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Fusion of Sclera and Periocular Features for Biometric System

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Abstract
This paper proposes the biometric verification system based on ocular features. We form the multimodal biometric system considering two recent biometric traits in ocular region- sclera region and periocular region. For feature extraction of sclera part we use simple technique which eliminates the expensive image enhancement process i.e Local Binary Pattern (LBP) and the matching scores are generated. For feature extraction of periocular region we use structured random projections and matching score are generated. From these matching scores the score level fusion is done with Extreme Learning Machine (ELM). This method has shown 94.40% of accuracy.
Keywords: *Local Binary Pattern, horizontal and vertical projection, Extreme Learning Machine.*

1. Introduction

Biometrics refers to the process of identifying a person based on physiological and/or behavioral characteristics. This technology eliminates the need of external token such as the password, ID cards, the traditional authentication means which can be easily forgotten on stolen. It relies on the person himself and thus possesses the crucial advantage which makes it attractive for variety of applications. Among the variety of biometric traits, the ocular region has become popular particularly because iris and retina have performed well in terms of accuracy and reliability. Like all of the biometric traits even these have some weaknesses along with its strengths. For eg., iris biometrics needs the co-operation from the user to avoid off-axis gaze direction with respect to the image capturing device which hampers the matching performance. The retina biometrics requires close eye contact with the capturing device which can be undesirable to few.

Besides iris and retina, the ocular region of human body includes other specific and identifiable patterns which can also be used as biometric trait. We are dealing with two such biometric traits namely, vasculature pattern seen on sclera part of eye and the periocular region. The sclera as a biometric trait has been studied limitedly. Derakshani et al. was first to introduce that blood vessels pattern on the sclera can be used as a biometric trait. Because of its relatively new exposition, very limited study work has been found out regarding its usage as biometrics. The blood vessel pattern on the sclera can be easily seen, is unique for each identity, is stable over the period of time and cannot be easily replicated. With an increasing age, even if, sclera dehydrates, collagen and elastic fibers deteriorate, a loss of glycosaminoglycans happens, and calcium salts and lipids accumulate, the blood vessels will not deteriorate [1].

Even with the sclera's established reliability for usage in biometrics and the advantages, there remains some issues to be addressed. The movement of the eyelids during capture can make the sclera image noisy. Also consider the possibility of no sclera region captured in the image at all. In such cases the periocular region will come to aid for recognition. Periocular region will remain exposed in spite of eyelid movements. It has also been proven that multi-modal biometrics performs well in terms of accuracy and universality.

In this paper, the fusion of sclera and periocular feature for biometric verification is proposed. The main focus will be on developing simple yet novel sclera feature template. The periocular feature extraction results will be complementary to the sclera feature extraction results and will come to an aid if the sclera template fails the recognition. Sclera matching score and periocular matching score will be fused at the score level using extreme learning machine (ELM).

This paper has been organized in the following sections. The section 2 is about the brief literature survey. The proposed method is described in section 3. The experimental evaluation and conclusion is described in section 4.

2. Literature Survey

As mentioned earlier, Derakshani et al. [2] was the first researcher to prove that sclera can be used as a biometric trait. In their work, for image enhancement, CLAHE and region growing method was used. For feature extraction Hu's invariant moment and minutiae based technique was adopted. 100% identification rate was achieved. But this was conducted in small in-house database. In their later works they proposed enhancement and registration schemes based on detection and removal of specular reflections for matching sclera vessels in [3]. Furthermore they adopted the wavelet transform and neural network for feature extraction and classification respectively, in [4].

Apart from these initial works, some ideas in literature which have shown good performances are noted below. Gabor filter bank was used for vessel enhancement and Line segment description for the feature extraction based on iris centroid by Thomas et al in [5]. In [6], same group evaluated the comprehensive sclera image quality measure for detecting if the image has a valid eye, also assess the image quality, evaluate the segmentation accuracy, and measure if the image has sufficient feature information for recognition. Crihalmeanu and Ross used multispectral images acquired in four spectral bands for accurate segmentation of sclera in [7]. Most of these works were of single modality except for [7]. Park et Al., introduced the periocular region as the biometric trait in [8]. Later biometric literatures have it used as isolated modality [9] & [10] and also in multi-modality [11], [12] & [13]. In [10] Xu et al. used Local binary pattern (LBP) on filtered image for feature extraction. Adams et al. used gradient orientation, LBP and scale invariant feature transform for feature extraction of periocular region in [9]. In [11], [12] & [13], the periocular trait as used in multimodal biometric system where iris feature template was fused with that of periocular region template to enhance the accuracy of overall system. In [17], for sclera template generation and matching scheme, angular grid reference frame and LBP is adopted and for periocular template generation and matching scheme, structured random projections is used. The fusion is done by extreme learning machine with total error rate minimization (TERELM). The method was tested on UBIRIS v1 database. Our work is somewhat similar to [19] but with some modification.

3. Proposed method

The proposed work method can be divided into four parts namely; image pre-processing, sclera feature extraction and obtaining the matching score between pair of image, periocular feature extraction and obtaining the matching score between pair of image and score level fusion of obtained scores. The image pre-processing involves sclera localization and periocular localization. For sclera feature template generation local binary pattern (LBP) is used. Structured random projections are used for periocular template generation. Both these scores are fused at score level using Extreme Learning Machine (ELM). Here, we eliminate the need of time consuming process of the angular grid construction in the [17], by bounding the sclera region into the closed boundaries. The maximum sclera region is, thus, used for template generation. Also for fusion we use simple ELM instead of (TERELM) and unlike [17] we test our method on UBIRIS v2 database. The Fig.1, shows the block diagram of overall system.

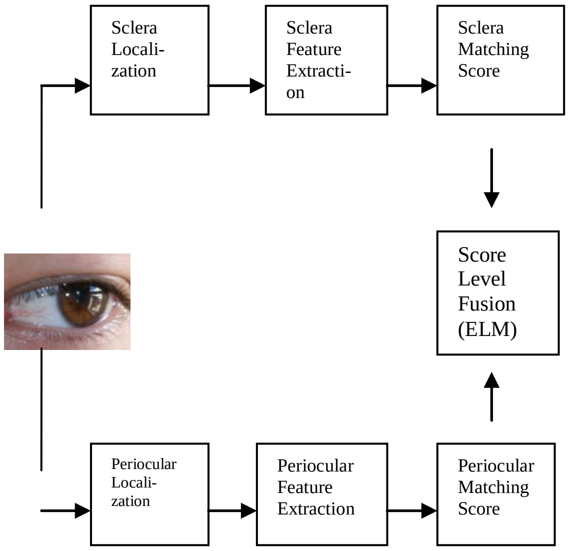

Figure 1: System Block Diagram

3.1 Image Pre-Processing

In the proposed method the high computation cost of vessel enhancement is eliminated. Image pre-processing consists of two parts sclera localization and periocular localization.

In sclera localization, firstly the color space conversion is done from RGB to HSV. This is because HSV color space conversion contains maximum sclera information [14]. The iris centre is found out using integro-differential operator. Using the centre coordinates image is partitioned into two parts left eye image and right eye image. These images are independently given to image binarization. After image binarization they are joined back together [14]. The region of interest is obtained by bounding the obtained area using morphological operation. The overall process is shown in Fig., 2 (a).

The image binarization is shown in Fig., 2(b). Here, we have an input image. This image goes through histogram equalization. The histogram equalized image and previous input image are given to low pass filtering separately. Gray value thresholding is performed on both the images. Small unwanted groups of pixels in the main ROI are eliminated using size thresholding. Both the images are joined together using OR operation [14].

This completes the sclera localization. To obtain the common region the obtained sclera mask of a pair of image are overlapped using simple element-wise AND operation. For this, to get the similar image dimensions zero padding was done and maximum region after overlapping was considered. The HSV values of pixels in this overlapped region for both the images were send for template generation.

For periocular localization, the sclera localization results were used. The entire rows comprising the sclera mask were given value 0, in the gray scale image of the eye. This modified image was given to periocular template generation.

3.2 Sclera Matching and Template Generation

For the feature extraction, we use multiresolution local binary pattern (MLBP) operator. LBP is invariant to monotonic gray level changes, robust against illumination changes, computationally efficient [17].

The circular neighbourhood in MLBP is shown in Fig., 3. h_c is the centre pixel. With respect to the centre pixel the gray scale values of these neighbourhood pixels are

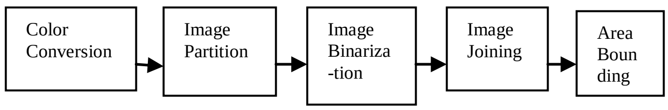

Figure 2 (a): Sclera localization

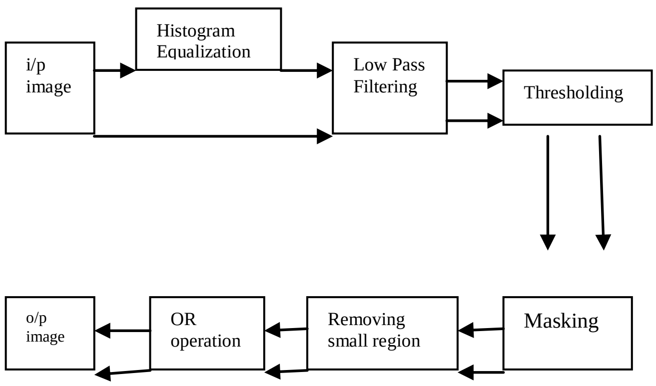

Figure 2 (b): Image Binarization

thresholded in MLBP operator. We define N the number of neighbourhood on circle of radius R. The binary value resulting from the MLBP operation is defined as follows:

$$MLBP_{N,R} = \sum_{N=0}^{N-1} G(h_N - h_c) \qquad \ldots \quad (1)$$

Where $G(x) = \begin{cases} 1\ldots\ldots\ldots\ldots x \geq 0 \\ 0\ldots\ldots\ldots\ldots x < 0 \end{cases}$

In most of the literature of LBP, the binary values are converted into the decimal values and histograms are plotted which is used as feature descriptor. Here we directly use the binary values obtained by thresholding as shown in (1). The obtained binary values are simply concatenated to form a single string as shown in (2).

$$x = [x_1, x_2, \ldots\ldots\ldots \ldots\ldots x_M]^T \qquad \ldots \quad (2)$$

where $x_i \in \{0,1\}, \forall i \in \{1,2,\ldots\ldots\ldots..M\}$ and $M = L \times N$ (L is the number of '1's in the overlapping mask obtained at image pre-processing and N is the number of neighbourhoods of MLBP operator).

The normalized hamming distance is utilized for obtaining the matching score between the two binary feature templates.

3.3 Periocular matching and Template Generation

Structured random projections [15] are used for feature extraction where we consider horizontal and vertical periocular features. This is done in two steps- formation of projection matrix and projection onto the matrix.

a) Formation of projection matrix

Here we generate two matrices one, R1 for extracting vertical features and other, R2 for extracting horizontal features. R1 has horizontal groups of 1's where the rest entries in matrix are 0. Similarly, R2 has vertical groups of '1's where the rest entries in matrix are 0. The position of this group of 1's in the basis in entire row (column in case of R2) is chosen randomly. We denote symbol p and s to represent the number of projection basis (projection size) and number of '1's in the basis (group size). The size of the projection matrix also depends on the size of the image. Suppose Q is the image of size x-by-y. The size of R1 will be p-by-x and the size of R2 will be y-by-p. The Fig. 4, shows example of R1 and R2 projection matrices.

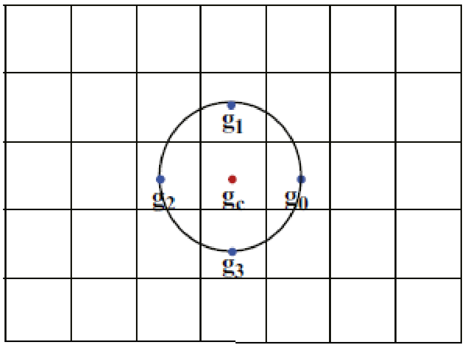

Figure. 3: Circular neighbourhood with N=4 and R=1 [17]

b) Projection onto matrix

R1 matrix is pre-multiplied to the input image Q as shown in (3). This multiplication adds all the vertical elements of the image residing in the position where group of '1's in R1 coincides. So the position of this group decides from which area features are to be extracted.

$$Y_v = R1 \bullet Q \qquad \ldots (3)$$

Y_v consist of compressed vertical components of the periocular region. The size of this projected feature is p-by-y.

Similarly R2 matrix is post multiplied as shown in (4).

$$Y_H = Q \bullet R2 \qquad \ldots (4)$$

Y_H consist of compressed horizontal components of the periocular region. The size of this projected feature is x-by-p

The Euclidean distance is used for obtaining the matching scores.

3.4 Score Level Fusion

The matching scores from sclera and periocular features are fused together at score level. Firstly the matching score from inter- identity and intra-identity comparisons are generated. Consider, $[x^+_{a1}, x^+_{a2}, x^+_{a3}]$, $a = 1, 2 \ldots m^+$ and, $[x^-_{b1}, x^-_{b2}, x^-_{b3}]$, $b =$

1, 2 ... m⁻ as vectors of intra and inter-identity matching scores from our three features i.e. sclera, R1 and R2 projections. The column wise min-max normalization is performed to normalize these scores. Then these are given to extreme learning machine (ELM).

a) Extreme Learning Machine

Extreme learning machine is learning algorithm for single hidden layer feed forward neural network (SLFN) [16]. The equation for SLFN with common activation function w (.) is written as shown in (5).

$$\sum_{j=1}^{N} \beta_j w(s_j x_i + b_j) = o_i \text{ , } i=1,2,\dots\dots\dots N \qquad \dots (5)$$

where N is number of hidden nodes. x_i is input vector, o_i is network output vector, b_j is threshold for j^{th} hidden node assigned randomly. s_j is randomly assigned weight vector connecting the input nodes to j^{th} hidden node. We use sigmoid function as activation function for SLFN. (5) can be written as

$$Y=T.B \qquad \dots (6)$$

where Y is output target vector.

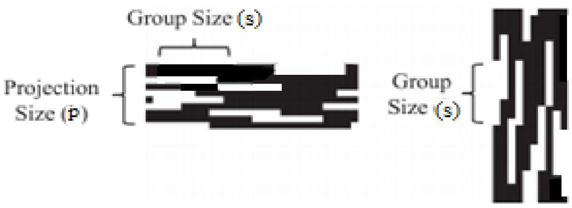

Figure 4: Projection matrices [19]

$$T = \begin{bmatrix} w(s_1.x_1 + b_1) & \dots & w(s_N.x_1 + b_N) \\ \vdots & \ddots & \vdots \\ w(s_1.x_n + b_1) & \dots & w(s_N.x_n + b_1) \end{bmatrix}_{n \times N} \qquad \dots (7)$$

$$B = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_N^T \end{bmatrix} \text{ and } Y = \begin{bmatrix} Y_1^T \\ \vdots \\ Y_n^T \end{bmatrix} \qquad \dots (8)$$

$$B = T^{\dagger} \; Y \qquad \dots (9)$$

where $T^{\dagger}$ is Moore Penrose generalized inverse of matrix T.

b) Steps for fusion

1) Fix the activation function w(x) and number of hidden nodes (*N*).
2) Randomly assign input weight s_i and bias $b_{i,}$ i=1… N
3) Calculate the hidden layer output matrix T for the train data.
4) Calculate the output weight B as shown in (9)
5) Calculate the hidden layer output matrix T_t for the test data.
6) Using above calculated T_t and B, calculate the output labels from (6).

4. Experimental Evaluation

4.1 Database and tools

The database utilized in the experiment for both sclera and periocular feature extraction is the UBIRIS v2 database [18] .

Only off angle images with iris at the corner of eye are considered as we are interested in maximum sclera region. This work has been tested on 374 images of group 11,12,14 and 15. This comprises of 90 identities of database. MATLAB 7.10.0 R2010a is used as platform for implementation.

4.2 Experimental results and settings

The parameter settings done for the experiments are show in Table 1. The results of sclera and periocular localization are shown in Fig. 5.

We performed series of experiment and found out that these setting gave better performance in terms of accuracy. We performed 5 runs of 10-fold cross validation. As the directional projections have utilized the random settings, we have performed experiments 15 times. The performed experiment has shown the accuracy of 94.40%.

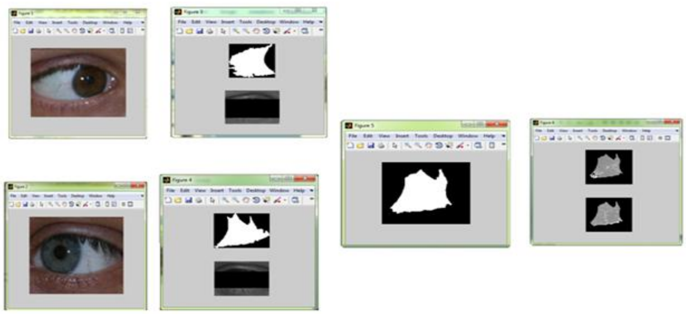

Figure 5: Sclera Localization results

Table 1. Parameter Settings

Parameters	***Value***
(N,R) (number of neighbors, Radius of circle) for LBP in circular neighborhood	(32,4)
Projection size(p) for Random projections	20
Group size(s) for Random projections	200
Number of hidden nodes for ELM	145

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