Adaptive Thresholding for Iris Recognition

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***Abstract*-This paper presents an intensity-based iris recognition system. The system exploits intensity distributions of iris textures. The textures are enhanced and extracted using local histogram equalization and quotient thresholding. This thresholding technique partitions an iris image into regions of foregrounds and backgrounds such that a ratio between these two regions is the same for all iris images in a database. The extracted iris features are encoded in a way to accommodate a fast matching using a table lookup technique. Computational cost of our proposed 1:1 matching is 9 millisecond. The accuracy of the proposed system evaluated using CASIAv.1.0 iris database is 0.001413%EER.**

I. Introduction

The term 'biometrics' refers to the science and technology of authentication using physiological or behavioral characteristics of human such as fingerprints, signatures, faces, and irises. Among the biometrics, an iris pattern is a highly accurate and reliable characteristic. Flom and Safir [1] reported that the iris patterns are unique to individual and stable over time and across environments (e.g. occupations, humidity ect.). The uniqueness of iris patterns is the product of dense collections of iris structures and textures such as pigment frills, furrows, freckles, and crypts. These textures can be perceived easily. In addition, an iris is a protected organ located behind the cornea, but in front of the lens. This makes personal authentication possibilities life long.

The most successful commercial iris recognition system is a ramification of an algorithm proposed by John Duagman [2]. He uses 2D Gabor filters to extract phase information of an iris. Matching score of two iris codes is evaluated using hamming distance. After his work, several works are introduced. Wildes [3] analyzes iris features using 2-level Laplacian pyramid. Correlation of the obtained images is used to evaluate their similarity. Ma [4] analyzes and extracts iris features using circular symmetry filters. Sun [5] uses zero-crossings of wavelet transform to extract iris features. He represents the features using five geometric moments. Wen Yang [6] suggests using a group of 2D Gabor filters to detect a set of points, named key points. These points represent local iris texture. K. Miyazawa [7] analyzed an iris using 2D DFT. Only the obtained phase components are used to evaluate the match between two irises.

In this paper, we propose an intensity-based iris recognition system. The system aims to extract visible iris textures, which generally have low intensity level. These iris textures are extracted using local histogram equalization and a quotient thresholding [8]. In quotient thresholding, the threshold values for each image in the database are adapted to illumination of the image. Differences between our work and work in [8] are:

- We proposed to use intensity position of the extracted iris features instead of using its shape information. In [8], the extracted features are fitted with various sizes of circles. Diameter of the fitted circle describes the iris features.
- A new and fast matching technique is introduced in this paper. The proposed iris code is encoded to accommodate matching method, also to compensate effects of elastic distortion.
- The proposed method works on an unwrapped iris image, instead of an iris ring. This is to ease matching implementation.

The rest of this paper is organized as follows: section 2 describes our proposed iris recognition. Section 3 illustrates our experimental results and discussions. The last section, section 4 is our conclusion.

II. The proposed iris recognition

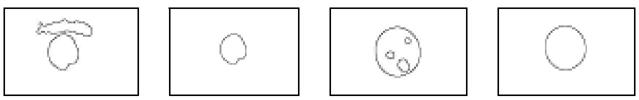
Our iris recognition approach is composed of five main steps: localization, normalization, feature extraction, feature encoding and matching. Their details are described in the following sections.

A. Iris Localization

Iris localization is to locate inner and outer boundaries of an iris. The inner boundary of an iris is a boundary separating the iris from the pupil, whereas the outer boundary is a boundary separating the iris from the sclera zone. Both boundaries can be located by exploiting intensity differences among organs (pupil, iris, and sclera) and a prior knowledge of circular-like shape of pupil and iris.

Since intensity level of a pupil is typically low and falls separately from intensity range of other eye components, pupil is detected using thresholding operation. Then, edge detection and edge thinning operations are applied over the thresholded regions. These operations yields edges belong not only to edges of the pupil but also of the other components such as eyelashes and reflected lights as shown in Fig. 1(a) and 1(c), respectively. To obtain only edges belong to the pupil, irrelevant edges are removed by examining its circular and diameter property. Fig. 1(b) and 1(d) shows corresponding results of Fig. 1(a) and 1(c), respectively. The obtained edges are fitted using circular model. The fitting results in two parameters: r-inner and center, which denoted radius of an iris inner boundary and its center position, respectively. The obtained center position is used as reference point for the rest processes of our recognition system.

The iris outer boundary is detected by exploiting intensity difference between iris and sclera. Contrast enhancement algorithm [9] is applied to the image in order to improve contrast nearby the boundary of iris and sclera. The outer boundary is located by searching for abrupt change of average intensity of pixels along arc defined in Fig.2. The search is started nearby the inner boundary and moving outward. The outer boundary is located where the first abrupt change of the obtained average intensity occurs.



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

Figure 1. Example results of pupil detection.

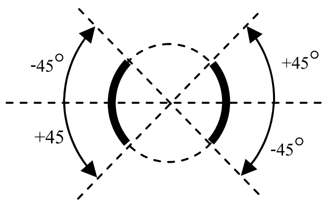


Figure 2. Arcs used in iris outer boundary detection.

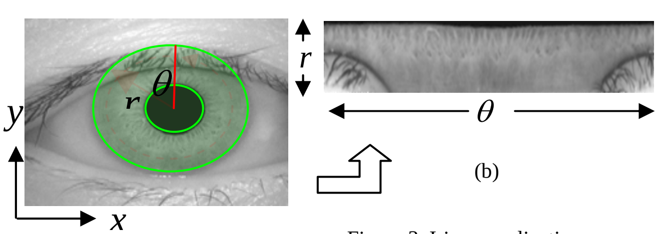
B. Iris Normalization

Generally, acquired images of one iris have different iris sizes depending on an amount of incoming light. To compensate this variation, the localized iris is normalized into a fixed size rectangle using (1).

$$r_{input} = \{(i/N)\times(R_{outer} - R_{inner})\} + R_{inner},$$

$$\theta_{input} = (2\pi \times j)/M \qquad (1),$$

where, $(r_{input}, \theta_{input})$ is a polar coordinate of a point (x,y) on an input image as shown in Fig.3(a). R_{inner} is an iris inner boundary. R_{outer} is an iris outer boundary. A point (i,j) is a corresponding point of $(r_{input}, \theta_{input})$ on the rectangle that has a size of $N \times M$. Fig. 3(b) depicts an example result of the conversion.



(a)

Figure 3. Iris normalization

C. Iris Feature Extraction

In this paper, iris features are extracted using quotient thresholding (QT) technique. The QT technique is an adaptive thresholding proposed in [8]. The technique aims to extract dark pigmented iris textures such as crypts, freckles and moles. As these textures are visible and generally have low intensity values, thresholding technique can be used to extract these textures. However, thresholding operation is sensitive to image illumination. In order to obtain similar but distinguishable iris features, algorithm in [8] was proposed to compensate non-uniform illumination inhibited within an iris image using local histogram equalization (LHE) and proposed to compensate non-uniform illumination occurred across iris images in a database using quotient thresholding (QT).

The LHE is used not only for compensating non-uniform illumination, but also for enhancing informative iris features. The QT is an adaptive thresholding technique aiming to compensate uneven illumination among iris images. The compensation is done by varying the threshold values resulting in image partitioning, based on its histogram. The threshold value is varied until a ratio between the obtained foregrounds and backgrounds reach a pre-specified value. This value is fixed for all images in a database. By fixing this ratio instead of fixing a threshold value, similar iris patterns could be extracted from images of an iris captured under different lighting conditions.

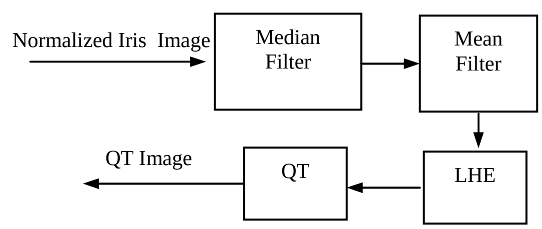
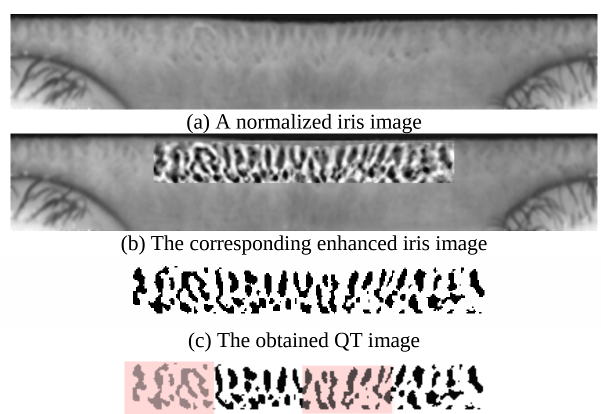


Figure 4. The proposed feature extraction algorithm.



(a) A normalized iris image

(b) The corresponding enhanced iris image

(c) The obtained QT image

(d) Four divided parts for QT encoding

Figure 5. Image results from algorithm's progressive

In [8], the described process is applied over a segmented iris ring directly. This paper, we propose to apply the LHE and QT over a normalized iris image instead. This is to facilitate iris feature encoding and matching procedures. In addition noise reduction using median and mean filters are applied prior the LHE. Fig. 4 shows our proposed feature extraction algorithm. Fig. 5(c) shows a result obtained from applied the proposed feature extraction on a normalized image shown in Fig. 5(a).

As our proposed is an intensity-based method, noises caused from eyelids and eyelashes can significantly degrade our system performance. To reduce this degradation, the proposed algorithm is performed only on area nearby pupil zone as indicated in Fig 5(b). Since eyelashes have very low intensity, they are usually segmented as one part of iris features. To reduce noisy pixels in our iris feature code, we invert the thresholded image before encoding the features. Surrounding pixels of dark iris textures are concerned in our proposed feature encoding and matching algorithm instead.

D. *Feature Encoding*

Instead of describing the obtained QT feature using its shape properties as in [8], we proposed to describe the QT features using its intensity position. Positions of the obtained foreground pixels, which represent iris features, are used to find the match between two irises. Its matching score is proportional to a number of matched foregrounds.

The encoding process is started from dividing the obtain QT image into 4 sections, indicated in Fig. 5(d). Each section has a size of 64 × 35 pixels. The background pixel is encoded as “0” and the foreground pixel is encoded as “1”. For each section, one row of QT image generates a 64-bit QT code. Therefore, one iris image generates a template of 1120 bytes of QT code.

E. *Feature Matching*

This step is to find similarity of two QT codes. Its similarity is measured by counting a number of matches between foregrounds extracted from two irises. As we encode the foregrounds as “1”, counting a number of matched foregrounds is equivalent to counting a total number of “1” resulted from performing AND operation between two QT codes.

Fast implementation of finding a total number of matched foregrounds is accomplished through a table lookup technique. A lookup table, called a matching score array, is created prior. Each cell of the array contains a normalized matching score, which is associated to a number of matched “1” between two binary QT codes. These two codes are row and column index of the cell.

To have a small size array, each row of the QT code, which is 64 bits, is separated into 4 parts. Each part is a 16-bit long. Thus, a matching score array of size 16x16 is used instead of an array of size 64x64.

Rotation and translation invariance can be achieved by shifting each part of the QT code in range of ±17 pixels horizontally and ±10 pixels vertically, independently. The maximum matching score of the shifted QT code represents its matching score. System matching score is a summation of the four best matching scores obtained from the four parts. The proposed method requires 102,900 times to perform AND operations. Therefore, $102{,}900 \times 4 = 411{,}600$ lookups are carried out.

III. EXPERIMENTAL RESULTS

We validated our proposed system using two databases: CASIA v.1.0 [10] and KSIP DB01R iris database [11]. The system performance is measured in term of Equal-Error-Rate (EER), which is equilibrium error of Fault Accept Rate (FAR) and Fault Reject Rate (FRR).

CASIA iris database is a public iris database. The database contains 756 iris images captured from 108 individual eyes, 7 images for each individual. This database requires $7c2 \times 108 = 2{,}268$ comparisons for generating the distribution of the intra-class matching distance and requires $108c2 \times 7^2 = 283{,}112$ comparisons for generating the distribution of the inter-class matching distance.

KSIP DB01R database contains 1920 iris images captured from 120 Thais volunteers. Eight images of their left and right eyes are captured. For this database, $8c2 \times 240 = 6{,}720$ comparisons are required for the distribution of the intra-class matching distance generation and $240c2 \times 8^2 = 1{,}835{,}520$ comparisons are required for inter-class matching distance generation.

TABLE 1
SYSTEM PERFORMANCE OF THE PROPOSED METHOD

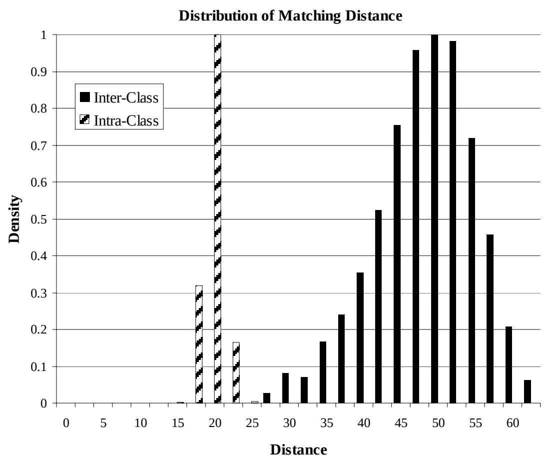
QT ratio	CASIA v.1.0	KSIP DB01R
0.05	0.234734	0.818184
0.10	0.003532	0.605192
0.15	0.003355	0.524651
0.20	0.001413	0.484872
0.25	0.007771	0.515969
0.30	0.066726	0.586786
0.35	0.081708	0.657789
0.40	0.094629	0.740491

Our first experiment is finding QT ratio, which yields the best system performance. Table I indicates the obtained EER for each QT ratio. Empirically, the best system performance is obtained when QT ratio equals to 0.20. It yields 0.001413% EER using CASIA database and 0.484872% EER using KSIP database. The distribution of intra-class and inter-class matching distance obtained using the QT method with 0.2 QT ratio is shown in Fig. 6.

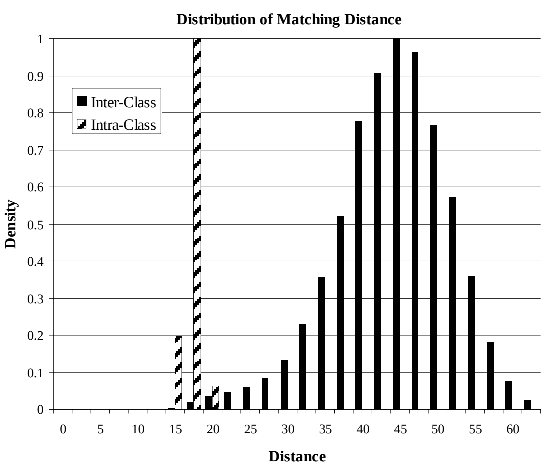
It is clearly seen that the proposed QT method is well perform with the CASIA iris database, but not with the KSIP iris database. This is due to inaccurate iris localization and occlusion problems. Irises in KSIP database is more difficult to locate, as pupils in CASIA database are manually filled with black circles and several pupils in KSIP database have their shape closed to an ellipsoid, not a circle. Fitting ellipsoid with circle often includes dark pupil regions within the segmented iris. In addition, KSIP irises are often occluded by eyelashes.

A reason for us to validate our system using CASIA database is that most existing iris recognition system evaluated their systems using this database. Table II indicates our proposed system performance comparing to existing methods

Computational cost of our proposed system is shown in Table III. Our system is carried out in C++ on PC Pentium IV 2.4 GHz with 512 MB RAM. Matching time of our proposed method is reduced by half when comparing to one in [8], which reported 17 millisecond. for 1:1 matching. Even though, the 1:1 matching time is reduced significantly. The proposed system still needs 9 seconds for 1000 irises comparisons. This timing should be reduced further for large database usage.



(a)



(b)

Figure 6. The distribution of inter- and intra- class matching distance of the proposed method using (a) CASIA v.1.0 database (b) KSIP DB01R database.

TABLE II
SYSTEM PERFORMANCE COMPARISONS (USING CASIA V.1.0)

Methods	EER (%)
Kazuyuki Miyazawa et al. [7]	0.0032
Peng Yao et al. [12]	0.2800
Chia-Te Chou et al. [13]	0.0229
Lu Chenhong [14]	0.1480
Thoonsangngam [8]	9.0810
Proposed method	0.0014

TABLE III
COMPUTATIONAL COST OF THE PROPOSED SYSTEM

Process	Computational Time (msec.)
Localization	234
Normalization	31
Enhancement	212
QT	16
1:1 Matching	9

IV. CONCLUSION

A new intensity-based iris recognition system is proposed in this paper. Intensity variations of iris textures are enhanced using local histogram equalization and are extracted using an adaptive quotient thresholding. Quotient thresholding partitions an iris image into regions of foreground and background such that a ratio between foregrounds and backgrounds is the same for all iris images in a database. Spatial corresponding between the obtained foreground pixels of the two irises is counted and used to measure its similarity. Effects of elastic distortions of an iris are reduced by partially match the extracted iris features. A system speed is reduced using a table lookup technique for searching for a matching score of two iris codes. Computational time of our proposed 1:1 matching algorithm is 9 msec. The proposed system accuracy is 0.001413%EER using CASIAv.1.0 and 0.484872%EER using KSIP DB01R.

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