An Efficient Retina Pattern Recognition Algorithm (RPRA) towards Human Identification

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Abstract – In this paper an automatic person identification algorithm is proposed based on retina pattern recognition. Our proposed method follows the steps firstly reference point detection to compensate the translational and rotational displacements, secondly blood vessel segmentation to identify blood vessel intersection points properly and finally matching the intersection points. The maximum principal curvature of the Hessian matrix of the intensity image is used for blood vessel extraction and number of matched blood vessel intersection points between two patterns is used to quantify the degree of matching. The validity of the results is then verified with concrete examples.

Keywords: Blood vessel intersection point detection, blood vessel segmentation, fovea center detection, optic nerve detection, retina pattern matching.

I. INTRODUCTION

Reliable automatic recognition of persons has long been an attractive goal. Recently it becomes significantly important in terms of anti-terrorism. Biometrics employs physical and behavioral characteristics to identify a person. Common biometric features are voice, fingerprint, gait, facial-thermo-gram, signature, face, palm print, hand geometry, iris and retina [6]. Fingerprint is the oldest, most popular and widely used by law enforcers. Iris and retina recognition is relatively new approach, compared to other biometric features [6]. Among the biometric features retina pattern is stable and reliable for identification. This makes the retina recognition is a prominent solution to security in the near future [6]. The problem involves capturing image of retina by special arrangements of devices, an effective preprocessing of captured image and generating features, which can describe the interclass and intra-class variability well. In this paper we proposed an Efficient Retina Pattern Recognition Algorithm (RPRA) towards Human Identification that can maintain large inter-class variability as well as small intra-class variability.
Rest of the paper is organized as follows. Section II illustrates Retina image acquisition process. Section III describes effective preprocessing of retina image. Section IV describes feature extraction and matching of retina pattern. Section V depicts experimental results and comparison with [1]. Finally, section VI concludes the paper.

II. RETINA PATTERN RECOGNITION ALGORITHM(RPRA)

Retina Pattern Recognition Algorithm (RPRA) for human identifications is discussed in the below subsections in the following three major steps:

A. Retina image acquisition
B. Image preprocessing
C. Feature extraction and matching of retina pattern

A. Retina image acquisition

Retina image acquisition requires special arrangements. This process is accomplished using a medical device Fundus Camera [1]. Images captured with this setup are of very high resolution, 1504 x 1000. Pictures of right eye are used for the analysis.

B. Image preprocessing

1. Reference Points Detection

We took Fovea Center and Optic Nerve as the reference points. These reference points will contribute to compensate the rotational and translational effect between different images.

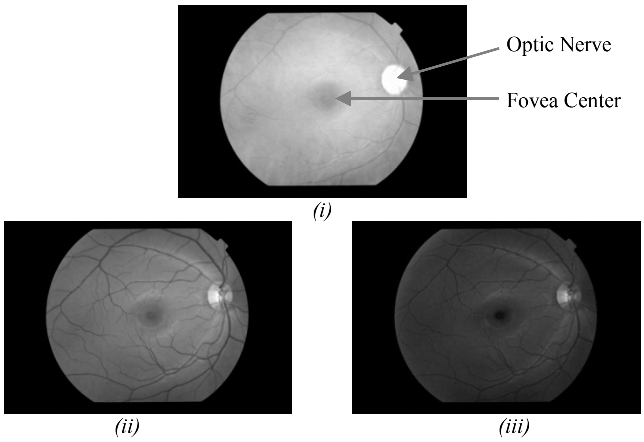


Fig. 1. (i) Red layer, (ii) Green Layer and (iii) Blue Layer of a Retina image

Blue layer of the intensity image of teitna is the best to locate Fovea Center and red layer for Optic Nerve [1]. As well the blood vessels can be easily identified in the green layer of the retina image[1].

i) Fovea Center Detection:

A fixed region in center of the blue layer of retina is used to detect Fovea Center. We took the center of the image by (1) [1].

$$\begin{aligned} X_{\max} &= W/2 + 0.1*W \quad & X_{\min} &= W/2 - 0.1*W \\ Y_{\max} &= H/2 + 0.1*H \quad & Y_{\min} &= H/2 - 0.1*H \end{aligned} \qquad (1)$$

After getting the image from the center a Gaussian convolution [4] is applied as:

$$I(x, y; x) = I(x, y) \otimes G(x, y; s) \qquad (2)$$

Where G is:

$$G(x, y; s) = \frac{1}{2\pi s^2} e^{-\frac{x^2+y^2}{2s^2}}$$

and **s** is a scale factor. For our case the value of **s** is taken 11. Also the kernel size is 39x39. Thus after applying the convolution operation on the central image of retina Fig 2(i), an image like Fig 2(ii) is found and finally after theresholding the image we ger image of Fig 2(iii).

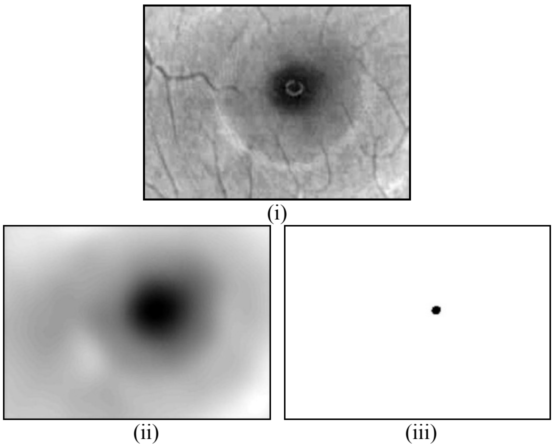


Fig. 2. (i) Center portion (ii) Convoluted Image (iii) Threshold Image of blue layer of Retina.

ii) Optic Nerve Detection:

A method of detecting optic nerve[1] is used to detect Optic Nerve from red layer of the retinal image.

2) Rotating and Separating a Circular Region

After detecting the reference points a fixed portion of image is taken on which all the further processing will be done. The distance between Fovea Center and Optic Nerve D_{FO} is

$$D_{FO} = \sqrt{(O_X - F_X)^2 + (O_Y - F_Y)^2} \qquad (3)$$

Where,
(O_X , O_Y) and (F_X , F_Y) are X and Y coordinates of Optic Nerve and Fovea Center respectively.

To make uniform patterns of retina images from all dataset we took pattern radius as 424 pixels. To remove the translational and rotational displacement Fovea Center is taken as the center of the pattern and Optic Nerve is placed at the same horizon of Fovea Center. After that we applied a k-mean filter [4] of size 5x5 to remove the noise and any unwanted signal on the pattern.

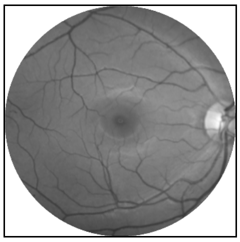


Fig. 3. Filtering is applied on the pattern

3) Blood vessel Segmentation

The second directional derivatives describe the variation in the gradient of intensity in the neighbourhood of a point. Since vessels appear as ridge-like structures in the images, we look for pixels where the intensity image has a local maximum in the direction for which the gradient of the image undergoes the largest change (largest concavity). The second derivative information is derived from the Hessian of the intensity image I(x, y) [2] [3] .

$$H = \begin{pmatrix} \partial_{xx} I & \partial_{xy} I \\ \partial_{yx} I & \partial_{yy} I \end{pmatrix} \qquad (4)$$

The maximum eigenvalue (λ_+) corresponds to the maximum principal curvature of the Hessian tensor, which is refered as maximum principal curvature. Thus, a pixel belonging to a vessel region will be weighted as a vessel pixel if $\lambda_+ >> 1$, we calculate the largest eigenvalue (λ_+) as follows:

$$\lambda_+ = \frac{\partial_{xx} I + \partial_{yy} I + \alpha}{2} \qquad (5)$$

Where

$$\alpha = \sqrt{(\partial_{xx} I - \partial_{yy} I)^2 + 4\partial_{xy}^2 I}$$

After applying the curvature feature we got largest Eigen value (λ_+) for each pixel in the intensity image. We take each largest Eigen value of each pixel as image intensity value. That is:

$$I(x, y) = \lambda_+(x, y) \qquad (6)$$

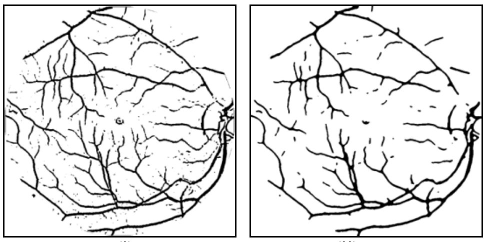
Then this image is filtered using a 5 x 5 average filter. The average of the maximum Eigen value is calculated as follows:

$$\mu = \frac{\sum \lambda_+(x, y)}{\text{total no of pixels}} \tag{7}$$

To get a binary image we threshold the image on value of μ as follows:

$$I(x, y) = \begin{cases} 0 & if \quad \lambda_+ \geq \mu \\ 1 & if \quad \lambda_+ < \mu \end{cases} \tag{8}$$

After applying principle curvature feature and average filter to the filtered image of Fig 3 we got the segmented binary image of Fig 4(i):



(i) (ii)

Fig. 4. (i) Segmented binary image after applying principle curvature feature and (ii) 5 x 5 average filters.

This image has some noises. To reduce the noise we apply a 5 x 5 median filter to this binary image.

4) Thinning the vessels into one pixel width

To thin the blood vessel into one pixel width we applied a two stage thinning algorithm. The stages are:

i) Blood Vessel Boundary Pixels Determination:

A pixel P is said to be a boundary pixel if P = 0 and at least one of its four neighbours at horizontal and vertical pixel is white. Fig 5 illustrates this concept.

X_3	X_2	X_1
X_4	P	X_0
X_5	X_6	X_7

Fig. 5. A pixel P and its Neighbor Pixels X_i

Let X(P) is the no of pixels surrounding P in horizontally and vertically. Then P is a boundary pixel if P = 0 and it satisfies equation (11)

$$X(P) > 0. \tag{9}$$

Where

$$X(P) = \sum_{i=1}^{i=4} c_{2i\%8}$$

$$c_i = \begin{cases} 1 & if \quad X_i = 0 \\ 0 & Otherwise \end{cases}$$

ii) Remove Boundary pixels that do not break vessel connectivity:

A boundary pixel P is changed to background pixel on the basis that removing this pixel does not disconnect the connected blood vessel. Let L(P) counts number of situations that break connectivity, C1(P) and C2(P) counts no of situations that can short the length of vessels. A boundary pixel P can be changed to background if it satisfies the following conditions.

Condition1:

$$L(P) = 0 \tag{10}$$

Where

$$L(P) = \sum_{i=0}^{i=7} b_i$$

$$b_i = \begin{cases} 1 & if \quad X_i = 0 \quad and \quad X_{(i+7)\%8} = 1 \quad and \quad X_{(i+1)\%8} = 1 \\ 0 & Otherwise \end{cases}$$

Condition2:

$$C1(P) = 0 \tag{11}$$

Where

$$C1(P) = X1(P) + X2(P) + X3(P)$$

$$X1(P) = \begin{cases} 0 & if \quad \sum_{i=1}^{i=3} b_i > 0 \\ 1 & Otherwise \end{cases}$$

$$X2(P) = \begin{cases} 0 & if \quad X_0 = 1 \quad and \quad X_4 = 1 \\ 1 & Otherwise \end{cases}$$

$$X3(P) = \begin{cases} 0 & if \quad \sum_{i=5}^{i=7} b_i > 0 \\ 1 & Otherwise \end{cases}$$

$$b_i = \begin{cases} 1 & if \quad X_i = 0 \\ 0 & Otherwise \end{cases}$$

Condition3:

$$C2(P) = 0 \tag{12}$$

Where

$$C2(P) = X1(P) + X2(P) + X3(P)$$

$$X1(P) = \begin{cases} 0 & if \quad \sum_{i=3}^{i=5} b_i > 0 \\ 1 & Otherwise \end{cases}$$

$$X2(P) = \begin{cases} 0 & if \quad X_2 = 1 \quad and \quad X_6 = 1 \\ 1 & Otherwise \end{cases}$$

$$X3(P) = \begin{cases} 0 & if \quad \sum_{i=7}^{i=9} b_{i\%8} > 0 \\ 1 & Otherwise \end{cases}$$

$$b_i = \begin{cases} 1 & if \quad X_i = 0 \\ 0 & Otherwise \end{cases}$$

Algorithm 1: Thinning(B):

1. For each vessel pixel in B determine boundary pixels.
2. Update = false.

3. For each boundary pixel P if removing P does not violate condition 1, 2 and 3 then change this pixel to background.
4. If at least one pixel is changed during step 3 set Update = true.
5. If Update = false then return.
6. Go to step 1.

After applying the Thinning algorithm1 on Fig 4(ii) we got Fig 6:

Fig. 6. Skeleton of segmented image

C) Feature Extraction and Pattern Matching

1) Intersection Point detection

After preprocessing we got a binary image of one pixel width blood vessel structure. Since the blood vessel structure are different for different person, the intersection point is also different. Hence We took the intersection points as matching feature. Let N(P) counts no of neighbour pixels that have color level black. Then we define a pixel P as an intersection point if P = 0 and conditions C1 and C2 all are satisfied.
Condition C1:

$$N(P) \geq 3 \tag{13}$$

Where

$$N(P) = \sum_{i=0}^{i=7} b_i$$

$$b_i = \begin{cases} 1 & \text{if} \quad X_i = 0 \\ 0 & \text{Otherwise} \end{cases}$$

Condition C2:

$$X(P) = 0 \tag{14}$$

Where

$$X(P) = \sum_{i=1}^{i=4} c_{2i\%8}$$

$$c_i = \begin{cases} 1 & \text{if} \quad X_i = 0 \quad \text{and} \quad (X_{(i+7)\%8} = 0 \quad \text{or} \quad X_{i+1} = 0) \\ 0 & \text{Otherwise} \end{cases}$$

After applying these we got the intersection points as Fig 7.

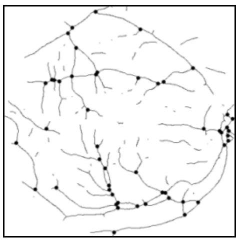


Fig. 7. Intersection Points Determined.

2) Template Generation

After finding the blood vessel intersection points of the input retina image, the background blood vessel skeleton is removed and keeps only intersection points. These intersection points collectively generate a template. Each template contains number of intersection points and coordinates of each intersection points. A template is shown in Fig 8:

Fig. 8. A template of Fig 7

3) Template Matching

For matching each template is divided into some sub regions each of which containing some intersection points. The degree of matching of different templates is measured by the closeness of intersection points between the templates. The intersection points in two different templates for same person can have some translational and rotational displacements. We ignored the rotational displacements due to very small variations in rotation and considered only the translational displacements. We subdivided the total template in to 8 x 8 same size regions. The matching between two templates is performed by following algorithm:

Algorithm 2: TemplateMatching(T1, T2)

1. totalmatched = 0
2. For each sub region S1 in T1 and corresponding sub region S2 in T2 do step 3 to 8
3. matched = 0
4. For each intersection point I1 in S1 do step 5 to 7
5. Find the intersection point I2 in S2 and 8 neighbour sub regions of S2 which has minimum distance D_{min} with I1.
6. If $D_{min} \leq D_{th}$ and I2 is not already matched then increment matched by 1.
7. Mark I2 as matched.
8. totalmatched = totalmatched + matched
9. Calculate percent of intersection point matching by the following equation:

$$PMatch = \frac{2 * totalmatched}{P_1 + P_2} * 100$$

Where P_1: Total number of intersection points in T1
P_2: Total number of intersection points in T2

10. Return PMatch

Finally we have taken the degree of matching as follows:

$$DegreeOfMatching = \max\{TemplateMatching(T1,T2), TemplateMatching(T2,T1)\}$$

In this algorithm the value of D_{th} has great significant on the result. This value represents the maximum offset by which the same intersection point on different template can be displaced. By observing, the value of D_{th} is selected as 11 in this work.

D) Experimental Results and Comparisons

1) Experimental Results

The proposed method is applied to a dataset [1] containing 18 retina images of 6 different persons each having 3 samples. We used sample1 as training pattern and sample2 and sample3 as testing patterns. Table 1 shows the comparison of sample1 with sample2 and sample3 of this 6 different persons. Figure 9 shows the corresponding graph showing this comparison. In Table 1 matching percentage of sample1 of person1 with sample2 of person1 is 81.72% means 81.72% blood vessel intersection points are matched between two different templates of person1. Another case of sample1 of person2 with sample2 of person1 is 12.90% means 12.90% blood vessel intersection points are matched between two templates of person1 and person2.

It is clear from the Table 1 and the Fig 9 that for every matching case that is comparing patterns of same person we get more than 80% and for every mismatching case that is comparing patterns of different persons we get less than 25%. The worst case matching value is 80.8% and worst case mismatching value is 23.9%.

To classify the testing pattern we used the threshold value θ as follows:

$$\theta = \frac{WorstCaseMatch + WorstCaseMismatch}{2} \tag{15}$$

TABLE 1. Comparison of sample1 with sample2 and sample3 of 6 different persons

Person No	Sample No	Sample 1 of					
		Person 1	**Person 2**	**Person 3**	**Person 4**	**Person 5**	**Person 6**
P1	**S2**	81.72%	12.90%	11.11%	11.24%	16.16%	13.86%
	S3	82.47%	13.33%	10.75%	17.20%	08.42%	13.08%
P2	**S2**	08.70%	84.78%	11.24%	06.82%	10.20%	18.00%
	S3	18.75%	80.90%	10.87%	04.35%	8.51%	16.98%
P3	**S2**	15.38%	08.79%	95.45%	13.79%	12.37%	20.20%
	S3	14.74%	06.82%	90.11%	15.38%	10.75%	13.33%
P4	**S2**	10.99%	15.38%	13.64%	82.76%	10.31%	10.10%
	S3	08.42%	11.36%	13.19%	90.11%	08.60%	17.14%
P5	**S2**	12.37%	08.25%	10.64%	08.60%	87.38%	07.62%
	S3	11.88%	10.64%	10.31%	10.31%	84.85%	09.01%
P6	**S2**	14.68%	09.17%	20.75%	13.33%	08.70%	85.47%
	S3	14.16%	13.21%	23.85%	11.01%	09.01%	82.93%

Fig. 9. Comparison of sample1 of person1 and person2 with sample2 and sample3 of 6 different persons.

The calculated value of θ is 0.524. That is when comparing two retina pattern if their calculated degree of matching is greater than the value of θ then these two patterns are in the same class. Otherwise these patterns are of different persons. For the dataset by using one sample as training pattern and two other samples as testing pattern gives classification rate of 100%.

2) Comparison with an existing system

One of the vital steps of retina preprocessing is the fovea center detection. In existing system there exist some deviations in determining the coordinates of the fovea center. Our proposed system removes some deviation and more accurately identify the coordinates of the fovea center. For retina images of same person fovea center to optic nerve distance should be near as close as possible.

In Table 2 we showed the standard deviation of the fovea center to optic nerve distance for images of the same person. The standard deviation should be as small as possible for accurate detection of fovea center and optic nerve. Fig 10 shows the standard deviation of determining fovea center for same person graphically.

TABLE 2. Standard Deviation of Fovea Center to Optic Nerve distance in existing and proposed system

Person No	Existing Method	Proposed Method
Person 1	07.00	04.72
Person 2	19.50	13.07
Person 3	04.72	05.03
Person 4	13.89	01.52
Person 5	08.62	02.00
Person 6	18.24	06.02

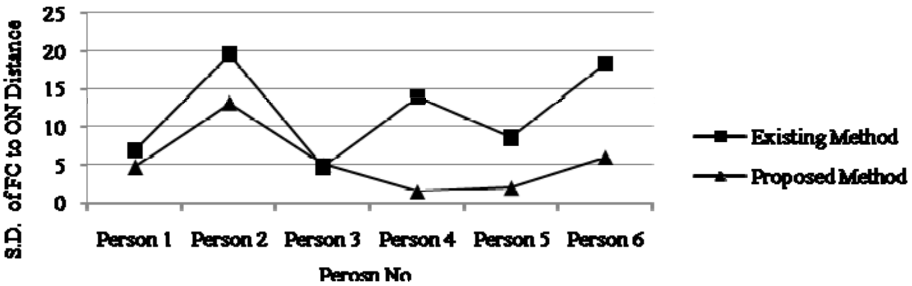


Fig. 10. Comparison of Existing and Proposed method for detecting Fovea Center

We see that almost all the cases we got lower standard deviation than existing system. Hence our method is more accurate than existing system. Finally the performance comparison between existing system and proposed system is given in Table 3.

TABLE 3. Performance comparison between existing system and proposed system

Performance Criteria	Existing System	Proposed System
Matching Case	More than 0.70	More than 0.80
Mismatch Case	Less than 0.30	Less than 0.23
Best Match	0.92	0.95
Worst Match	0.70	0.80
Best Mismatch	-0.07	0.04
Worst Mismatch	0.28	0.23
Inter-class Distance	0.40	0.57

E) Conclusion

We described an approach to identify a person by retina pattern matching. The results are very interesting. Although the number of images matched from dataset is not very high, still the results are indicative of the robustness of the method within the tolerable limit. Because we found large inter-class distance which will maintain the high classification rate even for larger dataset containing noise or other unwanted effects. The method is also quite insensitive to translational and rotational displacement. The space and time complexity is reasonable. Each retina image contains no more than 100 of intersection points. These intersection points are the key points to authenticate a person correctly. Space required for storing these intersection points into database for registration will not take too much memory. The comparison process is also efficient since we are comparing only the intersection points of different retina images instead of comparing retina images as a whole.

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