# A Novel and Efficient Feature Extraction Method for Iris Recognition

Jong-Gook Ko, Youn-Hee Gil, Jang-Hee Yoo, and Kyo-IL Chung

*ABSTRACT—With a growing emphasis on human identification, iris recognition has recently received increasing attention. Iris recognition includes eye imaging, iris segmentation, verification, and so on. In this letter, we propose a novel and efficient iris recognition method which employs a cumulative-sum-based grey change analysis. Experimental results demonstrate that the proposed method can be used for human identification in efficient manner.*

*Keywords—Biometrics, iris recognition.*

## I. Introduction

Many studies for iris recognition have been previously presented [1]-[3]. In the approach proposed in [1], iris feature extraction is a process of phase demodulation. An iris image is encoded into a compact sequence of multi-scale quadrature 2-D (two-dimensional) Gabor wavelet coefficients, whose most-significant bits comprise a 256-byte iris code. In [2] a zero-crossing representation of a one-dimensional wavelet transform was calculated to characterize the texture of the iris. In [3], a texture analysis approach was proposed. Multi-channel Gabor filtering was used to capture global and local details in an iris image. Additionally, independent component analysis (ICA) [4], and wavelet packets [5] for iris pattern analysis have been used.

We propose a novel and efficient approach to iris recognition based on iris feature extraction using cumulative-sum-based change analysis. This letter is organized as follows. Section II describes iris recognition using cumulative-sum-based change analysis including iris segmentation and image enhancement. In section III, experimental results are presented, and conclusions are given in section IV.

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## II. Iris Recognition Using Cumulative-Sum-Based Change Analysis

### 1. Iris Segmentation and Normalization

The iris region is isolated from an eye image with the approximation that the shape of the iris is a circle. Like Daugman's method in (1), the inner (pupil) boundary and outer (sclera) boundary of iris are located using an effective integro-differential operator:

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

where $I(x, y)$ is the original image, and the complete operator behaves as a circular edge detector which searches over the candidate domain iteratively with respect to increasing radius $r$ for the maximum contour integral derivative. Here, $G_\sigma(r)$ is a smoothing function, such as a Gaussian of scale $\sigma$. Figure 1 shows the result of iris segmentation.

The irises of different people may be captured in various sizes; therefore, the normalization of different-sized images to the same size is needed to achieve more accurate recognition.

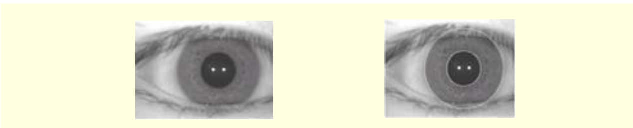

Fig. 1. Iris segmentation result.

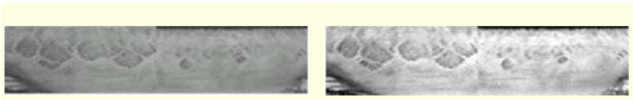

Fig. 2. Iris image normalization and enhancement: (a) normalized iris image and (b) enhanced iris image.

In Fig. 2(a), the size of the normalized image is 64×300. The areas just at the top and bottom of the iris are often hidden by eyelashes and/or eyelids; therefore, only the iris image data from the right side [45° to 315°] and the left side [135° to 225°] are transformed into a polar coordinate system. It is necessary to improve the contrast of the normalized iris image for iris feature extraction since it has low contrast as shown in Fig. 2(a). A histogram stretching method is used to obtain a well-distributed iris image as shown in Fig. 2(b).

## 2. Iris Feature Extraction and Verification

In this letter, a cumulative-sum-based [8] analysis method is used to extract features from iris images.

### *A. Feature Extraction Using Cumulative Sums*

**Step 1.** Divide normalized iris image into basic cell regions for calculating cumulative sums. One cell region has 3 (row) ×10 (col) pixels size. An average grey value is used as a representative value of a basic cell region for calculation.

**Step 2.** Basic cell regions are grouped horizontally and vertically as shown in Fig. 3 (Five basic cell regions are grouped together because experimental results show that much better performance is achieved when a group consists of five cells).

**Step 3.** Calculate cumulative sums over each group as in (2).

**Step 4.** Generate iris feature codes as shown in Fig. 4.

Cumulative sums are calculated as follows. Suppose that X1, X2,⋯, and X5 are five representative values of each cell region within the first group located on the left top corner of Fig. 3.

- Calculate the average $\overline{X} = (X1 + X2 + \cdots + X5)/5$.
- Calculate cumulative sum from 0: $S_0 = 0$.
- Calculate the other cumulative sums by adding the difference between the current value and the average to the previous sum:

$$S_i = S_{i-1} + (X_i - \overline{X}) \quad \text{for } i = 1, 2, \cdots, 5. \tag{2}$$

Cumulative sums are calculated by addition and subtraction, so the cumulative-sums-based feature extraction method creates a lower processing burden than other methods. After calculation, iris codes are generated for each cell using the following algorithm.

```
Iris_code_generation{
  for (2 times loop){ // for horizontal and vertical directions}
  MAX = max(S1,S2,⋯,S5);   MIN = min(S1,S2,⋯,S5);
  if Si located between MAX and MIN index
      if (Si on upward slope) set cell's iris_code to 1
      if (Si on downward slope) set cell's iris_code to 2 else
  set cell's iris_code to 0 }   }
```

This algorithm generates iris codes by analyzing cumulative

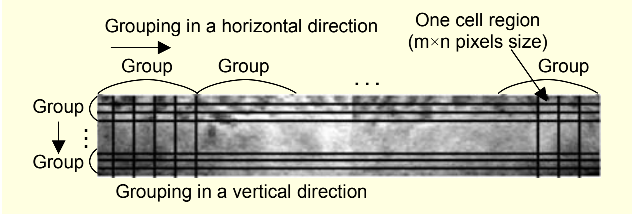


Fig. 3. Division of normalized iris image into cell regions and grouping of cell regions.

sums which describe the variations in the grey values of iris patterns. An upward slope of cumulative sums means that the iris pattern may change from darkness to brightness. A downward slope of cumulative sums means the opposite. An example of iris code generation is shown Fig. 4. Cumulative sums between max and min generate iris code 1 since they compose of upward slope. The fifth cumulative sum generates iris code 0 because it is not located between max and min as shown in Fig. 4(a). In Fig. 4(b), the second, third, and fourth cumulative sums generate iris code 2 since they compose the downward slope. Each cell has two iris codes: one for the horizontal direction, the other for the vertical.

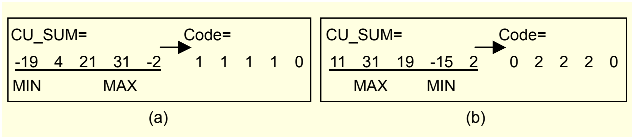


Fig. 4. Example of iris code generation.

### *B. Verification*

To calculate the similarity of two iris codes, Hamming distance is used. A lower Hamming distance indicates higher similarity.

$$HD = \frac{1}{2N}\left[\left(\sum_{i=1}^{N} A_h(i) \oplus B_h(i)\right) + \left(\sum_{i=1}^{N} A_v(i) \oplus B_v(i)\right)\right], \tag{3}$$

only when $A_h(i) \neq 0 \wedge B_h(i) \neq 0,\ A_v(i) \neq 0 \wedge B_v(i) \neq 0,$

where $A_h(i)$ and $A_v(i)$ denote the enrolled iris code over the horizontal and vertical directions, respectively; $B_h(i)$ and $B_v(i)$ denote the new input iris code over the horizontal and vertical directions, respectively; N is total number of cells; and ⊕ is the XOR operator.

# III. Experimental Results

Eye images for the experiment were acquired through a B/W CCD camera with two LED lamps around the lens. The images are 320×240 with an 8-bit grey value. The data includes a total of 820 images from 82 individuals (male 67, female 15) in sets of 10 eye images per person (left and right eyes). Performance evaluation of the proposed method was measured in terms of false rejection rate (FRR) and false acceptance rate (FAR). Figure 5 shows Hamming distances for the same persons in Fig. 5(a) and for different persons in Fig. 5(b). The y-axis and x-axis indicate the number of data samples and the Hamming distance, respectively. Table 1 shows FAR and FRR based on the Hamming distance. Recognition performance of the proposed method was 99.24% when the threshold was 26. The experimental results show that the proposed method is a promising and effective approach in iris recognition.

The proposed method was also evaluated using the CASIA iris database [6] with data from 108 people. For comparison with existing algorithms, we referred to [4] which showed recognition results of the existing algorithm on the CASIA iris database. From the results shown in Table 2, we conclude that the method in [1] and our own method show the best performance.

To compare computational complexity, we referred to [7] which showed the computation complexity of well-known existing algorithms. The proposed feature extraction scheme was performed in Matlab 6.0 on a 500 MHz PC with 128 M RAM for the same experimental environment as in [7]. Table 3 shows that the proposed method and the Boles' method consume less time than others for feature extraction.

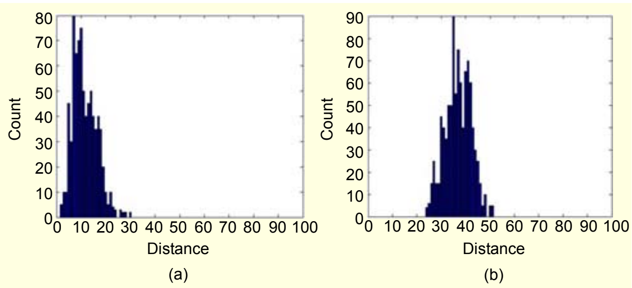


Fig. 5. Hamming distance results: (a) authentic and (b) imposter.

Table 1. FAR and FRR according to the hamming distance.

| HD (%) | FAR (%) | FRR (%) |
|---|---|---|
| 24 | 0 | 1.14 |
| 25 | 0.42 | 1.14 |
| 26 | 1.05 | 0.76 |
| 27 | 2.63 | 0.50 |
| 28 | 5.26 | 0.25 |

Table 2. Identification results on CASIA iris database.

| Methods | Recognition rate (%) |
|---|---|
| Daugman [1] | 99.37 |
| Boles [2] | 92.61 |
| Li Ma [3] | 94.33 |
| Y. Wang [4] | 97.25 |
| Proposed | 98.21 |

Table 3. Comparison of the feature extraction time.

| Methods | Feature extraction (ms) |
|---|---|
| Daugman | 682.5 |
| Boles | 170.3 |
| Li Ma | 244.2 |
| Tan | 426.8 |
| Proposed | 182.0 |

## IV. Conclusion

In this letter, a novel iris recognition method was proposed. This method employs iris feature extraction using a cumulative-sum-based change analysis. In order to extract iris features, a normalized iris image is divided into basic cells. Iris codes for these cells are generated by the proposed code generation algorithm which uses the cumulative sums of each cell. The method is relatively simple and efficient compared to existing methods. Experimental results show that the proposed approach has good recognition performance and speed. In the future, it would be necessary to experiment on a larger iris database in various environments to make the system more reliable.

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