A Reliable Iris Recognition Method for Non-Ideal Iris Images

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***Abstract*— This paper studies the iris recognition problem in the degraded iris images captured in non-ideal imaging conditions. In these circumstances iris recognition becomes challenging because of noisy factors such as the off-axis imaging, pose variation, image blurring, illumination change, occlusion, specular highlights and noise. The noisy iris images increase the intra-individual variations, thus markedly degrading recognition accuracy. To overcome these problems, we propose a new iris recognition algorithm for noisy iris images. First, we use a classification method which discriminates the ''left or right eye'' on the basis of the eyelash distribution and SR points. Since the iris pattern of the left eye differs from that of the right eye, the 1st step classification can enhance the accuracy of iris recognition. Second we normalize the irises to the same size without rubber sheet model. Our new method notably prevents iris texture deformation especially those images captured from long distances. Third, the separability between intra- and inter-classes is increased by using the 2nd step classification based on the ''color information'' of the iris region. They are measured by using the Euclidean distance calculated with the color space models such YCbCr, HSV, and lab. Finally, ''textural information'' of the iris region is used for classification. we apply 1-D Log Gabor filter on LTP map of iris region of gray scale images to afford sets of iris codes from iris textures. Experiments were conducted on the NICE.II training dataset selected from UBIRIS.v2 database. The results showed that the proposed method performed better than existing methods and showed that the decidability value was 1.9294.**

Keywords—Iris Recognition, Noisy Iris Images, Iris Normalization, Color Information,Textural Information

I. INTRODUCTION

The modern world has increasing demand for identification of human beings in widespread areas. The biometrics can provide a natural and convenient means for individual identification by examining the physical or behavioral traits of human beings (Jain et al., 2007). Among various biometrics identification technologies, iris recognition has been of particular research interest because of the characteristics of uniqueness, stability and non-invasiveness of iris (Daugman, 1993). In the past years, great advances have been made in constrained environments where the users are closely cooperative. The state of the art iris recognition techniques are reviewed by Bowyer et al. (2008). Recent research interest in the field has focused on recognition in less constrained imaging conditions. In such circumstances the iris images captured may be degraded due to off-axis imaging, image blurring, illumination variations, occlusion, specular highlights and noise (Proença et al., 2010). Robust iris recognition in such degraded images pose a grand challenge. Daugman (2007) reported some advances including accurate iris boundaries localization with active contour and image registration through Fourier-based trigonometry, among others. Proença and Alexandre (2007) investigated a classification method which combines multiple signatures for noncooperative iris recognition. Sun and Tan (2009) presented a general framework for iris feature representation based on ordinal measure. Fig. 1 shows examples of noisy iris images, each affected by various factors such as low illumination, off-angle, rotation, blurring, and occlusion by the eyelids, that by eyelashes, noises by glasses, or occlusion by ghost regions. Since these factors reduce the similarity between intra-classes, the recognition performance is drastically degraded. In this study, we stress multiple recognition techniques, each one based on a different rationale and exploiting different properties of the eye region. Furthermore, we show how their fusion can increase the robustness to the degraded data typically captured in unconstrained acquisition setups.

The remainder of this paper is structured as follows: Section II describes the steps for pre-classification, iris normalization, feature extraction and matching for the different approaches, and how their outputs are joined. Section III details the experimental process followed by a discussion of the obtained results. finally, Section IV states the conclusions.

II . THE PROPOSED METHOD

A.Classification of the Left or Right Eye

Since the iris patterns of the left eye are different from those of right eye (Daugman, 2004), the accuracy of iris recognition can be enhanced by pre-classification of left or right eye image. In detail, the gray textural shapes of left iris are different from those of right iris. To prove it, in previous research (Daugman, 2004), he measured the distribution of hamming distance (HD) between left and right irises from any given person by using iris recognition algorithm based on gray textural information. For that, 648 left/right iris pairs from 324 persons were compared. Experimental results showed that the mean HD was 0.497 with standard deviation of 0.03108. And when the distribution of HD was measured from 9,060,003 different iris comparisons based on 4258 different iris images of different persons, the mean HD was 0.499 with standard deviation of 0.0317 (Daugman, 2004). By conclusion, the results with different irises (the mean: 0.499, the standard deviation: 0.0317) are almost similar to those with left/right irises (the mean: 0.497, the standard deviation: 0.03108),

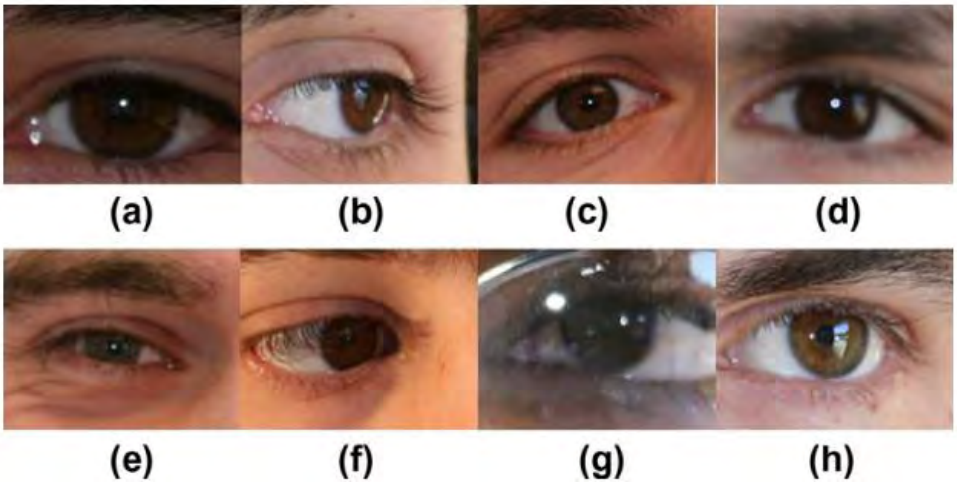

Fig.1. The noisy iris images NICE.II training dataset, 2009). (a) Low illumination. (b) Off-angle. (c) Rotation. (d) Blurring. (e) Occlusion by eyelids.(f) Occlusion by eyelashes. (g) Noises by glasses. (h) Occlusion by ghost region.

which represents that the patterns of left iris are different from those of right iris like different irises of different persons. To discriminate the left or right eye, we used method proposed by Kwang Yong Shin et al.[4].

In case that an input image is determined as "left eye" class, it is matched with only the enrolled images of left eyes. If it is determined as "right eye" class, it is matched with only the enrolled images of the right eyes. In case that an input image is determined as "undetermined eye" class, it is matched with all the enrolled images of the left or right eye.

B. Iris Normalization

Because illumination and camera-to-eye distances may be different for each photograph, irises may be captured with different size. Generally, such deformation would lead to error in matching. So it is necessary to normalize the irises to the same size to obtain an accurate iris recognition approach. Daugman proposed rubber sheet model for iris normalization (Daugman, 1993). Rubber sheet model, that is used as a basic part of iris recognition, Causes significant texture deformation and it degrades the results.

In this study we propose a new approach for iris normalization without changing circular shape to rectangular one. According to researches if the ratio of total normalized image including iris, pupil, eyelids and eyelashes is more than 4 times of iris region alone, recognition ratio highly degrades because of texture deformation through iris normalization by rubber sheet model. This problem is clearly visible about those images captured from long distances. So we need a method to normalize iris images to same size and at the same time is loyal to iris texture pattern. In our method, we normalize iris images in their original shapes. several researches normalize iris images to a 20*240 rubber sheet. So the iris region processed is formed of 4800 pixel. In this method we use bicubic interpolation with high speed and accuracy. We change the size of iris images so that it consists of 6200 pixels. We reach to this number by experiments and average size of iris images.

First, we calculate the coordinates of iris and pupil center and their radius by hough transform on segmentation binary mask images of NICE.II database. Then we repair noisy iris region by morphological operation. As we mentioned above, our iris region should consist of 6200 pixels. So the scale for bicubic interpolation is defined as follows:

$$s = \sqrt{6200/N} \tag{1}$$

In the above equation N denotes the number of repaired iris region pixels. the iris region obtained of this part consists of exactly 6200 pixels. After iris segmentation. We do the next processing steps on common region between input and enrolled images.

C. Feature Extraction based on iris color

Iris color correction: The color information shown in Fig. 1 can be used to identify the human eye. Different images of same class may capture in different illumination conditions that it undoubtedly degrades classification accuracy. correction of iris color method used here is defined as follows:

$$\begin{aligned} \hat{r}(i,j) &= 129 * r(i,j)/\bar{r} \\ \hat{g}(i,j) &= 129 * g(i,j)/\bar{g} \\ \hat{b}(i,j) &= 129 * b(i,j)/\bar{b} \end{aligned} \tag{2}$$

Where r, g and b are pixel intensity of red, green and blue components of original image and $\hat{r}, \hat{g}$ and $\hat{b}$ are pixel intensity of red,green and blue components of color corrected image, respectively. The values of $\bar{r}$, $\bar{g}$ and $\bar{b}$ are defined as follows:

$$\begin{aligned} \bar{r} &= 3\sum_i\sum_j r(i,j)/s \\ \bar{g} &= 3\sum_i\sum_j g(i,j)/s \\ \bar{b} &= 3\sum_i\sum_j b(i,j)/s \end{aligned} \tag{3}$$

Where s is the number of pixels.

The dissimilarity between input and enrolled images will be computed in YCbCr, HSI and lab color space models.We

use the Euclidean distance (ED) to measure the dissimilarity in each color space channel. The ED is calculated as follows:

$$E = \frac{1}{MN}\sqrt{\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}(P(x,y) - Q(x,y))^2} \quad (4)$$

where P(x,y) and Q(x,y) denote the values of the color channels at the (x,y) position of the enrolled image and an input image, respectively.

The input iris image is determined to be an imposter data by the following rules:

$$\begin{matrix} \text{NC, if } \}d\,(Cb_q, Cb_e)<T_1\} \text{ and } \}d\,(H_q, H_e)<T_2\} \text{ and} \\ \}d\,(a_q, a_e)<T_3 \text{ and } d\,(b_q, b_e) <T_4\} \\ \text{I, Otherwise} \end{matrix} \quad (5)$$

Cb_q , Cb_e denote blue components, H_q , H_e color components (hue), a_q , a_e color components of green to red and b_q , b_e color components of blue to yellow in lab color space of input and enrolled images. d is the Euclidean distance based on average value of color components and thresholds will be obtained by experiments. ‘‘I’’, represents ‘‘rejected as Imposter data’’. The NC represents ‘‘go to the Next Classification step’’. The same act will be done for color histogram values and the results of these two parts determine that input image goes to the next classification or it is an imposter data.

D. feature extraction based on iris texture

Local Texture Pattern (LTP) Map: The Local binary pattern (LBP) texture method is successful for iris recognition. Owing to the great success of LBP, recently many models, which are variants of LBP have been proposed for texture analysis. Among all the texture models, LBP is so popular owing to its simplicity, low dimensionality and efficiency. LTP proposed by A.Suruliandi et al.[12] provides more textural information than conventional LBP. It permits detection of the number of transitions or discontinuities in the circular presentation of the patterns. When such transitions are found to follow a rhythmic pattern, they are recorded as uniform LTP. Considering a local region, the relation between the central pixel gc and its neighbour is given by:

$$P(g_i,g_c) = \begin{Bmatrix} 0, \text{if } g_i \le (g_c - \Delta_g) \\ 1, \text{if } (g_c - \Delta_g) \le g_i \le (g_c + \Delta_g) \\ 9, \text{if } g_i > (g_c + \Delta_g) \end{Bmatrix} \quad (6)$$

where g_1, g_2,, . . ., g_8 are the pixel values of a local region, g_c is the value of the central pixel and Δ_g is a small positive value. Δ_g has more importance in forming the uniform patterns. Pattern unit matrix values are combined from the topmost bit to produce an 8 bit pattern string. The sum of the pattern string is the LTP value. The total number of bins required for LTP is 72. the uniform pattern concept is introduced to reduce the number of bins. Uniformity measure U defined in (7) can be used to find the uniform and non-uniform patterns. The pattern string having U ≤ 3 is considered as uniform and is represented by 45 bins (3 bins for U ¼ 0, 21 bins for U ¼ 2 and 21 bins for U ¼ 3). The patterns having U . 4 are termed as non-uniform and are characterized by a single bin. Hence, LTP requires only 46 bins.

$$U = |s(g_{p-1} - g_c) - s(g_0 - g_c)| + \sum_{p=1}^{p-1} s(g_p - g_c) - s(g_{p-1} - g_c) \quad (7)$$

Applying 1D Log-Gabor Filter on LTP Map: Gabor filters are able to provide optimum conjoint representation of a signal in space and spatial frequency. A Gabor filter is constructed by modulating a sine/cosine wave with a Gaussian. This is able to provide the optimum conjoint localization in both space and frequency, since a sine wave is perfectly localized in frequency, but not localized in space. Modulation of the sine with a Gaussian provides localization in space, though with loss of localization in frequency Gabor filters are a traditional choice for obtaining localized frequency information. They offer the best simultaneous localization of spatial and frequency information. However they have two main limitations. The maximum bandwidth of a Gabor filter is limited to approximately one octave and Gabor filters are not optimal if one is seeking broad spectral information with maximal spatial localization. An alternative to the Gabor function is the Log-Gabor function proposed by Field [1987]. Log-Gabor filters can be constructed with arbitrary bandwidth and the bandwidth can be optimized to produce a filter with minimal spatial extent.

$$G(w) = e^{\left(-\log\left(\frac{w}{w_0}\right)^2\right)/(2(\log(k/w_0)^2))} \quad (8)$$

Where w_0 is the center frequency.

Finally we apply 1D Log-Gabor filter on LTP map of iris image and the histogram of filter values is used as follows:

$$\begin{matrix} G; & \text{If } d(LG_q, LG_e) <T_1 \\ I; & \text{Otherwise} \end{matrix} \quad (9)$$

Where d has the following form:

$$d = \frac{\left(\sum_i |hist_{LGq} - hist_{LGe}|\right)}{N} \quad (10)$$

N is the number of pixels in common iris region of input and enrolled images.

III. EXPERIMENTS

The performance of the proposed work is evaluated in UBIRIS.v2 database (Proença et al., 2010) in which the iris images are captured when the subjects are at-a-distance and on-the-move. The less constrained imaging conditions introduced considerable noisy factors that makes recognition very challenging.

Iris Database and Evaluation Measures: Training + validation data set. The NICE.II provided a set of iris images chosen from the UBIRIS.v2 database in which the iris images as well as the ground truth (the binary images indicating the effective iris regions). The set comprises of 1,000 iris images from 181 different eyes that are captured at two different sessions. Among these images, 503 iris images from 78 different eyes are used for training which involves 124,318 interclass comparisons and 1,935 intraclass comparisons. The remaining ones are used for validation which involves 121,598 interclass comparisons and 1,658 intraclass comparisons. Test data set. To assess the quality of the selected filters, we choose a test data set from UBIRIS.v2 database in which the iris images do not appear neither in the training + validation data set. The test data set is comprised of 1,227 iris images from 114 eyes. All the 743,790 interclass matching results and 8,361 intraclass matching results are used for performance evaluation.

Evaluation measures: we selected the well-known receiver operating characteristic curves (ROC), the equal-error rate (EER) and the decidability (Daugman and Williams, 1996) index, given by Eq. 11.

$$d' = \frac{|m_{inter} - m_{intra}|}{\sqrt{(\sigma_{inter}^2 + \sigma_{intra}^2)/2}} \tag{11}$$

where $m_{inter}$and m_{intra}denotes the means of the interclass and intraclass comparisons and σ_{inter} and σ_{intra} are the respective standard deviations.

Decidability is defined as a function of mean and variance of intra- and inter-class scores. The higher the index, the better the discrimination ability of the system. The ROC curve is a graphical plot of the sensitivity, or true positive rate vs. false positive rate. The EER of a verification system means that the operating threshold for the accept/reject decision is adjusted so that the probability of false acceptance and false rejection becomes equal.

Table I. shows the comparisons of decidability value of the proposed method with other algorithms submitted to the Noisy Iris Challenge Evaluation-Part II (NICE.II). As shown in Table I. our new approach outperforms all other algorithms submitted to the Noisy Iris Challenge Evaluation-Part II (NICE.II) except of proposed method by Tieniu Tan et al. (2012). An important point about our proposed method is that we use eye features in comparison to Tieniu Tan et al. that skin feature is used in addition of eye feature that it obviously improves the results.

Fig. 2 and Fig. 3 show the ROC curves. As shown in Fig. 2 the recognition accuracy of the proposed method is higher than LBP and LBP with pre-classification of left or right images. The result also demonstrates that our method of applying 1D Log-Gabor filter on LTP map outperforms using 1D Log-Gabor filter and LBP separately.

In the final experiment we compare our method to proposed method with other algorithms submitted to the Noisy Iris Challenge Evaluation-Part II (NICE.II). It shows that our method is considerably close to proposed method by Tieniu Tan et al that skin and eye features are used.

TABLE I. THE IRIS RECOGNITION ACCURACY IN TERM OF DICIDABILITY VALUE.

METHOD	DI
[1].Tieniu Tan et al	2.5748
[2]. Qi Wang et al	1.8213
[3]. Gil Santos et al	1.7786
[4]. Kwang Yong et al	1.6398
[5]. Peihua Li et al	1.4758
[6]. Maria Marsico et al	1.2565
[7]. Peihua Li	1.1892
[8]. R. Szewczyk et al	1.0931
OUR PROPOSED METHOD	1.9294

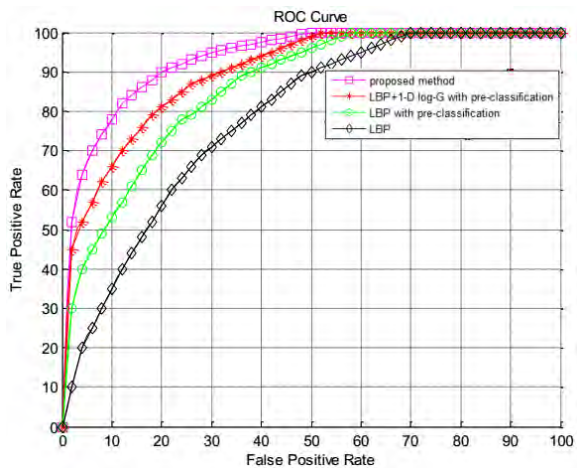

Fig.2. Results from LBP, LBP with preclassification, LBP with 1D Log Gabor filter and preclassification and the proposed method.

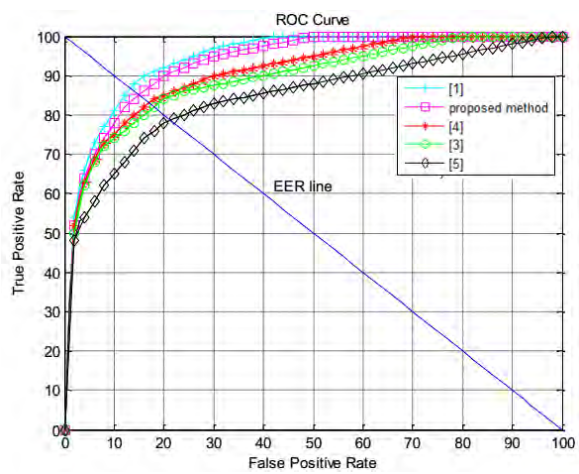

Fig.3. Results proposed method with other algorithms submitted to the Noisy Iris Challenge Evaluation-Part II (NICE.II) and the proposed method.

IV. CONCLUSION

In this paper we propose a new iris recognition method for the iris images degraded by noisy factors. The genuine and imposter matching are determined by pre-classification based on ‘‘left or right eye’’. Then we normalize iris region without rubber sheet model. Our normalization method prevents texture deformation occurs by rubber sheet model especially about those images captured from long distances. For feature extraction we use color and textural information of iris region. In our proposed method we apply 1D Log-Gabor filter on LTP map of iris region instead of using them separately. As the experimental results, decidability value end the EER of our propose method are 1.9294 and 15.14, respectively. Extensive experiments on the NICE.II training dataset have demonstrated the effectiveness and robustness of the proposed method.

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