effective for the face recognition task. This color configuration, together with an LDA method, achieves 65% face verification rate at 0.1% false accept rate on FRGC Experiment 4 using the FRGC Version 2 database. This paper, thus, applies the HVDA method in the YC_bC_r color space for improving face recognition performance.

2 Horizontal and Vertical 2DPCA

This section outlines the two versions of 2DPCA, namely the horizontal 2DPCA and the vertical 2DPCA.

2.1 Horizontal 2DPCA

Given image **A**, an $m \times n$ random matrix, the goal of 2DPCA is to find a set of orthogonal projection axes $\mathbf{u}_1, \cdots, \mathbf{u}_q$ so that the projected vectors $\mathbf{Y}_k = \mathbf{A}\mathbf{u}_k$ ($k = 1, 2, \cdots, q$) achieve a maximum total scatter [4]. The *image covariance* (*scatter*) *matrix* of Horizontal 2DPCA is defined as follows [4]:

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

where M is the number of training images, $\mathbf{A}_j$ is an $m \times n$ matrix denoting the j-th training image, and $\overline{\mathbf{A}}$ is the mean image of all training images.

The optimal projection axes $\mathbf{u}_1, \cdots, \mathbf{u}_q$ are chosen as the orthonormal eigenvectors of $\mathbf{G}_t$ corresponding to q largest eigenvalues $\lambda_1, \lambda_2, \cdots, \lambda_q$ [4]. After the projection of images onto these axes, i.e.,

$$\mathbf{X}_k = (\mathbf{A} - \overline{\mathbf{A}})\mathbf{u}_k, \; k = 1, 2, \cdots, q, \tag{2}$$

we obtain a family of *principal component vectors*, $\mathbf{Y}_1, \cdots, \mathbf{Y}_q$, which form an $m \times q$ feature matrix $\mathbf{B} = [\mathbf{X}_1, \cdots, \mathbf{X}_q]$. Let $\mathbf{U} = [\mathbf{u}_1, \cdots, \mathbf{u}_q]$, and Equ. (2) becomes

$$\mathbf{B} = (\mathbf{A} - \overline{\mathbf{A}})\mathbf{U} \tag{3}$$

The feature matrix **B** contains the horizontal 2DPCA features of image **A**.

2.2 Vertical 2DPCA

If the input of 2DPCA is the transpose of the $m \times n$ image **A**, then the *image covariance matrix* defined in Eq. (1) becomes

$$\mathbf{H}_t = \frac{1}{M} \sum_{j=1}^{M} (\mathbf{A}_j - \overline{\mathbf{A}})(\mathbf{A}_j - \overline{\mathbf{A}})^{\mathrm{T}} \tag{4}$$

Now, $\mathbf{H}_t$ is an $m \times m$ non-negative definite matrix. Let $\mathbf{v}_1, \cdots, \mathbf{v}_p$ be the orthonormal eigenvectors of $\mathbf{H}_t$ corresponding to the p largest eigenvalues. After projecting $\mathbf{A}^T$ onto these eigenvectors, we have

$$\mathbf{Y}_k = (\mathbf{A} - \overline{\mathbf{A}})^T \mathbf{v}_k, \ k = 1, 2, \cdots, p \tag{5}$$

Let $\mathbf{V} = [\mathbf{v}_1, \cdots, \mathbf{v}_p]$ and $\mathbf{C}^T = [\mathbf{Y}_1, \cdots, \mathbf{Y}_p]$, then we have

$$\mathbf{C}^T = (\mathbf{A} - \overline{\mathbf{A}})^T \mathbf{V} \text{ and } \mathbf{C} = \mathbf{V}^T (\mathbf{A} - \overline{\mathbf{A}}) \tag{6}$$

$\mathbf{C} = \mathbf{V}^T (\mathbf{A} - \overline{\mathbf{A}})$ contains the vertical 2DPCA features of image **A**.

Horizontal 2DPCA operates on image rows while Vertical 2DPCA operates on image columns, as image columns become image rows after the transpose operation.

3 Horizontal and Vertical 2DPCA Based Linear Discriminant Framework

This section discusses the Horizontal and Vertical 2DPCA based Discriminant Analysis (HVDA) method, which applies the YQC_r color configuration defined by combining the component images across two color spaces: *YIQ* and YC_bC_r.

3.1 Fisher Linear Discriminant Analysis

The between-class scatter matrix $\mathbf{S}_b$ and the within-class scatter matrix $\mathbf{S}_w$ are defined as follows [13]

$$\mathbf{S}_b = \frac{1}{M} \sum_{i=1}^{c} l_i (\mathbf{m}_i - \mathbf{m}_0)(\mathbf{m}_i - \mathbf{m}_0)^{\mathrm{T}} \tag{7}$$

$$\mathbf{S}_w = \frac{1}{M} \sum_{i=1}^{c} \frac{l_i}{l_i - 1} \sum_{j=1}^{l_i} (\mathbf{x}_{ij} - \mathbf{m}_i)(\mathbf{x}_{ij} - \mathbf{m}_i)^{\mathrm{T}} \tag{8}$$

where $\mathbf{x}_{ij}$ denotes the j-th training sample in class i; M is the total number of training samples, l_i is the number of training samples in class i; c is the number of classes; $\mathbf{m}_i$ is the mean of the training samples in class i; $\mathbf{m}_0$ is the mean across all training samples.

If the within-class scatter matrix $\mathbf{S}_w$ is nonsingular, the Fisher discriminant vectors $\boldsymbol{\varphi}_1, \boldsymbol{\varphi}_2, \cdots, \boldsymbol{\varphi}_d$ can be selected as the generalized eigenvectors of $\mathbf{S}_b$ and $\mathbf{S}_w$ corresponding to the d ($d \le c-1$) largest generalized eigenvalues, i.e., $\mathbf{S}_b \boldsymbol{\varphi}_j = \lambda_j \mathbf{S}_w \boldsymbol{\varphi}_j$, where $\lambda_1 \ge \lambda_2 \ge \cdots \ge \lambda_d$. These generalized eigenvectors can be obtained using the classical two-phase LDA algorithm [13].

In small sample size cases, the within-class scatter matrix $\mathbf{S}_w$ is singular because the training sample size is smaller than the dimension of the image vector space. To address this issue of LDA, A PCA plus LDA strategy, represented by Fisherfaces [3], was developed. In Fisherfaces, $N-c$ principal components are chosen in the PCA phase and then LDA is implemented in the $N-c$ dimensional PCA space.

To improve the generalization performance of the Fisherfaces method, the Enhanced Fisher Model (EFM) is developed [5]. The EFM method applies a criterion to choose the number of principal components in the PCA to avoid overfitting of the PCA plus LDA framework. In particular, a proper balance should be preserved between the *data energy* and the *eigenvalue magnitude* of the within-class scatter matrix. While the spectral energy should be preserved, the trailing eigenvalues of the within-class scatter matrix should not be too small in order to prevent the amplification of noise. It should be pointed out that this criterion is still applicable even when the within-class scatter matrix $\mathbf{S}_w$ is nonsingular.

3.2 Horizontal and Vertical 2DPCA Based Discriminant Analysis (HVDA)

In our algorithm, the horizontal feature matrix **B** derived by Horizontal 2DPCA and the vertical feature matrix **C** from Vertical 2DPCA are processed, respectively, by the EFM method for further feature extraction. The extracted features then apply the cosine similarity measure to calculate the similarity score between any pair of query and target images. After similarity score normalization, two kinds of normalized scores, i.e., the normalized scores from the horizontal discriminant features and the normalized scores from the vertical discriminant features, are fused at the classification level. The proposed HVDA framework is illustrated in Fig. 1. Some details on cosine similarity measure, score normalization and fusion strategy are presented below.

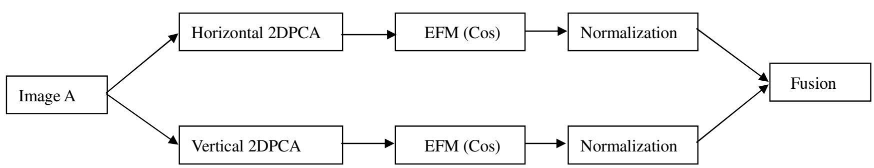


Fig. 1. Illustration of the proposed HVDA framework

The cosine similarity measure between two vectors $\mathbf{x}$ and $\mathbf{y}$ is defined as follows:

$$\delta_{\cos}(\mathbf{x},\mathbf{y}) = \frac{\mathbf{x}^T\mathbf{y}}{\|\mathbf{x}\|\cdot\|\mathbf{y}\|} \tag{9}$$

where $\|\cdot\|$ is the notation of Euclidian norm.

Suppose that there are M target images $\mathbf{x}_1,\mathbf{x}_2,\cdots\mathbf{x}_M$. For a given query image $\mathbf{y}$, we can obtain a similarity score vector $\mathbf{s}=[\mathbf{s}_1,\mathbf{s}_2,\cdots,\mathbf{s}_M]^T$ by calculating the Cosine similarity measure between each pair of $\mathbf{x}_i$ and $\mathbf{y}$. Based on the horizontal discriminant features, we can obtain the horizontal similarity score vector $\mathbf{s}^h$ and, based on vertical discriminant features, we can calculate the vertical similarity score vector $\mathbf{s}^v$. Each score vector is normalized by means of the *z*-score normalization technique [8]. The normalized scores are as follows:

$$\mathbf{s}_i^{new} = \frac{\mathbf{s}_i - \mu}{\sigma}\,, \tag{10}$$

where μ is the mean of $\mathbf{s}_1, \mathbf{s}_2, \cdots, \mathbf{s}_M$ and σ is their standard deviation. After score normalization, the horizontal similarity score vector $\mathbf{s}^h$ and the vertical similarity score vector $\mathbf{s}^v$ are fused using the sum rule, that is, the final similarity score vector is $\mathbf{s}^h + \mathbf{s}^v$.

3.3 HVDA in YQC_r Color Space

Recent research on color spaces for face recognition reveals that some color configurations, such as YQC_r, can significantly improve the FRGC baseline performance [7]. YQC_r is defined by combining the component images across two color spaces: YIQ and YC_bC_r.

YIQ is a color space formerly used in the National Television System Committee (NTSC) television standard [14]. The Y component represents the luminance information and I and Q represent the chrominance information. Remember that in the YUV color space, the U and V components can be viewed as x and y coordinates within the color space. I and Q can be viewed as a second pair of axes on the same graph, rotated 33° clockwise. Therefore, IQ and UV represent different coordinate systems on the same plane. The YIQ system is intended to take advantage of human color-response characteristics. YIQ is derived from the corresponding RGB space as follows:

$$\begin{bmatrix} Y \\ I \\ Q \end{bmatrix} = \begin{bmatrix} 0.2990 & 0.5870 & 0.1140 \\ 0.5957 & -0.2745 & -0.3213 \\ 0.2115 & -0.5226 & 0.3111 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{11}$$

The YC_bC_r color space is developed as a part of the ITU-R Recommendation B.T. 601 for digital video standard and television transmissions [14]. It is a scaled and offset version of the YUV color space. Y is the luminance component and C_b and C_r are the blue and red chrominance components, respectively. YC_bC_r is derived from the corresponding RGB space as follows:

$$\begin{bmatrix} Y \\ C_b \\ C_r \end{bmatrix} = \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} + \begin{bmatrix} 65.4810 & 128.5530 & 24.9660 \\ -37.7745 & -74.1592 & 111.9337 \\ 111.9581 & -93.7509 & -18.2072 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{12}$$

Our HVDA method first works on the three color components Y, Q and C_r to derive the similarity scores, and then fuses the normalized similarity scores using the sum rule.

4 Experiments

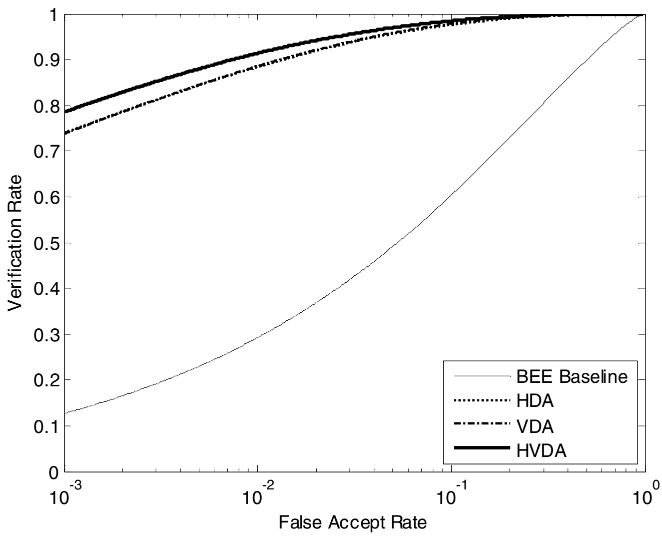
We evaluate our HVDA method using the FRGC version 2 database and the associated Biometric Experimentation Environment (BEE) [10]. The FRGC version 2 database contains 12,776 training images, 16,028 controlled target images, and 8,014 uncontrolled query images for the Experiment 4. The controlled images have good image quality, while the uncontrolled images display poor image quality, such as large illumination variations, low resolution of the face region, and possible blurring. It is these uncontrolled factors that pose the grand challenge to the face recognition performance. The BEE system provides a computational-experimental environment to support a challenge problem in face recognition or biometrics, which allows the description and distribution of experiments in a common format. The BEE system uses the PCA method that has been optimized for large scale problems as a baseline algorithm, which applies the *whitened cosine distance* measure for its nearest neighbor classifier [10]. The BEE baseline algorithm shows that Experiment 4, which is designed for indoor controlled single still image versus uncontrolled single still image, is the most challenging FRGC experiment. We therefore choose FRGC Experiment 4 to evaluate our method. In our experiment, the face region of each image is first cropped from the original high-resolution still images and resized to 64x64. Fig. 2 shows some example images used in our experiments.

Fig. 2. Example cropped images in FRGC version 2

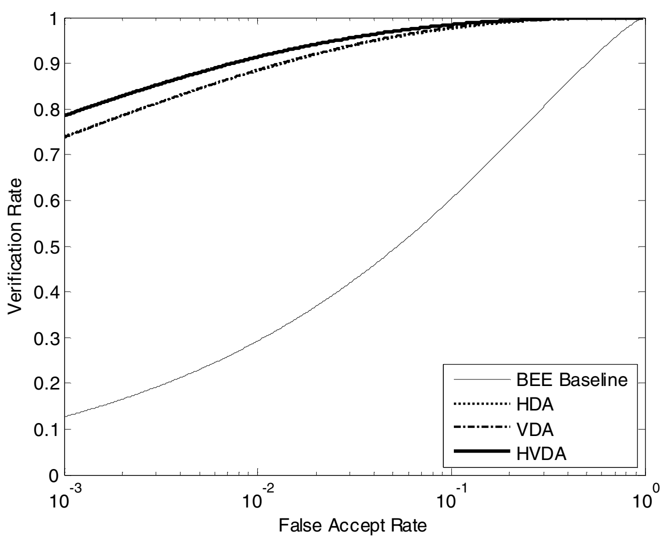
According to the FRGC protocol, the face recognition performance is reported using the Receiver Operating Characteristic (ROC) curves, which plot the Face Verification Rate (FVR) versus the False Accept Rate (FAR). The ROC curves are automatically generated by the BEE system when a similarity matrix is input to the system. In particular, the BEE system generates three ROC curves, ROC I, ROC II, and ROC III, corresponding to images collected within semesters, within a year and between semesters, respectively [12]. The similarity matrix stores the similarity score of every query image versus target image pair. So, the size of the similarity matrix is $T \times Q$, where T is the number of target images and Q is the number of query images.

The proposed HVDA method is trained using the standard training set of the FRGC Experiment 4. In the 2DPCA phase, we choose q=19 in horizontal 2DPCA transform and p=19 in vertical 2DPCA transform, respectively. In the EFM phase, we choose 1000 principal components in the PCA step and 220 discriminant features in the LDA step. The resulting similarity matrix is analyzed by the BEE system and the three ROC curves generated are shown in Fig. 3. The verification rates (%) when the False Accept Rate is 0.1% are listed in Table 1. Table 1 also includes the verification rates reported in recent papers for comparison [7, 9]. These results show that the

HVDA method achieves better face verification performance than those reported before. In addition, we can see that the fusion of Horizontal 2DPCA based Discriminant Analysis (HDA) and Vertical 2DPCA based Discriminant Analysis (VDA) can significantly improve the verification performance.

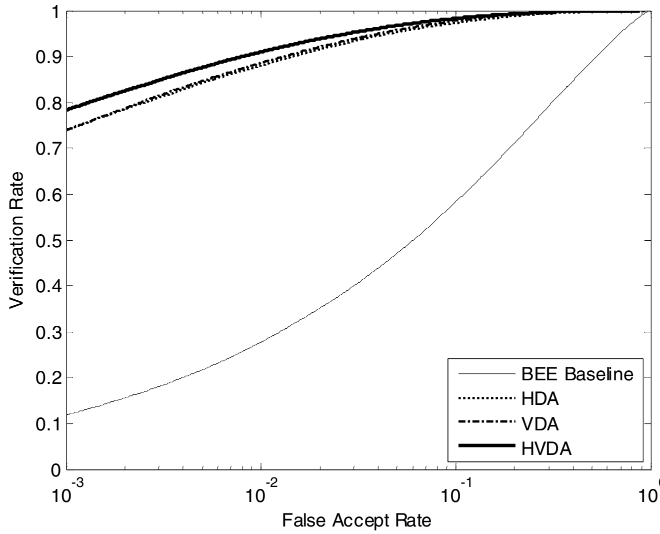


(ROC I)



(ROC II)

Fig. 3. ROC curves corresponding to the HDA, VDA, and HVDA methods and the BEE Baseline algorithm



(ROC III)

Fig. 3. (*continued*)

Table 1. Verification rate (%) comparison when the False Accept Rate is 0.1%

Method	ROC I	ROC II	ROC III
BEE Baseline	13.36	12.67	11.86
YQC_r +LDA [7]	64.47	64.89	65.21
MFM-HFF [9]	75.70	75.06	74.33
HVDA	**78.65**	**78.50**	**78.24**
HDA	73.90	73.96	73.89
VDA	73.38	73.73	73.97

5 Conclusions

This paper presents a *horizontal* and *vertical 2DPCA* based Discriminant Analysis (HVDA) method for face verification. The HVDA method first integrates the horizontal and vertical 2DPCA features, and then applies the Enhanced Fisher Model (EFM) to improve its discriminatory power. The HVDA method further takes advantage of the color information across two color spaces, *YIQ* and YC_bC_r for enhancing its performance. The proposed method has been tested on FRGC Experiment 4 using the FRGC version 2 database. Experimental results show the feasibility of the proposed method. In particular, the HVDA method achieves 78.24% face verification rate at 0.1% false accept rate based on the ROC III curve.

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