ELectronics EXpress

Efficient iris recognition system based on iris anatomical structure

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Abstract: The global rising security concerns propel growth of biometrics recognition techniques. Iris recognition is widely regarded as one of the most promising biometrics methods because of its high accuracy. Among the whole iris recognition process, how to capture the significant features in the iris pattern and to encode them efficiently is a hard task. In this paper, an innovative method is proposed to extract iris features according to iris anatomical structure characteristics. The proposed method can represent the iris pattern with less redundancy and moreover less computational demanding than traditional methods.

Keywords: biometrics, iris recognition, feature extraction, Log-Gabor

Classification: Science and engineering for electronics

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1 Introduction

The global rising security concerns propel growth of biometrics recognition techniques. The term 'biometrics' comes from the Greek words *bios* (life) and *metrikos* (measure). Biometrics relies on an anatomical or behavioral

DOI: 10.1587/elex.4.555
Received May 30, 2007
Accepted June 19, 2007
Published September 10, 2007

IEICE Electronics Express, Vol.4, No.17, 555–560

feature for automatic personal identification instead of the means by using PIN or ID card. Fingerprint, face, iris, palmprint, signature, gait etc. can all be employed as biometrics because they satisfy the fundamental requirements of biometrics: universality, distinctiveness, permanence and collectibility.

Iris recognition is one of the most promising biometrics techniques because of its high accuracy. It is based on the unique and extraordinary patterns of human iris (the annular part between black pupil and white sclera). An iris image is shown as Fig. 1. And an iris recognition system always include four steps, they are: 1) iris segmentation; 2) iris normalization; 3) feature extraction and encoding; and 4) matching. Among these steps, how to extract the most significant features from the iris pattern and how to encode it efficiently is the key problem.

Daugman first proposed to extract iris features with complex valued 2D Gabor wavelet, and quantized the local phase angles to yield the Iriscode [1]. In order to retain more of the available iris information, Wildes chose to make use of an isotropic band pass decomposition derived from application of Laplacian of Gaussian filters to the iris image [2]. Bole and Boashash seek to extract and represent the features of the iris pattern by the zero-crossings of 1D wavelet transform of the concentric circles on the iris [3]. Li Ma et al. constructed a new spatial filters to extract iris features, which are Gaussians modulated by circularly symmetric sinusoidal function [4].

But they all haven't looked further into the iris structure. Because the visual appearance of the human iris texture derives from its anatomical structure, it is more reasonable to seek to extract iris features based on the knowledge of its intrinsic property.

As shown in Fig. 1, the most significant features that contribute to recognition are mostly in the pupillary area. It is part of the iris pattern that close to the pupil, and is enriched with random radial furrows. The outer part of the iris is the ciliary area where exists fewer visible features than the pupillary area. Some concentric contraction furrows may exist in this area. The dividing line between the pupillary area and the ciliary area is collarette, which

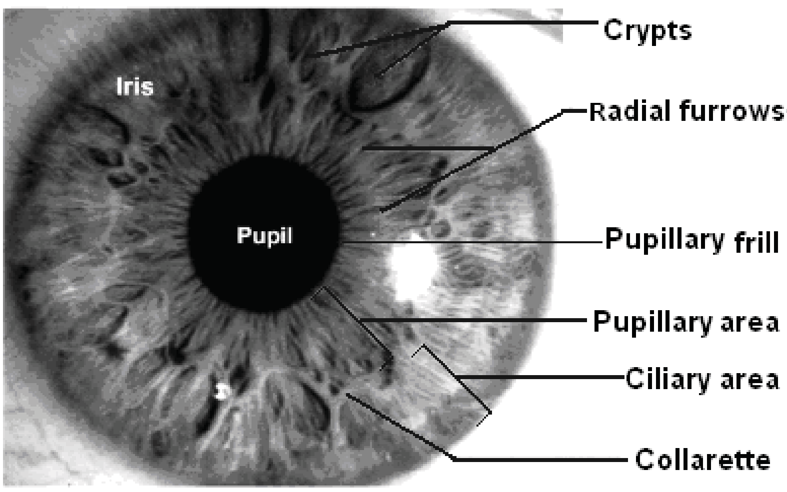

Fig. 1. The structure of the human iris.

DOI: 10.1587/elex.4.555
Received May 30, 2007
Accepted June 19, 2007
Published September 10, 2007

IEICE Electronics Express, Vol.4, No.17, 555–560

is an irregular zigzag closed loop around the pupil. And crypts are mostly around the collarette, so the appearance near the collarette is 'flowers', i.e. bigger blocks of texture.

In order to extract the most significant features in the pupillary area, some researches try to extract the features only inside the collarette by localize the collarette boundary [5]. That is a reasonable idea. But in practice, the collarette is very hard to detect in most cases because of its irregular zigzag shape and also its barely discernible grayscale contrast to other part of the iris texture. This situation is more notable for Asian people because of the sheltering of denser pigmentation. Unfortunately, in case of the collarette is false localized when matching, the whole recognition will be ruined inevitably and completely.

As a tradeoff, it is propose in this paper to divide the whole annular iris region into three virtual zones, and extract features in these three zones separately and differently according to the characteristics of their structures. The contribution of this paper is to make full use of the iris texture's anatomical structures with a somewhat obvious method, which can further improve the iris recognition performances.

2 The whole system

Our whole system also roughly divided into four parts: iris segmentation; iris normalization; feature extraction and then matching.

2.1 Iris segmentation

First, we localize the iris annular region from the whole image. The inner and outer boundaries are modeled as circles. In our method the well-known Integro-differential operator is used to localize the inner and outer circles.

$$\max\left(r, x_0, y_0\right)\left[G_\sigma\left(r\right) * \frac{\partial}{\partial r}\oint_{r,x_0,y_0}\frac{I\left(x,y\right)}{2\pi r}ds\right] \tag{1}$$

In Eq. (1), contour integration parameterized for size and location coordinates $(r,\ x_0,\ y_0)$ at a scale of analysis σ set by Gaussian function $G_\sigma\left(r\right)$ is performed over the iris image $I\left(x,y\right)$.

Then, we divided the whole annular iris region into three 'parallel' zones: Z_1, Z_2 and Z_3, according to its richness of the texture. The inner-most zone Z_1 corresponds to the pupillary area with abundant radial texture; the collarette is most likely to appear in the middle zone Z_2, and there may appear some crypts near the collarette; the outer-most zone Z_3, which corresponds to the ciliary area, is flat in texture and contains least information for recognition.

Because the outer circle of the iris is approximately constant, but the inner circle (pupil boundary) will change with the external stimulation, so the center of the outer circle is used as the origin to divide the iris region. Thus the boundaries of Z_2 and Z_3 are concentric circles, but the boundaries of Z_1 are not always concentric.

DOI: 10.1587/elex.4.555
Received May 30, 2007
Accepted June 19, 2007
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IEICE Electronics Express, Vol.4, No.17, 555–560

2.2 Normalization

Normalization means to compensate for the elastic deformation of iris texture, such as translation, overall scaling and angular scaling (pupil size changes) etc. In our method, the three zones of Z_1, Z_2 and Z_3 are then normalized separately into rectangle blocks N_1, N_2 and N_3 using the 'Rubber-sheet' model of Daugman's. It also works well on the area with non-concentric boundaries as Z_1.

It is noted that only the left section ($[-\pi/4, \pi/4]$) and right section ($[3\pi/4, 5\pi/4]$) of the zone Z_2 and Z_3 are used because they are most likely to be unaffected by eyelids and eyelashes.

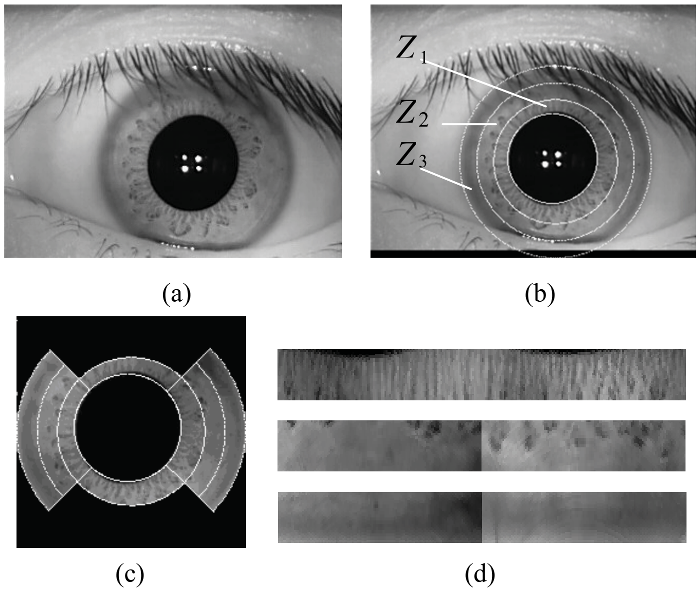

Fig. 2. The iris region is divided into three zones. (a) The original iris image. (b) The three zones of the iris image. (c) The ROI (region of interest); (d) The normalization of the three zones.

2.3 Iris feature extraction

Most iris recognition systems extract iris features using a constant filter or a bank of filters of many scales and orientation in the whole iris region. However, these methods will either under-represent the iris features or introduce a redundancy representation. If we have already get some a priori knowledge such as whether the image has a finer texture or a coarser texture and its approximate orientation, then we can choose specific filters accordingly instead of with a constant filter or a bank of filters with all scales and orientations, to strengthen its most significant features with less redundancy and less computational demanding.

In this case, N_1 should be analyzed in the finest scale and more orientations for its abundance of minute texture; N_2 should be analysis with a coarser filter because it always has bigger block of texture caused by crypts and collarette; and N_3 is the flatest part of the iris texture. It makes least contribution to recognition, so it can be analyzed even coarser.

The filter used in our method to encode the iris pattern is quadrature

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Log-Gabor filter which has Gaussian transfer function when viewed on the logarithmic frequency. It has a better capability to code natural images [6]. On the linear frequency scale the Log-Gabor function has a transfer function of the form:

$$G(\omega) = \exp\left(\left(-\log\left(\omega/\omega_0\right)^2\right)/2\left(\log\left(k/\omega_0\right)\right)^2\right) \tag{2}$$

where ω_0 is the filter's center frequency. The term k/ω_0 is set to be constant to obtain consistent filter shape. N_1, N_2 and N_3 are processed with filters of decreasing center frequency respectively.

Then the phase information is quantized into binary code according to Daugman's phase demodulation process. Thus three binary codes are generated for one iris sample, denoting C_1, C_2 and C_3 which derive from Z_1, Z_2 and Z_3 respectively.

2.4 Matching

The Compounded Hamming Distance is computed as the similarity measure of two iris samples I_1 and I_2. The Compounded Hamming Distance is defined as:

$$CHD = \alpha_1 HD_1 + \alpha_2 HD_2 + \alpha_3 HD_3 \tag{3}$$

where HD_i, $i = 1, 2, 3$ are the Hamming Distances of the codes $C_i(I_1)$ and $C_i(I_2)$ which are generated from the zones Z_i in the two iris samples I_1 and I_2; And α_i, $i = 1, 2, 3$ are the weights for these three Hamming Distances, they should satisfy $\alpha_1 + \alpha_2 + \alpha_3 = 1$. And α_1, α_2, α_3 have decreasing values with the decreasing contribution of the zone Z_1, Z_2 and Z_3 to recognition. A lower CHD value indicates a higher degree of similarity between two irises, while a higher value indicates a lower degree of similarity between two irises.

3 Experiments and analysis

In order to test the performance, we collected a set of iris samples. This set involves 200 different irises, and five samples were captured for each iris. Thus there are totally 1000 iris images with 320×240 pixels in 256 grey levels.

The recognition performance can be evaluated in the following three measures:

1) False Match Rate (FMR): The proportion of imposter attempts that generate CHD below threshold to the total impostor attempt;

2) False Non-Match Rate (FNMR): The proportion of genuine attempts that generate CHD above threshold to the total genuine attempt;

3) Equal Error Rate (EER): The value where the FMR and FNMR are equal.

It can be seen in Fig. 3 that EER, i.e., the crossing point of FMR curve and FNMR curve of the proposed method, achieves 0.65%, which is lower

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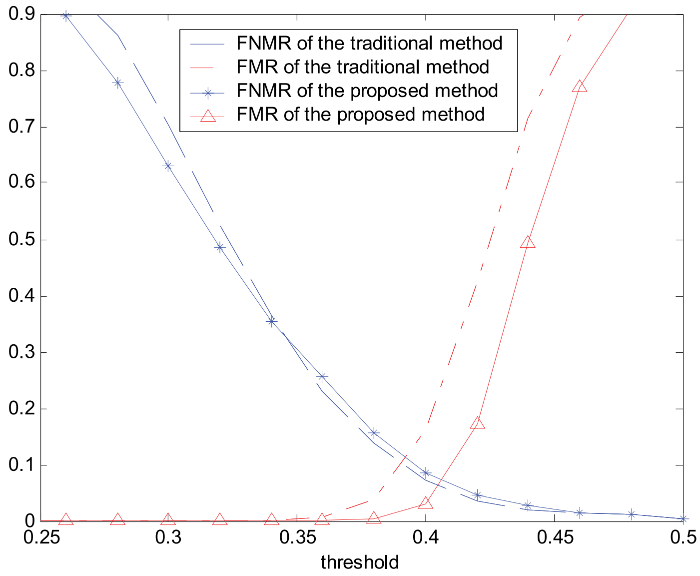

Fig. 3. Recognition results comparison.

than that of the traditional means that use a constant filter or a constant bank of filters in the whole iris region.

It is noted that the results is not that perfect as reported in other publications, it may because several reasons:

1) The iris images we used are non-ideal because we haven't put much restriction on the external conditions when capturing, which will have influences on the performance, especially in the case of iris distorts much due to pupil dilation and constriction.

2) If the preprocessing (localization and normalization) of the iris image is improved, the recognition performance will be better.

The parameters of the filters may not be the optimal. More experiments need to be done to find the optimal parameters.

4 Conclusion

Because the visual appearance of the human iris texture derives from its anatomical structure, in this paper we innovatively divide the iris pattern into three zones according to their different appearances caused by intrinsic structure. Then specific filters accordingly instead of a constant filter or a bank of filters with all scales and orientations are employed to capture the most significant features of iris pattern with less redundancy and less computational demanding than traditional methods. Experiments involve 1000 iris images of 200 different irises, the verification performance are encouraging comparing to the traditional means.

Acknowledgments

This work is supported by the National Natural Science Foundation of China (No. 60427002); and partly supported by the National Hi-Tech Research and Development Program (863) of China (No. 2006AA01Z119)

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