Eyebrow Shape-Based Features for Biometric Recognition and Gender Classification: A Feasibility Study

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Abstract

A wide variety of applications in forensic, government, and commercial fields require reliable personal identification. However, the recognition performance is severely affected when encountering non-ideal images caused by motion blur, poor contrast, various expressions, or illumination artifacts. In this paper, we investigated the use of shape-based eyebrow features under non-ideal imaging conditions for biometric recognition and gender classification. We extracted various shape-based features from the eyebrow images and compared three different classification methods: Minimum Distance Classifier (MD), Linear Discriminant Analysis Classifier (LDA) and Support Vector Machine Classifier (SVM). The methods were tested on images from two publicly available facial image databases: The Multiple Biometric Grand Challenge (MBGC) database and the Face Recognition Grand Challenge (FRGC) database. Obtained recognition rates of 90% using the MBGC database and 75% using the FRGC database as well as gender classification recognition rates of 96% and 97% for each database respectively, suggests the shape-based eyebrow features maybe be used for biometric recognition and soft biometric classification.

1. Introduction

In biometrics field, researchers focus on developing reliable personal identification systems by analyzing unique features of the human body, such as fingerprint, face, and iris [9]. The widely used iris pattern possesses a high degree of randomness and can achieve high performance. However, most iris recognition requires high quality input images and significant cooperation from the users. The recognition accuracy is severely affected when non-ideal images are used which possess motion blur, occlusion, and illumination artifacts. Recently, periocular biometric features, which include the eyelids, eyelashes, eyebrows, and the neighboring skin area, has been suggested as a potential method to improve the overall recognition performance when the iris image is poor [20]. Periocular biometrics largely focus on fine features such as skin texture. Typical texture measurement methods include Discrete Cosine Transformations [5], Gradient Orientation Histograms, or Local Binary Patterns [13, 15]. Despite the effectiveness of using texture based features for periocular recognition, these features could be significantly affected by non-ideal imaging conditions such as motion blur or illuminations artifacts.

Eyebrows can exhibit different shapes, colors, or textures due to natural growth or alteration. Because of this, eyebrow features have been suggested for possible use in forensic identification applications [6]. Due to the effects of non-ideal imaging conditions on the reliable extraction of texture based features, we focused our investigation on the shape-based features of the eyebrow region. Using eyebrow shape as biometric modality has the following possible benefits:

1. Eyebrow shape features are simple to calculate.
2. Eyebrow shape features may be more robust to varying illumination and motion blur than texture based features.
3. Eyebrow shape features result in a relatively small biometric template.

There has been previous research involving the use of eyebrows for the task of biometric recognition. Eyebrow has been considered as one of the most important features in facial recognition systems [19]. Rahal et al. built a multimodal biometric authentication system using the area of both eyebrows, the distance between the left and right eyebrow, in addition to the angles of a triangle formed by the positions of the left eyebrow, mouth, and the right eyebrow.

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These features were combined with fingerprint features to authenticate individuals [18]. Paleari et al. used external and internal positions of both eyebrows, along with other features such as mouth, eye, nose, and forehead to recognize subjects [14]. In the case of periocular based recognition, the presence of the eyebrow in periocular region images resulted in increased biometric identification accuracy compared to periocular region images which excluded the eyebrow [2]. Li et al. developed an eyebrow recognition system on a small database of 32 subjects [10, 11]. Two 758x576 high quality color eyebrow centered images were captured for each subject. The Fourier transformation of the eyebrow image was computed as features and used with a K-means classifier and HMMs to perform biometric recognition.

There are instances in which the quality of image is not sufficient for accurate biometric recognition. In these cases, soft biometric traits such as gender, ethnicity, age, and skin color can be used to improve the performance of the primary biometric system. Jain et al. [8] showed that with the knowledge of gender, ethnicity and height information, the performance of a fingerprint recognition system can be significantly improved. Lyle et al. [12] extracted gender and ethnicity information from the periocular region images and showed that fusion of the soft biometric information with texture based periocular recognition approach resulted in more accurate recognition.

This work investigates the use of shape-based eyebrow features for biometric recognition and gender classification using non-ideal images containing motion blur, varying illumination, and varying facial expressions. The rest of the paper is organized as follows: In section 2, the details of the proposed approach are described, including data acquisition, eyebrow shape feature extraction, and three classification methods for both biometric recognition and gender classification. In section 3, the experiment setup is presented; and also the results of biometric recognition and gender classification using non-ideal eyebrow images are reported. Finally, we conclude our research and outline future work in section 4.

2. Methods

Figure 1 shows an overview of our proposed biometric recognition and gender classification approaches. First, we selected images from different databases and manually segmented the eyebrow regions in the images; Second, we extracted shape features from the extracted eyebrows and divided the images into training and testing sets. In the training stage, three different classification methods were used for biometric recognition and gender classification. The classifiers were then applied to the test images and output identity label or gender label was assigned.

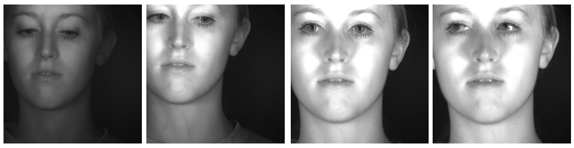

Figure 2. Examples of video frames from MBGC

Figure 3. non-blur frame vs. motion blur frame (zoomed in the left eyebrow from the first image and the last image in Figure 2

2.1. Experimental Dataset

We tested the efficiency of our methods for biometric recognition and gender classification using images from two publicly available biometric databases containing images captured under non-ideal imaging conditions.

2.1.1 MBGC Database

The Multiple Biometric Grand Challenge (MBGC) [16] database is constructed by capturing Near Infra-Red (NIR) facial videos as people walk through a portal. Although the resolution of the frames in the video is 2048x2048, most images are challenging for many biometric methods such as iris recognition or face recognition because of varying illumination, varying facial expressions (Figure 2) or motion blur (Figure 3). We established a data set of 634 face images from 91 distinct subjects by manually extracting frames from video sequences. After excluding the images with incomplete or no eyebrows, 493 left eyebrow images from 82 distinct subjects (31 females, 51 males) and 429 right eyebrow images from 76 distinct subjects (28 females, 48 males) were available for experimentation.

2.1.2 FRGC Database

The Face Recognition Grand Challenge (FRGC) [17] database is another widely used database for facial and periocular recognition. The database is composed of high resolution still facial images. We established a data set of ran-

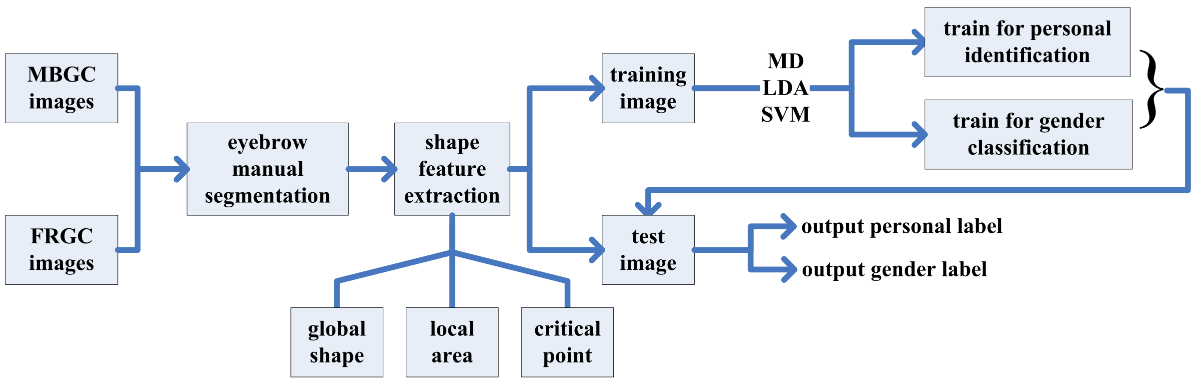

Figure 1. Overview of biometric recognition and gender classification approach using the single eyebrow region

Figure 4. Examples of left eyebrow images from FRGC

domly picked 50 male and 50 female subjects. For each subject, we randomly chose four left eyebrows on four different days, and four corresponding right eyebrows on the same day. Although it is common practice for individuals to alter their eyebrows, we did not observe cases in which eyebrow appearance varied between images of the same subject. The images chosen were captured under various illuminations and face expressions covering a span of four to eighty-eight days (Figure 4).

2.2. Feature Extraction

The features used were shape-based. As shown in Figure 5, we manually segmented the eyebrow region and recorded the positions (x, y) of endocanthion and exocanthion as reference points. Endocanthion is defined as the inner corner of the eye fissure where the eyelids meet. Exocanthion is defined as the outer corner of the eye fissure where the eyelids meet. We then extracted a total of nineteen shape-based features from each eyebrow. Each feature was normalized to scale [0 1] based on min-max normalization. We grouped similar features into three categories: global shape features (GSF), local area features (LAF), and critical point features (CPF).

2.2.1 Global Shape Features

We extracted three global shape features from each eyebrow independent of scale and rotation.

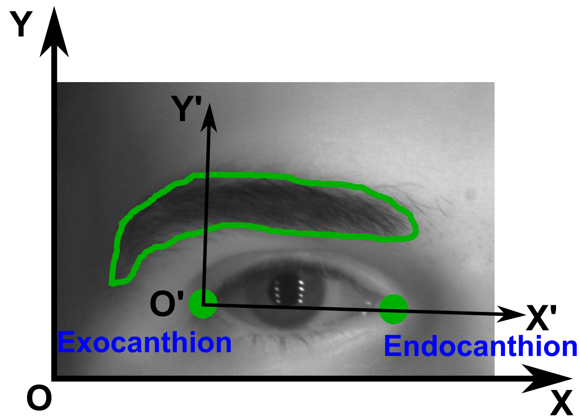

Figure 5. Manually extract eyebrow region and record the position of endocanthion and exocanthion

1. Rectangularity: It reflects how rectangular an eyebrow shape is. It is defined as the area of the eyebrow divided by the area of the minimum bounding rectangle.

2. Eccentricity: It specifies the eccentricity of the ellipse that has the same second-moments as the eyebrow region. It is defined as the ratio of the distance between the foci of the ellipse and its major axis length.

3. Isoperimetric quotient: It represents how a shape is similar to a circle. It is defined as the ratio of its area and that of the circle having the same perimeter.

2.2.2 Local Area Features

We extracted a total of eight local features by calculating the local area percentage of the eyebrow as illustrated in Figure 6. First, we divided the minimum bounding rectangle around the eyebrow region into four subregions of the same width. Assuming the whole eyebrow area is A and the area of eyebrow in each subregion is $A1$, $A2$, $A3$, and $A4$ respectively, we calculated the area percentage for each

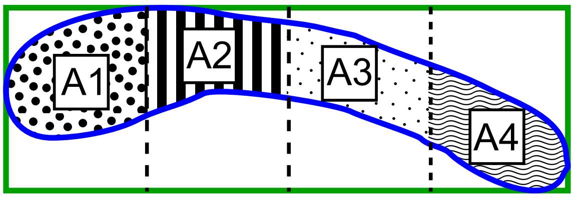

Figure 6. Local area percentage of the eyebrow

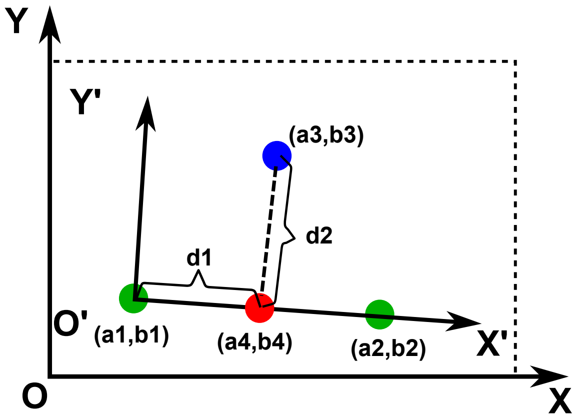

Figure 7. Coordinate system transform

subregion, which is $\frac{A1}{A}$, $\frac{A2}{A}$, $\frac{A3}{A}$, and $\frac{A4}{A}$. Similarly, we also divided the minimum bounding rectangle around the eyebrow region into four subregions of the same height and got another four area percentage features.

2.2.3 Critical Point Features

There are several critical positions on the eyebrow which may be unique for different subjects such as the leftmost and rightmost eyebrow ends, the highest eyebrow point, and the centroid of the eyebrow region. Due to the fact that images are taken at various distances and angles, the absolute position (x, y) of these critical points in the images are not directly comparable. In order to eliminate the scale and orientation variability and facilitate the comparison of critical points between different images, we transformed all pixels in the eyebrow region from the original Cartesian coordinate system XOY to new Cartesian coordinate system $X'O'Y'$ as depicted in Figure 5.

Figure 7 illustrates the detailed steps of transition to the new coordinate system. In this figure, $(a1, b1)$ is the original position of exocanthion, $(a2, b2)$ is the original position of endocanthion. The line going through both exocanthion and endocanthion can be described as in Equation 1.

$$y = kx + m \tag{1}$$

where k and m can be calculated through Equation 2 and Equation 3 respectively.

$$k = \frac{b2 - b1}{a2 - a1} \tag{2}$$

$$m = \frac{b1 \times a2 - b2 \times a1}{a2 - a1} \tag{3}$$

Assume point $(a3, b3)$ is a point in the eyebrow region and the projected point of $(a3, b3)$ on the line $y = kx + m$ is $(a4, b4)$, which can be calculated in Equation 4 and Equation 5 respectively.

$$a4 = \frac{(b3 - m) \times k + a3}{k^2 + 1} \tag{4}$$

$$b4 = \frac{b3 \times k^2 + a3 \times k + m}{k^2 + 1} \tag{5}$$

Then we calculated the Euclidean distance $d1$ and $d2$. Thus, the position of point $(a3, b3)$ in the new coordinate system (x', y') is defined as Equation 6.

$$(x', y') = \begin{cases} (d1, d2) & a4 \geq a1 \ and \ b3 \geq k \times a3 + m \\ (-d1, d2) & a4 < a1 \ and \ b3 \geq k \times a3 + m \\ (d1, -d2) & a4 \geq a1 \ and \ b3 < k \times a3 + m \\ (-d1, -d2) & a4 < a1 \ and \ b3 < k \times a3 + m \end{cases} \tag{6}$$

After converting the positions of all eyebrow pixels to the new coordinate system, we extracted the position of the leftmost eyebrow end, the rightmost eyebrow end, the highest eyebrow point and the centroid position of the eyebrow region. All the position numbers were normalized by dividing the distance between endocanthion and exocanthion. Thus, the eight critical points features (two for each position) can be directly compared.

2.3. Classification Methods

In this work, we used three different classifiers to perform biometric recognition and gender classification. The classifiers were Minimum Distance Classifier (MD), Linear Discriminant Analysis Classifier (LDA) and Support Vector Machine Classifier (SVM).

2.3.1 Minimum Distance Classifier

The simplest classifier is Minimum Distance Classifier. Given a set of M training samples x_i and a set of M labels y_i belong to L different classes, where $x_i \in R^N$ and $y_i \in \{1, 2, ..., L\}$, we first represent the kth class by its mean vector m_k which can be calculated by Equation 7.

$$m_k = \frac{1}{N_k} \sum_{i=1}^{N_k} x_i^{(k)} \quad k = 1, 2, ..., L \tag{7}$$

where N_k is the number of training sample which belong to class k and $x_i^{(k)}$ is the feature vector for each training sample belonging to class k.

For a given test sample x, it is classified to class k if its Euclidean distance to m_k is smaller than all other classes as indicated in Equation 8.

$$x \in k \ \text{ iff } \ D(x, m_k) = \min\{D(x, m_i) \ \ i = 1, 2, ..., L\} \tag{8}$$

Feature categories may play a more significant role in recognition/classification than the other categories, therefore we associated different weights to the feature categories. For each experiment, the weights of the three feature categories were varied in the range [0.1 0.9] in order to determine which combination of weights results in the best matching accuracy. For features within the same category, the weights were equally distributed.

2.3.2 Linear Discriminant Analysis Classifier

Linear Discriminant Analysis takes the feature vector of the training sample and utilizes the class specific information to maximize the between-class scatter and minimizes the within-class scatter. The optimal discrimination projection matrix W is chosen by Equation 9.

$$W = \arg\max_W \frac{|W^T S_B W|}{|W^T S_w W|} \tag{9}$$

where S_B is the between-class scatter matrix and S_W is the within-class scatter matrix. Further details on the LDA are available in [1].

For a given test sample x, it projects onto the LDA space $x_{LDA} = W^T x$ first, then we ran the Euclidean based Minimum Distance Classifier and assigned it to the corresponding class.

2.3.3 Support Vector Machine Classifier

Support Vector Machine [3] originally performs classification by constructing an N-dimensional hyperplane that optimally separates the data into two categories. Given a set of M training samples x_i and a set of M labels y_i belong to two different classes, where $x_i \in R^N$ and $y_i \in \{-1, 1\}$, the SVM classifier solves the following primal optimization problem in Equation 10.

$$\min_{\omega,b,\xi} \frac{1}{2}\omega^T\omega + C\sum_{i=1}^{M}\xi_i \tag{10}$$
$$\text{subject to } y_i(\omega^T\phi(x_i) + b) \geq 1 - \xi_i \ \ (\xi_i \geq 0)$$

where ω is a linear combination of a small number of data points, b is a bias term, ξ is an upper bound of the number of errors, C is a trade-off parameter between error and margin, and $\phi(\bullet)$ is a transform related to the kernel function $k(\bullet)$ by the Equation 11.

$$k(x_i, x_j) = \phi(x_i)^T\phi(x_j) \tag{11}$$

In general, the radial basis function (RBF) kernel is a reasonable choice since it can nonlinearly map samples into a higher dimensional space. The RBF kernel function is shown in Equation 12.

$$k(x_i, x_j) = e^{-\gamma||x_i - x_j||^2} \ \ \gamma > 0 \tag{12}$$

where γ is the kernel parameter.

For a multi-class classification, there are different implementations such as "one-against-one", "one-against-all". Hsu et al. compared different methods and concluded that "one-against-one" is a competitive approach [7]. Assume L is the number of classes in the training sample, then $L(L-1)/2$ classifiers are constructed, each one classifies the test data into one of the two classes. Each binary classification is considered to be a voting and the class with the maximum number of votes is assigned.

In this work, we used RBF kernel to train the training sample and use "one-against-one" strategy to perform biometric recognition and gender classification. We developed the SVM classifier using the LIBSVM software [4]. For each experiment, we searched for the best value of C in Equation 10 and γ in Equation 12 to achieve the highest matching accuracy.

3. Results

In this section, we discuss the results of both biometric recognition and gender classification when only non-ideal eyebrow images from MGBC database and FRGC databases are used. For each experiment, we present results of using shape-based features extracted from the left and right eyebrows separately.

3.1. Experiment Setup

We conducted a total of four experiments. Table 1 shows the information of eyebrow images in each experiment. For example in the first experiment, we used the left eyebrow from FRGC database, the total number of eyebrow images was 400 and the total number of subjects was 100. The set of images were collected evenly from male and female subjects. For each experiment, we used the same feature extraction techniques and compared the performances of three classification methods (minimum distance, linear discriminant analysis, and support vector machine). We conducted both biometric recognition and gender classification for each experiment.

Table 1. Information of eyebrow images in each experiment

experiment	database	eyebrow	images	subjects	male	female
1	FRGC	left	400	100	50	50
2	FRGC	right	400	100	50	50
3	MBGC	left	493	82	51	31
4	MBGC	right	429	76	48	28

A five fold cross validation scheme was used to evaluate the accuracy. In this setup, the original images are randomly partitioned into five subgroups. For each experiment run, one of the subgroups is selected as test data set and the other four subgroups are used as the training data set. This process is repeated five times with each subgroup being used exactly once as the test data set. The biometric recognition or gender classification accuracy was then averaged to produce a final estimation result. An open universe experiment setup is used, since there are instances in which the class of the test samples may not be among the class of the training samples.

3.2. Biometric Recognition

The rank one recognition rate of our approach for biometric recognition is shown in Table 2 and the cumulative match characteristic (CMC) curve is shown in Figure 8. Although only images considered non-ideal were used in the experiments, the rank-one recognition rate obtained is significant. Overall, the best recognition rate for MBGC eyebrow experiments was 89% for the left eyebrow and 91% for the right eyebrow, while the best recognition rate for FRGC eyebrow experiments was 78% for the left eyebrow and 72% for the right eyebrow. For the three classification methods used, the LDA classifier achieved the best recognition rate. The SVM classifier obtained similar results in MBGC experiments but lower recognition rates in the FRGC experiments. Both LDA and SVM classifiers demonstrated better performance than the MD classifier. The importance of different feature categories is also illustrated in Table 2. In experiments which used feature categories separately, the critical point features performed best. The detection error tradeoff (DET) curve of biometric recognition is shown in Figure 9 with the equal error rate (EER) indicated.

3.3. Gender Classification

In this work, we also investigated the use of eyebrow shape features for the task of gender classification. The recognition rates of our approaches for gender identification are shown in Table 3. The best recognition rate obtained for MBGC eyebrow experiments was 96% while the best recognition rate obtained in FRGC eyebrow experiments was 97%. For the three different classification methods used, the SVM classifier obtained the best recognition

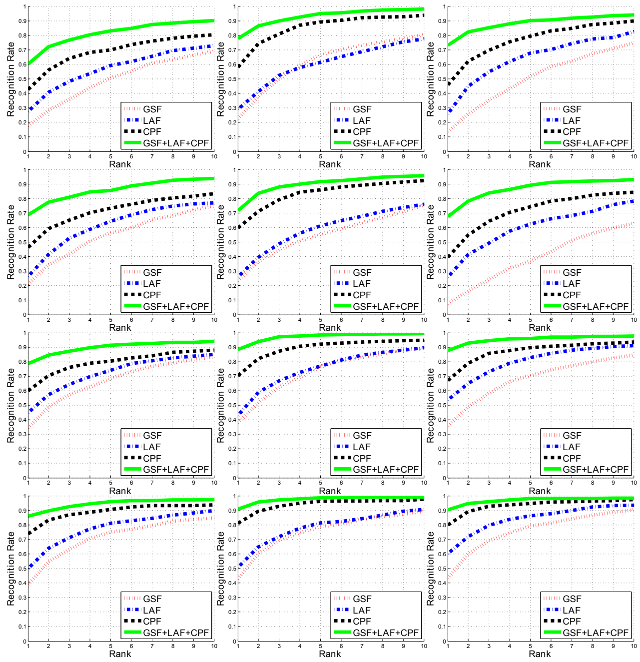

Figure 8. CMC curve of biometric recognition: the left column is using MD method, the middle column is using LDA method, the right column is using SVM method; the first row is using left eyebrow in FRGC, the second row is using right eyebrow in FRGC, the third row is using left eyebrow in MBGC, the fourth row is using right eyebrow in MBGC

rate. As illustrated in Table 3, the critical point features performed better compared to other feature categories for the task of gender classification.

The DET curve of gender classification and the EER value are illustrated in Figure 10. In this figure, using SVM classifier shows a significant lower EER value compared to the other approaches.

4. Conclusions

In this paper, our preliminary study demonstrates the feasibility of utilizing shape-based features extracted from non-ideal images for biometric recognition and gender classification. Images from two publicly available facial databases are used to demonstrate biometric recognition and gender classification performance. The results indicate the potential use of shape-based eyebrow features un-

Table 2. Biometric Recognition Rates

	MD				LDA				SVM			
	FRGC		MBGC		FRGC		MBGC		FRGC		MBGC	
	Left	Right	Left	Right	Left	Right	Left	Right	Left	Right	Left	Right
Global Shape Features	21%	18%	34%	39%	23%	23%	38%	43%	14%	7%	36%	43%
Local Area Features	26%	27%	45%	50%	29%	26%	43%	51%	26%	26%	54%	60%
Critical Point Features	46%	43%	60%	74%	58%	60%	70%	81%	46%	39%	67%	80%
All Features	69%	60%	79%	86%	78%	72%	89%	91%	73%	68%	88%	91%

Table 3. Gender Classification Rates

	MD				LDA				SVM			
	FRGC		MBGC		FRGC		MBGC		FRGC		MBGC	
	Left	Right	Left	Right	Left	Right	Left	Right	Left	Right	Left	Right
Global Shape Features	84%	82%	73%	78%	88%	87%	77%	80%	90%	87%	79%	80%
Local Area Features	72%	81%	70%	71%	74%	81%	69%	71%	82%	84%	78%	78%
Critical Point Features	77%	83%	73%	75%	93%	94%	86%	85%	93%	95%	89%	89%
All Features	92%	93%	89%	87%	96%	95%	91%	89%	97%	97%	96%	96%

der non-ideal image scenarios.

For future work, we will extend our work in the following ways. First, we will develop automated and semi-automated eyebrow segmentation methods to reduce the amount of manual work required to extract eyebrow regions. Second, we will integrate the gender classification with biometric recognition methods to achieve improved recognition performance. Finally, our future work will also involve the use of much larger data sets of lower quality images in order to determine the performance limitations of shape-based eyebrow features.

Acknowledgements

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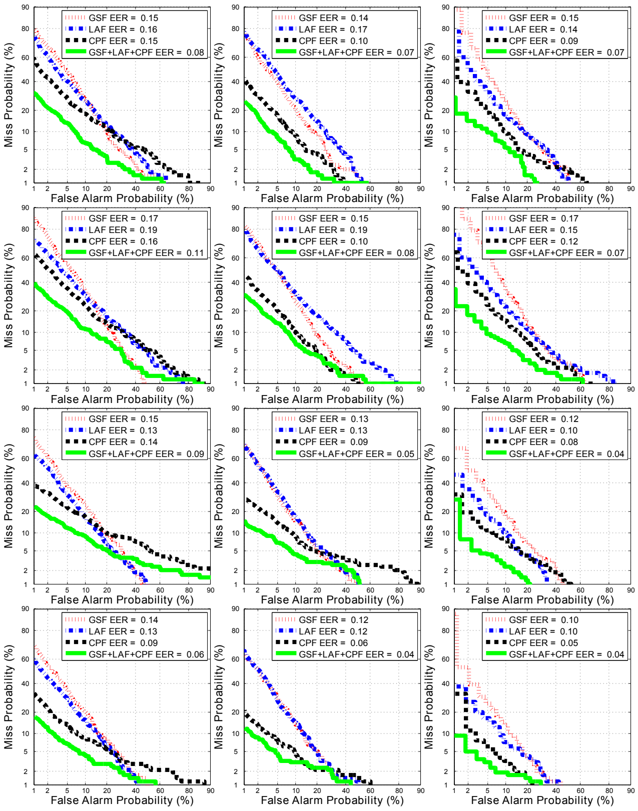

Figure 9. DET curve of biometric recognition: the left column is using MD method, the middle column is using LDA method, the right column is using SVM method; the first row is using left eyebrow in FRGC, the second row is using right eyebrow in FRGC, the third row is using left eyebrow in MBGC, the fourth row is using right eyebrow in MBGC

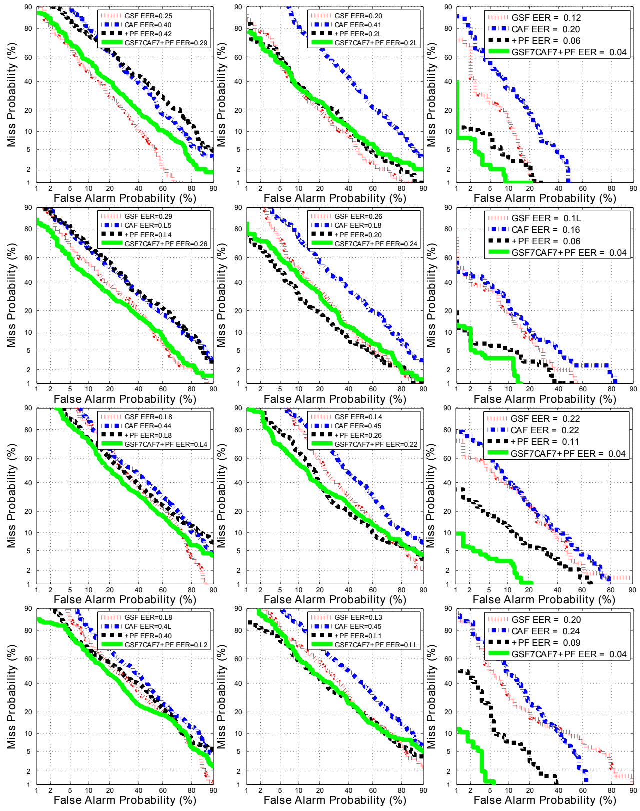

Figure 10. DET curve of gender classification: the left column is using MD method, the middle column is using LDA method, the right column is using SVM method; the first row is using left eyebrow in FRGC, the second row is using right eyebrow in FRGC, the third row is using left eyebrow in MBGC, the fourth row is using right eyebrow in MBGC

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