Investigating Useful and Distinguishing Features Around the Eyelash Region

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***Abstract*—Traditionally, iris recognition is always about analyzing and extracting features from iris texture. We proposed to investigate regions around eyelashes and extract useful information which helps us to perform ethnic classification. We propose an algorithm which is easy to implement and effective. First, we locate eyelash region by using ASM to model eyelid boundary. Second, we extract local patch around local landmarks. After image processing, we are able to separate eyelashes and extract features from the directions of eyelashes. Those features are descriptive and can be used to train classifiers. Experimental results show our method can successfully perform East-Asian/Caucasian classification up to 93% accuracy, which shows our proposed method is useful and promising.**

***Index Terms*—soft biometrics, ethnic classification, eyelash analysis, ASM**

I. Introduction

Traditionally, the focus of iris recognition is always on how to correctly segment iris out of the eye image, and how to perform feature extraction and iris matching so that the recognition rate for personal identity can be as high as possible. However, besides the iris texture, there are still other parts of the eye images which are interesting and may contain useful information. For example, the size of the eye, single or double-fold of upper eyelids, and the appearance of the eyelashes, may contain useful information for biometrics recognition.

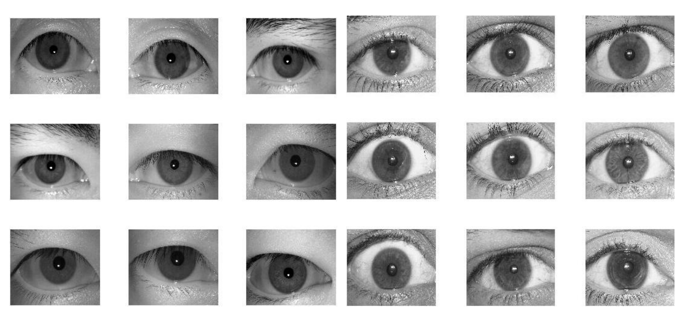
Of course, the information revealed from eye shape, eyelid or eyelashes, may not span a wide feature space which is rich enough to describe individual characteristics in personal basis. For example, two person who looks alike may share the same characteristics in appearance of eyelids or eyelashes. But people who belong to the same ethnic group may share a similar characteristics in appearance, and this characteristic may differ from other ethnic group in a great level. This can be verified by our empirical experience. Also, early psychological studies have shown that people are more easily to recognize faces belonged to their ethnic group [1], [2]. Although it is very hard to differentiate people into all nationalities in the world, it is quite easy for most people to distinguish people in a coarse level of ethnicity, like western people vs. eastern people, African vs. Caucasian, or Indian vs. Caucasian. Classification of the ethnicity of the subjects can be categorized into the field of "soft biometrics". The goal of "soft biometrics" is trying to recognize the ancillary information about the subjects, like gender, age or ethnicity [3].

In this paper, we are trying to explore the regions in an eye image which are always neglected by most iris recognition researchers, and investigate how to use such information for the use of "soft biometrics". Particularly, we would like to see if there is any useful information revealed in eyelashes region which can help us to classify the ethnicity of the subjects. We will review previous related work in Section II, summarize the observation of the eyelash region in Section III. Our proposed algorithm is presented in Section IV. Experimental setting and the results are presented in Section V. Finally the conclusion will be shown in Section VI, and future works in Section VII.

II. Previous Work

There is not too much literature which addresses the issue of soft biometrics. Jain et al. investigated the usefulness of soft biometrics information and they claimed by combining information for ancillary information, performance of biometrics system can be enhanced [4]. Lu and Jain proposed an ensemble scheme which integrates the LDA analysis for face images at different scales to perform ethnicity classification [5]. They show that although the performance of ethnicity classifier may not be perfect, it still can help to improve the face recognition system. Gutta and Weshsler proposed a hybrid classification architectures for gender and ethnic classification of human faces. The hybrid approach consists of an ensemble of RBF networks and inductive decision trees [6]. They show their method is robust and flexible and achieve recognition result as good as [5].

Qiu et al. proposed to learning-based method to extract features from iris pattern to perform ethnic classification [7]. Their proposed method is able to learn a finite vocabulary set (called "Iris-Texton") from given iris texture, and use Iris-Texton histogram as features to capture the difference between iris texture. By using SVM on the feature, they can achieve correct classification rate of 91.02%.



(a) (b)

Figure 1. Example eye images of different ethnicity. (a) East-Asian. (b) Caucasian.

III. Goal and Observations of eyelashes regions

Different than most existed research, in this paper, our goal is to explore the possibility of soft biometrics recognition through information we can get from ancillary part of input image. There are many different ethnicities in the world, but they can be categorized mainly into western and eastern. Particularly, the outside appearance of East-Asian people is quite different than that of Caucasian.

Let us take a look at some example images. Figure 1 (a) and (b) shows a few example images for East-Asian and Caucasian, respectively. There are quite a few main differences we can find among these two groups of images. First, Caucasian eyes have double-fold upper eyelid, while East-Asian eyes have single-fold ones. Second, the iris texture of them seems different. Third, the directions of upper eyelashes of them are quite different. These three factors are just examples from observation, not a exclusive list. Different people may observe more difference among them. Also note that the above observation, though derived by inspecting these two groups of images, can be generally applied to most Caucasian and East-Asian eyes. Most Caucasian and East-Asian people have such characteristics in common.

In this paper, we would like to set our goal as to investigate whether there is useful information which can be extracted from eyelash region, to help us distinguish the ethnicity of the subject. Specifically, our focus is to distinguish subjects between East-Asian and Caucasian, by looking into eyelash direction.

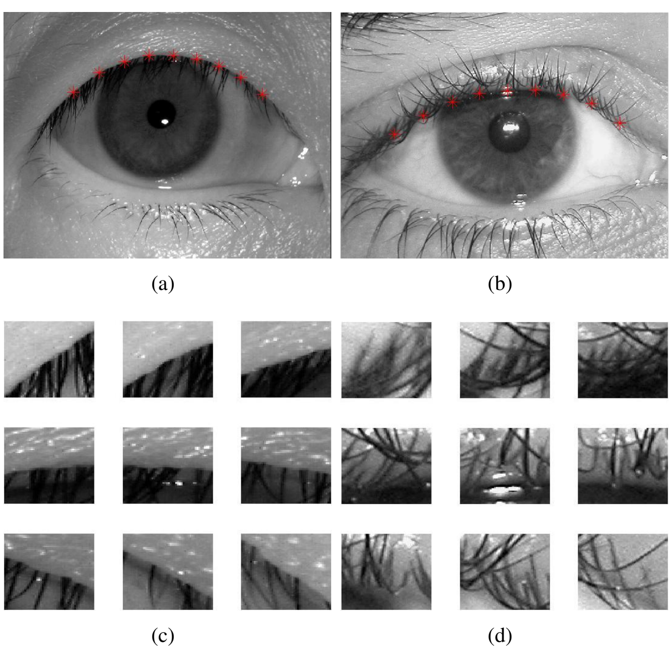


Figure 2. Local region along the upper eyelids of eye images. (a) example eye image of an East-Asian; (b) example eye image of a Caucasian; (c) local regions (patches), picked from nine points evenly spread on upper eyelid boundary in (a); (d) local regions (patches), picked from nine points evenly spread on upper eyelid boundary in (b)

We can start this task by simply observe the difference around eyelashes regions between example image pair of East-Asian and Caucasian. We can take one image from each group

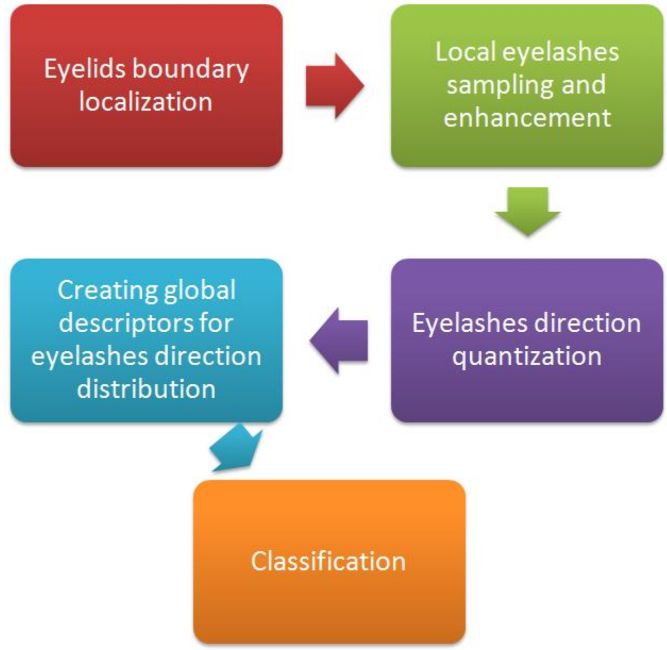


Figure 3. Flow chart of the proposed method for ethnicity classification

(East-Asian and Caucasian) to be an example. Figure 2(a) is one of the images shown in Fig. 1(a) and Fig. 2(b) is picked from Fig. 1(b). They represent a typical example image of East-Asian and Caucasian ethnic group, respectively. By closely inspecting the upper eyelashes regions, we can see there are significant differences in the direction of eyelashes on the upper eyelid boundary. To show those differences more clearly, we locate the upper eyelid boundary, and zoom into nine local patches which evenly spread along the entire contour of upper eyelid. The red dots on Fig. 2(a) and Fig. 2(b) indicate the location where local patches are taken. The zoom-in version of the local patches of Fig. 2(a) are shown in Fig. 2(c), and local patches of Fig. 2(b) are shown in Fig. 2(d).

From Fig. 2(c) and (d), we can clearly observe the difference of the direction of the eyelashes between East-Asians and Caucasians. For East-Asians, their eyelashes tend to extend in more vertical direction. The eyelashes are easily approximated with straight lines. And when they are approximated with straight lines, those lines would have high absolute slope values. In terms of statistical language, we can say that the distribution of the absolute value of slope of East-Asian's eyelashes is more clustered to large numerical value.

On the contrary, for Caucasians' eyelashes, first, they tend to be more curly, and cannot be simply approximated with straight lines. Second, even if we approximate their eyelashes with piece-wise straight lines, the absolute value of the slopes of those lines can be either very high or very low. In terms of statistical language, we can say that the distribution of the absolute value of the slope of Caucasians' eyelashes spread more evenly across the parameter space.

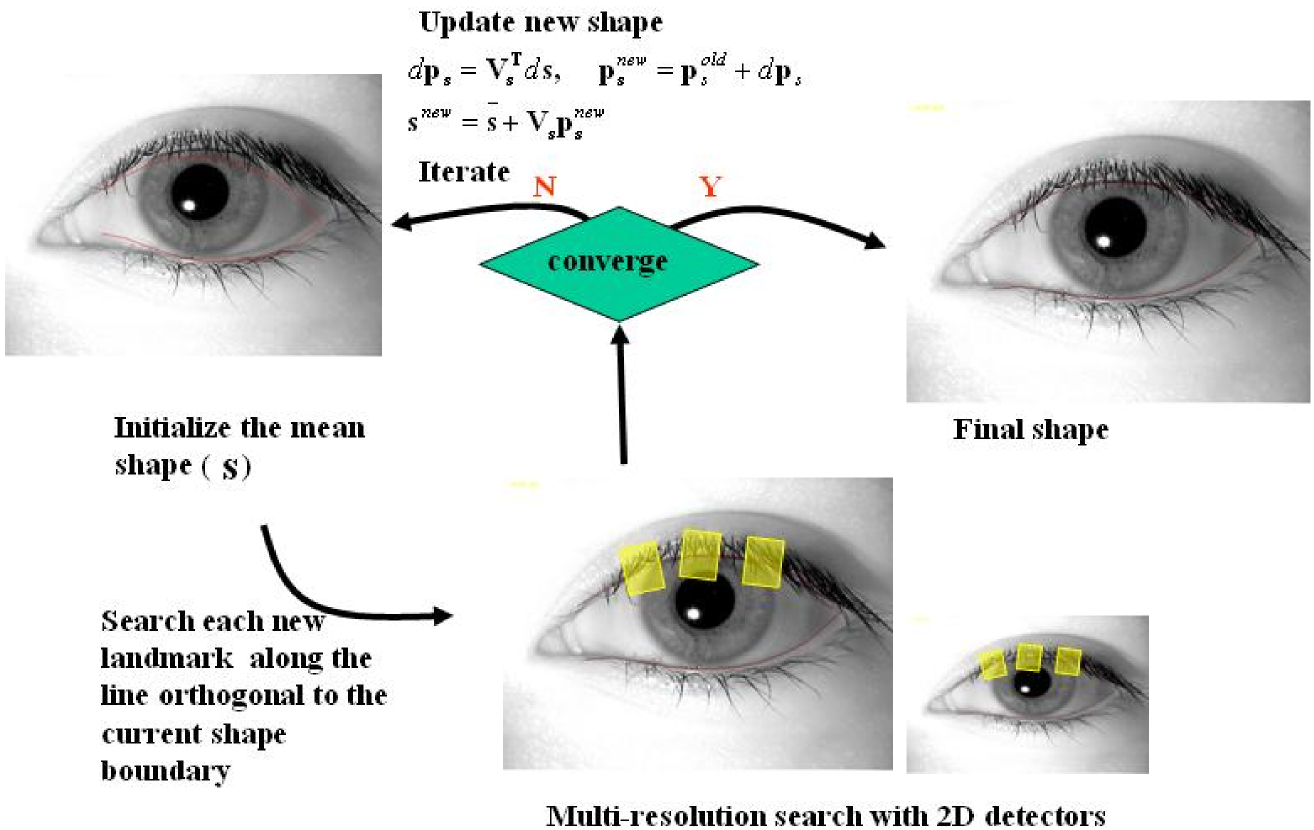


Figure 4. An overview of the ASM searching with 2D profile searching. After initializing the mean shape after pupil detection, new landmarks are searched along the line, orthogonal to the current shape boundary. Two-dimensional profile searching uses more information than one-dimensional profile searching and can be considered as 2D feature detection. Using a coarse to fine search (from low resolution to high resolution), the shape is updated iteratively, until no change on the current shape is observed.

IV. Proposed method

Given the insight from Section III, we propose a statistical, learning-based method which is able to automatically extract the local patches of eyelash region, analyze the distribution of local eyelashes, and extract features. Those features can be stored as template to be used in the future in order to perform ethnicity classification.

Our proposed method consists of five stages, as shown in Fig. 3. We will illustrate each of the stage in following subsections.

A. *Eyelids boundary localization*

The first stage is called “Eyelids boundary localization”. For an input eye image, we would like to find out where the true upper eyelid boundary is, in order to extract local patches from it. We propose to use Active Shape Model (ASM) to recover the eyelid boundaries. ASM has been shown to be an effective way for analyzing the shape of objects. The shape model can be obtained from Principal Component Analysis (PCA). This process is known as the Point Distribution Model (PDM), which is a method for representing the mean geometry of a shape and some statistical modes of geometric variation inferred from a training set of shapes. The general procedure of an ASM algorithm can be divided into aligning, modeling and searching steps. First, manually labeled shapes are first aligned to deal with global geometric transformations, such as scale, translation, and rotation. This method is known as Procrustes Analysis [8], which is a classical technique for normalizing different shapes by analyzing statistical distribution of the shapes. In the next part of this step, the normalized shapes s for the ASM model can be expressed by a mean shape $\bar{\mathbf{s}}$ and a linear combination of the base vectors and projection coefficient vector $\mathbf{p_s}$. This can be written as:

$$\mathbf{s} = \bar{\mathbf{s}} + \mathbf{V_s}\mathbf{p_s} \quad (1)$$

where $\mathbf{V_s}$ indicates the eigenvector matrix of the shapes. Then, the modeling around each landmark point (local appearance models) needs to be performed with the 2nd order statistics, mean $\bar{\mathbf{g}}$ and variance $\mathbf{\Sigma}$.

In order to search the shapes in new images, a mean shape is initialized around the possible locations of the target shape. Then, each local appearance model selects new landmark positions along the direction of the normal to the current shape. The criteria for selecting new points is to choose the minimum Mahalanobis distance along the normal to the current shape boundary for each point:

$$f(\mathbf{g_s}) = (\mathbf{g_s} - \bar{\mathbf{g}})^T \mathbf{\Sigma}^{-1} (\mathbf{g_s} - \bar{\mathbf{g}}) \quad (2)$$

Finally, the current shape is refined by the new points updated by the local appearance models. By assuming

$$d\mathbf{s} = \mathbf{V_s} d\mathbf{p_s} \tag{3}$$

where the displacement vector $d\mathbf{s}$ can be calculated by the pixel difference and used for updating the shape parameter $d\mathbf{p_s}$. The new shape, reconstructed by the parameter, is iteratively refined until no changes on the current shape is observed. For the eyelid boundary detection, we initialize the mean shape after pupil detection. Then, new landmarks are searched along the line, orthogonal to the current shape boundary. Two-dimensional profile searching uses more information than ome-dimensional profile searching and can be considered as 2D feature detection. Using a coarse to fine search (from low resolution to high resolution), the shape is updated iteratively, until no change on the current shape is observed. This is illustrated in Fig. 4.

B. Local eyelashes sampling and enhancement

After we precisely locate the upper eyelid boundary, the next step is to extract the local features of eyelashes. We achieve this goal by two steps.

First, we evenly sample nine points on the recovered upper eyelid boundary. We extract nine local patches, center at each point on the boundary. Two examples of this step are shown in Fig. 2, when we talked about observation of eyelashes regions.

The differences of pixel intensity between eyelashes and skin may vary according to different subject and race. Therefore, we need to enhance the contrast. In second step, in order to compensate the variation among different ethnic groups and enhance contrast, we apply histogram equalization onto every local patch.

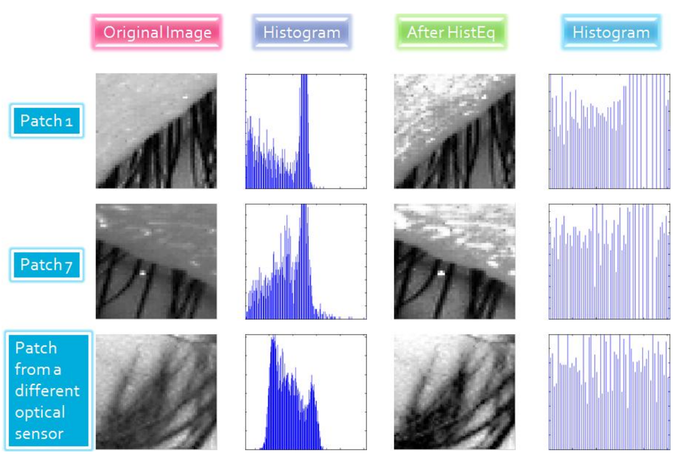


Figure 5. Effect of histogram equalization applied on local patches on eyelashes regions. The first column shows the original local patch. The second column shows their corresponding image histogram. The third and fourth column shows that after applying histogram equalization, how the image and image histogram changed, respectively.

Figure 5 shows some example images to illustrate effect of histogram equalization on local patches. Before applying histogram equalization, we can see from the image histogram that the distribution of the pixel intensity is pretty uneven, with strong density accumulated on the middle and lower values, but almost no density spread on high values. But after applying histogram equalization, the distribution of the pixel intensity becomes much better, with relatively equal among of distribution across all possible values. Note that this fact holds true across different sensors, which demonstrate the necessity and robustness of the second step of the proposed algorithm.

C. Eyelashes direction quantization

At this step, we would like to differentiate eyelashes from other parts of the image, like eyelid or sclera. After eyelashes are identified and localized, we can further analyze their directions.

To localize eyelashes and separate them from backgrounds, we use hard threshold value on pixel intensities as a binary classifier. As stated in Section IV-B, after applying histogram equalization, the distribution of the pixel values become evenly across possible range. Therefore, a carefully chosen threshold of intensity is enough to separate eyelashes from backgrounds. The threshold can be fine-tuned with optimization techniques like gradient descent or Nelder-Mead nonlinear optimization [9].

After eyelashes are identified in a local patch, we would like to extract features which describe the distribution of the direction of eyelashes. We achieve this goal by convolving images with a series of uni-directional edge filters whose edge span whole 360 degree in two-dimensional space. The filter bank we used is shown in Fig. 6.

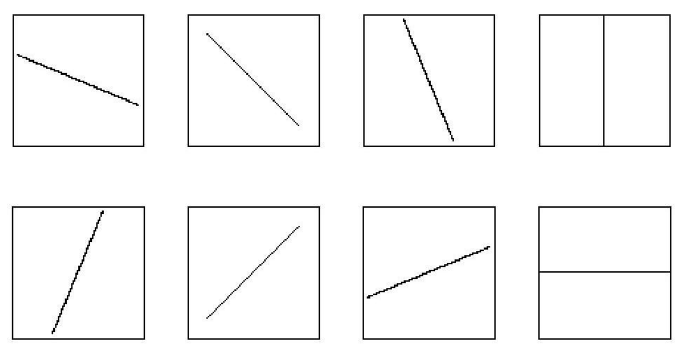


Figure 6. Eight filters we used for directional feature extraction.

We use eight uni-directional edge filters, and the angular difference between each filter is 45 degree. In this way, it can completely describe the the direction of a target object. After convolved with those eight uni-directional edge filters, the direction of eyelashes in a local eyelash map will be captured and quantized into eight bins. The value in each bin tells how many percentage of the eyelash in this local patch extend themselves in this direction.

Figure 7 shows examples of a few local patches, localized eyelashes, and quantized features. The upper row of Fig. 7 shows three example local patches from East-Asian eyes, while the lower row of Fig. 7 shows another three example local patches from Caucasian eyes. Note that most authentic eyelashes regions in local patches are correctly picked up and shown in the localized eyelash map. Also, the histograms correctly describe the major direction of the eyelashes.

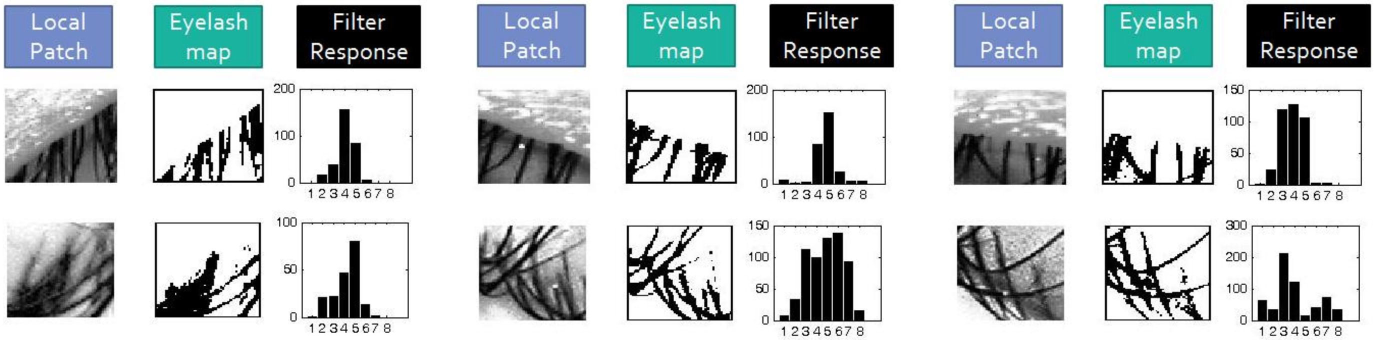


Figure 7. Example images of local patches, recovered eyelashes maps, and the filter responses, quantized into eight bins.

D. Creating global descriptors for eyelashes direction distribution

As stated in Section IV-B, we sample nine points which are evenly spread on upper eyelid boundary. From Section IV-C, we know that for each point, a local patch is extracted and a feature vector is generated. The length of the feature extracted for each local patch is eight, since the number of filter bank we used is eight. Therefore, for one eye image, the total number of features is 8x9=72. We use those 72 features as a global descriptor to describe the distribution of the direction of eyelashes in one image.

E. Classification

After a descriptive feature set can be extracted from every input image, the problem reduced to a standard machine learning/pattern recognition problem. We can use any popular method in machine learning to perform training and classification. In this paper, the classification method we use is one of its simplest kind, which is one-nearest-neighbor (1NN) method. This method is easy to implement. The training is easy and require almost no time. The classification stage may cost more time depends on the size of the training data. But we can always perform clustering method on top of the training data to make the representation of template more compact. We will describe our experiment in more detail in Section V.

V. Experiments and Results

A. Database

We use two iris datasets in our experiment. The first is collected in CMU, with SecuriMetrics PIER 2.3 device. We call it CMU-PIER dataset. CMU-PIER contains 107 iris classes, and for each class, three iris images are collected. The subject in CMU-PIER are all East-Asians (Chinese, Korean or Japanese). The size of the images in CMU-PIER is 640x480.

The other dataset we use is UBIRIS.v1. The camera model used to capture UBIRIS.v1 is Nikon E5700. It is composed of 1877 images collected from 241 persons during September, 2004 in two distinct sessions. In our experiment, we only use session 1 of this dataset. We picked 107 iris classes out of the original 241 classes in order to have the same number of class as in CMU-PIER. For each class, we also picked 3 images, out of originally five images, in order to make it the same as the condition in CMU-PIER. The subjects in UBIRIS.v1 are all Caucasians. The size of images in UBIRIS.v1 is 800x600.

B. Training and Testing

For both CMU-PIER and UBIRIS.v1, we randomly pick six classes and use all of their images as our training data, for East-Asian and Caucasian classes, respectively. We use all of the remaining images (101 classes) in both datasets as our test data. The ratio of the number of images between training and test data is 6:101. The test data is roughly 16 times more than the training data.

For every image from training data, we locate the upper eyelid boundary, extract features from local patches and combine all features into a global descriptor, as described in Section IV. For every test image, we do the same thing, and compare the Euclidean distance of its global feature to that of all training data, and classify the test image as the same ethnicity as the training data which is closest to it in 72-dimensional feature space.

We repeat the experiment 30 times, each time we re-select the training data randomly in order to get a fair estimation of the performance of the proposed method.

C. Results

The ethnicity recognition rate is plotted in Fig. 8. X-axis is the iteration number, and Y-axis is the recognition rate. Note that each iteration is independent from other iteration, and the training classes have been re-selected randomly.

Figure 8 presents result in three levels. It shows the recognition rate for East-Asian images and Caucasian images separately. It also shows an overall recognition rate, which is the average value of the above two because the number of test data from each ethnic group is the same. Table I shows statistics of the ethnicity recognition rate.

Table I
MAXIMUM, MINIMUM AND MEAN OF THE ETHNICITY RECOGNITION RATE, ACROSS 30 ITERATIONS.

Ground truth for test images	East-Asian	Caucasian	Overall
Minimum of recognition rate (%)	85.15	96.37	92.24
Maximum of recognition rate (%)	90.43	100	94.39
Average of recognition rate (%)	88.06	98.39	93.23

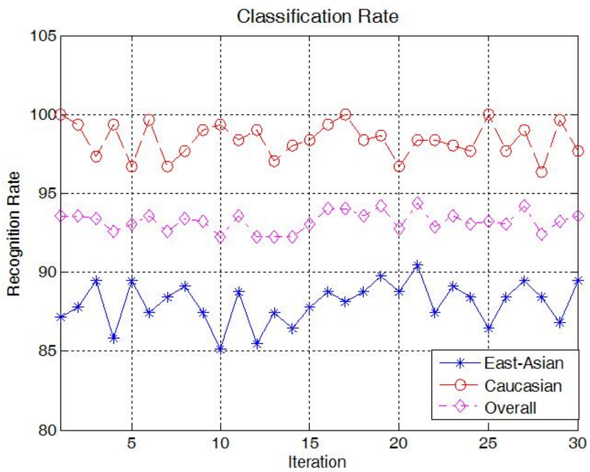


Figure 8. Ethnicity recognition rate of the proposed algorithm, versus the iteration number. The plots show the recognition rate for each of East-Asian and Caucasian datasets, as well as the overall performance.

VI. Conclusions

First of all, from Table I and Fig. 8, we can see our proposed algorithm works pretty well, considering it is one of the pioneer work in this field. The minimal recognition rate for overall dataset is 92.24%, and the average recognition rate is 93.23%.

Second, we can see that the recognition rate for East-Asian seems to be lower than Caucasian. This suggests East-Asians' eyes are easily got confused with Caucasians' eye, but Caucasians' eyes are very easy to be recognized in our scheme. We suspect that the reason is because the underlying distribution of East-Asian is quite different than that of Caucasian. Therefore, more advanced modeling technique need to be applied in order to solve this problem.

VII. Future works

Our future work is to investigate why the recognition performance for East-Asian is worse than that for Caucasian, and modify our model in order to improve the performance. We may also like to explore other unused regions in eye images, like eyelid boundary curvature, tear duct location or eyebrow appearance, to extract useful information for soft biometrics. Finally, we can apply proposed method on other soft biometric trait, such as gender or left/right eye classification.

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