On the Reliability of Eye Color as a Soft Biometric Trait

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Abstract

This work studies eye color as a soft biometric trait and provides a novel insight about the influence of pertinent factors in this context, like color spaces, illumination and presence of glasses. A motivation for the paper is the fact that the human iris color is an essential facial trait for Caucasians, which can be employed in iris pattern recognition systems for pruning the search or in soft biometrics systems for person re-identification.

Towards studying iris color as a soft biometric trait, we consider a system for automatic detection of eye color, based on standard facial images. The system entails automatic iris localization, followed by classification based on Gaussian Mixture Models with Expectation Maximization. We finally provide related detection results on the UBIRIS2 database employable in a real time eye color detection system.

1. Introduction

Soft biometric traits are weak biometric descriptive characteristics, which are common among humans, often non permanent, and can serve the purpose of differentiating subjects. These characteristics have as an advantage, that their acquisition does not require the consent and cooperation of the surveillance subject. Furthermore their evaluation can be enrolment-free, since the classes training can be performed in advance on individuals out of the specific authentication group. In the recent years several traits have been identified as potentially descriptive or complementary features for person identification. The identification of such traits, e.g. eye color, hair color, height, age, gender etc, has brought to the fore the need to efficiently extract and categorize them. In this work we focus on extraction and categorization of eye color.

Eye color detection in the context of soft biometric traits, constitutes a new research path, focusing on eye color information which had been disregarded by classical iris pattern and texture recognition methods.

1.1. The Human Iris Color

The human ocular region bears a plethora of biometric traits with different importance, e.g.: iris, sclera and retina patterns, eyes and eye brow shape and size and finally the eye color. Eye color has been neglected, probably for the reason that 90% of humans have brown eyes. The distribution of eye colors characterizing Caucasian and specifically European subjects is of a bigger deviation than in the rest of the world, as an example of the German speaking region proves in [11].

Eye color is determined by the amount and type of pigments in the eye's iris and is genetically inherited. It is of more permanent character than other soft biometric traits. A study [7] though shows that eye color changes over the span of 40 years.

The extraction of eye color is of very sensitive character, since the area is small (around 11mm) and color itself is difficult to be deduced because of its illumination sensitivity. A further difficulty is the variable size of the pupil (mainly due to illumination), from 3-4mm up to 5-9mm. Then again, positive factors for the feasibility of eye color detection are the smaller and lower-priced surveillance sensors, which are increasingly available, and furthermore provide higher resolutions.

1.2. Related Work

Few preliminary scientific works on eye color exist, as on subjectivity of human eye color grading [2][4], on human analysis of eye color photographs [3] and first preliminary detection attempts [5][6]. We clearly differentiate our work, by presenting a full automatic eye color detection system and furthermore by providing insight on related pertinent factors.

The current work is a study towards a robust eye color detector, which can be employed as a trait of multiple facial soft biometric trait systems, c.f. [1]. Such systems can be used for person recognition, re-identification or validation of official documents, like passports or driving licenses.

The knowledge of the study can be as well used to develop a robust preprocessing step of an iris identification system. In such an application the reliability of the overall system is not expected to increase, since iris identification is one of the most reliable biometrics, but the computational complexity and time can be improved by pruning the search, c.f. [14].

For the sake of completeness, additionally, a robust automatic iris region extraction method is presented which relies on circle detection by using Hough transform.

The paper is structured as follows. In Section 2 we describe an automatic eye color detection algorithm, which contains an automatic iris extraction and Gaussian mixture models for classification. Related results on the reliability are presented in 2.2. Section 3 offers a preliminary study on factors with an impact on eye color detection, like illumination, camera sensors, presence of glasses and consideration of the left or right eyes.

2. Iris Color Detection

In designing an automatic eye color detection system, the choice of the method for iris extraction as well as the color classification have to meet the criteria of reliability, of time and of computational efficiency. In accordance with these aspects in this Section we present an iris extraction technique and a classification method. We jointly examine them on a large color irises database captured in visual light, the UBIRIS2 [9]. It contains 261 subjects featuring diverse illuminations and iris positions. We manually annotated a subset of the database and obtained the following four eye color sets for both, training and testing (about 3/4 and 1/4, respectively):

- Black: 100 images
- Brown: 85 images
- Blue: 81 images
- Green: 60 images

Those color groups were specified, as on the one hand they are most common and human distinguishable and on the other hand, sufficient images are available in the database for the following modeling. We proceed to describe the applied automatic iris extraction method, which is the first step of the two step eye color detection technique we present.

2.1. Automatic Iris Extraction

In the automatic iris region extraction part, the main assumption is that the eyes are detected and sub-images of the face, framing the eye region are available. This assumption is justified by the high performance rates of the OpenCV implementation of the Viola and Jones face detection algorithm [15], which reliably provides face and eye coordinates. Hence, the selected images of the UBIRIS2 database-subset are cropped around the eyes and resized to have fixed a width of 200 pixels.

Firstly, the images are converted to grayscale and the areas of light pixels surrounded by darker pixels are filled based on morphological reconstruction [12]. In this way, strong reflections are removed. Next, vertical edges are found using the Sobel approximation to the derivative.

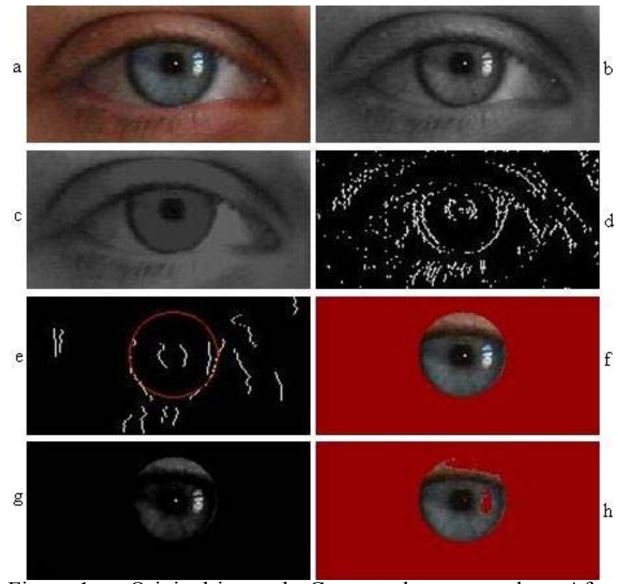

Figure 1: a. Original image b. Converted to grayscale c. After filling operation d. Detected vertical edges e. Vertical edges after morphological processing and the detected iris circle f. Extracted iris g. Difference image where reflections are highlighted h. Final iris image.

Hence, misleading horizontal edges that are mostly created by the eyelids are avoided. After removing the small outliers by using morphological operations, circles in the binary images are detected by Hough transform. For each detected circle, an overlapping score is calculated by the ratio of the detected portion of the circle to the whole circle parameter and the candidate with the highest score is selected as the iris [13].

Finally, within the iris circle, the difference between the original grayscale image and the image in which the reflections removed by the filling operation is calculated. This difference image highlights the reflections present in the iris. Afterward, a mask is constructed based on a threshold which filters out the pixels with high intensity. The whole approach is illustrated in Figure 1.

2.2. Gaussian Mixture Models and Color Spaces

Manual region of interest (ROI) extraction

Towards the statistical modeling, the selected and annotated subset of UBIRIS2 images is manually cropped to avoid effects of reflections or traces of the pupil. An illustration of the manual performed color extraction is shown in Figure 2.

The four probability density functions (pdf), one for each color, are then computed considering all pixels of the extracted region of interest (ROI), using 3-component Gaussian mixture models (GMM). The GMM parameters are estimated using the expectation maximization (EM) algorithm. We refer to this step as training and perform it for the four color spaces: RGB, HSV, CieLAB and CieLuv in order to assess the color space best suited for eye color description.

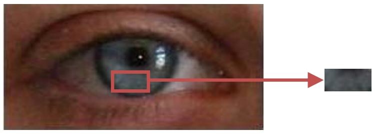

Figure 2: Manual iris color extraction.

For the testing step, the set of images is again manually cropped and posterior probabilities over all observed pixels are computed, followed by a majority vote decision on the detected eye color. The analysis is performed on manually extracted images to prove the suitability of GMM for color distinguishing. The best results are acquired surprisingly on the RGB color space; see Table I, for which reason, the rest of the paper considers solely the RGB color space.

TABLE I

GMM RESULTS FOR MANUAL SEGMENTATION OF EYE COLOR

Black	Brown	Blue	Green
100%	100%	87,5%	81,8%

There is two cases of wrong detections: in the first case blue is confused for green and in the second case, green for brown.

Automatic region of interest (ROI) extraction

Furthermore, the test was performed on automatically extracted color irises of UBIRIS2 images (see Section 2.1), where we again compute pixel by pixel, 4 pdf-s by the means of GMM and EM for the training.

For the testing again the posterior probabilities for a new, again automatically segmented testing set are computed. This time the majority vote rule is extended and contains the following considerations. An eye appears as brown, green or blue, if it contains pigments representing those colors, but the brown, green or blue fraction does not necessarily have to possess the highest percentage. Mainly the pupil and the dark boundary contribute to a higher occurrence of black color, and often brighter irises enclose a multitude of further dark pigments, which constitute in patterns.

In black eyes on the other hand, the black percentage is at least 2/3 of the iris pixels.

The following rules were deduced from the above considerations and adhere with priority to the majority vote rule:

1. If the iris contains more than 70% of black pixels, the detected color is black,
2. If black is the majority, but accounting less than 50%, then the second strongest color is the detected color.
3. If black is the majority, but accounting less than 50% and brown and green are in the same range, the detected color is green.

The related results following those rules can be found in Table II. The values in the diagonal, highlighted in gray, represent the true detection rates. All other fields illustrate the confusions between the real and estimated eye colors.

TABLE II

GMM RESULTS FOR AUTOMATICALLY SEGMENTATION OF EYE COLOR

Det\Real	Black	Brown	Green	Blue
Black	90,9%	5,26%		6,25%
Brown		89,48%	14,28%	
Green	4,55%		78,58%	18,75%
Blue	4,55%	5,26%	7,14%	75%

Two examples of confusions are provided in Figure 3. In the first case a green eye is confused to be black. It is to be noted that the pupil, iris boundary, lashes and an unfavorable illumination establish a high percentage of the image and thus of the black pixel fraction. In the second case a blue eye is detected as green. On the one hand the eye contains greenish pigmentation, and on the other hand the presence of the lid and pupil account to the wrong estimation.

Figure 3: Wrong detected eye colors.

3. Influential Factors

Eye color detection is a challenging task, especially under real life conditions, mainly due to the small size of the ROI and the wet glass-like surface of the apple of the eye. Smallest external changes may have impact on the perception and detection of eye color. To understand the magnitude of the impact we here study following pertinent and frequently occurring factors: illumination variation, presence of glasses, difference in perception of observation of left and right eye, and finally the influence of two camera sensors.

For this study we used eight subjects (see Table III), with different eye colors. For each subject we produced 7 different images: four of the images under real life illuminations, one image with a second camera sensor, and finally two images, one for each pair of glasses.

TABLE III

EYE COLOR DATABASE FOR INFLUENTIAL FACTORS STUDY

Subjects	8
Eye colors	8: a) dark brown, b) brown, c) hazel, d) green-brown, e) light green, f) green-blue, g) blue, h)light blue

Camera sensors	2: a) white balanced Cannon 400D, b) webcam Logitech 1.3Megapixel
Illuminations	4: (in office) a) daylight, b) daylight + room electric lights, c) flashlight, d) fluorescent table light
Pair of glasses	2

For the further analysis the ROIs were extracted manually (see Figure 2) to eliminate any traces of the pupil and light reflections.

The performed study on the presented database considers red and green chromaticities, following similar skin locus studies and we note that:

$$r = \frac{R}{R+G+B} \text{ and } g = \frac{G}{R+G+B}.$$

3.1. Illumination Variation

The spectrum of incoming light plays a major role in many biometrical applications, especially in color based ones. Intuitively, it is expected that illumination has a strong impact on eye color as well. That is why we here study the subjects of the own recorded database in 4 real illumination conditions.

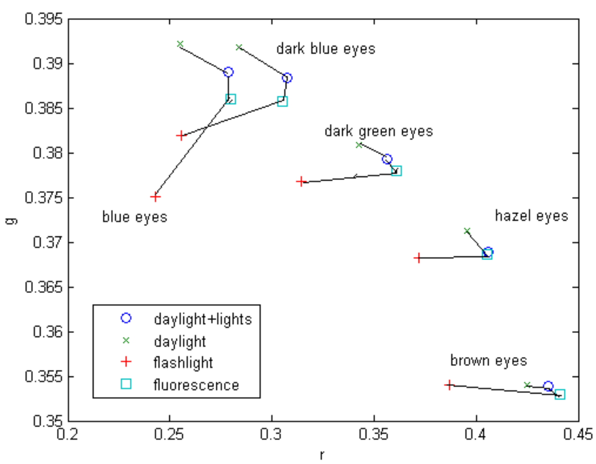

Figure 4: Illumination variance of eye colors.

We here captured the subjects of our database in following 4 illuminations conditions: daylight and office lights, daylight, flashlight and a fluorescent table light. Clear shifts in the eye colors can be observed. For higher conciseness and to avoid occurring overlaps we portrayed only 5 subjects.

It is clear that a robust eye detection technique must consider and cope with illumination variations. Towards this illumination estimation has to be performed. A self suggesting illumination estimation method is proposed by [10], where the color of the eye sclera serves as a reference white.

3.2. Glasses Influence

The presence of glasses is another interfering factor, primarily examined in the context of face recognition and naturally of importance in the current eye color detection study.

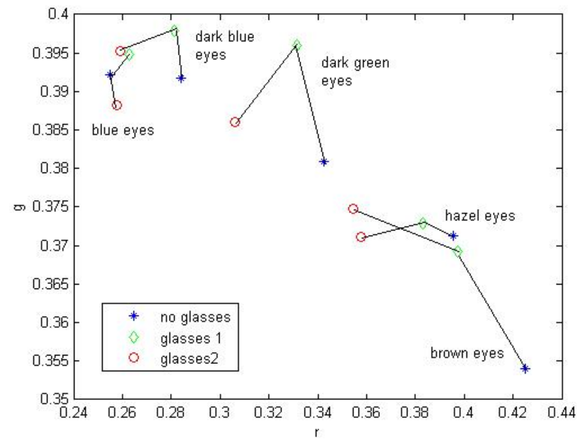

Figure 5: Eye colors behavior with and without glasses (constant illumination).

For this investigation the subjects were asked to put on 2 different pair of glasses. It is interesting to compare this graph with the one illustrating illumination variation (Figure 4) in order to comprehend the immense drift eye glasses cause in eye color. It is evident that a stable eye color detection system should include a priori glasses detection.

To detect the presence of glasses in an efficient and robust manner, we suggest the following algorithm: a histogram normalization to even out illumination changes, followed by Canny edge detection on the area between the eyes. Finally horizontal line detection indicates the presence of the frame part of the glasses. This algorithm was deduced from [8].

For eye color detection in the case of presence and absence of glasses a robust eye color detector should be able to compensate the color shift due to glasses.

3.3. Consideration of Left and Right Eye Color

We here show that the strong illumination influence has not only impact on images captured under different illumination conditions, but also on the color perception of left and right eye. Although none of our subjects has the seldom condition of heterochromia (different iris colors of left and right eye), a drift between the colors of left and right eye can be observed. For this graph the illumination condition was constant daylight falling side-fed on the face of the subjects, in order to achieve a maximum illumination difference between left and right eye.

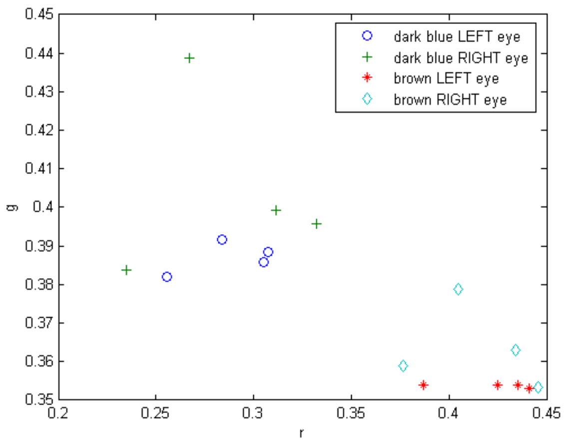

Figure 6: Eye colors of left and right eyes for 2 subjects (for 4 different illuminations).

3.4. Camera Sensors

Finally, for the sake of complicity we proceed to provide a graph on the shift between two camera sensors (Logitech Webcam and Cannon 400D). The measured color data is clearly influenced by the characteristics of the cameras.

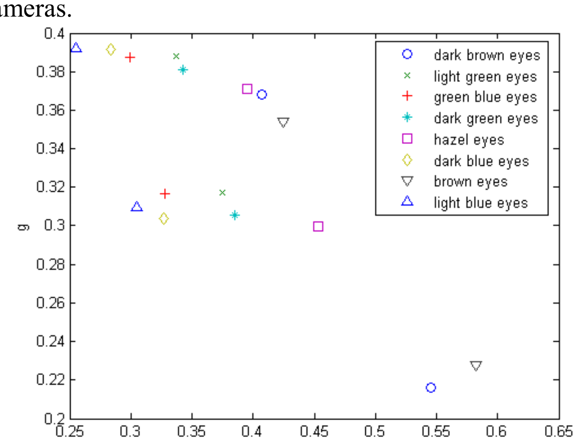

Figure 7: Eye colors captured with two camera sensors (constant illumination).

We note that the presented study identifies each one of the examined influential factors as strongly disturbing for eye color detection. The measure of importance for each one of them is ascertained by the embedding application.

4. Conclusions

In this work we presented an automatic, but static eye color detection system, which enclosed an automatic extraction of the iris region, and an adhered color classification performed by the means of Gaussian Mixture Model. We have jointly employed the system on UBIRIS2 database and provided related results.

Additionally towards enhancing the eye color detector to be more robust and dynamic, we have studied the impact of relevant external factors. We have identified and illustrated color shifts due to variation of illumination, presence and absence of glasses, the difference of perception of left and right eye, as well as due to having two different camera sensors. Essential shifts in the color space were denoted and have to be considered for robust eye detection. Our study showed that all those factors have strong impact on the estimated eye color.

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