Bayesian Approach for Sclera Recognition

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Abstract: *Researchers are trying to find new biometrics to provide more options for human ID. Here, we propose a new approach for human ID: sclera recognition. Sclera patterns can be used for human classification and identification since the blood vessel structure of the sclera is unique to each person. Even twins do not have same sclera patterns. Sclera can be acquired at a distance under visible wavelength illumination. But extracting blood vessel pattern is a challenging research problem because images of sclera vessel patterns are often defocused and/or saturated and, most importantly, the vessel structure in the sclera is multilayered and has complex nonlinear deformations.*
First, a new method for sclera segmentation which works for colour images is developed. Then, a Gabor wavelet-based sclera pattern enhancement method to emphasize and binarize the sclera vessel patterns is designed. For recognition we go for a probabilistic based classifier such as Bayesian to improve the accuracy. Our experimental results show that sclera recognition can achieve comparable recognition accuracy to iris recognition in the visible wavelengths. Thus, sclera recognition is a promising new biometrics for positive human ID.
Keywords: *Biometric, Sclera recognition, Sclera Segmentation, blood vessel pattern recognition, Baye's Algorithm.*

I. Introduction

Biometrics refers to technologies for measuring and analysing a person's physiological or behavioural characteristics. These characteristics are unique to individuals hence can be used to verify or identify a person. Recognition deals with establishing a person's identity from a set of identities. In recognition technique, the input feature data is checked against all the data stored in the database. Leading biometrics technology includes fingerprint, face, iris, retina, gait, and voice. No biometric is perfect or can be applied universally. Each biometric have its own advantages and disadvantages. For instance, face recognition is the natural way that humans identify a person, but people's faces could change dramatically over years and this change could affect recognition accuracy. Next, the fingerprint pattern is very stable over a person's life, and its recognition accuracy is high. However, fingerprint recognition cannot be applied for ID at a distance. Fingerprints may cause some hygiene issues and public health concerns since it is a contact-based biometric. The accuracy of iris or fingerprint recognition is higher than facial recognition but iris recognition needs to be performed in the near-infrared (NIR) spectrum which requires additional NIR illuminators. This makes it very challenging to perform remote iris recognition in real-life scenarios. Overall, no biometric is perfect or can be applied universally. Researchers are trying to find new biometrics to provide more options for human ID. Sclera can be acquired at a distance under visible wavelength illumination. In this paper, we propose a new human ID method: sclera recognition. Our experimental results show that sclera recognition can achieve comparable recognition accuracy to iris recognition in the visible wavelengths.

This paper is organized as follows. In Section II the background of sclera and sclera vessel patterns is covered. In Section III, an automatic segmentation approach both in colour images is proposed. The given test Sclera image was pre-processed to remove noise. Gabor wavelets of various scale and orientation were convolved with denoised sclera image for feature extraction and enhancement. Then a line descriptor method that can extract patterns at different orientations is designed, which made it possible to achieve orientation-invariant matching. In addition, test feature matrix is checked with that of training feature matrix by means of naïve Bayesian classifier. In Section IV, experimental results are added and then, conclusions is drawn in Section V.

II. Background

The sclera is the white and opaque outer protective covering of the eye. The sclera completely surrounds the eye, and is made up of four layers of tissue — the episclera, stroma, lamina fusca, and endothelium. The conjunctiva is a clear mucous membrane, made up of epithelial tissue, and consists of cells and underlying basement membrane that covers the sclera and lines the inside of the eyelids1. In general, the conjunctival vascular is hard to see with the naked eye at a distance. For young children, the blood vessels in

sclera area could be blue, but for adults, the blood vessels are red in colour. The structure of the blood vessels in the sclera are well suited to be used as a biometric — they are an internal organ that is visible without undue difficulty and they are anecdotally stable over time and unique for each person. Therefore, the vein patterns in the sclera could be used for positive human identification. In previous works, identification of users using the sclera region has been referred to as 'conjuctival vasculature recognition.' However, as the conjunctiva is the top-most transparent layer of the sclera and images of the sclera region capture more than just this top-most layer, it is more accurate to refer to the system as performing 'sclera recognition.'
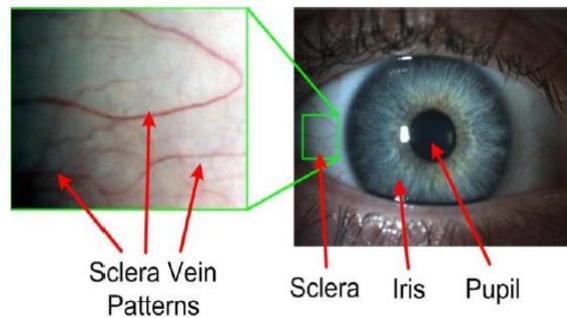

Fig. 1. Structure of the eye

A. Sclera Recognition Challenges

Sclera recognition has several technical difficulties that make it difficult to implement in practice including the eye is a moving structure, and the sclera vascular patterns move and are deformed with this movement (including the movement of the eye and eyelids, and dilation/contraction of pupil).The sclera is reflective, so the sclera patterns may be out-of-focus or saturated. Most importantly, the vascular patterns in the sclera are composed of multiple layers, and as a result, there is complicated non-linear deformation of the patterns as the eye and/or the surrounding tissues move.
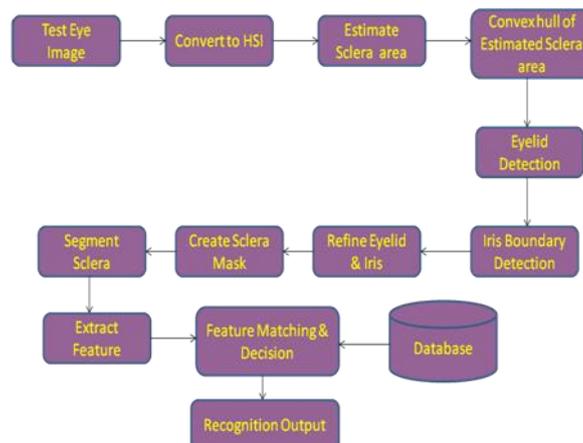

Fig 2. Block Diagram

III. Module Description

A. Sclera Area Estimation

Compute the colour distance map with the help of following 2 equations and then, calculate the sclera map.

$$CDM_1 = \begin{cases} 1, & \begin{array}{l} R>95, G>40, B>20, \\ \max(R, G, B)-\min(R, G, B) >15, \\ |R-G|>15, R>G, R>B \end{array} \\ 0, & else \end{cases}$$

$$CDM_2 = \begin{cases} 1, & \begin{array}{l} R>220, G>210, B>170, \\ \max(R, G, B)-\min(R, G, B) >15, \\ |R-G| \leq 15, R>B, B>G \end{array} \\ 0, & else \end{cases}$$

$$S_1(x, y) = \begin{cases} 1, & CDM1(x, y) \ OR \ CDM2(x, y) =0 \end{cases}$$

0,   else

Fig.3. Test Eye Image

The given test image is converted into HSI colour space model. To obtain the sclera map concerning white part of eye, fix the threshold values in the corresponding colour components.

$$S_1(x, y) = \begin{cases} 1, & \begin{aligned} & \text{If } H(x, y) \leq th_h \\ & \text{and } S(x, y) \leq th_s \\ & \text{and } V(x, y) \geq th_v \end{aligned} \\ \\ 0, & \text{else} \end{cases}$$
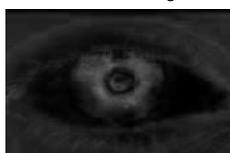

Fig.4. Saturation Image

B. Iris Boundary Detection

Convert the given test colour eye image into gray scale image and then find the edges by applying horizontal canny filter upon it. Greedy angular search method is applied on the edge binary image to find the pupil and iris boundaries.

Fig.5. Canny Image

C. Refinement of Eyelids and Iris

The iris and eyelid boundaries are refined using a Fourier representation. A dynamic programming approach is used to determine a globally maximal path. Describe the path by computing the Fourier expansion of the data. Truncate the number of coefficients used to describe the path, and re-computing the final boundary from the truncated coefficients.

D. Segment Sclera using Sclera Mask

Having refined the upper and lower eyelids and the iris boundaries, the detected sclera region is segmented. The mask of the segmentation result is up sampled back to the original images size using a simple interpolation method.

(a)

(b)

Fig. 6. (a) Sclera Mask (b) Sclera

E. Feature Extraction by Gabor Convolution

The image is first filtered with Gabor filters with different orientations and scales. Design of Gabor filters is accomplished by tuning the filter with a specific band of spatial frequency and orientation by appropriately selecting the filter parameters; the spread of the filter σ x, σ y, radial frequency f, and the orientation of the filter θn. After Gabor convolution features will be extracted from the line segments. Sclera feature enhancement and extraction method incorporates a Gabor filter-based vein enhancement method, and a novel line descriptor to extract and describe the vein structure in the presence of noise and deformation. As a result, the sclera vascular patterns are often blurry and/or have very low contrast. It is important to enhance the vascular patterns before feature extraction. Daugman shows that the family of Gabor filters, which are Gaussian weighted sinusoids, are good approximations of the vision processes of the primary human visual cortex. Because the vascular patterns could have multiple orientations, in this research, a bank of directional Gabor filters is used for vascular pattern enhancement:

$$G(x, y, \vartheta, s) = e^{-\pi ((x-x_0)2+(y-y_0)2 \div s2)} e^{-2\pi i (\cos \vartheta (x-x0) + \sin \vartheta (y-y0))}$$

where $(xx0, yy0)$ is the centre frequency of the filter, ss is the variance of the Gaussian, and ϑ is the angle of the sinusoidal modulation. For this work, only the even filter was used for feature extraction of the veins. Experimentally, the even filters response was determined to adequately identify the veins, so the odd filter was not used to reduce the computational time. The image is first filtered with Gabor filters with different orientations and scales:

$$IF(x, y, \vartheta, s) = I(x, y) * G(x, y, \vartheta, s)$$

where $I(x, y)$ is the original intensity image,

(x, y, ϑ, s) is the Gabor filter, $I(x, y, \vartheta, s)$ is the Gabor filtered image at orientation θ and scale ss. Both θ and S are determined by the desired features to be extracted in the database being used. For example, in the UBIRIS database, the typical vein width was around 4 pixels wide, so the filters were constructed with a filter bandwidth of 3, 4, and 5 pixels, respectively. Similarly, it was determined experimentally that, for the UBIRIS database, four angular orientations were adequate for accurate vein enhancement and extraction. In a practical system, these parameters would be set by examining exemplar data all the filtered images are fused together to generate the vein-boosted image, (x, y):

$$F(x, y) = \sqrt{\sum_{\vartheta \in} \sum_{s \in s} (IF(x, y, \vartheta, s))^2}$$

An adaptive threshold, based on the distribution of filtered pixel values, is used to determine a threshold to binarize the Gabor filtered image,

$$\begin{cases} t \end{cases} B(x,y) = \begin{cases} 1, F(x,y) \end{cases} > \text{argmin } t \| \sum p_{edge}(x) - T_p |$$

where $B(x, y)$ is the binary vein mask image, $F(x, y)$ is the vein-boosted image, and $p_{edge}(x)$ is the normalized histogram of the non-zero elements of $F(x, y)$. In practice, the zero elements of the filtered image are a significant portion of the image, and in general, the vascular patterns have higher magnitude than the background. Therefore, Tp is selected to be 1/3.
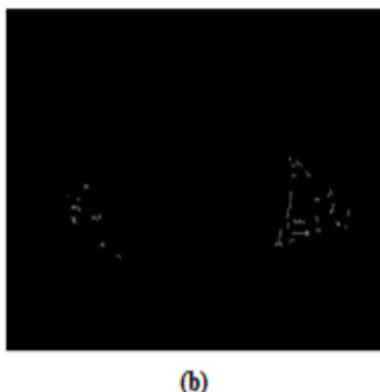

(a)

(b)
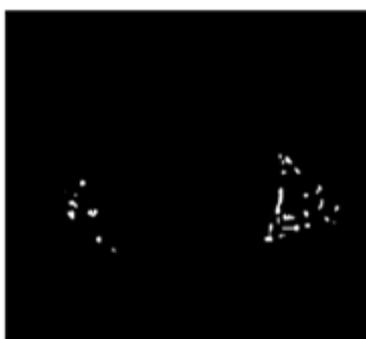
Fig. 7. (a)After Thresholding - Edge Strength (b) After Morphological Operation - Binary Vessel Image

1) Feature Matching and Decision

Each line segment in the test template is compared with the line segments in the target template for matches. Matching value lies in the range of 0 – 1. The Dmatch – Matching Distance Threshold is given by:

$$m(S_i, S_{j)} = \begin{cases} w(S_i)w(S_j), & \begin{array}{l} d(S_i, Sj) \leq D_{match} \\ \text{and} \\ |\theta_i - \theta_j| \leq \theta_{match} \end{array} \\ 0, & \text{else} \end{cases}$$
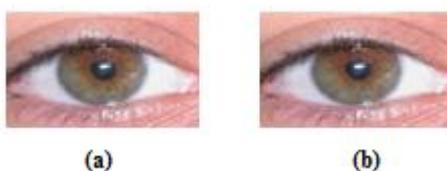

(a)   **(b)**

Fig. 8. (a) Test Image (b) Recognised Image

IV. Experimental Results

Four possible recognition results are generated correctly matching (True Positive: TP), correctly not matching (True Negative: TN), incorrectly matching (False Positive: FP), incorrectly not matching (False Negative: FN). The False Accept Rate(FAR), False Reject Rate(FRR)

$$FAR = \{ FP \div (TN + FP) \} \times 100\%$$
$$FRR = \{ FN \div (TP + FN) \} \times 100\%$$

The above values can be used to evaluate the performance of the system.
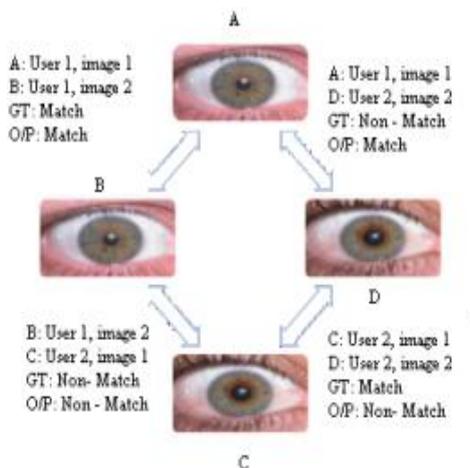For FAR= 0.1%, FRR= 80%

Fig.9. Example Matching Results

V. Conclusions

Thus the proposed methodology differs from its predecessor in the following ways:

a) The parent methodology takes into account only the sclera structure for identification or recognition whereas the method that has been proposed takes into account the length of the structure of the sclera which will save more memory space when it comes to hardware implementation.

b) The parent technique uses matching score algorithm to classify and compare the test sample with database to generate a match or identification whereas the proposed technique uses Bayesian classification algorithm which is much faster and effective than matching score algorithm.

Thus a new methodology for sclera recognition has been proposed. In addition, sclera recognition can be combined with other biometrics, such as iris recognition or face recognition (such as 2-D face recognition) to perform multimodal biometrics rate. To conclude, sclera recognition is very promising for positive human ID. The computational complexities of sclera matching using matching score algorithm gives low accuracy and complex. Test feature matrix is checked with that of training feature matrix by means of naïve Bayesian classifier.

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