Iris Recognition Method Using Random Texture Analysis

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Abstract

In this paper, we present a fast, simple and very powerful method for identifying human beings based on features of their iris texture. A very simple approach is presented to extract texture features of highly random iris texture on the contrary to current approaches that use complex mathematical description of the iris texture for feature extraction. The proposed method is tested with more than 700 images of the CASIA image database, the results of which show a significant improvement in iris recognition in comparison to the existing methods.

Key Words
Pattern Recognition, Biometric, Iris Recognition.

1. Introduction

Traditional methods of human identity verification such as using keys, certificates, passwords, etc., can hardly meet the requirements of identity verification and recognition in the modern society. These methods are either based on what a person possesses (a physical key, ID card, etc.) or what a person knows (a secret password, etc.), and have certain weaknesses. Keys may be lost, ID cards may be forged, and passwords may be stolen. In recent years, biometric identification is receiving growing attention from both academia and industry to overcome the aforementioned weaknesses.

Biometrics can be defined as features used for recognizing and identifying a person based on his physiological or behavioural characteristics; and today, it is a common and reliable way to authenticate the identity of a living person. The process matches the individual's pattern or template against the records known by the system.

Reliable automatic recognition of individuals has long been an attractive goal. As in all pattern recognition problems, the key issue is the relation between interclass and intra-class variability: objects can be reliably classified only if the variability among different instances of a given class is less than the variability between different classes.

A wide variety of biometric methods have been marshalled in support of this challenge. The resulting systems are based on automated recognition of retinal vasculature, fingerprints, hand shape, handwritten signature, face, and voice.

Universality, uniqueness, permanence, measurability, and user friendliness are the most important factors for evaluating different biometric methods. In addition, for identification applications requiring a large database of people's records, simplicity and efficient comparison of biometric IDs are essential.

Considering the above requirements, iris patterns appear as an interesting alternative for reliable visual recognition of persons when imaging can be done at distances of less than a meter (without contact) and when there is a need to search very large databases without incurring any false matches despite a huge number of possibilities.

The pattern of human iris differs from person to person, even between monocular twins. Since irises react with high sensitivity to light, causing the iris size and shape change continuously, counterfeiting based on iris patterns is extremely difficult. However, the pattern is so highly detailed that it is also difficult to recognize it.

The iris pattern can contain many distinctive features such as arching ligaments, furrows, ridges, crypts, rings, corona, freckles, and a zigzag collarette. Thus, the iris is gifted with the great advantage that its pattern variability among different persons is enormous.

Iris begins to form in the third month of gestation and the structures creating its pattern are largely complete by the eighth month. Features of the iris remain stable and fixed throughout life. In addition, iris is protected from the external environment behind the cornea and the eyelid. These characteristic make iris a unique alternative for human recognition.

A general iris recognition system is composed of four steps. First, an image containing the user's eye is captured by the system. Then, the image is pre-processed to normalize for the scale and illumination effects of the iris and localize the iris in the image. Third, features representing the iris patterns are extracted. Finally, the recognition decision is made by means of matching.

In contrast to current feature extraction approaches which are based on complex mathemathical description of the iris texture, a very simple and novel approach is presented in this paper to extract features from the highly random iris. The method is based on the fact that any relation between subparts of a random texture is a random variable.

The presented method is tested with more than 700 images of CASIA image database and results of the method show a significant improvement in iris recognition performance in comparison to current methods.

The paper is organized as follows. Section 2 describes pervious work on iris recognition methods. Section 3 presents details of the proposed approach. Section 4 gives experimental results obtained for the CASIA database. Finally, section 5 summarizes the conclusions and our plans for future work.

2. Related Work

The French ophthalmologist Alphonse Bertillon seems to be the first to propose the use of iris pattern (color) as a basis for personal identification. In 1981, after considerable studies on the great variations of human eye iris, Flom and Safir [1] also suggested the use of iris as the basis for biometric recognition. In 1987, they began collaborating with the computer scientist John Daugman of Cambridge University in England to develop an iris identification software and published the first promising results in 1992 [2]. Later, similar efforts were reported by Wildes, Boles and Sanchez-Reillo, whose methods differed both in the iris feature representation (iris signature) and pattern matching algorithms.

The Wildes' solution [3] uses Hough transform for iris localization. He models eyelids with parabolic curves. A Laplacian pyramid (multi-scale decomposition) is applied to represent distinctive spatial characteristics of the human iris. Wildes applied a modified normalized correlation for the matching process.

The Boles' prototype [4], on the other hand, works based on a one-dimensional representation of the grey level profiles of the iris followed by detecting the wavelet transform zero-crossings of the resulting representation.

The Daugman's system [5, 6] is implemented exploiting integrodifferential operators to detect iris inner and outer boundaries. 2-D Gabor filters are applied to extract unique binary vectors constituting an iris code. Daugman uses a statistical matcher (logical exclusive OR operator) which computes the average Hamming distance between two codes (bit to bit test agreement).

Since a standard reference database of iris images does not exist, a performance comparison of the described systems is not trivial. However, in terms of recognition rates (FAR, FRR), the commercial success of the patented Daugman's system speaks in his favour. Indeed, Daugman's mathematical algorithms have been contributing to a patented commercial solution. This biometric identification platform processes iris recognition through a specific optical unit that enables non-invasive acquisition of iris images, and a data processing unit.

There are also some recent efforts in this field. Lim [7] uses Haar wavelet transform and LVQ network for texture coding. Noh [8] uses the composition of multi-resolution analysis and principle component analysis of the texture.

Based on the reported work in the literature, it can be concluded that most representation methods make use of multi-resolution analysis to detect the distinctive spatial characteristics of the human iris. Experimental results have shown that multi-resolution techniques lead to a good performance.

3. The Proposed Method

In this paper, we use a fast and accurate circle detection method that is based on gradient vector pair concept [8]. The method is called "Fast Circle Detection", or FCD. Suppose that we have a dark circle on a bright background, as shown in Figure 3.a. The gradient vectors of the circle we search for are in the form shown in Figure 3.b. These vectors' directions are outward the circle, because the circle is darker than its background. Due to the symmetry of the circle, for each gradient vector there is another gradient vector in its opposite direction. The method calls these vectors, vector pairs.

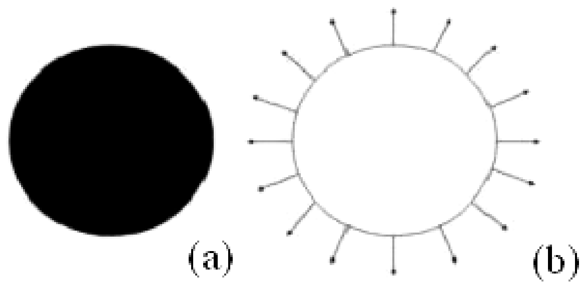

Figure 1. (a) A black circle on a white background, (b) Gradient vectors of (a)

After finding vector pairs, a candidate circle is considered for each pair of vectors. Such a circle has its center at the midpoint of P1 and P2, and its radius is equal to half the distance between P1 and P2. The desired circles are extracted from the candidate circles produced in the previous step, by means of clustering.

The FCD is a general circle detection method which can be applied to a wide range of applications. Also, if the definition of Vector Pair is changed, then it can be used for the detection of other shapes such as arcs, ellipses, and spheres. There is an extension for the FCD that uses certainty factors and improves the FCD performance in noisy images [9].

The FCD and its extension were applied to iris localization application [10]. Results show significant improvement in iris localization performance in comparison with current methods [11]. Figure 2 shows a typical result of the proposed localization method.

As mentioned before, current methods widely use texture descriptor filters and wavelets (especially Gabor family). We applied a very simple but effective method that showed surprisingly good results in comparison to the current methods. The main idea of the approach is as follows.

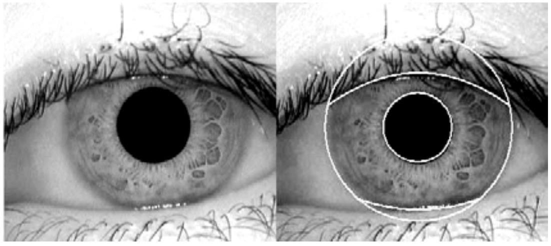

Figure 2. Output result of the proposed approach

Based on current findings, iris texture is a very random and complex texture. There is no dependency between different parts of the iris texture. Considering this assumption, suppose we have three blocks, A, B, and C of the random texture (for example, textures shown in figure 3). The main idea used here is:

The probability of "A being more similar to B (rather than C)" is equal to the probability of "A being more similar to C (rather than B)".

If we measure similarity between two texture blocks with ψ, then the above assumption will be represented as:

$$P(\psi(A,B)>\psi(A,C)) = P(\psi(A,B)<\psi(A,C)) \quad (1)$$

Now, we can consider a status bit for each three blocks of a random texture. If A is more similar to B, the status bit of A will be set; otherwise it will be reset. If the considered texture block is fully random, then the probability of the set and reset actions of the status bit will be equal.

In iris recognition, the random texture is divided into some blocks and every three neighbouring blocks are considered, as has shown in figure 3. A bit will then be assigned to each block according to its relation with its neighbouring blocks. The texture description code is then composed of these bits.

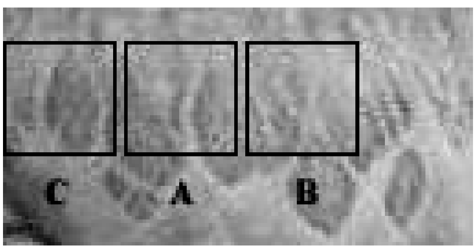

Figure 3. Example of neighbor blocks in iris texture

After normalizing the iris texture, we omit parts of the iris texture that contain eyelids and eyelashes. Then a circular shift is applied and two useful parts of the texture (left and right 112-degree cone segments of iris) are extracted. Figure 8 shows these steps.

Each extracted segment is divided into smaller blocks and these blocks are used as the basic blocks for similarity checking and status bit extractions. According to the division and the number of basic blocks, a code for the texture will be presented. For example, if there are 15 basic blocks (3x5) for each segment and the similarity function applied for the left-right and up-down neighbors of each block, then 60 bits will be produced (2 segment, 15 block for each segment and 2 bit for each block).

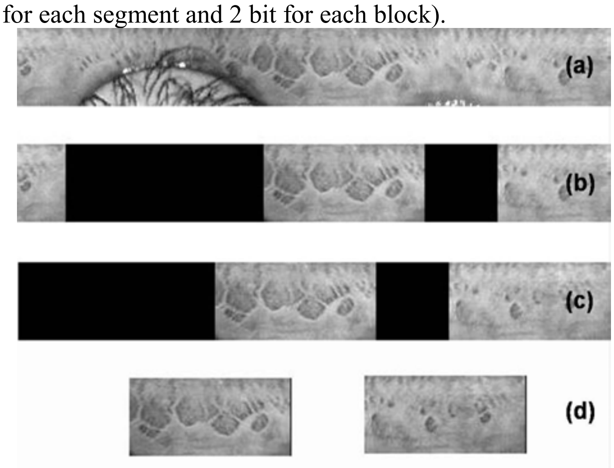

Figure 4. Postprocessing for the iris texture: (a) Normalized iris texture (b) Omitting useless regions (c) Circular shift (d) Extraction of iris segments

The final binary codes can be compared just like Daugman's approach: simple XORing of codes and counting the different bits.

The above description constitutes the main idea of the proposed approach. The following section will describe details of our implementation and the results.

3. Experimental Results

After normalizing the iris texture, we obtain a 360*64 pixel rectangle. Then the parts corresponding to the eyelides and eyelashes are omitted and after a circular shift of the image, the two useful parts of texture are extracted as two 112*64 images.

We will show that one of these blocks is sufficient for the recognition purpose, so we just considered the image extracted from the left 112-degree cone of the iris texture. It should be mentioned that there is no biologocal reasone for this selection. We just consider a constant rule for the texture extraction from images.

The selected image is divided into 8x8 pixel basic blocks and the similarity relation is calculated for up-down and left-right neighbouring blocks of each basic block. In our implementation, similarity between two basic blocks is calculated via simple 2D Gabor analysis of the textures. A 2D Gabor filter with three positive peaks which extends over 8x8 blocks is applied. The following filter is used:

$$G(x,y) = e^{-\pi\left[(x-x_0)^2/\alpha^2+(y-y_0)^2/\beta^2\right]}.e^{-2\pi i\left[u_0(x-x_0)^2+v_0(y-y_0)^2\right]} \quad (2)$$

where (x_0, y_0) specify position of the filter center on the image, (α,β) specify the effective width and length of the filter, and (u_0, v_0) specify modulation, which has spatial frequency $\omega_0 = \sqrt{u_0^2 + v_0^2}$. The following values are used for the parameters:

$$\alpha = 1.2, \beta = 1.0, u_0 = 0.75, v_0 = 0$$

The result of filtering a basic block with this filter is a complex number. The absolute distance of the complex numbers related to each two basic blocks is considered as the similarity measure of the two basic blocks.

After omitting the edge blocks, 65 basic blocks (13*5) are retained for code extraction, and a 130-bit code is produced for the input image.

About 92 classes of images of database (92*7=644 images) were used for the evaluation of the recognition step of the method.

We implemented the approach in Matlab 6.1 environment and all tests were done using a system with 1.8GHz Pentium IV processor and 512MB RAM. Also, CASIA image database was used as the input database [12].About 92 classes of images (92*7=644 images) were suitable for the recognition purpose.

After applying the proposed code extraction algorithm and calculating identification code for each input image, 644 extracted codes were produced and saved in our database. Then, we applied the matching algorithm and the distance of each code with all other codes was calculated. To resist against head tilt effects, we perform two 4-bit left and right shifts. Thus, for each image, 5 codes were calculated and the minimum distance of these codes with other images was considered. After 414092 comparisons, a 1.3% classification error was observed. Figure 5 shows the histogram of distance between the produced codes.

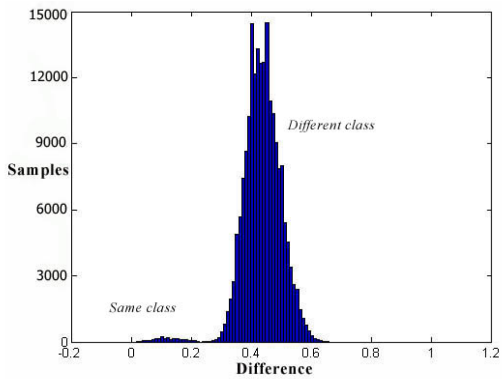

Figure 5. Histogram of the distance of codes for the simple method

In another experiment, three images of a peroson were considered as input and the average of the produced codes was considered as the code for the person. Four other images were considered as the test images. As expected, the final result improves significantly. After 135'056 comparisons, no error was observed. Figure 6 shows the histogram of the distances between codes in this case. The statistical information obtained from these experiments is presented in Table 1.

According to this Table, the Simple method shows some overlap between classes (about 5%); but the averaging method fully separates them. The distance between the maximum distance of two similar codes (from same person) and the minimum distance of different codes is about 8%. Thus, there is a very good separablity between the two classes. Also, the Equal Error Rate (EER) parameter for the Simple and Averaging methods was found to be about 10-5 and 10-7, respectively.

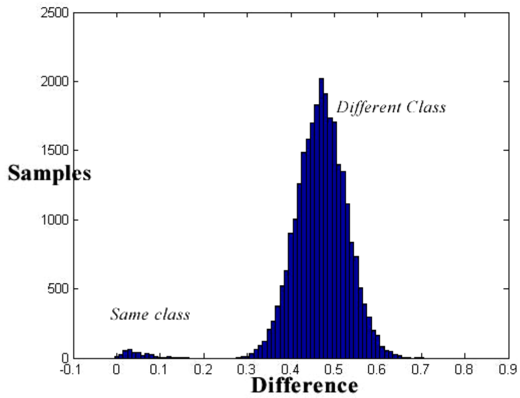

Figure 6. Histogram of the distance of codes for averaging method

In the averaging method, the average bit of the identification code is 0.492. This represents a very good binomial variable.

Table 1. Evaluation of the Simple and Averaging Methods

Statistical Parameter	Simple Method	Averaging Method
Average of class of same codes	12.22%	4.8%
Standard deviation of class of same codes	0.0470	0.0327
Maximum distance between same codes	29.52%	18.07%
Average of class of different codes	43.07%	48.75%
Standard deviation of class of different codes	0.0562	0.0615
Minimum distance between different codes	24.76%	26.80%

The separablility power of each method was determined by:

$$d = \frac{|\mu_1 - \mu_2|}{\sqrt{\frac{\sigma_1^2 + \sigma_2^2}{2}}} \quad (3)$$

where μ_1 and σ_1 are the mean and standard deviation of the distance of the codes belonging to the same person and μ_2 and σ_2 are the mean and standard deviation of the distance of the codes belonging to different persons. Table 2 shows the results for the proposed and the Daugman's methods.

As mentioned before, two 112*64 images were extracted for each iris image. Comparing the related codes for these images extracted from the same iris image indicates interesting results. The average of the left and right segment distances was 48.63%, standard deviation 0.402 and minimum distance 32.12%. This shows that each part of an iris texture is significantly different from the other parts of it.

Table 2. Seperability value for the Daugman's and the Proposed methods

Method	d
Daugman	7.2
Proposed method	6.07
Proposed method (averaging)	8.92

The effect of the size of basic blocks on the method was also studied. Table 3 presents the seperability factor, EER, and distance between maximum distance of the same person codes and minimum distance of different person codes.

Table 3. Effect of size of basic blocks

Size of basic block	d	EER	Reliability Distance
4x4	6.22	10^{-5}	4%
8x8	8.52	10^{-7}	8%
12x12	6.41	10^{-5}	5%
16x16	5.03	10^{-4}	3% overlap
32x32	3.22	10^{-2}	7% overlap

According to Table 3, the best performance results for 8x8 basic blocks. Figure 7 shows the FAR/FRR curves for the proposed method [13].

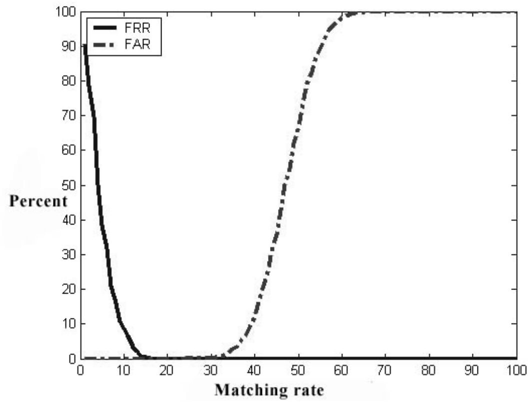

Figure 7. FAR/FRR curves for the proposed method

3. Conclusions and Future Work

In this paper, we presented a novel iris recognition method. The method uses a very fast and accurate algorithm for iris localization. We applied a very simple but effective idea for feature extraction. A final 260-bit code is generated for each input image. This code is compared to other codes using the XOR operator and decision making is made by thresholding the difference of the codes.

The results showed no error in identification and significant improvement of classification ratio and EER. An 8.52 classification rate and 10^{-7} EER are observed during the method evaluation. The proposed identification code is 130 bits long. Based on the high accuracy and speed, simple implementation and very short length of the identification code, the proposed method is very suitable for iris recognition applications.

For future work, we are going to apply the feature extraction method in other random texture images such as those of fingerprints.

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