Personal Identification from Iris Images using Localized Radon Transform

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Abstract

Personal identification using iris images has invited lots of attention in the literature and offered higher accuracy. However, the computational complexity in the feature extraction from the normalized iris images is still of key concern and further efforts are required to develop efficient feature extraction approaches. In this paper, we investigate a new approach for the efficient and effective extraction of iris features using localized Radon transforms. The feature extraction process exploits the orientation information from the local iris texture features using finite Radon transform. The dominant orientation from these Radon transform features is used to generate a binarized/compact feature representation. The similarity between two feature vectors is computed from the minimum matching distance that can account for the variations resulting from translation and rotation of the images. The feasibility of this approach is rigorously evaluated on two publically available iris image databases, i.e. IITD iris image database v1 and CASIA v3 iris image database. We also investigate the multi-scale analysis of iris images to enhance the performance. The experimental results presented in this paper are highly promising and suggest the computationally attractive alternative for the online iris identification.

1. Introduction

The iris-based biometric recognition has invited lot of interest in the biometric literature [1-4], [7-8] and is highly suitable for large scale applications for human identification. It has extremely rich textures which offer reliable and unique personal identification. The iris texture is highly unique, even in case of identical twins and even between the left and right eyes of an individual. Since the dimensionality of iris texture is very high, recognition decisions can be made at a confidence level high enough to support reliable and rapid searches throughout extremely large sized databases. Reference [1] provides an excellent review on the various aspects of iris recognition and there are new efforts to establish iris recognition from a distance [8].

This paper investigates a new approach for iris identification using localized Radon transform (LRT). The LRT can be efficiently employed to characterize the textures in iris images which offer unique features for the personal identification.

2. Image Normalization and Enhancement

The image normalization (iris segmentation and mask generation) and enhancement employed in this work is same as detailed in reference [4]. Figure 1 shows two samples of automatically segmented and unwrapped iris image from IITD v1 and CASIA v3 database.

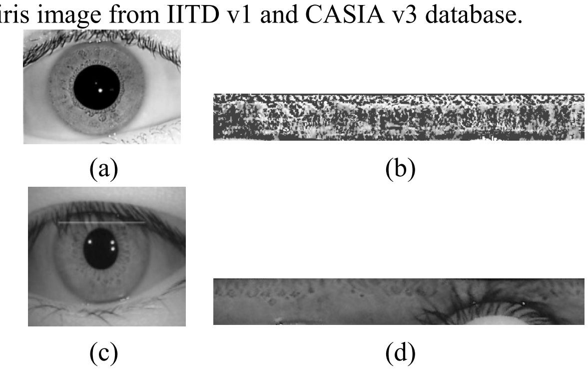

Figure 1. (a) 320 × 240 pixels iris image from the IITD iris database, (b) the corresponding unwrapped and enhanced 432 × 48 pixel image, (c) 640 × 480 pixel image sample from CASIA v3 database and (d) corresponding 512 × 64 pixel unwrapped image.

3. Feature Extraction using LRT

The LRT of a discrete image $g[m, n]$ on a finite grid R_q^2 can be defined as:

$$s[L_\theta] = M_g(\theta) = \sum_{(x,y)\in L_\theta} g[x,y] \quad (1)$$

where $R_q = \{0, 1, \ldots, q-1\}$, q is a positive integer, and R_q^2 is centred at (x_0, y_0). The L_θ represents set of points on R_q^2 such that

$$L_\theta = \begin{cases} \{(x,y) \mid y = \tan(\theta) \times (x - x_0) + y_0, x \in R_q\}, & \theta \neq \frac{\pi}{2} \\ \{(x,y) \mid x = x_0, y \in R_q\}, & \theta = \frac{\pi}{2} \end{cases} \quad (2)$$

where $\theta \in [0, \pi)$ and denotes the angle between line L_θ and the positive x-axis, and L_θ is the line passing through the centre (x_0, y_0) of R_q^2.

The orientation of the line-like patterns is estimated from the values of LRT and since we are interested in the dark line-like features in the iris image, the orientation that corresponds to the minimum value is

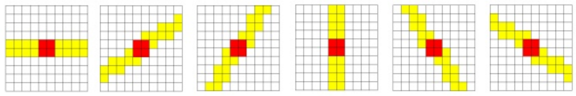

Figure 2. Computing Localized Radon Transform in a 10 × 10 pixel region in the directions of 0°, π/6, π/3, π/2, 2π/3, 5π/6 and the L_θ is 2 pixel wide.

selected as the dominant direction. This can be mathematically be represented as follows:

$$O_p(x_0, y_0) = arg\left(min_p(s[L_\theta])\right),\ p = 1, 2, \dots, D \quad (3)$$

where the $O_p(x_0, y_0)$ represents the estimated direction of pixel $g[x_0, y_0]$, and D represents the number of directions (*i.e.* in Figure 2, D = 6 since six directions were selected). This operation is repeated as the centre of lattice R_q^2 moves over all the pixels in the image [9]. At each position, the dominant orientation O_p is computed to form the feature vector of iris image.

4. Generating Matching Scores

A. Score Generation

In this experiment two types of matching scheme were considered. The score function for the direct matching of two feature vectors *R* and *T*, without mask, is defined as follows:

$$Score(R,T) =$$
$$min_{\forall i\in[0,2w],\forall\, j\in[0,2h]}\left(\frac{\sum_{x=1}^{m}\sum_{y=1}^{n}\phi\left(\widehat{\boldsymbol{R}}(x+i,y+j),\boldsymbol{T}(x,y)\right)}{\sum_{x=1}^{m}\sum_{y=1}^{n}(\widehat{\boldsymbol{R}}(x+i,y+j)\oplus -1)}\right) \quad (4)$$

where $\hat{R}$ is the registered feature image with width and height expanded to $2w + m$ and $2h + n^{\dagger}$, and $\oplus$ is the exclusive-or operator that output one while two operands are different and zero otherwise, while

$$w = floor\left(\frac{m}{8}\right),\ h = floor\left(\frac{n}{3}\right) \quad (5)$$

$$\widehat{\boldsymbol{R}}(x,y) = \begin{cases} R(x-w,y-h) & x\in[w+1,w+m],\ y\in[h+1,h+n] \\ -1 & otherwise \end{cases} \quad (6)$$

$$\phi(J,K) = \begin{cases} 0 & if\ J = K\ or\ J = -1 \\ 1 & otherwise \end{cases} \quad (7)$$

The match score function for matching two feature vectors *R* and *T*, with the corresponding masks M_R and M_T , is defined as follows:

$$Score(R,T,M_R,M_T) = \min_{\forall i\in[0,2w],\forall\, j\in[0,2h]}$$
$$\left(\frac{\sum_{x=1}^{m}\sum_{y=1}^{n}\psi(\widehat{\boldsymbol{R}}(x+i,y+j),\boldsymbol{T}(x,y),M_R(x+i,y+j),M_T(x,y))}{\sum_{x=1}^{m}\sum_{y=1}^{n}M_R(x,y)\cap M_T(x,y)}\right) \quad (8)$$

where $\hat{R}$, *w* and *h* are same as defined in (6) and (5) respectively, while

$$\psi(J,K,M,N) =$$
$$\begin{cases} 0\ if\ M = N = 1\ and\ J = K \neq -1\ or\ J = -1 \\ 1 \quad otherwise \end{cases} \quad (9)$$

B. Score Combination

We introduced some nonlinearity in the combining multi-scale matching scores to achieve further performance improvement. The exponential nonlinearity [2] was employed since it favorably scales up the higher score values and attenuates the lower score values, which can potentially help to further separate the distribution of genuine and imposter matching scores. The weighted combination of scores for every i^{th} user, $\forall i$ = 1, 2, …, U, where U is the total number of users, can be achieved as follows:

$$\hat{s}_i = \sum_{j=1}^{L}\left(w_j \times exp\ (s_{ij})\right) \quad (10)$$

where $\hat{s}_i$ is the combined matching score of i^{th} user, L represents the total number of scales, $\sum_{j=1}^{L} w_j = 1$ and $w_j \in [0\ 1]$, w_j represents the weight corresponding to the j^{th} scale, and s_{ij} represents i^{th} user's matching score from the j^{th} scale iris features.

5. Experiments and Results

The proposed approach for the iris identification using LRT was rigorously investigated on two publically available iris databases, *i.e.* IITD v1 [6] and CASIA iris image database v3 [5] respectively. The verification results were achieved by using 5-fold and 7-fold cross validation for IITD and CASIA database respectively, and the average of results are presented. In this work, the first seven images from all the 411 left eyes in CASIA v3 database were employed to simply limit the complexity. The IITD v1 database has 5 images from each of 224 subjects and all of the available left eye images were employed. This approach of cross-validation generated 1,120 (224 × 5) genuine and 249,760 (224 × 223 × 5) imposter scores for the IITD v1 database; 2,877 (411 × 7) genuine and 1,179,570 (411 × 410 × 7) imposter scores for the CASIA v3 database. In order to analyze the performance from the proposed approach, four sets of experiments were performed on above databases and discussed in the following section.

A. Results from the IITD version 1 Database

(1) In this set of experiments, the LRT is used to extract the orientation features from the normalized iris images and the matching scores are generated as detailed in section 4. The proposed approach of LRT based iris identification achieves equal error rate (EER) of 0.53% without the usage of multi-scale iris features (table 1). It should be noted that the experimental results achieved here (EER = 1.71%) are *significantly better* than those presented in [4] on the same database (log Gabor EER = 2.81%, Haar 3.40%) by using the same protocol.

(2) In the second set of experiments multi-scale nonlinear score combination was investigated. The LRT was used to generate the feature vectors of the iris images at three different dyadic scales (*i.e.* full scale, 1/2 scale and 1/4 scale). The normalized iris image was

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†Relatively large amount of shifting in both directions was employed to account for the segmentation errors, translational and rotational variations, in the normalized images.

decomposed (down sampled) only in horizontal direction which contains more information as compared to vertical direction. Firstly, equation (4) is used to compute the matching scores among feature templates for different scales (mask were not employed because of difficulty in effectively extracting reliable masks from such low resolution iris images); secondly, the final matching scores are generated by using equation (10). This method is diagrammatically illustrated in figure 3. The parameters as well as the weights are empirically computed (only from the training data) and selected so that the best performance in terms of EER can be achieved. As can be observed from table 1, the multi-scale LRT approach improves the performance, but marginally, for the IITD database.

Table 1: Results from IITD version 1 database.

	LRT		Multi-scale LRT			Template Size (Byte)
Parameters	*w*	*l*	*w*	*l*	*s*	
	4	36	4	36	1	648
			3	35	1/2	576
			2	20	1/4	648
EER	0.53%		0.44%			
DI [4]	5.93		6.83			

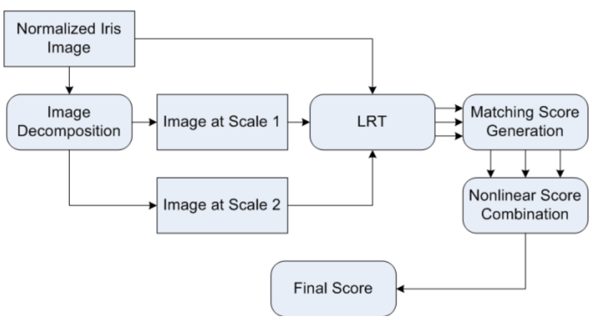

Figure 3. The block diagram for the LRT based multi-scale iris identification investigated in this work.

Table 2: Results from CASIA version 3 database.

	LRT		Multi-scale LRT			Template Size (Byte)
Parameters	*w*	*L*	*w*	*l*	*s*	
	3	45	3	45	1	1881
			2	24	1/2	2048
			2	18	1/4	1024
EER	2.82%		2.31%			
DI	3.22		3.51			

B. Results from the CASIA v3 Database

In this set of experiments the experimental results were obtained from the CASIA iris v3 image database and are summarized in table 2. The matching scores are computed using equation (8). It can be noticed that the experimental results are highly promising as we achieve the average EER of 2.82%. The results obtained in table 2 suggest that an improvement in EER can be achieved by using multi-scale decomposition of normalized iris images.

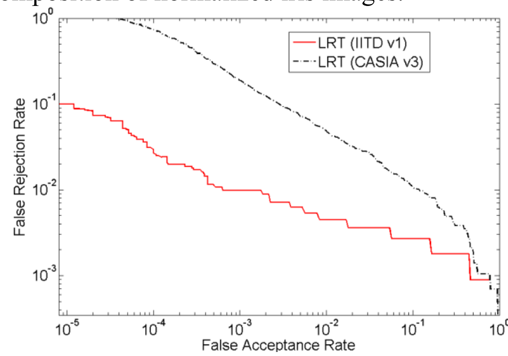

Figure 4. The comparative performance of LRT from IITD v1 and CASIA v3 iris image database.

6. Discussion (Comparison with Related Work)

The computational complexity of LRT based feature extraction is significantly lower as it just requires simple summation operations. Therefore it favorably compares with the conventional Gabor filters [10] which require expensive convolution operation at every pixel. For instance, using a set of $\mathrm{K} \times \mathrm{K}$ Gabor filters on an $\mathrm{M} \times \mathrm{M}$ image to extract O orientations requires $\mathrm{K}^2 \times \mathrm{M}^2 \times \mathrm{O}$ multiplications and $(\mathrm{K}^2 - 1) \times \mathrm{M}^2 \times \mathrm{O}$ additions; on the other hand, applying LRT to an $\mathrm{M} \times \mathrm{M}$ image to extract O orientation features with line width w and length K just requires $\mathrm{w} \times \mathrm{K} \times \left(\frac{\mathrm{M}}{\mathrm{w}}\right)^2 \times \mathrm{O}$ additions. For simplicity let us reasonably assume that the computational complexity of multiplication and addition are equivalent in the sense of complexity (although the exact computational complexity of multiplication is greater than addition). According to this assumption, the number of operations required from LRT based feature extraction is still about 2Kw times smaller as compared with those from the spatial convolution based Gabor filter. Furthermore, *the LRT operation has associated down sampling effect, which further reduces the dimensionality of the resulting feature vector*. For example, while applying LRT to an image of size $\mathrm{M} \times \mathrm{N}$ using line width w, the output feature vector is of size $\left(\frac{\mathrm{M}}{\mathrm{w}}\right) \times \left(\frac{\mathrm{N}}{\mathrm{w}}\right)$, *i.e. the size of feature vector is w^2 times smaller than the original image*. In most cases the line-like features in the iris image are more than one pixel width, which means that the LRT operation will significantly save computations in most of the times/cases. Since the efficiency of computing the matching scores depend on the size of feature vectors, smaller feature vector will further improve the effective matching or authentication time. It may be worth mentioning that the LRT is also highly suitable for parallel implementation which will further increase the computational efficiency.

References [11] and [12] have effectively illustrated the performance improvement using multi-scale analysis of biometric data. Therefore it is prudent to examine multi-scale analysis for the iris identification and to ascertain the performance improvement. The experimental results (section 5) show that although the multi-scale score combination improved the performance marginally for the IITD v1 database, the improvement was noticeable regarding the results from CASIA v3 database (see table 1-2). One plausible explanation for these inconsistent improvements may be that the performance gain through this approach, *i.e.* multi-scale analysis, may vary depending on different databases and number of classes of the database. In addition, if the resolution of the normalized iris images is high enough to allow higher levels of scale decomposition, the performance can be significantly higher. Moreover, the additional computations required are quite limited due to the down sampling. Therefore, the multi-scale approach can be a viable option for performance improvement in several applications, especially those with high computational power and/or high imaging resolution. The separation between genuine and imposter scores from different scales shown in figure 5 suggests that the performance improvement is contributed from all of the three scales.

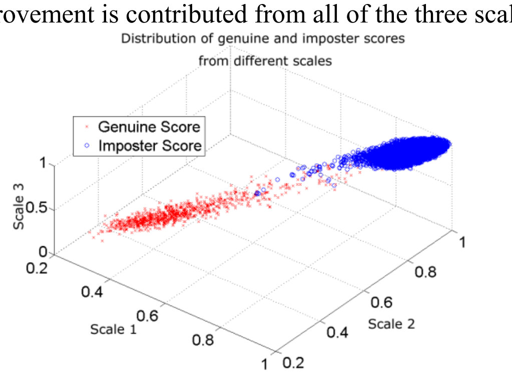

Figure 5. Distribution of matching scores from different dyadic scales (IITD v1 database).

7. Conclusions

This paper has investigated a new approach for the personal identification using localized Radon transform (LRT). The orientation details of the unique iris textures were extracted using LRT. The experimental results presented in this paper using LRT are highly promising on both of the two public databases, *i.e.* achieve an EER of 0.53% and 2.82% on IITD v1 and CASIA v3 databases respectively (CASIA v1 database was also investigated, and the resulting EER was 0.24%, result are not presented to conserve space). The proposed approach requires significantly smaller computational operation for the feature extraction and therefore highly suitable for applications where the speed is of prime consideration. *Our analysis suggests that LRT based feature extraction approach requires about* $2Kw$ *times (K and w stands for the filter size and chosen line width) fewer operations as compared to those from the conventional Gabor filter based approach*. In addition, the size of template (feature vector) is reduced by a factor of w^2 as compared to the popular Gabor filter based approach. Therefore the approach investigated in this paper can be computationally attractive alternative for the online personal identification using iris images. The feasibility of multi-scale analysis of iris images was also investigated for the performance improvement and critically assessed. The LRT based feature extraction can also be employed for characterizing multispectral iris features [3] and worth investigating in the further extension of this work.

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