Soft Biometric Classification Using Periocular Region Features

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***Abstract*— With periocular biometrics gaining attention recently, the goal of this paper is to investigate the effectiveness of local appearance features extracted from the periocular region images for soft biometric classification. We extract gender and ethnicity information from the periocular region images using grayscale pixel intensities and periocular texture computed by Local Binary Patterns as our features and a SVM classifier. Results are presented on the visible spectrum periocular images obtained from the FRGC face dataset. For 4232 periocular images of 404 subjects, we obtain a baseline gender and ethnicity classification accuracy of 93% and 91%, respectively, using 5-fold cross validation. Furthermore, we show that fusion of the soft biometric information obtained from our classification approach with the texture based periocular recognition approach results in an overall performance improvement.**

I. INTRODUCTION

The periocular biometric is gaining attention lately as a means of improving robustness of face or iris biometric modalities [15], [17]. Periocular region is the area surrounding the eye, and is generally considered to be one of the most discriminative regions of the face. It has been shown that periocular region can be independently used for recognition and can aid face or iris recognition [18], when the inherent biometric content in the source images is poor (for example, due to the poor quality of an image). It has also been suggested that periocular features can potentially be used for soft biometric classification. In this paper, we explore the utility of appearance based periocular features for soft biometric classification, and using the soft biometric information for improving the recognition performance of appearance based periocular features.

Soft biometric information can be used to classify an individual in broad categories but is not sufficiently discriminative to perform recognition tasks [9]. For example,the knowledge about gender, ethnicity, age, or other traits such as height, weight, dimensions of limbs, skin color, hair color, etc., can be termed as soft biometrics. While such information is too broad to identify an individual, it can be valuable to narrow down the search space, or actually help improve results while performing identification. Although there is a wide variety of soft biometric traits that can be gathered from an individual, only a limited number of traits can be gathered from a given sensor. For example, from a camera set up to acquire face images for facial recognition,

This research was funded by the Office of the Director of National Intelligence (ODNI), Center for Academic Excellence (CAE) for the multi-university Center for Advanced Studies in Identity Sciences (CASIS).

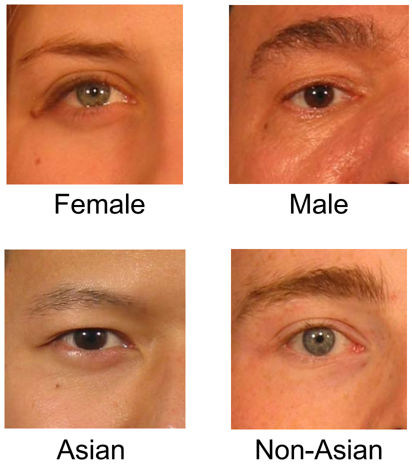

Fig. 1. Examples of right periocular region images for different classes. Top row shows the gender classes while the bottom row shows the ethnicity classes considered in this work.

soft biometric traits such as gender, ethnicity, or age can be determined with a lot more accuracy than height or weight. Due to the popularity of the face biometric, facial images have been used extensively to obtain gender and ethnicity information. Table I lists some of the key approaches in this area. All of the approaches listed in the table follow the strategy of training classifiers for a given set of classes in order to perform classification. It can be seen that a majority of the approaches rely on the appearance information present in face images. Typical feature representation used for this purpose include grayscale pixel intensities (used directly or represented in terms of PCA eigenvectors), Local Binary Patterns (LBP), Haar wavelets, and Gabor wavelets among others. The classifiers of choice are Adaboost (along with various variants of boosting), SVM, Neural Networks, and LDA among others. While each of the classifiers has its own advantages and limitations, SVM seems to be the most popular choice for gender and ethnicity classification due to its relatively high accuracy and generalizing ability.

In this work, we focus on gender and ethnicity classification of individuals using periocular images instead of full face images. The aim is to explore whether periocular images carry enough information to reliably obtain similar soft biometric information to that obtained from face images. Additionally, with the increasing interest in periocular biometrics, this work also aims to use the soft biometric

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Approach	Features	Classifier	Dataset	Recognition	
				Ethnicity	Gender
Gutta et al. [7]	grayscale pixel intensities	Neural Networks using SVM and DTs	FERET	92 % (Caucasian, South Asian, East Asian, African)	96%
Moghaddam and Yang [14]	low-res grayscale images	SVM	FERET (1755 total images)	-	97%
Balci and Atalay [1]	PCA eigenvectors	Multi-layer Perceptron	FERET (500 training, 260 testing)	-	92%
Wu et al. [19]	grayscale pixel intensity	LUT weak classifier based Adaboost	FERET, WWW pictures for training 2600 WWW pictures for testing	-	88%
Hosoi et al. [8]	Gabor wavelet transform with retina sampling	SVM	HOIP dataset	Asian - 96%, European- 93%, African - 94%	-
BenAbdelkader and Griffin [2]	local and global features (eigenfaces)	SVM, FLD	FERET, PIE, and Univ. of Essex (12964 total images)	-	85 %
Lapedriza et al. [10]	DOG, LOG filters on facial fragments	Adaboost, Jointboost	FRGC (controlled and uncontrolled lighting)	-	92 %
Lu et al. [11]	range and pixel intensity	SVM	376 subjects, 1240 scans	98% (Asian, Non-Asian)	91%
Yang et al. [22]	normalized face images	SVM, LDA, Adaboost	11500 Chinese Snapshot images	-	97%
Yang and Ai [21]	LBP, Haar like features	Adaboost	FERET, PIE	97% (Asian, Non-Asian)	93%
Makinen and Raisamo [12]	grayscale pixel intensity, Haar like, features, LBP	SVM, NN, Adaboost	IMM face dataset, FERET 304 training 107 testing	-	84%
Xu et al. [20]	Haar (appearance)	SVM	FERET, AR, misc. web images (1000 test subjects)	-	92%
Gao and Ai [6]	ASM based landmarks for normalization (grayscale intensities)	SVM, Adaboost, Probabilistic Boosting Trees (PBT)	15300 Chinese Snapshot 10100 Consumer images	Ethnicity specific gender classification	97%

TABLE I

A SUMMARY OF THE GENDER AND ETHNIC CLASSIFICATION APPROACHES USING FACE IMAGES. THE RECOGNITION RESULTS ARE THE BEST COMBINED RESULTS REPORTED.

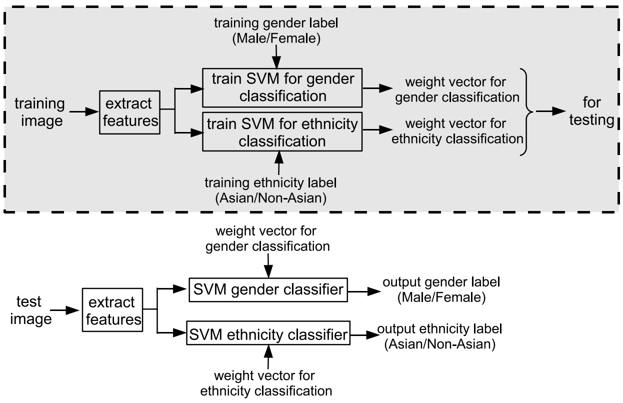


Fig. 2. Overview of the proposed gender and ethnicity classification approach.

classification results to improve previously reported periocular based recognition results. Figure 1 shows some examples of the periocular images belonging to different classes, i.e., male and female genders and different ethnic groups considered in this study. We exploit the appearance cues present in the periocular image such as texture and grayscale pixel intensities, with the inherent assumption that the relative success of these features in discriminating various classes in face images would also translate well to the periocular images.

Figure 2 shows the overview of our soft biometric classification approach, which is divided into training and testing stages. In the training stage, a preprocessed periocular image is used to extract appearance features which are used for training an SVM classifier. Gender and ethnicity classification proceeds separately, and two weight vectors are obtained from each of the trained SVM. In the testing stage, appearance features are extracted that act as input to the SVM classifiers that output class labels associated with gender and ethnicity information. The results of this classification are further used in the recognition process to improve the overall recognition performance. The next section describes our soft biometric classification approach along with the data acquisition and preprocessing steps, followed by experimental results.

II. APPROACH

Our approach is divided into three steps: collection and preprocessing of the periocular data, feature extraction, and classification.

A. *Periocular Data*

The visible spectrum periocular images are obtained from high resolution frontal face images belonging to the FRGC dataset [16] that are captured under different conditions. The high resolution still face images ($\approx$ 1200$\times$1400, 72 dpi) allow for the periocular texture to be imaged in significant detail. Also, the ground truth eye centers are provided, making it easier to crop out the periocular images and scale them to the required size. In this work, we scale the cropped periocular images to the uniform size of 251×251 pixels. The distance of the subject from the camera is assumed to be constant for controlled settings, hence the effects of scale change are assumed to be negligible.

The FRGC dataset also provides the ground truth labels for gender and ethnicities of the subjects. The gender distribution of the FRGC subjects is 57% male and 43% female. There are subjects of various ethnicities in the FRGC dataset, but they are primarily divided into three classes: Caucasian (68%), Asian (22%), and Other (10%). In this paper, we consider only two ethnic classes: Asian and Non-Asian because the Other class is thinly represented in the dataset. This bias in the population leads to very few training samples in that class, which results in poor classification performance. This aspect is described in detail in Section III.

For preprocessing, the images are converted to grayscale and histogram equalization is performed. To eliminate the effect of texture and color in the iris and surrounding sclera area, an elliptical mask of neutral color is placed over the center of the periocular region image. The dimensions of the ellipse are predefined based on the dimensions of the input periocular image rather than the dimensions of the subject's eye. The underlying assumption is that the change in size of the eye is mostly on account of its varying amount of opening and not so much due to changes in scale. This, coupled with the fact that the images are aligned and scaled to a fixed size, allows the placing of a fixed size ellipse on the eye such that a significant amount of periocular skin is still visible.

B. Features Extraction

The features we use for this work are grayscale pixel intensities and periocular texture calculated by Local Binary Patterns. Grayscale pixel intensity features are computed by taking the preprocessed $m \times n$ grayscale periocular image and reshaping it to a vector of size $1 \times (m \cdot n)$ and scaling it to the range $[0,1]$. However, using the 251×251 image is a large feature vector, so the images were downsampled to 50×50 pixels prior to reshaping. Texture features are computed with Local Binary Patterns. LBPs measure commonly observed intensity patterns in a local pixel neighborhood, such as spots, line ends, edges, corners, and other distinct texture patterns. For this work, LBP features were computed on separate blocks of the preprocessed image and then concatenated and converted to vector form, similar to LBP feature extraction in [17].

C. Classification

We use Support Vector Machines (SVM) for gender and ethnicity classification. The basic training principal of SVM's is to find the optimal hyperplane that separates the classes with a maximum margin [3]. Given a set of M training samples x_i (i.e., LBP or grayscale pixel representation for an image) and a set of M labels y_i (i.e., Male/Female or Asian/Non-Asian), where $x_i \in R^N$ and $y_i \in \{-1,1\}$, a SVM classifier finds the optimal hyperplane that correctly classifies the largest portion of the training samples while maximizing the distance of either class to the hyperplane (the margin). A test sample x is classified using the discriminating hyperplane, defined by:

$$f(x) = w \cdot \phi(x) + b, \text{ where } w = \sum_{i=1}^{M} \alpha_i y_i \phi(x_i) \qquad (1)$$

where w is the weight vector, b is a bias term, $\phi(x)$ is a transform related to the chosen kernel function by the equation $k(x,x_i) = \phi(x) \cdot \phi(x_i)$, and the sign of $f(x)$ determines the class of x. Determining the optimal hyperplane is equivalent to finding all $\alpha_i > 0$. Any vector x_i from the training set corresponding to a nonzero α_i is a support vector of the optimal hyperplane.

For a linear SVM, the kernel function is simply the dot product in R^N, while the kernel function in a nonlinear SVM projects the training samples to a space of higher dimensionality. Once the points are projected, the nonlinear SVM finds the optimal hyperplane in the new, higher dimensional space. Nonlinear kernels allow for a better separation of data which is not linearly separable. Polynomial and radial basis function (RBF) kernels, as shown below, are examples of kernels used in nonlinear SVMs.

- Polynomial: $k(x,x_i) = ((x \cdot x_i) + 1)^p$
- RBF: $k(x,x_i) = e^{-\gamma \|x-x_i\|^2}$, $\gamma > 0$

For our approach we use a linear SVM and a nonlinear SVM with a RBF kernel using the LIBSVM software [4]. RBF parameters are chosen for each experiment after running a grid search as mentioned in [5] for the best values of γ and C, where $C > 0$ is the penalty parameter for the error term. Overall, the results for the nonlinear SVM are higher than those for the linear SVM, so only the nonlinear results are reported.

III. EXPERIMENTAL RESULTS

In this section we discuss the soft biometric classification results, and their fusion with the local appearance based periocular recognition techniques to improve overall performance. First, we describe the experimental setup.

A. Experimental Setup

We experiment on the left and right periocular images and the corresponding face images from the FRGC face dataset. We use the same feature extraction and classification technique for both face and periocular images. There are a total of 404 subjects in our experiments. Each subject has multiple face images captured under different conditions giving us a total of 2116 face, left, and right periocular images. These 2116 images for each of the face, left and right periocular region are divided into 5 sets for our experiments: 1 gallery set (G), and 4 probe sets (P1, P2, P3, P4). The gallery images are captured under controlled lighting, with neutral expression, and in the same session. The P1 set of images are captured under controlled lighting, with neutral expression, but in a different session. The P2 set consists of images captured under controlled lighting, alternate expression, and in the same session. The set P3 is similar to P2 except the images are captured in a different session. The P4 set has images captured under uncontrolled lighting. There are two images per subject in set G and generally one image per subject in sets P1 through P4, but each probe set may not have images of all subjects. In total there are 808 images in G, and 356, 402, 353, and 197 images in P1, P2, P3, and P4, respectively.

For evaluating soft biometric classification performance, we perform 7 experiments using various combinations of training and test sets for each periocular region and the face. The training and test set configurations for these experiments are labeled as (ALL,ALL), (G,ALL), (G,G), (G,P1), (G,P2), (G,P3), and (G,P4). For each of these experiments we use 5-fold cross validation for reporting the classification accuracy. Testing is performed on subjects not used in training. A 5-fold cross validation scheme means images belonging to 80% of the subjects are used for training at a given time, while the other 20% of subjects are used for testing. The cross validation scheme is set up such that each subject is tested exactly once. The experiment (ALL,ALL) can be considered as the baseline, where we use all 5 image sets to draw the training samples from and test on all the available test images (images of the subjects not used in training). The experiment (G, ALL) means training is done only on images drawn from the set G, while testing is performed on all the available test images. This means training at a given instant is done on the gallery images of 80% of the subjects, and testing is done on all the images belonging to the rest of the subjects. Similarly, the experiments (G,G), (G,P1), (G,P2), (G,P3), and (G,P4) perform 5-fold cross validation on individual test sets while using the set G for drawing training samples. While drawing training samples, we try to keep the gender or ethnicity ratio the same as that observed in the entire population of our test set.

B. Gender and Ethnicity Classification

The accuracy of our approach for gender classification using LBP texture and grayscale intensity features for all the experiments described previously are shown in Table II. In addition to the left, right periocular regions and face, we also report results by combining the results left and right periocular region. On an average, for the right periocular region, the gender classification accuracy of about 93% is obtained using the LBP features considering all the experiments except (G, P4). The corresponding numbers for the left periocular region and face are around 90% and 94%, respectively. The classification accuracy for the grayscale pixel values is less across the board as compared to the LBP features, which is expected since local LBP features are less sensitive to noise and monotonic illumination changes. A large drop-off in accuracy is observed in the case of (G, P4), which consists of test images captured under uncontrolled illumination, while the training images are all captured under controlled lighting. Apart from this the set P4 consists of challenging images with blurring, and people wearing glasses. The SVM trained on the grayscale pixel values is the worst in such a situation. If a gender-wise analysis is done on the results, it can be seen that overall, males are classified with somewhat higher accuracy than the females, except again in experiment (G,P4), where females outperform males significantly. Also, the right periocular does better than the left and is comparable to the face results. This could be due to the uneven lighting of the face such that left part appears darker as compared to the right part. Females are also more likely to wear makeup than males, and that could be a factor affecting the classification accuracy of these genders. For all of these experiments, the male to female ratio was about 3:2.

Similar to the gender classification, accuracy of our approach for ethnicity classification using LBP texture and grayscale intensity features are shown in Table III. On average except for the experiment (G,P4), the right, left periocular region, and face classification accuracies are 90%, 91%, and 92%, respectively. Similar to gender classification, higher accuracies are obtained using LBP features than the grayscale pixel values. Also, there is a significant drop-off in performance for the (G,P4) experiment for both the feature representations, with grayscale pixel intensity based features seeming to suffer the most due to bad quality images in P4. A clear pattern emerges in case accuracy for each class with Non-Asians outperforming Asians across the board. This could very well be due to the skewed ratio of the Non-Asian to the Asians which is about 3:1. This was one of the reasons why we decided to merge the other classes present in the original FRGC labels with the Caucasian class to create a Non-Asian class. For the three class ethnicity classification problem, the results for the Other class were consistently worse than those for the Asian and Caucasian classes. Figure 3 shows some examples where our approach failed to correctly classify the periocular images. Some of the reasons for misclassification were glasses, presence of hair in the periocular region, misalignment, and excessive blurring.

C. Periocular Recognition Using Soft Biometrics

Using an approach similar to those reported in [13], [17], we use the LBP features obtained from the periocular and face images to compute recognition scores for experiments (G,P1), (G,P2), (G,P3), and (G,P4). These scores are fused with the corresponding soft biometric classification results to obtain a combined performance. The LBP vectors in a probe set are matched with all the vectors in the gallery set (G) and the match scores are normalized using the min-max normalization scheme. ROC is computed for this baseline matching. For fusing the gender and ethnicity information, we modify the way the ROC is computed. A match is considered to be made if the scores agree (for a given threshold) and the gender and ethnicity labels agree for the given pair of images. In this manner, gender and ethnicity information can also be independently fused with the LBP scores in order to obtain four curves per experiment: LBP, LBP+gender, LBP+ethnicity, and LBP+gender+ethnicity. These plots for all four experiments for both periocular regions and the

Local Binary Patterns													
Tr. Set	Test Set	Right Periocular (R)			Left Periocular (L)			L + R			Face		
		Male	Female	Overall	Male	Female	Overall	Male	Female	Overall	Male	Female	Overall
ALL	ALL	95.8	91.1	93.4	95.0	89.3	92.1	98.1	96.0	97.0	96.1	93.8	95.0
G	ALL	90.3	92.2	91.3	90.8	88.2	89.5	95.6	96.2	95.9	92.0	92.2	92.1
G	G	96.0	92.3	94.1	93.4	92.3	92.8	98.2	97.1	97.6	97.4	92.6	95.0
G	P1	93.1	95.7	94.4	91.7	88.5	90.1	96.8	96.4	96.6	95.9	95.0	95.4
G	P2	96.4	90.3	93.3	93.5	85.8	89.7	97.6	94.8	96.2	96.4	91.0	93.7
G	P3	94.9	89.8	92.3	92.6	86.9	89.7	97.7	95.6	96.7	95.4	91.2	93.3
G	P4	40.2	93.8	67.0	69.2	78.8	74.0	74.4	96.3	85.3	46.2	90.0	68.1
Grayscale Pixel Intensity													
ALL	ALL	93.5	85.7	89.6	92.8	86.0	89.4	96.8	93.8	95.3	94.2	91.6	92.9
G	ALL	85.6	89.8	87.7	89.8	84.0	86.9	92.1	94.2	93.1	90.0	85.8	87.9
G	G	93.4	91.7	92.5	94.4	89.7	92.1	96.2	94.9	95.5	94.2	91.0	92.6
G	P1	92.2	92.8	92.5	92.2	86.3	89.3	95.4	97.8	96.6	93.6	89.9	91.7
G	P2	93.1	87.1	90.1	94.4	83.9	89.1	96.4	92.3	94.3	95.6	82.6	89.1
G	P3	94.0	84.7	89.3	94.4	81.0	87.7	97.2	92.0	94.6	95.4	76.6	86.0
G	P4	9.4	91.3	50.3	48.7	62.5	55.6	50.4	92.5	71.5	43.6	80.0	61.8

TABLE II

GENDER CLASSIFICATION RESULTS FOR THE VARIOUS EXPERIMENTS DESCRIBED. OVERALL CLASSIFICATION ACCURACY IS THE AVERAGE OF THE ACCURACIES OBTAINED FOR THE INDIVIDUAL CLASSES.

Local Binary Patterns													
Tr. Set	Test Set	Right Periocular (R)			Left Periocular (L)			L + R			Face		
		Asian	Non-Asian	Overall	Asian	Non-Asian	Overall	Asian	Non-Asian	Overall	Asian	Non-Asian	Overall
ALL	ALL	85.1	98.3	91.7	85.4	97.6	91.5	89.8	98.9	94.4	91.1	98.4	94.8
G	ALL	79.8	97.1	88.5	84.7	94.7	89.7	87.4	98.7	93.1	86.0	97.3	91.6
G	G	85.4	98.1	91.8	86.3	97.1	92.0	88.6	98.9	93.8	88.7	97.8	93.3
G	P1	80.6	98.1	89.3	85.7	96.1	91.9	90.8	98.8	94.8	87.8	98.8	93.3
G	P2	84.9	96.6	90.8	86.8	96.3	91.5	88.7	98.6	93.6	88.8	96.6	92.6
G	P3	81.6	96.9	89.3	86.7	96.1	91.4	87.8	98.4	93.1	88.8	98.1	93.4
G	P4	22.7	93.2	58.0	60.0	74.1	67.0	65.7	98.1	81.9	48.5	92.6	70.6
Grayscale Pixel Intensity													
ALL	ALL	83.4	94.8	89.1	83.2	96.0	89.6	89.6	98.2	93.9	85.8	96.5	91.4
G	ALL	83.1	91.1	87.1	77.0	94.5	85.8	87.4	97.5	92.5	83.6	93.9	88.7
G	G	85.4	95.8	90.6	81.1	94.3	87.7	88.2	97.5	92.9	85.9	96.1	90.9
G	P1	80.6	95.0	87.8	85.7	94.2	90.0	87.8	97.3	92.5	83.7	96.5	90.1
G	P2	84.0	95.6	89.8	80.2	93.9	87.1	88.7	98.0	93.3	85.9	96.3	91.1
G	P3	81.6	92.9	87.3	83.6	93.7	88.7	87.7	96.5	92.1	84.7	96.5	90.6
G	P4	77.1	56.2	66.7	0.0	98.2	49.1	77.1	98.8	88.0	60.0	72.8	66.4

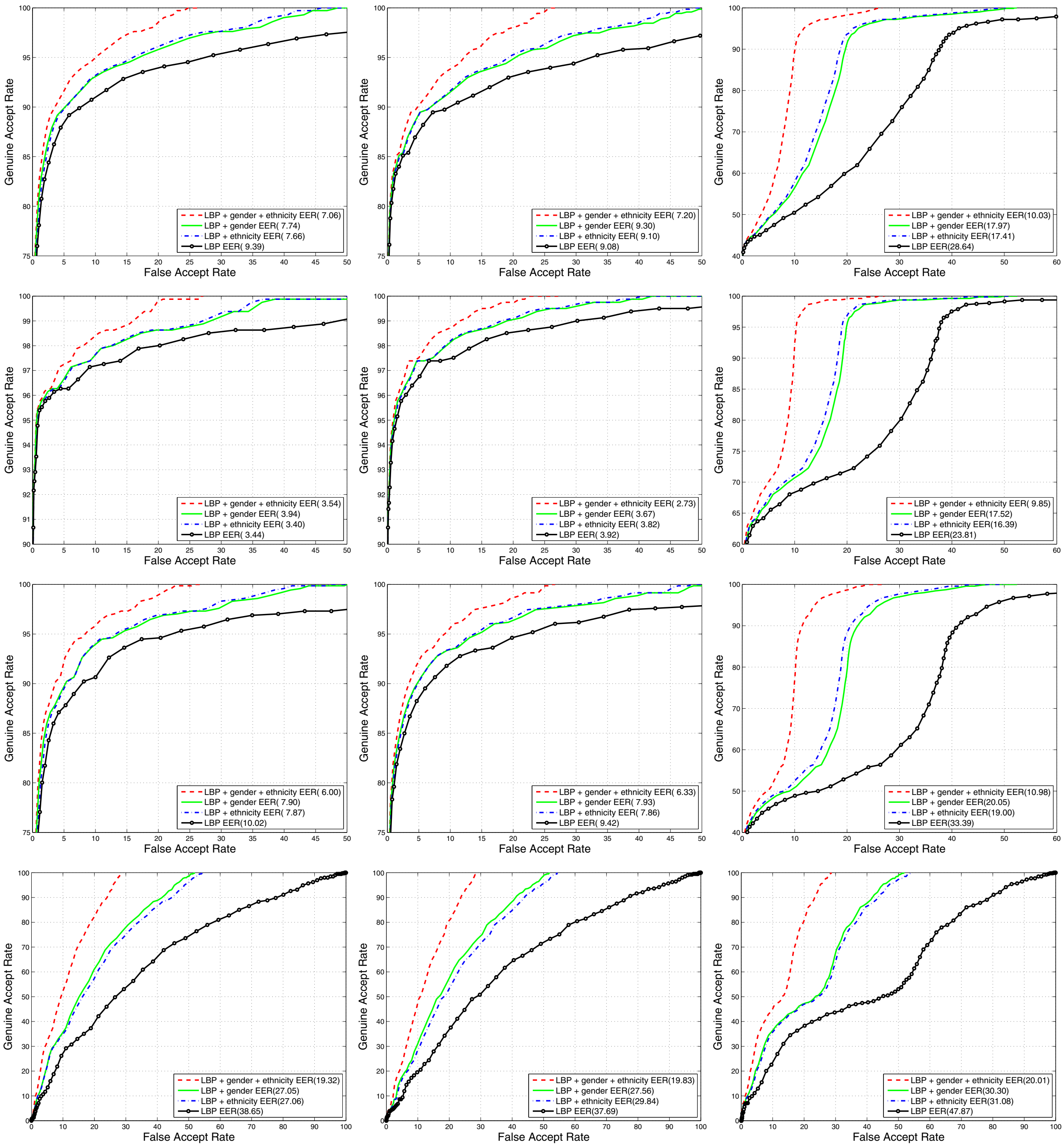
TABLE III

ETHNICITY CLASSIFICATION RESULTS FOR THE VARIOUS EXPERIMENTS PERFORMED USING THE PERIOCULAR REGION AND FACE IMAGES. THE ETHNIC CLASSES CONSIDERED HERE ARE ASIAN, AND NON-ASIAN. OVERALL CLASSIFICATION ACCURACY IS THE AVERAGE OF THE ACCURACIES OBTAINED FOR THE INDIVIDUAL CLASSES.

face are shown in Figure 4. The equal error rates (EER) obtained by these curves are listed in Table IV. It can be seen from Figure 4 and Table IV that using the soft biometric information improves the overall recognition results. It can also be seen that the periocular regions outperform face by a large margin. This does not mean that periocular is superior to face. It should be noted that the recognition approach used for face is local appearance based, similar to the approach used for periocular recognition. This may not be the ideal for face for the given dataset. So, while we should exercise caution in interpreting the robustness of periocular region vis-a-vis face, it is also clear that soft biometric information obtained from periocular region can improve periocular based recognition.

IV. CONCLUSIONS AND FUTURE WORK

This paper describes a soft biometric classification approach using appearance based periocular features. The experiments presented in this paper for visible spectrum data obtained from FRGC dataset indicate that periocular features can be effectively used in gender and ethnicity classification. The soft biometric information thus obtained can be effectively used for improving the performance of existing periocular based recognition approaches. The problem of classification is dependent on the kind of data available for training, and the bias in population affects the class specific classification accuracy. The experiments also indicate that the soft biometric classification accuracy obtained using the periocular region is comparable to that obtained by using the entire face. Future work includes refining the ethnicity classification to more than two classes, experimenting with



Left Right Face

Fig. 4. Effect of soft biometric classification on recognition performance. From top to bottom: ROC from the probe lists P1, P2, P3, and P4 compared to the gallery.

different classifiers and feature representations, and incorporating classification based on additional traits such as age, skin color, and hair color.

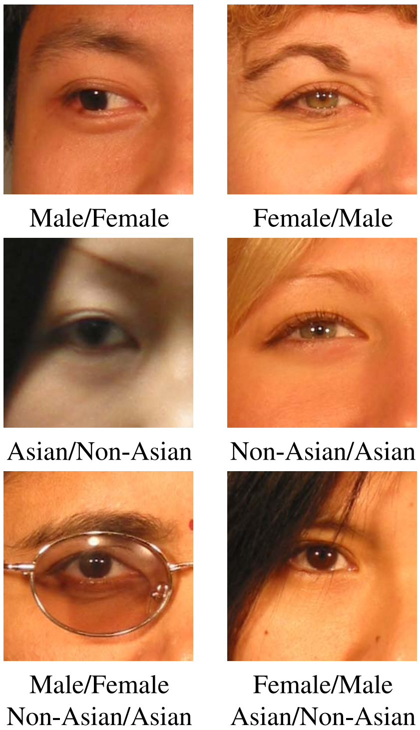


Fig. 3. Some images that the approach failed to classify correctly. Label below each image indicate the ground truth label and the incorrect label produced by our approach. The top row shows some examples of gender misclassification, the middle row shows images for which the ethnicity labels were incorrect, and the third row shows images for which both the labels were incorrect.

Left Periocular Region				
	(G,P1)	(G,P2)	(G,P3)	(G,P4)
LBP	9.39	3.44	10.02	38.65
LBP + gender	7.74	3.90	7.90	27.05
LBP + ethnicity	7.66	**3.40**	7.87	27.06
LBP + gender + ethnicity	**7.06**	3.54	**6.00**	**19.32**
Right Periocular Region				
LBP	9.08	3.92	9.42	37.69
LBP + gender	9.30	3.67	7.93	27.56
LBP + ethnicity	9.10	3.82	7.86	29.84
LBP + gender + ethnicity	**7.20**	**2.73**	**6.33**	**19.83**
Face				
	P1	P2	P3	P4
LBP	28.64	23.81	33.39	47.87
LBP + gender	17.97	17.52	20.05	30.30
LBP + ethnicity	17.41	16.39	19.00	31.08
LBP + gender + ethnicity	**10.03**	**9.85**	**10.98**	**20.01**

TABLE IV

COMPARISON OF THE EERS OBTAINED FOR VARIOUS RECOGNITION EXPERIMENTS.

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