Iris Recognition Based on Multichannel Gabor Filtering*

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Abstract

A new approach for personal identification based on iris recognition is presented in this paper. The body of this paper details the steps of iris recognition, including image preprocessing, feature extraction and classifier design. The proposed algorithm uses a bank of Gabor filters to capture both local and global iris characteristics to form a fixed length feature vector. Iris matching is based on the weighted Euclidean distance between the two corresponding iris vectors and is therefore very fast. Experimental results are reported to demonstrate the performance of the algorithm.

1. Introduction

In recent years, with the development of information technology and the increasing need for security, intelligent personal identification has become a very important topic. Traditional methods for personal identification are based on token (a physical key, ID card) or knowledge (a secret password, PIN). These methods suffer from various problems. For example, ID cards may be forged or lost, and passwords may be forgotten or guessed. Biometric measurements (such as fingerprints or voiceprints) which are physiological or behavioral characteristics unique to an individual have 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][5]: chemical composition of body odor; facial features and thermal emissions; features of the eye, i.e., retina and iris; fingerprints; palm-prints; hand geometry; handwritten signature; voiceprint; gait; gesture; etc.

Of all these patterns, fingerprint identification and speaker recognition have received considerable attention over the last 25 years. Recently, with the changes of human's requirement, face recognition and iris based authentication have been studied widely [4].

The human iris, as shown in Figure 1, 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 patterns of retinal blood vessels, but an iris image can be more easily obtained than a retina image. Compared with other biometrics (such as face, fingerprints, voiceprints, etc.), iris is more stable and reliable for identification [1]. Since the iris is an overt body, iris recognition systems can be non-invasive to their users [7][8], which is a very important factor for practical applications.

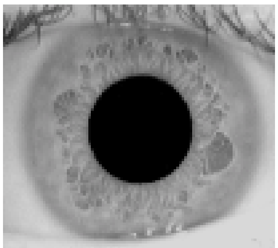

Figure 1. Example of an iris image.

A general iris recognition algorithm includes image preprocessing, feature extraction, and classifier design. Section 2 describes image preprocessing which mainly involves iris localization, iris normalization and iris image enhancement and denoising. Feature extraction uses a bank of Gabor filters to capture both local and global details in an iris as a fixed length feature vector. This method is introduced in detail in Section 3. Section 4 discusses iris matching based on the weighted Euclidean distance. Experiments and results are reported in Section 5. Conclusions are drawn in Section 6.

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2. Image preprocessing

A captured iris image contains not only the region of interest (iris) but also some 'unuseful' parts (e.g. eyelid, pupil etc.). So, the image cannot be used directly. In addition, a change in the camera-to-face 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. For the purpose of recognition, the original image needs to be preprocessed to localize iris, normalize iris, and reduce the influence of the factors mentioned above. The preprocessing is described in the following subsections.

2.1. Iris localization

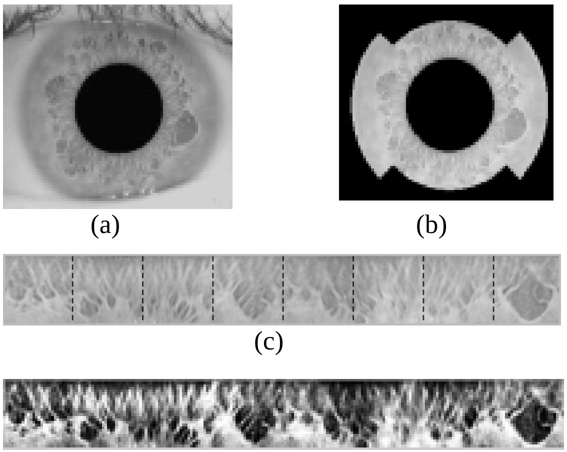
Both the inner boundary and the outer boundary of a typical iris can approximately be taken as circles. However, the two circles are usually not co-centric. The method we employed for iris localization includes simple filtering, edge detection, and Hough transform. The overall method is very efficient and reliable. An example of iris localization is shown in Figure 2b. We can see that the iris can be exactly localized using this technique.

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 map the iris ring to a rectangular block of texture of a fixed size (64x512). According to the requirement of feature extraction, this block is then divided into eight smaller subimages. The size of each subimage is 64x64. The result after iris normalization is shown in Figure 2c.

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. All these may affect subsequent feature extraction and pattern matching. We enhance the iris image by means of local histogram equalization and remove high-frequency noise by filtering the image with a low-pass Gaussian filter. In order to obtain more well-distributed texture images, the 8 subimages are separately processed. Figure 2d shows the preprocessing result of an iris image. From Fig. 2c and 2d, we can see that the method of enhancement and denoising is very effective.



(a) (b) (c) (d)

Figure 2. Image preprocessing: (a) Original iris image; (b) Image after iris localization; (c) Eight unwrapped texture images; (d) Eight unwrapped texture images after enhancement and denoising.

3. Iris feature extraction

The iris has a particularly interesting structure and provides abundant texture information. So, it is desirable to explore representation methods which can describe global and local information in an iris. We present a new representation which can obtain both global and local information for an iris. The proposed scheme of feature extraction is to map the iris ring to a rectangular block image which is anti-clockwise divided into eight subimages and then to analyze the 8 subimages. A feature vector consists of an ordered sequence of the features extracted from the local information contained in the 8 subimages. Thus, the feature elements capture the local information and the ordered sequence captures the invariant global relationships among the local patterns. Gabor filtering is a well-known technique in texture analysis. It can not only extract useful information in specific bandpass channels but also decompose this information into biorthogonal components in terms of spatial frequencies. We filter each subimage at different directions with different frequencies, and then obtain a feature value from each filtered subimage. A feature vector is a collection of all the features from each filtered subimage. Detailed description of this method is presented as follows.

3.1. Gabor filtering

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 sinusoidal functions. It is shown that the functional form of Gabor filters conforms closely to the receptive profiles of simple cortical cells, and Gabor filtering is an effective scheme for image representation [12].

A two-dimensional (2D) even Gabor filter can be represented by the following equation in the spatial domain:

$$G(x, y; \theta, f) = \exp\left\{-\frac{1}{2}\left[\frac{x'^2}{\delta_{x'}^2} + \frac{y'^2}{\delta_{y'}^2}\right]\right\}\cos(2\pi f x')$$

$$x' = x\cos\theta + y\sin\theta \qquad (1)$$

$$y' = y\cos\theta - x\sin\theta$$

where f is the frequency of the sinusoidal plane wave along the direction θ from the x-axis, $\delta_{x'}$ and $\delta_{y'}$ are the space constants of the Gaussian envelope along x' and y' axes respectively. Further details of Gabor filters may be found in [10][12].

The frequency parameter f is often chosen to be of power 2. In our experiments, the central frequencies used are 2, 4, 8, 16, and 32 cycles/degree. For each central frequency f, filtering is performed at $\theta = 0^o, 45^o, 90^o$ and 135^o. So, there are a total of 20 Gabor filters with different frequencies and directions. Each subimage is respectively filtered by these Gabor filters. This leads to a total of 160 (20 for each subimage) output images from which the iris features are extracted. The choices of the parameters of Gabor filters are discussed in [14].

3.2. Feature vector

In our algorithm, the feature value is the average absolute deviation (AAD) of each output image defined as follows

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

where N *is* the number of pixels in the image, m is the mean of the image, and $f(x,y)$ is the value at point (x, y). The AAD feature is a statistic value similar to variance, but experimental results show that the former gives slightly better performance than the latter.

The average absolute deviation of each filtered image constitutes the components of our feature vector. These features are arranged to form a 1D feature vector of length 160 for each input image.

4. Classifier design

For simplicity, iris matching is based on computing the weighted Euclidean distance (WED) between the corresponding feature vectors. WED is defined in the following:

$$WED(k) = \sqrt{\sum_{i=1}^{BN} A_i \sum_{j=1}^{N} (f_{(i,j)}^k - f_{(i,j)})^2} \qquad (3)$$

where A_i denotes the ith weighting coefficient, BN and N are the number of subimages and the total number of features extracted from each subimage respectively. $f_{(i,j)}$ and $f_{(i,j)}^k$ denote the jth feature component of the ith subimage of the unknown iris and that of iris indexed by k. Here, we set the weighting coefficients A_i for different feature sets extracted from different subimages. These coefficients are determined according to empirical results.

The nearest neighbor classifier is used in the algorithm. Features of an unknown iris are compared with those of irises in database. It is identified as iris indexed by k if the weighted Euclidean distance mentioned above is a minimum at k and this minimum is also less than a reasonable threshold.

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. These initial angle values are $-10^o, -5^o, 0^o, 5^o, 10^o$ (note in practical applications, it is very unlikely to have very large rotation angles as the user’s face is usually nearly upright). We thus define five templates which denote the five rotation angles for each iris class in the database. This brings extra computational expense. However, since the template generation is an off-line process, it is not a very serious problem. When matching the input feature vector with a class’ templates, the minimum of the five scores is taken as the final matching distance.

5. Experiments and results

For the purpose of testing the performance of this proposed algorithm, we constructed an iris image database which contains 500 iris images (unlike fingerprint and face, there is no reasonably sized public-domain iris database). These images are from 25 different volunteers and captured by a home-made digital optical sensor as shown in Figure 3.

Figure 3. Iris sensor.

Each individual provides 20 images (10 for each eye). The total number of iris classes is therefore 50. We captured these images in two different sessions. During an initial session, everyone provides 10 images (5 for each eye). On a second session approximately one month later, 10 more images of each person are acquired. Both male and female subjects are among the volunteers. Six samples from our iris database are shown in Figure 4.

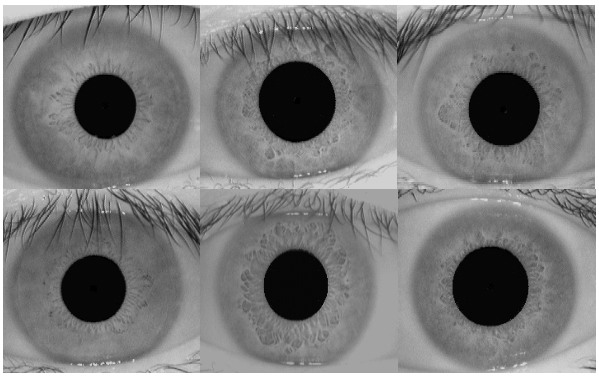


Figure 4. Iris Samples.

5.1. Experimental results

We test the algorithm in two modes: 1) verification and 2) identification. For each iris pattern, we randomly choose several samples for training and the rest for testing. Identification results are summarized in Table 1 and Figure 5 depicts the results of verification.

Table 1. Identification results.

No. of training samples	Identification rate
1	86.18%
2	92.63%
3	95.68%
4	97.59%
5	99.09%

When we obtain an iris image, environments (illumination, occlusion by eyelids, pose of eye etc.) are always variant. So a template constructed from too few samples cannot accurately represent an iris class. The results of Table 1 show that the more samples are used for training, the higher the identification rate. This is very reasonable as the template in the database is more robust if there are much more samples used for training.

When doing tests in verification mode, for each iris pattern, we use five images for training. Fig.5 is the receiver operating characteristic (ROC) curve that is a plot of genuine acceptance rate against false acceptance rate. Points in this curve denote all possible system operating states in different tradeoffs. It shows the overall performance of a system. The ideal ROC curve is a step function at the zero false acceptance rate. Fig.5 shows that the algorithm performs well in verification mode.

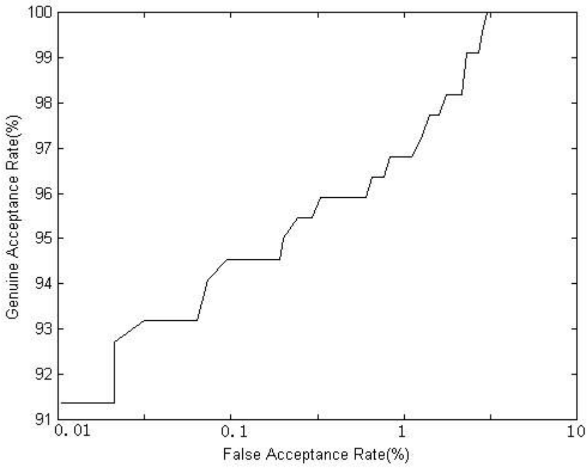


Figure 5. ROC curve for verification.

5.2. Comparison with existing methods

In 1991, Johnson reported to actually realize a personal identification system based on iris recognition [6]. Subsequently, a prototype iris recognition system was documented by Daugman in 1993 [7]. Wildes described a system for personal verification based on automatic iris recognition in 1996 [9]. In 1998, Boles proposed an algorithm for iris feature extraction using zero-crossing representation of 1-D wavelet transform [11]. Our early work on iris recognition was described in [15]. All these algorithms are based on gray image, and color information was not used in them. The main reason is that a gray iris image can provide enough information to identify different individuals.

The method described in this paper localizes the iris in an image based on edge detection approach, whereas Daugman makes use of a deformable model and Wildes uses a histogram-based model-fitting method. Compared with their methods, our scheme is expected to be more reliable and faster. The prototype of Wildes relied on image registration and image matching, which is computationally very demanding. Both systems of Daugman and Wildes are sensitive to illumination variations. In our method, an iris is localized and unwrapped to form a block of texture which is made up of eight subimages. The texture subimage is locally enhanced by means of histogram equalization, and the feature value is the average absolute deviation (AAD) of each output image. All these make our method tolerant to illumination variations. Compared with zero-crossing representation of 1D wavelet transform as used by Boles [11] which employed only the information along the circle, our method explores 2-D texture analysis that can process much more useful information.

In our previous work [15], we regard unwrapped rectangular block as a whole texture image and extract global features (mean and variance) from filtered texture image. But experimental results show that global features alone cannot represent an iris well. We therefore modify our original algorithm from image preprocessing to feature extraction. The algorithm described here can capture both local and global details in an iris and obtain much better results. With a much larger iris database than that used in [15], our new method achieves much higher identification rate.

6. Conclusions

A new algorithm for iris recognition has been presented. The proposed algorithm extracts both global and local information of the iris. Each iris image is filtered with Gabor filters and then a fixed length feature vector is obtained. Experimental results show that our algorithm can effectively distinguish different persons by identifying their irises. It is also computationally efficient and insensitive to illumination and noise. Our future work will focus on more robust iris features as well as iris recognition from image sequences.

Acknowledgments

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