

Iris Image Classification Based on Color Information

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Abstract

Iris recognition systems using iris images captured in visible light have several advantages compared to using near infrared (NIR) images, and draw attention from biometrics researchers. The acquisition of color iris image does not ask for special cameras, and reserves the color information of iris. The color information can be used as an important clue for iris classification which improves performance of iris recognition on non-ideal iris images. In this paper, we propose a novel color feature for iris classification, named as iris color Texton using RGB, HSI and $l\alpha\beta$ color spaces. Extensive experiments are performed on three databases. The proposed iris color Texton shows advantages in iris image classification based on color information.

1 Introduction

Most of traditional iris recognition systems use NIR iris images as their inputs [4], due to the clear iris texture in NIR images. However, iris recognition systems in the visible wavelength draw much attention from the biometrics research field recently. A research team from Universidade da Beira Interior releases the UBIRIS.v1 [8] and UBIRIS.v2 [9] databases containing color iris images captured under visible wavelength. NICE:II is an iris classification contest using color iris images [2]. There are some advantages of visible wavelength iris images: include the important color information of irises; are captured by standard RGB cameras which are common and cheap; do not need NIR illuminating equipment; are easy to combine with other security systems using standard RGB cameras. However, visible wavelength images bring challenges to iris recognition algorithms. Iris texture details in visible wavelength images are not as clear as the ones in NIR

images. More reflection and shadow shows in the iris images caused by ambient lighting which may cover major area of iris. Figure 1 shows examples.

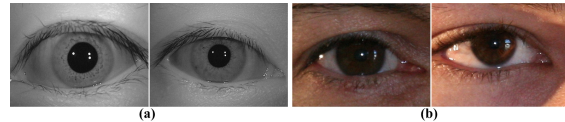


Figure 1: Iris images: (a) NIR (CASIA database [1]); (b) visible wavelength (UBIRIS.v2 database [9]).

The color based iris image classification has drawn attentions from the research field. The iris color is a significant sign of people, which has been used as an important aspect of people description. The color based iris classification, which classifies a query image into a small subset, can reduce the system search time and improve the accuracy of iris recognition. Some research work about the iris color has been done. Fu et al. [5] conducted artificial color filter experiments on a small collection of high quality color iris images. Puhan et al. [10] proposed to compute two types of color indices (blue and red indices) using C_b and C_r components respectively in the YC_bC_r color space for iris indexing. Jayaraman [6] also adopted the YC_bC_r color space and texture information for iris indexing.

There methods achieve promising results, which show that the color information is an important clue for iris classification. However, the color based iris image classification is still a challenge problem because the ambient lighting influences the eye color a lot. Iris images captured in practical environment are non-ideal. Due to the reflection and refraction of iris, color of iris image is sensitive to ambient lighting. Large speckles and shade are likely to form and occlude the iris texture which may change the iris color in images. Figure 2 shows iris images from same iris in different color.

We will introduce a novel iris color representing



Figure 2: Examples of iris images from same iris under different ambient lighting conditions from UBIRIS.v2 database [9]: (a)-(b) image pairs of two irises.

method named as iris color Texton, which combines a pixel value in RGB, HSI and $l\alpha\beta$ color spaces as color feature and represents iris images by Texton voting method. This strategy conquers the problem of comparing two objects based on too many different colors in color space. The iris color Texton is inspired by the Major Colors [3] and previews iris classification method [11].

The remainder of this paper is organized as follows: Section 2 introduces the iris color Texton; Section 3 presents experiments; Section 4 concludes the paper.

2 The proposed iris color Texton

In this section, we will introduce the proposed iris color Texton method for color iris image classification. The whole iris classification method includes three steps: iris image preprocessing, color feature extraction and classifying. The iris image preprocessing mainly involves localization, segmentation, and normalization. In this work, the resolution of normalized iris image is 66×540 (in polar coordinates) and the normalization is performed on each color channel, and more details can be found in [14, 15].

2.1 Color model

The RGB and HSI are widely used color models. Most of color images are stored in the form of RGB color model. HSI, for hue, saturation, and intensity, is common in computer vision applications. The $l\alpha\beta$ color model [13] can minimize correlation between channels, and has been used for color transfer between images successfully in [12]. The conversion from RGB to $l\alpha\beta$ color space defined as follows:

$$\begin{bmatrix} L \\ M \\ S \end{bmatrix} = \begin{bmatrix} 0.3811 & 0.5783 & 0.0402 \\ 0.0606 & 0.3804 & 0.0453 \\ 0.0241 & 0.1228 & 0.8444 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

$$\begin{bmatrix} l \\ \alpha \\ \beta \end{bmatrix} = \begin{bmatrix} \frac{1}{\sqrt{3}} & 0 & 0 \\ 0 & \frac{1}{\sqrt{6}} & 0 \\ 0 & 0 & \frac{1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & -2 \\ 1 & -1 & 0 \end{bmatrix} \begin{bmatrix} \log L \\ \log M \\ \log S \end{bmatrix}$$

where l represents the achromatic channel, and α and β are chromatic yellow-blue and red-green opponent channels. We use RGB, HSI and $l\alpha\beta$ color spaces due to their different characteristics and complementation.

2.2 Iris color Texton

Only using one color space, taking the RGB for example, it yields a total of 16.8 million different colors by using one byte to represent each color. It is difficult to evaluate whether two object's color are same or not with so many colors. Generally, the iris color lies in a certain spectrum range, so it is unnecessary to use all the colors in the color space. We propose the iris color Texton method for classification task.

Textons are defined as mini-templates that represent certain appearance primitives in images, which share the same idea with codes. The iris Texton has been successfully used for the NIR iris image classification based on texture analysis [11]. The main procedure of Texton methods includes: learning a vocabulary from training images; optimizing the learned vocabulary; representing iris images by using frequency histogram of the learned vocabulary.

In this paper, we use color feature as low level feature for iris Texton, so we call the method as iris color Texton. We combine values of a pixel in the RGB, HSI and $l\alpha\beta$ color spaces in series as color feature (9-D vector, $[r, g, b, h, s, i, l, \alpha, \beta]$, these values are normalized into $[0, 1]$). A normalized iris image produces 35640 (66×540 pixels) color features. First, several clustering centers are learnt by K-means from each iris image as Major colors, which constitute the training feature pool. The number of Major colors is set by experiments (512 in our experiments). Then, the iris color Texton vocabulary is learnt by using the K-means from the training feature pool. Last, a simple vocabulary optimization is done: abandoning Textons near maximum value corresponding to specular spots; abandoning Textons near to zero corresponding to shadow. Figure 3 is illustration of the iris color Texton vocabulary learning.

During the iris image coding phase, for each pixel, the visual color feature projects to its k nearest neighbor codes in the Texton vocabulary. Through an image, a statistical histogram of the codes appearing is calculated as feature to represent the image color.

In a normalized iris image, color changing along the vertical direction of is obvious, and there exists self-similarity along the horizontal direction. So we divide a normalized iris image into three equal parts along vertical direction. We extract color feature from each part respectively, and connect these feature to form final feature vector, as shown in Figure 4.

To improve the robustness of methods, we use diffusion distance [7] to evaluate the dissimilarity of color between two irises. Considering two m-D histogram-

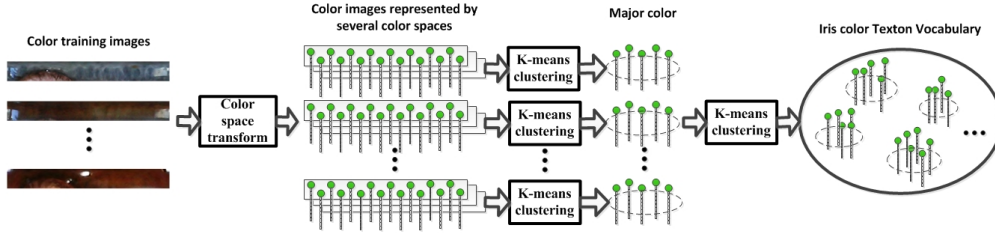


Figure 3: Illustration of the iris color Texton vocabulary learning.

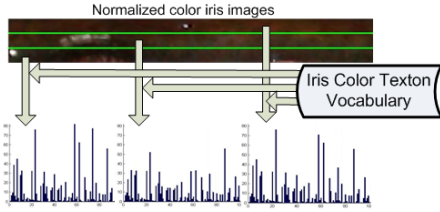


Figure 4: Computing iris color Texton histograms.

s $h_1(x)$ and $h_2(x)$, the diffusion distance is defined as $K(h_1, h_2) = \sum_{l=0}^L k(|d_l(x)|)$, where $d_0(x) = h_1(x) - h_2(x)$, $d_l(x) = [d_{l-1}(x) * \phi(x, \sigma)] \downarrow_2$, $l = 1, \dots, L$, L is the number of pyramid layers, and σ is the constant standard deviation of the Gaussian filter ϕ . We use the L_1 norm as $k(*)$ and $L = 2$.

3 Experiments and Results

We conduct experiments on three color iris image databases: UBIRIS.v1 [8] (45 images in low quality which barely include iris part are abandoned); UBIRIS.v2 [9] (7000 iris images which can be correctly localized are used); the training database of NICE:II [2]. The first database is captured on constrained condition, whereas the latter two are captured by same device on non-constrained condition.

In practice, it is impractical to classify iris images into several classes manually. One important ground truth is that iris images of a same iris are in same color. To evaluate the performance and feasibility of the proposed method, we conduct two experiments: "one-against-all" comparison experiments evaluated by decidability values, and iris classification evaluated by Correct Classification Rate (CCR).

3.1 One-against-all comparison experiments

The one-against-all comparison gives a set of intra-class dissimilarity values $D_I = \{D_{I_i} | i = 1, 2, \dots, M\}$

Table 1: Results evaluated by decidability value(d) of different color features used for iris matching.

| | NICE:II | UBIRISv1 | UBIRISv2 |
|----------------|---------|----------|----------|
| RGB | 0.7246 | 0.9645 | 0.6033 |
| $Y C_b C_r$ | 0.7026 | 0.8679 | 0.5831 |
| HSI | 0.9159 | 0.9986 | 0.7868 |
| $l\alpha\beta$ | 1.0197 | 1.3722 | 0.8848 |

and a set of inter-class dissimilarity index $D_J = \{D_{J_j} | j = 1, 2, \dots, N\}$. The decidability value $d = \frac{|\overline{D_I} - \overline{D_J}|}{\sqrt{(\text{std}(D_I))^2 + \text{std}(D_J)^2} / 2}$ is used as evaluation measure, where $\overline{D_I}$ and $\overline{D_J}$ denote means of the intra-class and inter-class comparisons, and $\text{std}(*)$ is standard deviation. For each color space, we calculate three histograms on three channels of an image, and connect them as the final feature. For a fair comparison, every histogram has same number (256) of bins. The RGB, $Y C_b C_r$, HSI, and $l\alpha\beta$ color spaces are compared, and results are shown in Table 1. The HSI and $l\alpha\beta$ color space show better results, and the RGB is better than the $Y C_b C_r$. So we use the RGB, HSI and $l\alpha\beta$ color spaces.

3.2 Color cues for iris image classification

The classification experiments are performed on three databases introduced above respectively. We randomly select one image of each eye in the database for training, and the rest for testing. The series connected RGB, HSI and $l\alpha\beta$ histogram feature and iris color Texton feature are adopted, comparing to only using RGB histogram feature. The K-means is employed to cluster training iris images into 2-10 classes. If iris images from same eye are classified into same class, it means the classification results are correct. CCR is the percentage of correct classification, and CCR curves changing with the number of classes are shown in Figure 5. With the increase of the number of classes, CCR descends.

The proposed iris color Texton method shows advantages on the NICE:II training database and UBIRIS.v1

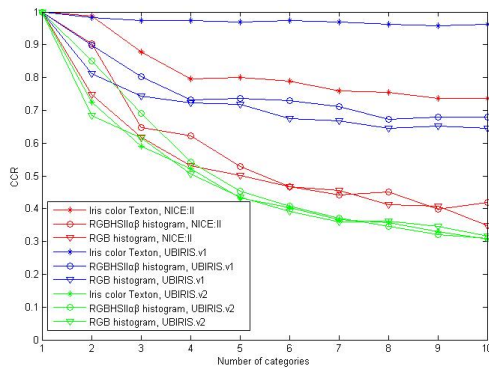


Figure 5: CCRs change with the number of classes.

database. Combining three color spaces are better than only using single color space. The classification results on constrained condition database (UBIRIS.v1) achieve comparable performance with the texture based method [11]. The misclassification rates increase on UBIRIS.v2 databases, since there are large ambient lighting changes which make same iris appears in very different colors, and Figure 6 shows an example.



Figure 6: Examples of misclassified images, these three images belong to a same iris.

For the NICE:II [2], we employ the RGB, HSI and $l\alpha\beta$ histogram feature. The dissimilarity of two irises is regarded as degree of confidence about difference of their colors. On the training database, we improve the decidability value from 2.1 to 2.5 [15] by using color feature. For the contest, a decidability value $d = 2.5748$ is obtained, which is the best result in NICE:II.

4 Conclusions

In this paper, we propose a novel color feature called iris color Texton for iris image classification. The iris color Texton regards values of a pixel in different color spaces as feature, and represents iris image color by histogram of the learnt iris color Texton vocabulary. The RGB, HSI and $l\alpha\beta$ color spaces are adopted due to their complementarity. The iris color Texton method is robust to illumination variation. Fusing color with texture analysis can improve the performance of iris recognition significantly, and make the system more robust to environment variation and low quality images. NICE:II

contest results indicate the usefulness and importance of color information for iris recognition systems.

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