Iris Recognition Using Circular Symmetric Filters

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Abstract

This paper proposes a new method for personal identification based on iris recognition. The method consists of three major components: image preprocessing, feature extraction and classifier design. A bank of circular symmetric filters is used to capture local iris characteristics to form a fixed length feature vector. In iris matching, an efficient approach called nearest feature line (NFL) is used. Constraints are imposed on the original NFL method to improve performance. Experimental results show that the proposed method has an encouraging performance.

1. Introduction

The recent advances of information technology and the increasing requirement for security have resulted in a rapid development of intelligent personal identification based on biometrics. Physiological or behavioral characteristics unique to an individual is called biometric measurement (such as fingerprints or voiceprints) which has the capability to reliably distinguish between an authorized person and an imposter. Generally, physiological and behavioral characteristics used in biometrics include the following [1][4]: facial features and thermal emissions, retina, iris, gait, voiceprint, gesture, fingerprints, palm-prints, handwritten signature, hand geometry etc. These biometric measurements provide a robust approach to a wide range of applications such as identity authentication and access control. Of all these patterns, fingerprint identification has received considerable attention over the last 25 years. Face recognition and speaker recognition have also been studied widely [4], whereas iris recognition is a more recent method for personal identification.

The human iris, as shown in Figure 1a, has an extraordinary structure and provides abundant texture information. The spatial patterns that are apparent in the iris are unique to each individual [3]. Individual differences that exist in the development of anatomical structures in the body result in the uniqueness. In particular, the biomedical literature [2] suggests that iris is as distinct as fingerprints. Compared with other biometrics (such as face, fingerprints, voiceprints, etc.), iris is more stable and reliable for identification [1]. Furthermore, since the iris is an overt body, iris based personal identification systems can be non-invasive to their users [6][7], which is a very important factor for practical applications.

This paper presents an iris recognition algorithm using a bank of circular symmetric filters. Section 2 describes image preprocessing which mainly involves iris localization, normalization and image enhancement and denoising. Section 3 provides a detailed introduction to the circular symmetric filters and feature extraction. Section 4 discusses iris matching based on an improved nearest feature line method. Experiments and results are reported in Section 5. Conclusions are drawn in Section 6.

2. Image preprocessing

An iris image, as shown in Figure 1a, contains not only the region of interest (iris) but also some 'unuseful' parts (e.g. eyelid, pupil etc.). In addition, a change in the camera-to-eye distance may result in the possible variation in the size of the same iris. Furthermore, the brightness is not uniformly distributed because of non-uniform illumination. Before extracting features from the original image, the image needs to be preprocessed to localize iris, normalize iris, and reduce the influence of the factors mentioned above. Such preprocessing is described in the following subsections.

2.1. Iris localization

Both the inner boundary and the outer boundary of a typical iris can approximately be taken as circles. However, the two circles are usually not co-centric. The iris is localized in two steps: (1) approximate region of iris in an image can be found by projecting iris image in horizontal and vertical direction. (2) the exact parameters of these two circles are obtained by using edge detection and Hough transform in a certain region determined in the first step. An example of iris localization is shown in Figure 1b.

2.2. Iris normalization

Irises from different people may be captured in different size, and even for the iris from the same person, the size may change because of the variation of the illumination and other factors. Such elastic deformations in iris texture affect the results of iris matching. For the purpose of achieving more accurate recognition results, it is necessary to compensate for these deformations. Here, we anti-clockwise unwrap the iris ring to a rectangular block of texture of a fixed size (64x512) by piecewise linear mapping. The distortion of the iris caused by pupil dilation can thus be reduced. The result after iris normalization is shown in Figure 1c.

2.3. Iris image enhancement and denoising

The normalized iris image still has low contrast and may have non-uniform illumination caused by the position of light sources. In order to obtain more well-distributed texture image, we enhance iris image by means of local histogram equalization and remove high frequency noises by filtering the image with a low-pass Gaussian filter. Figure 1d shows the preprocessing result of an iris image. From Fig. 1d, we can see that finer texture characteristics of the iris become clearer than that in Fig. 1c. The method of enhancement and denoising is very effective.

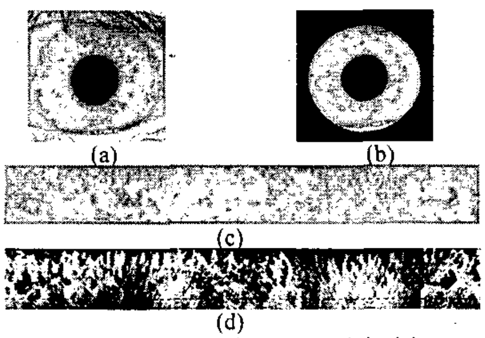

Figure 1. Image preprocessing: (a) Original image; (b) Detected iris region; (c) Unwrapped image; (d) Iris image after enhancement and denoising, where the region of interest used in feature extraction is above the dotted line.

3. Feature extraction

The iris has a particularly interesting structure and provides abundant texture information. So, it is desirable to explore representation methods which can capture local underlying information in an iris. From the viewpoint of texture analysis, the local spatial patterns in an iris mainly involve frequency information and orientation information. But in experiments, we find that orientation is not a crucial factor when analyzing the characteristics of a small iris region such as a 10x10 region. That is, in a small iris region, frequency information accounts for the major differences of the irises from different people. We thus propose an effective scheme to capture these discriminating frequency information. Because the majority of useful information of the iris is in specific frequency band, a bank of circular symmetric filters is constructed to capture them. For a preprocessed iris image (e.g. Figure 1d), the texture of the iris becomes coarser from top down. So, we use filters at different frequencies for different regions in the image. A feature value is obtained from each smaller region in the filtered image. A feature vector is an ordered collection of all the features from each local region. Detailed description of this method is presented as follows.

3.1. Circular symmetric filter

In the spatial frequency domain, we can extract the information of an image at a certain scale and at a certain orientation by using some specific filters, such as multichannel Gabor filters [9]. In recent years, Gabor filter based methods have been widely used in computer vision, especially for texture analysis. Gabor elementary functions are Gaussians modulated by oriented complex sinusoidal functions. Here, we utilize a circular symmetric filter (CSF) which is developed on the basis of Gabor filters. The difference between Gabor filter and circular symmetric filter lies in the modulating sinusoidal functions. The former is modulated by an oriented sinusoidal function, whereas the latter a circular symmetric sinusoidal function. A CSF is defined as follows:

$$\begin{aligned} G(x,y,f) &= \frac{1}{2\pi\delta_x\delta_y}\exp\left[-\frac{1}{2}\left(\frac{x^2}{\delta_x^2}+\frac{y^2}{\delta_y^2}\right)\right]M(x,y,f) \\ M(x,y,f) &= \cos\left[2\pi f\left(\sqrt{x^2+y^2}\right)\right] \end{aligned} \tag{1}$$

where $M(x,y,f)$ is the modulating function, f is the frequency of the sinusoidal function, δ_x and δ_y are the space constants of the Gaussian envelope along the x and y axis respectively. We can obtain a bandpass filter with a specific center frequency by setting the frequency parameter f. The choice of the parameters in Equation (1) is similar to that of Gabor filter [10]. The circular symmetric filter can capture the information of an image in specific frequency band, whereas it cannot provide orientation information because of its circular symmetry.

In experiments, we find that the top-most 75 percent section (48x512) of an unwrapped iris image provides the most useful texture information for iris recognition (see Fig. 1d). Additionally, the occlusion of the eyelids is also rarely up to this section. So we extract features only in this section called the region of interest (ROI) shown as the region above the dotted line in Fig. 1d. As mentioned above, different iris regions have different frequency components. We therefore vertically divide the ROI into three local regions and filter each local region with a CSF at different frequency. The frequency parameters are decided by analyzing the spectra of the local iris regions.

3.2. Feature vector

We extract feature information in each 8x8 block in the filtered image, which results in a total of 384 feature values. In our algorithm, the feature value is the average absolute deviation (AAD) of each filtered block defined as follows:

$$V = \frac{1}{N}\left(\sum_{N} | f(x,y) - m |\right) \tag{2}$$

where N is the number of pixels in the image block, m is the mean, and $f(x,y)$ is the value at point (x, y).

The average absolute deviation of each filtered block constitutes the components of our feature vector. These features are arranged to form a 1D feature vector of length 384 for each input image.

4. Classifier design

In iris matching, we use an efficient classification method named the nearest feature line (NFL) by Li. In the original NFL method [14], there is a potential problem. That is, a feature line can extend infinitely in feature space, which can cause false classification. For example, the distance between a point and a feature line may be small, but this point can be far away from the two points which form the feature line. Zhao et al. proposed an improved NFL method used in retrieval of video shot [15]. The concept of shot activity was added to constrain the feature line, which is effective in their experiments. Here, we improve the NFL method by limiting the extent of the feature line and redefining the distance when a point is out of a certain range of the feature line. Our improved NFL method defines the distance between an unknown point p_x and a feature line $\overline{p_i p_j}$ as follows:

$$D(p_x, \overline{p_i p_j}) = \begin{cases} \| p_x - p_i \| & \beta < T_1 \\ \| p_x - p'_x \| & T_1 \le \beta \le T_2 \\ \| p_x - p_j \| & \beta > T_2 \end{cases} \tag{3}$$

where p'_x is the projection of p_x on the feature line $\overline{p_i p_j}$, β called the position parameter, T_1 and T_2 are two thresholds. The original NFL method corresponds to the case when $T_1 = -\infty$ and $T_2 = +\infty$. In our experiments, we choose $T_1 = -0.5$ and $T_2 = 1.5$ which produce better results than the original NFL method. The detailed description of the NFL can be found in [14].

It is desirable to obtain a representation for the iris which is scale, translation, and rotation invariant. In our algorithm, the scale and translation invariance are achieved by normalizing the original image at the preprocessing step. Approximate rotation invariance is obtained by unwrapping the iris ring at different initial angles. Seven initial angle values are used in experiments. We thus define seven templates which denote the seven rotation angles for each iris class in the database. When matching the input feature vector with a class' templates, the minimum of the seven scores is taken as the final matching distance.

5. Experiments

To evaluate the performance of the proposed algorithm, we build a new iris image database which contains 1088 iris images (unlike fingerprints and face, there is no reasonably sized public-domain iris database). These images are from 109 different volunteers and captured by a home-made digital optical sensor. The new database includes two parts. One is our previous database [13] which contains 500 images from 25 people. Each individual provides 20 images (10 for each eye). These images are captured in two different stages. In the first stage, five images of each eye are acquired. Four weeks later, five more images of each eye are obtained. The other part contains 588 images from 84 people. Each individual provides 7 images of the left eye. These images are also captured in two stages, which is similar to the acquisition of images of the first part. Capturing images on different date provides a challenge to our method. The total number of iris class is thus 134 (2x25+84). Four samples from our iris database are shown in Figure 2.

Figure 2. Iris Samples.

5.1. Experimental results

We test the proposed algorithm in two modes: 1) identification and 2) verification. For each iris class, we randomly choose three samples for training and the rest for testing. In identification tests, an average correct classification rate of 99.85% is achieved. The second nearest curve from horizontal axis of Figure 3 shows the results of verification. It is the false match rate (FMR) and false non-match rate (FNMR) curve which measures the accuracy of iris matching process and shows the overall performance of an algorithm. Points in this curve denote all possible system operating states in different tradeoffs. Three typical system operating states of the proposed method are listed in Table 1.

Table 1. Verification results

False match rate (%)	False non-match rate (%)
0.001	3.56
0.01	2.17
0.1	0.83

5.2. Comparison with existing methods

In 1991, Johnson first reported to realize a personal identification system based on iris recognition [5]. Subsequently, a prototype iris recognition system was documented by Daugman in 1993 [6]. Wildes described a system for personal verification based on automatic iris recognition in 1996 [7]. In 1998, Boles proposed an algorithm for iris feature extraction using zero-crossing representation of 1-D wavelet transform [8]. Our early work on iris recognition was described in [12][13]. All these algorithms are based on gray image, and color information was not used. The main reason is that a gray iris image can provide enough information to identify different individuals. The methods proposed by Daugman and Wildes are the best two among all these algorithms. Daugman's method is based on phase code using Gabor filters. Wildes's method relies on image registration and image matching, which is computationally very demanding. Our previous methods [12][13] use Multichannel Gabor filters to extract both local and global details in an iris. Here, we also compare the current method with these methods on our database in two modes (verification and identification). Because Wildes's method only works in verification mode [7], we did not test the performance of this method in identification mode. Table 2 tabulates the identification results and Figure 3 describes the verification results.

Table 2. Identification results

Method	Correct classification rate
Our previous method	93.20%
Daugman's method	100%
Our new method	99.85%

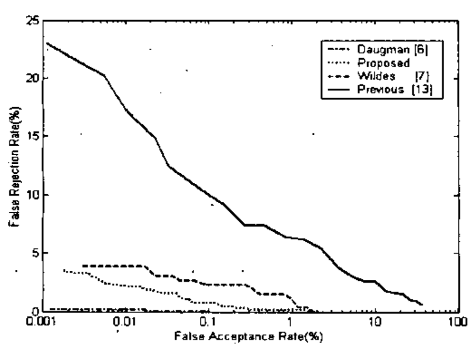

Figure 3. FMR vs FNMR.

From Table 2 and Figure 3, we can see the performance of our new method is much better than that of our previous method [13]. The reason is that the current new method captures much more local texture information in an iris. Compared with the method of Wildes, our method achieves higher recognition rate. In two test modes, Daugman's method is a little better than ours. In fact, the dimensionality of the feature vector in his method is much higher than ours. The feature vector consists of 2048 components in his method, while only 384 in our method. That is, his method extracts features in much smaller local regions. These make his method a little better than ours. Now, we are working on more precisely representing the variation of texture of the iris in local region and reducing the dimensionality of the feature vector. Thus, we expect to further improve the performance of the current method.

6. Conclusions

In this paper, we have presented a new and effective algorithm for iris recognition. The proposed algorithm uses a bank of circular symmetric filters to extract local texture information of the iris. Each iris image is filtered with these filters and then a fixed length feature vector is constructed. An improved nearest feature line method is used in iris matching. Experimental results have shown that the proposed algorithm achieves high performance.

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