XU Guang-zhu, ZHANG Zai-feng, MA Yi-de

An image segmentation based method for iris feature extraction

CLC number TP39

Abstract In this article, the local anomalous blocks such as crypts, furrows, and so on in the iris are initially used directly as iris features. A novel image segmentation method based on intersecting cortical model (ICM) neural network was introduced to segment these anomalous blocks. First, the normalized iris image was put into ICM neural network after enhancement. Second, the iris features were segmented out perfectly and were output in binary image type by the ICM neural network. Finally, the fourth output pulse image produced by ICM neural network was chosen as the iris code for the convenience of real time processing. To estimate the performance of the presented method, an iris recognition platform was produced and the Hamming Distance between two iris codes was computed to measure the dissimilarity between them. The experimental results in CASIA v1.0 and Bath iris image databases show that the proposed iris feature extraction algorithm has promising potential in iris recognition.

Keywords iris recognition, image segmentation, ICM

1 Introduction

With the fast development of communication technology and internet, and with the physical and virtual active space extending continually for mankind, the demand for accuracy, security, and practicability in identification methods is increasing much faster than before. How to rapidly and correctly recognize a person to ensure information security has become a crucial social problem to be resolved in this information age. Biometrics recognizes a person based on his/her physiological or behavioral characteristics and has received significant attention as it has many advantages over traditional methods in security, credibility, and convenience [1, 2].

The human iris is an annular part between pupil and sclera (as shown in Fig. 1) and its complex structure has many distinctive features such as furrows, ridges, crypts, and a zigzag collarette (as shown in Fig. 1). The iris is distinct for every person and even twins have different iris patterns. At the same time the iris is protected from the external environment by being placed behind the cornea and the eyelids. Not being subject to deleterious effects of aging, the small-scale radial features of the iris remain stable and fixed from about one year of age throughout one’s life. All these advantages allow iris recognition to be a promising topic of biometrics and to receive significant attention for its high uniqueness, reliability, being collectable, and being noninvasive [3–10].

A typical iris recognition system commonly includes six stages (as shown in Fig. 2): iris image capture, iris segmentation, iris normalization, iris preprocessing (eyelids/eyelashes detection and iris image enhancement), feature extraction, and matching. In this study, the focus is on iris feature extraction and matching.
Since 1994, after the first patent for automatic iris recognition method was awarded to Professor J. Daugman, iris recognition has come into focus from the academic business, and government points of view. More and more iris recognition algorithms are being presented. J. Daugman used the 2-D Gabor filter to generate a 256-byte code by quantizing the local phase angle according to the outputs of the real and imaginary part of the filtered image, and compared two irises by computing the Hamming Distance between the pair of iris codes [4, 5]. Wildes made use of Laplacian pyramid constructed with the fourth resolution levels to generate iris codes and exploited a normalized correlation-based goodness-of-match values and Fisher’s linear discriminant function for pattern matching [7]. A bank of Gabor filters were used to capture both local and global iris characteristics in Li Ma’s algorithm [8]. Iris matching is based on the weighted Euclidean distance between two corresponding iris vectors. Boles [9] obtained the iris representation of 1-D signals composed of normalized iris images via the zero-crossing of the dyadic wavelet transform. It made use of two dissimilarity functions to compare a new pattern with the reference patterns. The system proposed by Tisse et al. used the “analytic image” concept (2D Hilbert transform) to extract pertinent information from the iris texture [10].

In the proposed algorithm, which is different from all the above-mentioned methods, the local anomalistic blocks such as crypts, furrows, and so on in the iris image are initially used directly and clearly as iris features. A useful image segmentation tool named ICM neural network was introduced initially to segment those anomalistic blocks. ICM neural network is a simplified model of pulse-coupled neural network (PCNN), which has special advantages for image segmentation and can output pulse image series. In the proposed system, the normalized iris image was put into ICM neural network after enhancement processing. And the fourth output pulse image produced by ICM neural network was chosen as the iris code. Finally, the Hamming Distance was computed as a measure for the dissimilarity of the two irises. The recognition results in CASIA v1.0 [16] and Bath [23] iris image databases show that the proposed iris feature extraction method has promising potential in iris recognition.

The remainder of this article is organized as follows: Section 2 introduces iris segmentation and normalization method used in this study and describes the details of iris image enhancement. Detailed descriptions of the proposed iris feature extraction method using ICM neural network are explained in Sect. 3. Section 4 reports the experiments and results. The conclusion is given in Sect. 5.

2 Segmentation, normalization and enhancement

In this research, the iris area was segmented out using the method of an early study by the authors [11]. For CASIA v1.0 [16] and Bath [23] iris galleries, the segmentation accuracy is 98.42% and 98%, respectively. Then the normalization of the segmented iris area was implemented to compensate the stretching and shrinking of the iris texture caused by the changing of pupil size and to break the non-concentricity of the iris and the pupil using the rubber sheet model [4, 5]. In this study, the iris area was transformed into a rectangular region with fixed size. For CASIA v1.0 the size is 360x72, and for Bath the size is 1440x200. The following steps were used to obtain the enhanced iris image:

1) Divide the normalized iris image into 720 small blocks with fixed size of 6x6 (for Bath iris image database the size is 24x10) and calculate the mean of each block to estimate the background illumination.

2) Extend the coarse estimation of background illumination above to the same size as the normalized iris image using bi-cubic interpolation.

3) Subtract the background illumination from the iris image to get an iris image with uniform brightness.

4) Enhance the image with uniform brightness by means of
5) Use the mean filter to eliminate the noises coming from the capture device and circumstances to get the enhanced iris image.

3 Iris feature extraction and matching

From the enhanced iris image in Fig. 3, it can be seen that some distinctive features of the iris image such as furrows, ridges, and crypts are more visible than before. If these features can be segmented out efficiently, the iris pattern can be described using them. But some iris features tend to be extremely soft in some areas of an iris image, even after enhancement. Therefore, some current segmentation methods are difficult to be implemented for iris features segmentation. In this research, a novel image segmentation method based on ICM neural network has been introduced to extract the iris features.

3.1 The ICM neural network

ICM neural network is a simple version of the PCNN model proposed by Eckhorn and Johnson [12, 13], which is especially designed for image processing and is computationally faster than the full PCNN model. This type of neural network does not need any training, and generates a sequence of binary pulse images for the input digital image. Two similar images will produce similar pulse images. On the other hand, images that differ will produce pulse images that differ in the corresponding regions of the input images. These output images can be used for different image processing tasks such as image segmentation [14].

The basic simplified structure of an ICM neuron for a two-dimensional input image is shown in Fig. 4. In the ICM neural network, the state oscillators of all neurons are represented by a 2D array $F$ (the internal neuron state; initially $F_{ij} = \theta_{ij} = 0$) and the threshold oscillators of all the neurons by a 2D array $\theta$ (initially $\theta_{ij} = 0$). Thus, the state $F_{ij}$ and threshold $\theta_{ij}$ and output $Y_{ij}$ of the $ij$th neuron can be computed as follows:

$$F_{ij}[n+1] = fF_{ij}[n] + S_{ij} + W_{ij}Y_{ij}[n] \quad (1)$$

$$Y_{ij}[n+1] = \begin{cases} 1; & \text{if } F_{ij}[n+1] > \theta_{ij} \n 0; & \text{otherwise} \end{cases} \quad (2)$$

$$\theta_{ij}[n+1] = g\theta_{ij}[n] + hY_{ij}[n+1] \quad (3)$$

where $S_{ij}$ is the stimulus (the input image is scaled so that the largest pixel value is 1.0); $Y_{ij}$ is the firing state of the neuron ($Y$ is the output image); $f$, $g$, and $h$ are scalars (in this research, they are 0.4, 0.32, and 10 respectively); $W_{ij}Y$ describes the inter-neuron communications (in this research, only the 24-connected areas of the $ij$th neuron is taken into account with consideration about the time consumption. And the value in $W$ is in inverse proportion to the distance between the nearby neuron and the $ij$th one); and $n=1, 2, ..., N$ is the iteration number (in this method $N=4$). The scalars $f$, $g$, and $h$ are decay constants and thus less than 1. The ICM neural network outputs a binary pulse image $Y$ after each iteration [15].

From the Fig. 4 and Eqs. (1)–(3), one can see that the neurons corresponding to those pixels with similar characteristics can fire together and finish image segmentation after the stimulus and communication come from the image and other neurons. Comparing with other image segmentation methods based on "hard" threshold, this approach considers not only the gray value of each pixel but also the communication with other pixels and has the characteristics similar to "soft" threshold and is very fit for image segmentation.

3.2 Feature extraction and matching

In this part, the enhanced iris image is put into the ICM neural network mentioned earlier. The fourth output pulse image is used as the iris code in the algorithm used for this study with considering the time consumption. In the experiments, features extracted were only from the top-most 70% of the section (corresponding to the regions closer to the pupil) of the input iris image because the iris regions close to the sclera contain few texture characteristics and are easy to be occluded by eyelids and eyelashes. Figure 5 illustrates the process.
Fig. 5 Iris coding process

To determine whether the two irises belong to the same class, the Hamming distance between them is computed directly as follows:

$$HD = \frac{\left|\text{CodeA} \oplus \text{CodeB}\right|}{18,000}$$  \hspace{1cm} (4)

where Code A and Code B are the two iris code templates to be matched, and the 18,000 is the number of bits to be compared (for Bath the number is 201,600). The XOR operator $\oplus$ can detect the disagreement between any pair of iris code templates. The resulting Hamming distance is a fractional measure of dissimilarity.

4 Experimental results and discussion

To evaluate the proposed iris feature extraction algorithm, the CASIA v1.0 [16] and Bath [23] iris image databases are used. CASIA v1.0 iris image database contains 756 “non-ideal” images from 108 different objects. Each of the iris images is an 8 bit gray scale with a resolution of 320 x 280. In these experiments, all the parameters of the iris recognition system were carefully selected through rigorous experimentations. The accuracy rate of iris segmentation in CASIA v1.0 is 98.42%. The Bath iris image gallery includes 1,000 images coming from 50 different eyes, and each eye has 20 images with a resolution of 1,280 x 960. The accuracy rate of iris segmentation in Bath iris image database is 98%.

4.1 Experimental results

In this research, 744 images in CASIA v1.0 and 980 images in Bath iris image database are used for identification experiments. Some images in CASIA v1.0 and Bath are shown in Fig. 6.

In CASIA v1.0, each eye has seven images, which were captured in two sessions: three samples were collected in the first session and four in the second session. In iris matching stage for CASIA v1.0, three images were taken for training purpose and the remaining four images for testing, which is as same as the method used by Ref. [17]. The performance results are based on three error rates: false accept rate (FAR) and false reject rate (FRR) and the overall accuracy rate. The comparison results of different algorithms are shown in Table 1 for CASIA v1.0. Here, the data of the Ref. [17] is cited for comparison. The reason for choosing the data is that the Ref. [17] used the same image gallery and also divided the image database into two similar parts for training and matching. Also, Ref. [17] is one paper special for comparing the performances of different iris recognition methods; therefore, the data it contains is more meaningful. But, unfortunately, Ref. [17] does not give the number of the images used for experiments. As is known, there is no method that has 100% accuracy for iris segmentation in CASIA v1.0 image database. The method adopted by the authors in Ref. [11] has the highest segmentation accuracy rate when compared with other segmentation approaches in CASIA v1.0. To show this, the data in Ref. [18] is cited (as shown in Table 2). Reference [18] is a special paper for comparing the performances of different segmentation methods; therefore, the comparison in Table 2 is meaningful. From the data in Table 2, one can see that this segmentation algorithm has the highest accuracy rate.

Table 1 Performance comparisons of some popular algorithms in CASIA v1.0 iris database

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>FAR/FRR/%</th>
<th>Overall accuracy rate/%</th>
<th>Image number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avila [19]</td>
<td>0.03/2.08</td>
<td>97.89</td>
<td>Unknown</td>
</tr>
<tr>
<td>Li Ma [20]</td>
<td>0.02/1.98</td>
<td>98.0</td>
<td>Unknown</td>
</tr>
<tr>
<td>Tisse [10]</td>
<td>1.84/8.79</td>
<td>89.37</td>
<td>Unknown</td>
</tr>
<tr>
<td>Daugman [4]</td>
<td>0.01/0.09</td>
<td>99.90</td>
<td>Unknown</td>
</tr>
<tr>
<td>Proposed method</td>
<td>0.01/2.82</td>
<td>97.17</td>
<td>744</td>
</tr>
<tr>
<td>Proposed method</td>
<td>0.02/1.78</td>
<td>98.11</td>
<td>744</td>
</tr>
</tbody>
</table>

Table 2 Iris segmentation accuracy rate of different methods in CASIA v1.0 iris database

<table>
<thead>
<tr>
<th>Methodology</th>
<th>Accuracy rate/%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daugman [5]</td>
<td>54.44</td>
</tr>
<tr>
<td>Wilds [7]</td>
<td>86.49</td>
</tr>
<tr>
<td>Masek [21]</td>
<td>83.92</td>
</tr>
<tr>
<td>Liam and Chekima [22]</td>
<td>64.64</td>
</tr>
</tbody>
</table>

From Table 1 one can see that the proposed iris recognition method based on ICM neural network has encouraging performance. Figure 7(a) shows the Hamming Distance distribution of inter-class and intra-class comparisons in CASIA v1.0 image database. Where $d'$ is one measure of the decidability [3], which is a function of the magnitude of
difference between the mean of the intra-class distribution $\mu_i$, the mean of the inter-class distribution $\mu_d$, and also the standard deviation of the intra-class and inter-class distributions, $\sigma_i$ and $\sigma_d$ respectively (as shown in Eq. (5)). The higher the decidability $d'$, the greater is the separation of intra-class and inter-class distribution, which allows for more accurate recognition [3]. Figure 7(b) is the receiver operating characteristic (ROC) curve that is a graphical representation of the tradeoff between genuine acceptance and false acceptance rates. Points in this curve denote all possible system operating states in different tradeoffs. It shows the overall performance of a system [3].

$$d' = \sqrt{\frac{\mu_i - \mu_d}{\sigma_i^2 + \sigma_d^2}}$$  \hspace{1cm} (5)

For Bath iris image database, all images of one eye were captured at one session. And all the images are used for recognition experiments. Figure 8 shows the Hamming Distance distribution of inter-class and intra-class comparisons in the gallery. Table 3 shows the error rates of the experiment. The ROC curve in this test is not presented because the error rates are 0%.

Table 3 Performance of the proposed method in Bath iris database

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>FAR/FRR/%</th>
<th>Overall accuracy rate/%</th>
<th>Image number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed method</td>
<td>0/0</td>
<td>100</td>
<td>980</td>
</tr>
</tbody>
</table>

4.2 Discussion

Some false rejected and false accepted examples in CASIA v1.0 with their Hamming Distance values are shown in Fig. 9 (in this case the separation point is at HD=0.43). The reason for false rejection is that the iris regions are occluded so badly by eyelids and eyelashes that there is insufficient useful information for matching (as shown in Fig. 9(a)). There are two reasons for false acceptance. One is that eyelids and eyelashes occluded the iris badly and some eyelids/eyelashes areas are taken as the iris region in iris matching process. The other is that iris textures of some objects are not so clear that two different iris images are very similar (as shown in Fig. 9(b)) especially when the pupil is extended too much. All the above-mentioned cases can be resolved at some level by using iris image quality evaluation and by improving the capture device.
5 Conclusions

This article presents a novel method for iris feature extraction using ICM neural network. The main contributions of this article include two points. One is that this method initially introduces image segmentation concept into iris feature extraction and gives a clear definition for iris features. The second is that this article finds a useful image segmentation tool to segment those iris features. The experimental results in CASIA v1.0 and Bath iris image databases show the proposed iris feature extraction method has promising potential in iris recognition application. More tests and comparisons in other bigger image databases with different methods constitute future work.

Acknowledgements This work is supported by the National Natural Science Foundation of China (6057201), the 985 Special Study Project of Lanzhou University Foundation (LZ985-23-1-58262-7). Authors wish to acknowledge Institute of Automation, Chinese Academy of Sciences for providing CASIA v1.0 iris database [16]. Authors also thank Bath University for providing the Bath Iris Database [23].

References
3. Daugman J. Biometric Decision Landscape, Technique Report No. TR482. Cambridge, UK: Computer Laboratory, University of Cambridge, 1999


Biographies: XING Ji-peng, from Hubei, Ph. D. Candidate in Department of Electronic Science and Technology, Huazhong University of Science and technology, interested in the research on VLSI design and wireless sensor networks and embedded systems.

ZOU Xue-cheng, a professor and doctoral advisor in the Department of Electronic Science and Technology, Huazhong University of Science and Technology. His research interests include design of VLSI, research of RFID system, and information security SoC design.

From p. 101


Biographies: XU Guang-zhu, received the B. S. degree and Ph. D. degree in radio physics from Lanzhou University in 2002 and 2007 separately. He is currently associate professor of China Three Gorges University. His major research interests include biometrics, neural network, digital image processing and analysis, pattern recognition.

ZHANG Zai-feng, received the B. S. degree in mechanism manufacture and equipments from Lanzhou institute of technology in 1990. In 2002, he received the M. S. degree in communication and information system from Lanzhou University. He is currently pursuing the Ph. D. degree in biometrics in the school of information science and engineering of Lanzhou University. His current research interests include biometrics, digital signal processing, digital watermark, pattern recognition, etc.

MA Yi-de, received the B. S. and M. S. degrees in radio technology from Chengdu University of Engineering Science and Technology in 1984 and 1988, respectively. In 2001, he received the Ph. D. degree from the Department of Life Science, Lanzhou University. He is current professor in School of Information Science and Engineering of Lanzhou University and interested in the research on artificial neural network, digital image processing, pattern recognition, digital signal processing, computer vision, etc.