Facial Asymmetry Quantification for Expression Invariant Human Identification*

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ABSTRACT

We investigate the effect of quantified statistical facial asymmetry as a biometric under expression variations. Our findings show that the facial asymmetry measures (AsymFaces) are computationally feasible, containing discriminative information and providing synergy when combined with Fisherface and Eigen-face methods on image data of two publically available face databases (Cohn-Kanade and Feret).

1 Motivation

Human facial asymmetry has long been a critical factor for evaluation of facial attractiveness [20] and expressions [16] in psychology and anthropology, albeit most studies are carried out qualitatively using human observers as judges, or only local feature lengths are measured (e.g. length of ears).

Intrinsic facial asymmetry in individuals is affected by multiple factors, including growth, injury, and age-related change. Individuals in the general population display a wide range of variations in the amount of facial asymmetry (Figure 1). *Extrinsic facial asymmetry* is caused by viewing orientation, illuminations, shadows, and highlights. In our initial work, the goal is to find an answer to the question: **Is intrinsic facial asymmetry useful for human identification under expression variation?** To answer this question, our investigation is focused on images with minimal extrinsic factors. Only if facial asymmetry is found to be a cue for human identification, the next step will be to investigate the recovery of intrinsic facial asymmetry from noisy image data.

In the psychology literature, it has been reported that facial attractiveness for men is inversely related to recognition accuracy [14], and asymmetrical faces are considered less attractive [20]. For face recognition by humans, a small yet statistically significant decrease in recognition performance is observed when facial asymmetry is removed from images [21]. These results suggest that facial asymmetry is used by humans for recognition. We therefore explore the explicit representations of facial asymmetry and particularly discriminating sub-dimensions within these representations for automatic human identification.

Figure 1: *Left: original face. Middle: a perfectly symmetrical face made of the left half of the original face. Right: a perfectly symmetrical face made of the right half of the original face. Notice the difference in nasal regions in both individuals caused by left-right asymmetry.*

Bilateral anatomical symmetry of humans and other animals has been exploited successfully in other fields for classification e.g. [10, 4, 6]. To the best of our knowledge, work done in human identification with expression variations has not used *quantified facial asymmetry* as the essential cue. Previous work on facial expression analysis, e.g. [24, 5, 19, 3], is almost exclusively focused on expression recognition and coding. Martinez [12] used half faces and local regions

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on each side of the face separately for human identification, and found that left and right faces produce different recognition rates under the same expression. Different from [12], facial asymmetry is quantified directly in our work [11].

2 Quantification of Facial Asymmetry

Asymmetry is a structural descriptor of an object that cannot be captured by a single local measure (e.g. either left or right half face alone). Bilateral reflection symmetry is defined with respect to a reflection line/plane, and human faces possess such a natural reference line/plane.

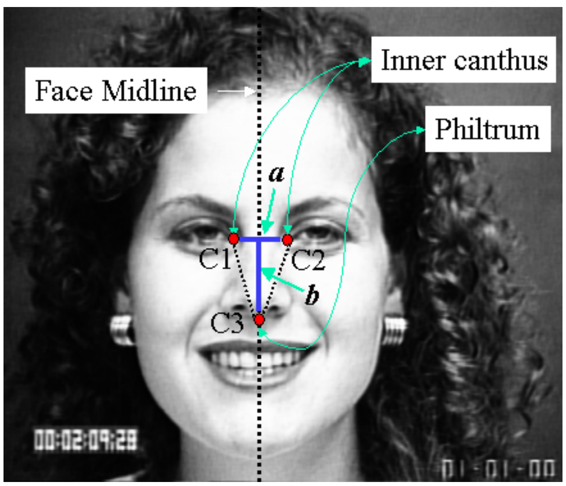


Figure 2: Each face image is normalized using three feature points: left and right inner canthi (C_1, C_2) and the philtrum (C_3), by an affine transformation as follows (1) rotation: rotate $\overline{C_1C_2}$ into a horizontal line segment, (2) X-scaling: scale $\overline{C_1C_2}$ into length a, (3) X-skewing: skew the face image horizontally such that C_3 is located on the perpendicular line going through the midpoint of C_1, C_2, (4) Y-scaling: scale the distance between C_3 and $\overline{C_1C_2}$ to length b.

2.1 Face Image Preprocessing

In order to measure and compute facial asymmetry conveniently we establish a common coordinate in each face image. First, we identify three feature points on each face: the inner canthus of each eye, C_1, C_2, and the philtrum C_3 (Figure 2). Second, we define *face midline* as the line going through the mid point of line segment $\overline{C_1C_2}$, and the philtrum C_3. Third, we transform the face midline to a fixed line vertically centered in each face image. This is done by moving $[C_1, C_2, C_3]$ into their normalized positions, see Figure 2 for details. It may be helpful to point out that although a face image is transformed during this process, the amount of facial asymmetry **with respect to the face midline** is preserved by the topological property of affine transformations [13]. The three facial feature points (two canthi and a philtrum) are marked manually in the first frame and then tracked using the Lucas-Kanade algorithm [9]. In a related study, comparison of tracked points showed a high correlation (≥ 0.95) with manually marked final position [23]. Each image is then cropped into a 128×128 squared image with face midline centered vertically (Figure 3). All normalized faces have their inner canthi and the philtrum on the same pixel locations. In our experiment these three points are: $C_1 = [40, 48], C_2 = [88, 48]$ and $C_3 = [64, 84]$, thus $a = 48$ and $b = 36$ respectively (upper-left corner has coordinates [0,0]).

2.2 Facial Asymmetry Measurements

Once a face midline is determined, each point on the normalized face image has a unique corresponding point on the other side of the face image. For a given normalized face density image I, a coordinate system defined on the face with X axis perpendicular to the face midline and Y axis coincides with the face midline, its vertically reflected (w.r.t. axis Y) image I', and their corresponding "edged" images I_e, I'_e (applying edge extraction algorithm on I, I'), we can define the following two facial asymmetry measurements

Density <u>D</u>ifference *D-face*:

$$D(x, y) = I(x, y) - I'(x, y) \tag{1}$$

Edge Orientation <u>S</u>imilarity *S-face*:

$$S(x, y) = \cos(\phi_{I_e(x,y), I'_e(x,y)}) \tag{2}$$

where $\phi_{I_e(x,y), I'_e(x,y)}$ is the angle between the two edge orientations of images I_e, I'_e at pixel point x, y. Figure 4 displays three normalized faces, and their respective *D-face* and *S-face*. We call these *AsymFaces*. *S-face* is bilaterally symmetrical, and the left and right of *D-face* are opposite of each other. Therefore, half of *D-* and *S-faces* contains all the information needed. We denote these half faces as $\mathbf{D_h}$ and $\mathbf{S_h}$ with dimension 128×64. We call each of these dimensions a *feature*. See Table 1 for a complete set of notations used in the rest of this paper.

These two asymmetry measurements capture facial asymmetry from different perspectives; *D-face* is affected by the left-right relative intensity variations of the face while *S-face* is affected by the zero-crossing of the intensity field. The higher the value of *D-face* the more *asymmetrical* the face, and the higher the value of *S-face* the more *symmetrical* the face.

Figure 3: Sample normalized faces from Cohn-Kanade AU-Coded Facial Expression Database [7]. Each column represents one subject at neutral, peak frames of joy, disgust and anger expression video sequences, respectively.

Table 1: Terms for different AsymFaces are defined. Datasets for face recognition experiments are also defined.

Notation	Definition	Size
D-face	Intensity Difference image	128×128
S-face	Edge Orint. Similarity image	128×128
$\mathbf{D_h}$	Left half of *D-face*	128×64
$\mathbf{S_h}$	Left half of *S-face*	128×64
D_{hx}	column-mean of $\mathbf{D_h}$ on X	1×64
D_{hy}	row-mean of $\mathbf{D_h}$ on Y	128×1
S_{hx}	column-mean of $\mathbf{S_h}$ on X	1×64
S_{hy}	row-mean of $\mathbf{S_h}$ on Y	128×1
DataSet 1	60 PCA on $\mathbf{D_h}$ of 55 subjects **3** frames from each exp. seq.	60×495
DataSet 2	D_{hy} of all distinct frames of 55 subjects	128×2677
DataSet 3	S_{hy} of all distinct frames of 55 subjects	128×2677

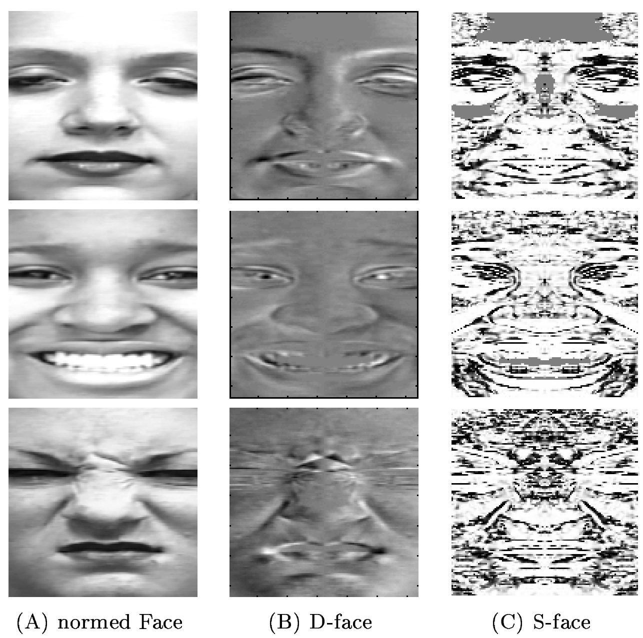


Figure 4: *(A) normalized face , (B)* D-face, *and (C)* S-face.

3 Facial Expression Image Data

The Cohn-Kanade AU-Coded Facial Expression Database [7] is used to investigate the relationship between facial asymmetry and recognition. This dataset consists of video sequences of subjects of different races displaying distinct facial expressions, such as anger, disgust or joy (Figure 3). Each subjects was videotaped under one of the three lightings: 1) ambient lighting, 2) a single high intensity lamp, or 3) dual high intensity lamps with reflective umbrellas. Video sequences range in length from 8 to 65 frames, and each frame is a grey-scale image of 640x480 pixels.

As an initial attempt, we use frontal facial images which have the least lighting distortions. This is for the purpose of isolating the intrinsic from extrinsic factors, and finding out how these intrinsic facial asymmetry alone may contribute to human identification under facial expression variations. We have experimented with human identification using a random subset of the dataset on 55 subjects, each with 3 expression video sequences: joy, anger and disgust. A total of 2677 frames is used in our experiments with 922 for joy, 945 for anger and 810 for disgust.

4 Feature Space Dimension Reduction

Each *AsymFace* $\mathbf{D_h}$ or $\mathbf{S_h}$ has 8192 ($128 \times 64 = 8192$) dimensions (Table 1). These dimensions are not all independent of each other, nor are they equally useful for human identification. In order to (1) find the most discriminative combination of facial asymmetry features, and (2) reduce the computation cost, we have experimented with several ways to reduce and select certain subspaces in the full dimensionality of the AsymFaces.

4.1 Principle Component Analysis

PCA is done on an 8192×495 matrix to produce **Dataset 1** defined in Table 1. $8192 = 128 \times 64$ is the total number of pixels in each $\mathbf{D_h}$, and 495 comes from taking three frames (neutral,peak and middle frames) from each of the three expressions of each subject ($3 \times 3 \times 55 = 495$). After examining their eigen values, the top 60 components are kept. The dimensions are thus reduced from 8192 to 60 (DataSet 1 in Table 1) making the automatic face identification tasks computationally feasible.

4.2 Feature Averaging

We computed the mean values of $\mathbf{D_h}(\mathbf{S_h})$ along X and Y axes: D_{hx} (1×64) and D_{hy} (128×1) to obtain DataSets 2 and 3 in Table 1. Figure 5 shows the smoothed D_{hy} surfaces of video sequences from two distinct subjects, each with three expressions: joy, anger, disgust, consecutively. Despite changes in expressions, spatiotemporal surfaces' similarity of each person across different expression sequences and dissimilarity between individuals can be observed (Figure 5). This observation suggests that the facial asymmetry measure we defined is more indicative of human identity than of expressions.

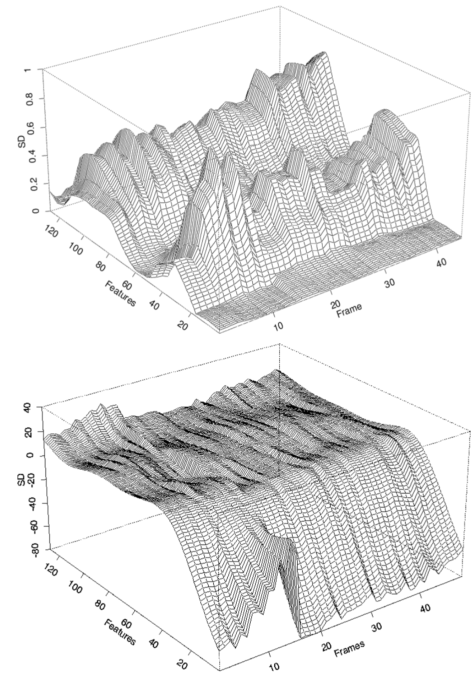


Figure 5: *Top: smoothed D_{hy} sheet of subject 85. Bottom: smoothed D_{hy} sheet of subject 10. The three axes in both plots represent, from left-to-right, joy-anger-disgust video frame sequences consecutively; from front to back, each row on the AsymFace D_{hy} from forehead towards the chin; and the height is the* D-face *value.*

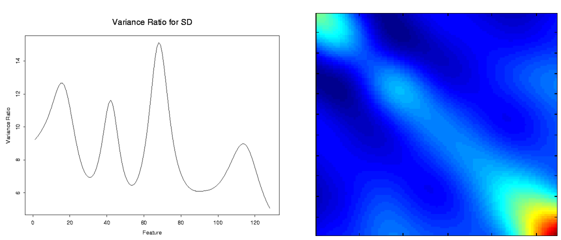
4.3 Discriminative Feature Subset Selection

Each dimension in the full range of facial asymmetry measures is NOT equally discriminative for face identification. In a feasible search space, we automatically (and objectively) choose a subspace with the highest discriminating power. For a feature F with C total classes, we define a variance ratio as follows

$$vr(F) = \frac{Var(F)}{\frac{1}{C}\sum_{i=1..C}\frac{Var_i(F)}{min_{i\neq j}(|mean_i(F)-mean_j(F)|)}}$$

where $mean_i(F)$ is the mean of feature F's values in class i. This variance ratio is the ratio of the variance of the feature between subjects to the variance of the feature within subjects, with an added penalty for features which may have small intra-class variance but which have close inter-subject mean values. Image (a) of Figure 6 shows this ratio for D_{hy}.

The features that have higher variance ratios are more discriminative. This figure shows which rows among all the AsymFaces (**DataSet 2**) are more discriminating than others. The row with the highest value corresponds to the nasal bridge region. This is consistent with our observations in Figure 1. Contrary to intuition, the regions varied most in facial asymmetry during facial expression (e.g. mouth, eyes) are usually NOT the most discriminative feature for human identification. The nasal bridge is relatively stable during expression variations. The 3 peaks after that are, roughly, at the row levels of mid-forehead, inner-eye corner and between mouth and chin. In comparison, image (b) of Figure 6 shows the mouth region varies the most. We have employed both exhaustive searches and heuristic forward selection [2] searches to find the most discriminating feature subsets from AsymFaces for human identification.



(a) (b)

Figure 6: (a) The smoothed variance ratio for D_{hy} of **DataSet 2** shows which rows of the AsymFace are the most discriminative. From left to right is from forehead to chin. The highest peak is around nasal bridge area. (b) The covariance matrix of D_{hy} shows the asymmetry of the mouth region varies the most.

5 Face Identification

Expression Video Sequences Data[7]

We have designed five types of experiments to demonstrate whether the facial asymmetry measure we defined can contribute to expression invariant human identification. They are: (1) - (3) training on two expressions, and testing on the images from the third unseen expression. (4) training on all neutral expression frames and testing on peak expression frames of all three expressions; (5) the inverse of (4); High classification rates from these experiments would suggest that the measurements we used for this data set contain information about human identity invariant of varied expressions.

Classification rates using Linear Discriminant Analysis (LDA) on AsymFaces have reached between 82% and 96.3% on the five different training/testing setups specified above using datasets 2 and 3 [11] (Table 1).

The Fisherfaces method [1] uses the Fisher Linear Discriminant (FLD) to achieve class specific linear projections of the given image set. PCA is done on the original images to reduce the dimension to $C-1$, where C is the total number of classes. We have implemented this method and tested it on **Dataset 1**. Good results from Fisherfaces are expected since all the images are registered and normalized, the only factor that may cause error is the expression variations. Fisherfaces results can be found in Table 2.

When Fisherfaces and AsymFaces are combined using LDA (concatenating the two feature vectors forming a larger feature space), the Fisherfaces classification errors are reduced by 50% to 100% (0% error). This is done by concatenating both top eigen vectors (1-10, 1-15) directly computed from normalized face images and automatically selected features from AsymFaces, then applying LDA on the five experimental setups (Table 2). Refer to [11] for more complete experimental results.

Feret Database[15]

In order to test the generality of our facial asymmetry measure, we also tested 110 pairs of images from 110 subjects, among which 107 pairs are randomly chosen from Feret database (frontal faces only) and 3 pairs of frames from Cohn-Kanade AU-coded facial expression database (Figure 7). The training set is composed of 110 images, each of them is one of the pairs for one subject. The testing set contains the other image in the pair. We used eigen-face approach [22] on the original image and on AsymFace *S-face*s, finding the nearest neighbor in their major PCA components. The results show that classification rate using *S-faces* alone is significantly better than chance ($p << 0.001$). When combining *S-face* with eigen-faces, the classifi-

Figure 7: Normalized faces from Feret (107) and Cohn-Kanade databases (3) in the same manner as described in Figure 2.

Table 2: Improved results are shown, in contrast to Fisherfaces (FF) results, when combining Fisherfaces computed from the normalized face images directly with AsymFaces (AF) computed from the eigen vectors of $\mathbf{D_h}$ (**DataSet 1** defined in Table 1). In each case, the AF feature subset is selected using forward selection algorithm with respect to the variance ratio value. Improvement rate = (%Error(FF) - %Error(FF+AF))/%Error(FF).

PCA Face Features	Auto selected Features from top 60 PCA values of $\mathbf{D_h}$	Training Data	Testing Data	Fisherfaces %Error	FF + AF %Error	Improvement Rate
1:10	1,2,9,10,12,13,23,28	joy & anger	disgust	13.3%	3.0%	77.4%
1:15	1,3,4,12,18,20,21,47,60	joy & anger	disgust	8.5%	1.8%	78.8%
1:10	1,2,5,6,8,10	joy & disgust	anger	10.3%	4.8%	53.4%
1:15	1,3,4,10,15,23,46,55	joy & disgust	anger	6.7%	1.8%	73.1%
1:10	1,2,6,12,23,43,48	anger & disgust	joy	27.9%	13.3%	52.3%
1:15	1,2,4,7,14,27,30,43,50	anger & disgust	joy	19.4%	9.7%	50.0%
1:10	1,2,4,7,12,24,28,47	neutral	peak	9.7%	0.6%	93.8%
1:15	2,4,16,19,26	neutral	peak	3.6%	0.0%	100.0%
1:10	1,2,5,6,7,9,17	peak	neutral	8.5%	1.8%	78.8%
1:15	1,15,23	peak	neutral	6.1%	2.4%	60.7%

cation improvement rate is 38% (error rate changes from 15% to 9.3%).

6 Discussion

Previous work in psychology suggests that facial asymmetry contributes to human identification. In this work, we found that similar benefits may be obtained in automated face recognition.

In this work we have studied the use of facial asymmetry for human identification under expression variations. We have proposed two quantitative measures of facial asymmetry and demonstrated that (1) *D-face* and *S-face* measures are easy and fast to compute (feasibility); (2) the asymmetry of automatically selected facial regions captures individual differences that show robustness to variation in facial expression (discriminative); (3) quantified facial asymmetry provides significant improvement when combined with conventional face recognition algorithms (orthogonality).

The most interesting finding in our work is that the combination of AsymFaces and Fisherfaces (eigenfaces) improved face classification rates by 38% to 100%. This result suggests that facial asymmetry measurements may provide unique, complementary information to Fisherface (eigen-face) representation.

A limitation of our current approach is that a frontal view with consistent lighting is required. There exist very large databases (e.g., drivers license, passport, national ID) for which frontal views are available. In natural settings it is often possible to obtain a frontal view. One application of facial asymmetry quantification is for frontal view selection from video frames. Figure 8 demonstrates such an application for both visual and thermal images of a subject.

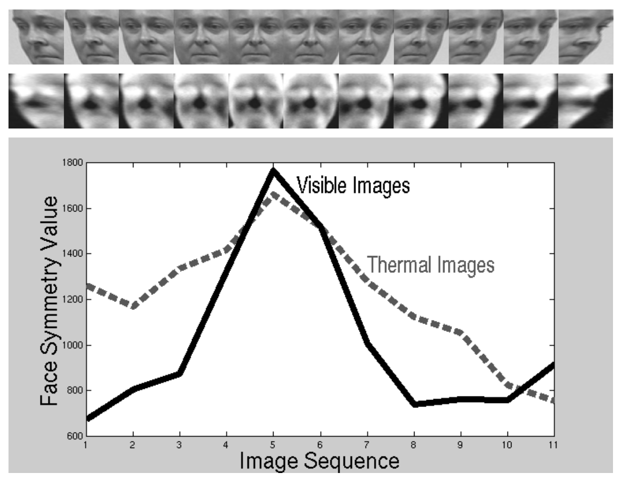


Figure 8: *Top: a video sequence of a subject being viewed from different angles. Middle: the corresponding thermal image sequence of the same subject. Bottom: the Edge Orientation Similarity plots (*S-face*) for both image sequences.*

In general, the frontal view case is still important and not an adequately solved problem. We expect facial asymmetry analysis will serve as a useful cue for recognition rate improvement, for example: datasets with large age differences. Little is known about the effects on recognition rate due to changes in facial asymmetry with development (i.e., infant to child to adult) [18, 8];

Potential contributions of quantitative asymmetry to psychological and biological science include improved measurement of facial attractiveness, which is limited currently to use of subjective measures, as well as identification of children with congenital malformations. These malformations often manifest in subtle (and not so subtle) variation from symmetry [17].

Our current work includes studying the issue of how to distill intrinsic facial asymmetry from images cluttered with extrinsic facial asymmetries, examining the effects of extrinsic factors of facial asymmetry, temporal variations of facial asymmetry, and more superior image feature combination schemes for optimal face classification.

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