

An Augmented Linear Discriminant Analysis Approach for Identifying Identical Twins with the Aid of Facial Asymmetry Features

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Abstract

In this work, we have proposed an Augmented Linear Discriminant Analysis (ALDA) approach to identify identical twins. It learns a common subspace that not only can identify from which family the individual comes, but also can distinguish between individuals within the same family. We evaluate the ALDA against the traditional LDA approach for subspace learning on the Notre Dame twin database. We have shown that the proposed ALDA method with the aid of facial asymmetry features significantly outperforms other well-established facial descriptors (LBP, LTP, LTrP), and the ALDA subspace method does a much better job in distinguishing identical twins than LDA. We are able to achieve **48.50%** VR at 0.1% FAR for identifying family membership of identical twin individuals in the crowd and an averaged **82.58%** VR at 0.1% FAR for verifying identical twin individuals within the same family, a significant improvement over traditional descriptors and traditional LDA method.

1. Introduction

Identical twins are genetically determined to have highly similar appearance. The state-of-the-art facial recognition algorithms and feature descriptors aim to maximize the similarities among all the facial images from one subject, and at the same time maximize the dissimilarities among different subject classes. But they will run into troubles in the case of identical twins since images from different subject classes have highly similar images. Even though identical twins have highly similar faces, we believe that the micro asymmetry features can still be very different between identical twins. As shown in Figure 2, photographers have heuristically shown that the human face is asymmetric [2]. If one side of the face is mirrored to synthesize a new face, the mirrored look using left side appears to be very different from the one using the right side of the face. From this novel

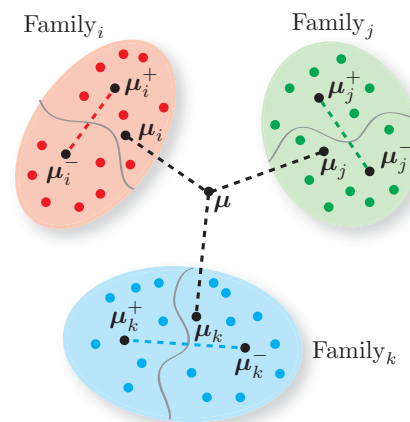


Figure 1. Idea of the proposed ALDA method, where we maximize the distance between family mean μ_i and the global mean μ (black dash lines), as well as the distance between individuals mean face μ_i^+ and μ_i^- within each family (colored dash lines).

viewpoint, we will investigate the facial asymmetry biometric and its performance in distinguishing identical twins.

The two major contributions are: (1) We have developed a novel subspace learning method called Augmented Linear Discriminant Analysis. It learns a common subspace which succeeds in both determining the family membership of test individual and the actual identify within the family. (2) We have constructed facial asymmetry features that capture the minute difference between identical twins and such features yield much better identification performance than many well-established facial descriptors like local binary patterns, local tertiary patterns, and local tetra patterns.

Rest of this paper is organized as follows: Section 2 lists several prior work on twin recognition. We detail the proposed method in Section 3. In Section 4, various facial asymmetry features are described. Facial alignment method is introduced in Section 5. Section 6 gives a brief description of the database. Section 7 details the identification and verification experiments respectively. Finally, we present some conclusions of our work in Section 8.



Figure 2. Face synthesis by mirroring one side of the face [2]. Faces do look very different when mirroring from different side.

2. Related Work

The first study on identical twin biometrics can be dated back to Sun *et al.* [19] in 2010. They collected multiple biometric traits (fingerprint, face, and iris) of 66 pairs of twins (51 pairs of identical/monozygotic twins and 15 pairs of non-identical/dizygotic twins) at the fourth Annual Festival of Beijing Twins Day in China. Their multi-modal experiments show that face recognition (using Cognitec FaceVACS system) performs the worst in distinguishing identical twins compared with fingerprints and iris. However, the low performance of face recognition system may be due to the non-ideal image quality. The facial images are captured using a USB camera with VGA resolution under non-uniform background and some illumination variations. The subjects are mostly teenagers (average age being 16.8) which makes identical twin recognition a harder problem since the older they are, the more distinguishable facial patterns will show.

Phillips *et al.* [14] carried out by far the most extensive investigation of face recognition performance on identical twins. The experimental dataset consists of images taken from 126 pairs of identical twins (252 people) on the same day at the Twins Days Festival [3] in Twinsburgh, Ohio in August 2009 as well as 120 pairs (240 people) at the same event one year apart in August 2010. Among all the subjects collected, 24 pairs (48 people) came both year. They evaluated the face recognition performance using three of the top submissions to the Multiple Biometric Evaluation (MBE) 2010 Still Face Track [1] in order to measure the performance of the state-of-the-art commercial face recognition systems on distinguishing twins. The commercial face recognition technology providers are [7]: (1) Cognitec, (2) Dalian University of Technology, (3) L1 Identity Solutions, (4) NEC, (5) Neurotechnology, (6) PittPatt, (7) Sagem, (8) Surrey University, (9) Toshiba, (10) Tsinghua University. The results showed that the best performance on distinguishing identical twins would require ideal conditions (minimum time lapse/same day collection, studio lighting conditions and neutral expression), and when the conditions are less ideal (with a time lapse/one year apart collection, illumination variations, and expression variations), the performance significantly drops. They also found out that gender does not affect the performance while age does. Their results demonstrated that it is easier to distin-

guish identical twins over 40 years old than under.

Srinivas *et al.* [18] investigated the usefulness of facial marks as biometric signatures in distinguishing identical twins. They defined and characterized a set of facial marks (*e.g.* mole, freckle, birthmark, scar, pimple and so forth) that are manually annotated by three observers. Then they characterized twin face images using geometric distribution of annotated facial marks along with their respective categories using weighted bipartite graph matching technique. Their experiments on twin dataset of 295 images from 157 unique subjects (Twins Days Festival [3] in Twinsburgh, Ohio) showed that the position of certain facial marks appears to be similar for twins.

Biswas *et al.* [6] explored human capacity to distinguish between identical twins. They conducted experiments with different viewing times and imaging conditions, on 186 twin subjects collected from Twins Days Festival [3]. Their study showed that humans can perform the task significantly better if they are given sufficient time and are prone to make more mistakes when images differ in imaging conditions. The response from observers in their experiment suggested that humans look for facial marks such as moles, freckles, scars, *etc.* to make their decision and perform worse when the images lack such marks.

More recently, Pruitt *et al.* [15] adopted three commercial face matchers (Cognitec, VeriLook, and PittPatt) and a baseline matcher employing Local Region PCA, to distinguish between identical twins. The images of subjects were acquired at the Twins Days Festival [3] in 2009 and 2010 with different expressions (neutral and smiling). They carried out extensive experiments (5,800 images from 2009 and 1,635 images from 2010) using aforementioned face matchers and examined three covariates (expression, lighting and eyewear). They concluded that the most significant variables that can affect recognition systems seems to be expression and lighting variations. They also claimed that the glasses would not affect much since the eye region is masked in their experiments.

Klare *et al.* [9] studied the distinctiveness of different facial features (multi-scale local binary patterns, scale invariant feature transform and facial marks) to distinguish between identical twins. The experimental results indicated features that perform well in distinguishing identical twins are sometimes inconsistent with the features that best dis-

tinguish two non-twin faces. They analyzed different facial components, *i.e.* eyes, eyebrows, nose and mouth, with the aid of Active Shape Model and PittPatt Face Recognition to detect and align facial landmarks. They adopted the random sampling linear discriminant analysis (RS-LDA) method for discriminative subspace learning and later modified to be Twin RS-LDA that maximizes the difference energy between twin pairs as opposed to the difference energy between all pairs of subjects. Their evaluation was carried out on 87 pairs of identical twins (174 subjects) from Twins Days Festival [3]. Their research showed that the saliency of facial features alters from standard face recognition tasks to distinguishing between identical twins and by fusing face matching scores, more twins can be distinguished.

In this work, however, we tackle the problem from a different and novel point of view: the facial asymmetry analysis between identical twins. With the aid of proposed subspace modeling method called augmented linear discriminant analysis, we focus on comparing and analyzing the facial asymmetry features against traditional descriptors under the scenario of identifying and verifying identical twins.

3. Augmented Linear Discriminant Analysis

We have proposed the Augmented Linear Discriminant Analysis (ALDA), a new approach for discriminant subspace learning, especially for identifying identical twins.

We start by reviewing the basics in Fisher Linear Discriminant Analysis (LDA). LDA [5] aims to find the projection such that the ratio of the between-class scatter and the within-class scatter is maximized. The between-class scatter \mathbf{S}_B and the within-class scatter \mathbf{S}_W are defined as:

$$\mathbf{S}_B = \sum_{i=1}^C N_i (\boldsymbol{\mu}_i - \boldsymbol{\mu})(\boldsymbol{\mu}_i - \boldsymbol{\mu})^\top \quad (1)$$

$$\mathbf{S}_W = \sum_{i=1}^C \sum_{\mathbf{x}_k \in C_i} (\mathbf{x}_k - \boldsymbol{\mu}_i)(\mathbf{x}_k - \boldsymbol{\mu}_i)^\top \quad (2)$$

where $\boldsymbol{\mu}_i$ is the mean image of class C_i , $\boldsymbol{\mu}$ is the mean image of all the images, C is the total class number, and N_i is the number of images in class C_i .

The optimal projection \mathbf{w} is chosen such that the Fisher criterion is satisfied, *i.e.*, the ratio of between-class scatter and within-class scatter is maximized:

$$\mathbf{w}^* = \arg \max_{\mathbf{w}} \frac{\mathbf{w}^\top \mathbf{S}_B \mathbf{w}}{\mathbf{w}^\top \mathbf{S}_W \mathbf{w}} \quad (3)$$

where $\{\mathbf{w}_i | i = 1, 2, \dots, m\}$ is a set of generalized eigenvectors of \mathbf{S}_B and \mathbf{S}_W , corresponding to the m largest generalized eigenvalues $\{\lambda_i | i = 1, 2, \dots, m\}$. The upper bound of m is $C - 1$, where again C is the total number of classes. This generalized eigenvalue problem can be shown as:

$$\mathbf{S}_B \mathbf{w}_i = \lambda_i \mathbf{S}_W \mathbf{w}_i \implies \mathbf{S}_W^{-1} \mathbf{S}_B \mathbf{w}_i = \lambda_i \mathbf{w}_i \quad (4)$$

This only holds when \mathbf{S}_W is invertible. However, in the face recognition problem, \mathbf{S}_W is very often singular due to the fact that the rank of \mathbf{S}_W is at most $(N - C)$, where N is the total number of training images, which is much smaller than the image dimension. To overcome this problem and make LDA work, a separate PCA step is applied to reduce the dimensionality of the images to $(N - C)$ and then standard LDA is executed to reduce the dimension to $(C - 1)$.

LDA maximizes the between-class scatter \mathbf{S}_B , which essentially tries to push each class mean $\boldsymbol{\mu}_i$ to be as far from the global mean $\boldsymbol{\mu}$ as possible. The within-class scatter is supposed to be minimized, which means that all the data points from the same class should be as close to the class mean as possible, which explains the compactness of each class. However, in the case of identifying identical twins, the discriminant subspace learned should be capable of: (1) identifying from which family this subject \mathbf{x}_i comes, and (2) identifying the individual within that particular family.

To simultaneously accomplish the two tasks, we augment the LDA objective function as follows:

$$J(\mathbf{w}) = \max_{\mathbf{w}} \frac{\mathbf{w}^\top (\mathbf{S}_B + \mathbf{S}'_B) \mathbf{w}}{\mathbf{w}^\top \mathbf{S}_W \mathbf{w}} \quad (5)$$

where \mathbf{S}'_B is defined as:

$$\mathbf{S}'_B = \sum_{i=1}^C N_i (\boldsymbol{\mu}_i^+ - \boldsymbol{\mu}_i^-)(\boldsymbol{\mu}_i^+ - \boldsymbol{\mu}_i^-)^\top \quad (6)$$

The $\boldsymbol{\mu}_i^+$ and $\boldsymbol{\mu}_i^-$ denote the mean of two individuals from the same family respectively. The idea of ALDA is depicted in Figure 1, where we not only want to push each family away from the global mean, but also, push each individual in the same family to be far from each other. In other words, we want to maximize the totally length of the black dash lines as well as all the colored dash lines. The solution to the new optimization is again obtained by the generalized eigen-value problem with augmented scatter matrix.

4. Facial Asymmetry Features

In this section, we describe several facial asymmetry features that are later proven to be capable of distinguishing between identical twins and yield better classification results than traditional facial descriptors: local binary patterns (LBP) [13], local tertiary patterns (LTP) [20] and local tetra patterns (LtrP) [12]. The final asymmetry features are built by concatenating the following individual asymmetry features to describe the asymmetry level of a human face.

Kurtosis We can view each row of the face image as one random variable x_i which takes many different values according to that particular row, then the entire image can be represented by joint distribution of all x_i . Essentially, the joint distribution is $f_{\mathbf{x}}(x_1, x_2, \dots, x_n) = f_{\mathbf{x}}(\mathbf{x})$. If the

face is symmetric, we can say that each x_i should follow a Gaussian distribution, and x_i should follow some skewed distribution if the face is asymmetric. Based on this, a symmetric face can be described as a multivariate Gaussian distribution as follows:

$$f_{\mathbf{x}}(\mathbf{x}) = \frac{1}{(2\pi)^{k/2} |\Sigma|^{1/2}} \exp\left(\frac{(\mathbf{x} - \mu)^\top \Sigma^{-1} (\mathbf{x} - \mu)}{-2}\right) \quad (7)$$

Next, we employ kurtosis as a measure of nongaussianity in the joint distribution:

$$\text{kurt}(x_i) = E\{x_i^4\} - 3(E\{x_i^2\})^2 \quad (8)$$

where the random variable here have zero mean. The kurtosis ensemble is a good indicator for face asymmetry.

Negentropy Similar to the kurtosis method, negentropy is also widely used as a measure for nongaussianity. Negentropy $J(\mathbf{x})$ is a normalized differential entropy defined as follows:

$$J(\mathbf{x}) = H(\mathbf{x}_{Gauss}) - H(\mathbf{x}) \quad (9)$$

where $H(\mathbf{x}) = -\int p_x(\eta) \log p_x(\eta) d\eta$ is the entropy of a random vector \mathbf{x} and \mathbf{x}_{Gauss} is a Gaussian random vector of the same correlation and covariance matrix as \mathbf{x} . The reason we benchmark the entropy against the entropy of a Gaussian distribution is because that a Gaussian variable has the *least* entropy among all random variables of equal variance according to one of the fundamental results in information theory. Therefore, we can also utilize negentropy as a measure of face asymmetry.

Harris-Laplace Detector We analyze the mid-level facial asymmetry using the Harris detector. The face image is divided into multiple 8×8 subregions, and after the Harris detector scans the entire image, the number of keypoints located in each of the subregions is served as an indicator of facial asymmetry. Intuitively, if the face is near-symmetric, the number of keypoints in any subregion should be close to the number of keypoints in the mirrored counterpart.

When the traditional 2D Harris detector is combined with Gaussian scale space representation, the Harris-Laplace detector is formed, which is scale-invariant. The key points localized by Harris detector are rotation and illumination invariant using the second moment matrix below:

$$M(\mathbf{x}) = \sum_{x,y} w(x,y) \begin{bmatrix} I_x^2(\mathbf{x}) & I_x I_y(\mathbf{x}) \\ I_x I_y(\mathbf{x}) & I_y^2(\mathbf{x}) \end{bmatrix} \quad (10)$$

where $w(x,y)$ is the isotropic Gaussian weighting function, and I_x, I_y are the pixel intensity derivatives in the x and y direction at point \mathbf{x} .

When incorporating with Gaussian scale space representation, the scale-adapted second moment matrix becomes:

$$M(\mathbf{x}, \sigma_I, \sigma_D) = \sigma_D^2 g(\sigma_I) \otimes \begin{bmatrix} L_x^2(\mathbf{x}, \sigma_D) & L_x L_y(\mathbf{x}, \sigma_D) \\ L_x L_y(\mathbf{x}, \sigma_D) & L_y^2(\mathbf{x}, \sigma_D) \end{bmatrix}$$

where $L_x(\mathbf{x}, \sigma_D)$ and $L_y(\mathbf{x}, \sigma_D)$ are the respective derivatives applied to the Gaussian-smoothed image using a kernel with scale σ_D , and σ_I denotes the current scale at which the Harris corner points are detected.

Symmetry Distance After we divide the face image into multiple subregions like in the Harris-Laplace detector method, we can compute the distance between pixels in one subregion with that in the mirrored subregion. We utilize the L_p norm as distance measure, where $p = 1, 2, \dots, k$. So the symmetric distance (SD) is computed as:

$$\text{SD}_p^{(r)}(\mathbf{x}^{(r)}, \mathbf{x}'^{(r)}, p) = \left(\sum_{i=1}^{n^2} |x_i^{(r)} - x_i'^{(r)}|^p \right)^{1/p} \quad (11)$$

where $\mathbf{x}^{(r)}$ and $\mathbf{x}'^{(r)}$ are pixels inside mutually mirrored subregions denoted as r , and there are totally n^2 pixels inside each subregion.

Additionally, we add the Frobenius norm as the similarity measure between the two matrix from the paired subregions using:

$$\text{SD}_F^{(r)}(\mathbf{x}^{(r)}, \mathbf{x}'^{(r)}) = \sqrt{\sum_{i=1}^n \sum_{j=1}^n |x_{ij}^{(r)} - x_{ij}'^{(r)}|^2} \quad (12)$$

So the final symmetry distance descriptor for subregion r is nothing but the concatenation of all the $\text{SD}_p^{(r)}$ and $\text{SD}_F^{(r)}$. We can scan through all the subregions to obtain final SD descriptor for the entire face as a measure asymmetry.

Fourier Analysis The frequency domain facial asymmetry representation [11] analyzes the Fourier domain phase spectra. Under a frequency domain representation, the frequency spectrum of the signal contains two components at each frequency: magnitude and phase. In the case of 2D image, the phase component captures more of the image information or intelligibility than the magnitude component, so that it is very important when constructing the image [8]. The significance of phase component has also been applied to biometrics [16].

The Fourier transform has symmetry properties that constitute the frequency domain facial asymmetry representation. Any 1D sequence $x(n)$ can be expressed as the sum of an even part $x_e(n)$ (symmetry part), and an odd part $x_o(n)$ (asymmetry part): $x(n) = x_e(n) + x_o(n)$, where $x_e(n) = \frac{x(n) + x(-n)}{2}$ and $x_o(n) = \frac{x(n) - x(-n)}{2}$. When a Fourier transform is applied on a real sequence $x(n)$, the even part $x_e(n)$ transforms to the real part of the Fourier transform and the odd part $x_o(n)$ transforms to the imaginary part. In [11], three asymmetry features were defined based on the imaginary components:

- *I-Face*: frequency-wise imaginary components of Fourier transform of each row slice, and the resulting

size of the I-Face feature should be $m \times \frac{n}{2}$ where the original facial image is of size $m \times n$. The halving of the second dimension is due to the symmetry property of the Fourier transform.

- *Ave I-Face*: frequency-wise imaginary components of Fourier transform of averages of two-row slices. The resulting feature size is $\frac{m}{2} \times \frac{n}{2}$.
- *E-Face*: energy of the imaginary components of the Fourier transform of row slices of the face, and the resulting feature is a vector of length m .

For these three features, the higher their values, the greater level of asymmetry is shown in the image, and vice versa. The averaging over two rows will smooth our the noise to some extent, but averaging over too many rows will lose information and thus jeopardize the intelligibility of the feature. The authors in [11] claimed that the two-row smoothing is optimally selected after experiments. Here we will follow the convention of two-row averaging.

In addition to the aforementioned three features from the imaginary components, we will add the counterparts from the real components. What’s more, we want to see how averaging works on E-Faces, so we will add two-row averaging energy face to both imaginary and real components feature. Finally, we would like to see how the ratio between imaginary energy and real energy can play a role in distinguishing identical twins. With this modification, we now have 10 feature types as shown in Table 1:

5. Facial Image Alignment

In this section, we introduce a two-step coarse-to-fine alignment procedure for preprocessing the facial image.

5.1. Coarse Alignment of Facial Image

We first use active shape model (ASM) [17] to perform a loose crop of the face region. The ASM automatically detects 79 facial landmarks as in Figure 3 (a), and by using these landmarks locations, we can rotate and generate a loose crop of face of size 700×700 as in Figure 3 (b).

5.2. Fine Alignment of Facial Image

Once the loose crop is obtained, we will then generate the tight crop which will be used for the experiments.

The reason why we adopt a two-step coarse-to-fine alignment procedure is that we are going to investigate the facial asymmetry biometrics in distinguishing between identical twins, and these features need to be extracted from a perfectly aligned faces. As illustrated in Figure 3 (b), the ASM has already coarsely aligned the face crop by making the line connecting centers of two eyes horizontal and by making the nose tip intersect central vertical line. Next, we will initialize a tight crop window as shown in Figure 3 (c) which

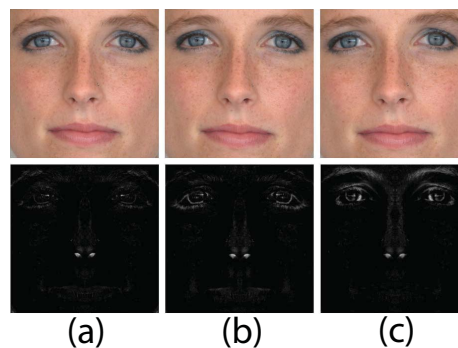


Figure 4. Using D-Face as measurement to find the optimal alignment. (a) optimally aligned face, (b) less optimally aligned face, and (c) worst aligned among the three.

is centered and of size 640×640 , so the margin on all sides is 30 pixels. Then, by rotating this tight crop window and horizontally shift it, we are trying to find the optimal position of the window so that the tightly cropped face can be optimally aligned.

We will adopt a spatial domain asymmetry indicator D-Face [10] as a measurement of fine alignment. D-Face is the absolute difference between the original face image with its flipped version (flipped about the central vertical line). Examples of D-Face of three alignments of the same face is shown in Figure 4. Although the 3 alignments show only slight difference, the D-Face can tell us that image (a) is the best aligned and (c) is the worst aligned since it has the most white color in the D-Face (highest energy).

Figure 3 shows the rotation and horizontal shift of the tight crop window. Figure 3 (c) and (d) demonstrate 2 different rotations on the same horizontal shift offset and Figure 3 (d)(e)(f) show the same rotation on 3 different horizontal shift offsets.

Since the objective function (D-Face) to be minimized is not a convex function of rotation angle θ and horizontal shift offset δ , we cannot use gradient descent method to find the optimal solution for θ and δ . Instead, a simple greedy search method will be applied to find the best combination of the two parameters. In our evaluation, θ and δ are confined to be a small range because slight rotation and shift will lead to optimal solution.

6. Database

The dataset we evaluate our algorithm on is ND-TWINS-2009-2010 database [4]. Face images were acquired in 2009 and 2010 at the Twins Days Festival in Twinsburg, Ohio [3]. The number of images collected are as follows [14]: “the 2009 collection yielded 17,486 face stills from 252 twin subjects (126 pairs), of whom 34 (17 pairs) appeared in each of the two days of the Festival. In 2010, data collection yielded 6863 face stills from 240 twin subjects (120

I-Face	Average-I-Face	Energy-I-Face	Average-Energy-I-Face	Energy-I-Face / Energy-R-Face
R-Face	Average-R-Face	Energy-R-Face	Average-Energy-R-Face	Energy-R-Face / Energy-I-Face

Table 1. The 10 facial asymmetry and symmetry features used in our experiments to distinguish between identical twins.



Figure 3. Rotate and horizontally shift the tight crop window in order to find the optimal alignment. (a) Localizing 79 landmark points using ASM, (b) loose crop image from ASM, (c) tight crop window initialization, (d)(e) 2 different rotations on the same horizontal shift offset, (e)(f)(g) same rotations on 3 different horizontal shift offsets.

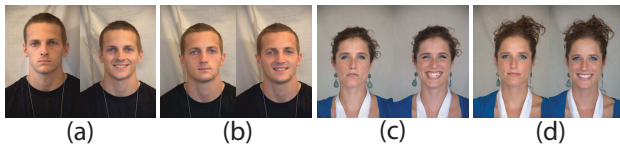


Figure 5. Example twin images from Notre Dame twin database. (a) and (b) are identical twins, (c) and (d) are identical twins. Two expressions: blank stare (neutral) and happy (smiling) are shown for each person. These four images are frontal, no glass and taken inside.

pairs), of whom 10 (5 pairs) came both days. There were 48 twins (24 pairs) who participated in both 2009 and 2010 acquisitions, and two twin subjects (one pair) participated in both days of both years. Finally, one set of identical triplets participated in 2010". Images are taken in three lighting environment: (1) inside the tent under studio lighting, (2) outside sunny, and (3) outside rainy. Two facial expressions are blank stare (neutral face) and happy (smiling face). Subjects are asked to wear no glass, and to wear two different eyepieces: glass and prism (thick glass). Different poses with yaw ranging from 0-180 degrees are also taken. The majority of the subjects are Caucasians. Examples of two twin pairs are shown in Figure 5.

7. Experiments for Identifying Identical Twins

7.1. Experiment I: Identify Identical Twins in the Crowd

In the first experiment, we aim at identifying identical twin individual in the crowd. By using the proposed Augmented Linear Discriminant Analysis method for subspace learning, we evaluate the performance of asymmetry features against traditional facial descriptors on traditional LDA method.

Experimental Setup We carry out the 1-to-1 verification matching between 1 image and all the remaining images in the database. We train the proposed ALDA and

LDA subspace using the same training images, with class label information. The entire database is partitioned with 30% training and 70% testing. We evaluate the asymmetry features against raw pixel and LBP/LTP/LTrP. The experimental results will be a set of receiver operating characteristic (ROC) curves along with the verification rate (VR) at 0.1% (0.001) false accept rate (FAR) and the equal error rate (EER) reported.

In this experiment, we utilize all the images from the ND-TWINS-2009-2010 database that are frontal. As mentioned in Section 6, the whole database includes images of various poses, different lighting conditions (inside, sunny and rainy), different eyepieces (no glass, glass and prism), and two expressions (blank stare and happy). Since in this paper we are investigating the facial asymmetry features in distinguishing between identical twins, we confine ourselves to use only the frontal face images.

The images are aligned and resized to 128×128 . After feature extraction, and projection onto the leaned discriminant subspace, a normalized cosine distance (NCD) is adopted to compute the distance between the projected feature vectors \mathbf{x} and \mathbf{y} from different images using: $NCD = d(\mathbf{x}, \mathbf{y}) = \frac{-\mathbf{x} \cdot \mathbf{y}}{\|\mathbf{x}\| \|\mathbf{y}\|}$, and a similarity matrix Sim_{ij} is acquired, where each entry in the similarity matrix is the NCD between i^{th} and j^{th} feature vector.

Experimental Results Table 2 shows the VR at 0.1% FAR as well as the EER for Experiment I and Figure 6 shows the ROC curves. We find out that for identifying identical twin individual in the crowd, the proposed ALDA subspace method significantly outperforms the traditional LDA on all types of features considered in this experiment. Also, traditionally well-established descriptors such as LBP/LTP/LTrP perform *not* much better than the raw pixel, sometimes even worse. On the contrary, the facial asymmetry features do increase the verification rate. To be more specific, the best VR we obtain is 48.5% at 0.1% FAR using asymmetry features with ALDA, while the best we can get from the traditional LDA is 27.9% VR at 0.1% FAR.

	VR	EER
<i>Pixel (LDA)</i>	0.223	0.407
<i>LBP (LDA)</i>	0.171	0.346
<i>LTP (LDA)</i>	0.239	0.214
<i>LTrP (LDA)</i>	0.271	0.190
<i>Asym. Feat. (LDA)</i>	0.279	0.188
<i>Pixel (ALDA)</i>	0.302	0.201
<i>LBP (ALDA)</i>	0.323	0.198
<i>LTP (ALDA)</i>	0.422	0.243
<i>LTrP (ALDA)</i>	0.343	0.175
<i>Asym. Feat. (ALDA)</i>	0.485	0.142

Table 2. VR at 0.1% FAR and EER for **Experiment I**.

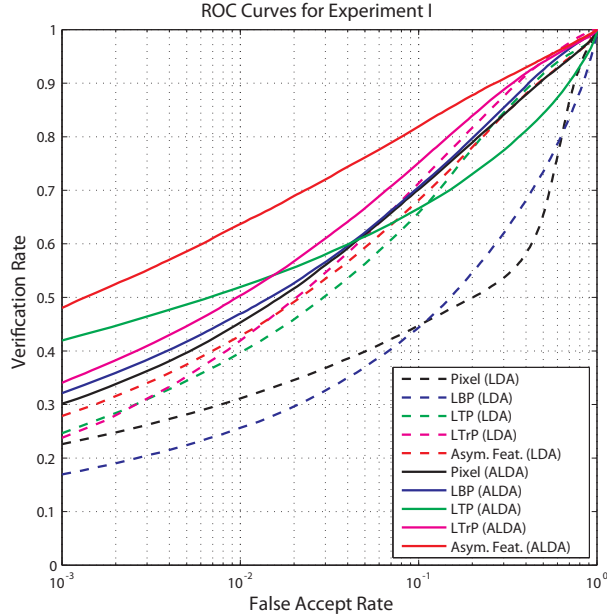


Figure 6. The ROC curves for **Experiment I**.

In this case, we see a 20.6% leap in the verification rate by adopting the proposed ALDA method.

7.2. Experiment II: Verify Identical Twins within the Family

In order to examine whether the proposed ALDA method can find projection vectors that also well distinguish twin individuals in the same family, we evaluate the facial asymmetry features on all the families in the database, against the state-of-the-art and very successful descriptors in face recognition field.

Experimental Setup We focus on verifying twin_A against twin_B in the same family. Per this idea, we conduct an 1-to-1 verification matching experiment within each identical twins families and acquire the VR at 0.1% (0.001) FAR, and in the end report the averaged VR throughout all the families using all the aforementioned features, with projections onto traditional LDA and proposed ALDA basis.

For the image selection, we will consider both of the two expressions because we want to see how asymmetry bio-

metrics can capture subjects' behavioral changes on faces. Both full face images and periocular images will be evaluated on three resolutions. The subspace training procedure is the same as in the Experiment I.

Experimental Results Table 3 shows the verification rate at 0.1% false accept rate averaging over all families. First 5 rows employ the traditional LDA methods for subspace learning on raw pixel, LBP, LTP, LTrP, and asymmetry features, and next 5 rows utilize the proposed ALDA methods to learn the subspace on the same features. Both of the two expressions in the database are considered: blank stare and happy. Experiments on both full face and periocular crop are carried out on three different resolution: small (S), medium (M), and large (L) size. For full face images, small sized image is 128×128 , medium 320×320 , and large 640×640 , while for periocular images, small sized image 50×128 , medium 125×320 , and large 250×640 .

From our experimental results in Table 3, we can draw the following conclusions:

(1) Using ALDA for subspace modeling yields much better performance than traditional LDA method, because ALDA enforces individuals from the same family to be far from each other in the projection space.

(2) Compared with blank stare faces, faces with happy expressions generally yield higher VR for both traditional features like LBP, LTP, LTrP, and the proposed facial asymmetry features. This is because of the subject-dependent uniqueness of facial behavior.

(3) In traditional face recognition setup, LBP/LTP/LTrP should perform much better than raw pixel, because they capture the discriminative features of each subject. These discriminative features aims at maximizing similarities among images from the same or similar-looking subject. But, this criterion breaks in the case of identical twins since images from the other member of the same family are highly similar. That is why, in our experimental setup, LBP/LTP/LTrP does not display much advantage over raw pixel. Generally speaking, in the verification experiments, LBP/LTP/LTrP actually performs worth than the raw pixel.

(4) On the contrary, when using the facial asymmetry features, we are able to improve the VR by a great margin. To be more specific, using asymmetry features, the best VR achieved is **82.58%** at 0.1% FAR using ALDA on large-sized periocular image with smiling expression. While the best VR achieved using LDA is 75.17% at 0.1% FAR on small-sized full face images also with smiling expression.

(5) We also find out that, for the facial asymmetry features, image resolution does not affect the performance too much. This shows that facial asymmetry biometrics is resolution independent and can work well on both low resolution and high resolution images.

(6) What's more, considering only the periocular region (only less than 40% of the full face) is equivalent to full

Avg VR at 0.1% FAR	Blank Stare (neutral face)						Happy (smiling face)					
	Full Face			Periocular			Full Face			Periocular		
	S	M	L	S	M	L	S	M	L	S	M	L
Pixel (LDA)	0.5830	0.5821	0.5816	0.5818	0.5817	0.5788	0.6020	0.5995	0.5993	0.5983	0.5955	0.5969
LBP (LDA)	0.5477	0.5466	0.5455	0.5351	0.5303	0.5285	0.5257	0.5233	0.5226	0.5306	0.5289	0.5291
LTP (LDA)	0.5830	0.5818	0.5852	0.5826	0.5835	0.5817	0.5911	0.5918	0.5930	0.5929	0.5973	0.5944
LTrP (LDA)	0.5488	0.5501	0.5508	0.5516	0.5503	0.5581	0.5630	0.5690	0.5687	0.5649	0.5673	0.5680
Asym. Feat. (LDA)	0.7288	0.7237	0.7230	0.7393	0.7293	0.7296	0.7517	0.7503	0.7466	0.7381	0.7320	0.7305
Pixel (ALDA)	0.7404	0.7326	0.7301	0.7524	0.7441	0.7406	0.7379	0.7361	0.7321	0.7484	0.7420	0.7365
LBP (ALDA)	0.7383	0.7495	0.7532	0.7366	0.7455	0.7454	0.7541	0.7598	0.7633	0.7576	0.7695	0.7752
LTP (ALDA)	0.7845	0.7962	0.7961	0.7895	0.7948	0.7951	0.8060	0.8190	0.8193	0.7956	0.8070	0.8093
LTrP (ALDA)	0.7317	0.7327	0.7225	0.7253	0.7152	0.7106	0.7511	0.7586	0.7562	0.7412	0.7432	0.7495
Asym. Feat. (ALDA)	0.8017	0.8027	0.8025	0.7953	0.7952	0.7952	0.8211	0.8216	0.8216	0.8254	0.8253	0.8258

Table 3. Averaged VR at 0.1% FAR over all the identical twins families for **Experiment II**.

face in terms of the performance, and sometimes it is even preferable to use periocular region instead of full face for our best verification rates come from periocular images.

(7) Facial images in this database are taken at the same time or at most one year apart. This is actually the worst-performance scenario for our facial asymmetry features because the larger gap between the query image and gallery image, the more distinct asymmetry features can be found and characterized. In real life scenarios, these facial asymmetry features will perform even better.

8. Conclusion

In this work, we have proposed an Augmented Linear Discriminant Analysis approach to identify identical twins. It learns a common subspace that not only can identify from which family the individual comes, but also can distinguish between individuals within the same family. We evaluate the ALDA against the traditional LDA approach for subspace learning on the Notre Dame twin database. We have shown that the proposed ALDA method with the aid of facial asymmetry features significantly outperforms other well-established facial descriptors (LBP/LTP/LTrP), and the ALDA subspace method does a much better job in distinguishing identical twins than LDA. We are able to achieve **48.50%** VR at 0.1% FAR for identifying family membership of identical twin individuals in the crowd and an averaged **82.58%** VR at 0.1% FAR for verifying identical twin individuals within the same family, a significant improvement over traditional descriptors. It is safe to draw the conclusions that our proposed ALDA method with the aid of facial asymmetry features can very well tell identical twins apart in the real-world application.

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