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Efficient Iris Recognition Method for Large Scale Database

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Abstract

In general, personal identification using the iris is means for identifying each individual by using the unique pattern of iris. Even twins have different iris pattern image, and each right eye and left eye has a different pattern for the same individual. Thus, the iris has the best characteristics that reflect the personal differences of the human body. In this paper, we proposed an efficient iris recognition method for large scale database. The Zernike moment is used for filtering out the candidate iris data from large scale database and the multiple SVM is applied for iris recognition. The proposed method proved to be an efficient searching method because the process did not match one-to-one feature data during the searching iris database.

Keywords: *Biometrics, Iris recognition, Zernike Moment, SVM*

1. Introduction

People have unique physiological characteristics which can be used for identifying individuals. Biometric studies using the characteristics have been actively proceeding in recent years. These features include human fingerprint, voice, iris, face shape, hand shape, genetic traits, and handwritten signature. Some examples of biometric features with high reliability that are used for security systems, ATM, etc, such as the company security check or airport entrance security systems. Research is continuously being performed for higher reliability [1-2].

Fingerprint or iris patterns are entirely different from each person, even in twins, and the pattern formed in the early childhood years does not change during entire life time. It is natural that these features will be used for identifying individuals. But the fingerprints used for identifying features may be influenced by the skin damage due to cracking, etc., and can be forged by the rubber coating. Also, the speech recognition suffers from the inevitable distortion of the voice of the speaker according to the age. Face recognition can be influenced by the length of the human hair, face deformation caused by aging, and changes in the expression. In contrast, the iris has lower possibility of damage because it is an important part of the body, and therefore it has an excellent uniqueness and invariant features relative to other features.

The advantage of the study using the iris has been actively carried out by Daugman and Boles, and since then, many algorithms have been proposed [3-11]. In 1993,

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Daugman, who works for the University of Cambridge in the United Kingdom, proposed an algorithm based on 256 bytes Hamming code using Gabor transform. Many commercialized products in these days are based on this algorithm.

In this paper, the filtering capacity of the candidate in the large scale iris database using the Zernike moments is proposed and a multiple SVM is employed for recognizing an input iris.

The conventional methods have to compare input iris data with the data in the large scale database by rotating input data for rotation invariant matching. This kind of processing method results in increased processing time proportionately as the data size is increasing. The conventional methods also try to match features with one to one correspondence. That is why the conventional processing methods spend lots of processing time in the large scale database. Also, the conventional iris system uses the multiple image registration for the same person to improve the recognition rate that results in increasing recognition cost.

2. Processing

2.1 Iris Area Extractions

Preprocessing starts from finding the pupil region and the iris region. In order to design a system which is intolerant of iris location, it is necessary to find the position of the center of the iris. In this paper, we employed Circular Edge Detection method which uses both pupils and iris information to extract iris area extraction. The circular edge detection technique is to find the maximum rate of change of the circumference using various center and radius.

The location of center (x_0, y_0) is positioned in any region to find the boundary of the pupil, as shown in Figure 1.

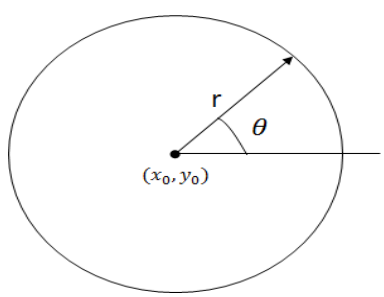

Figure 1. A Schematic Graph of the Circular Boundary Detector

The gray brightness information of the pixels presented on the circumference with radius r is summed up by using the equation 1.

$$\oint_{x_0,y_0,r} \frac{I(x,y)}{2\pi r} ds \quad (1)$$

In equation 2, the maximum changes in the circumference as the radius changes is determined to find the center (x_c, y_c) of the circular edge detector, where $I(x,y)$ is the input image and $G_{0(r)}$ is the Gaussian smoothing function[5].

$$\max(x_0, y_0, r) \left| G_0(r) * \frac{\delta}{\delta r} \oint_{x_0,y_0,r} \frac{I(x,y)}{2\pi r} ds \right| \quad (2)$$

The reason for applying this function is to limit the rate of change maximized in a non-pupil boundary due to the noise, such as eyebrow, eyelid, and iris image in the reflected light.

2.2 Iris Normalization

The iris region is located between the pupil and sclera. Therefore, if the pupil and iris boundary is detected, then the iris region is also obtained. Iris region is thereby normalized, except a remaining portion without changing the entire iris region at a constant rate through the polar coordinate conversion. The reason is that most of the energy of the iris pattern is distributed around the cavity to minimize the eyelid and brow effect. The normalization procedure is to extract the consistency features all the time, irrespective of the change of the area of the iris and the pupil image by varying the distance between the camera and the face or the surrounding environment.

The eye images captured by a camera seem to be rubber movements in which the center of pupil and iris is different. Thus, to solve this situation, the modeling is that poster another circular ring having the radius iris over the varying radius of another circle such as a rubber plate. Figure 2 shows the polar transformation through the rubber movement.

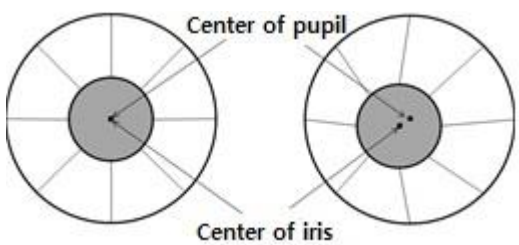

Figure 2. Changes in the Iris Center with Rubber Movement

Coordinate of the iris pattern which is consisting of (r, θ) has r between the [0, 1] and θ available between [0, 2π]. It is thus transforming into the polar coordinate iris image $I(\mathrm{r}, \theta)$ can be expressed as Equation 3.

$$\mathrm{I}\big(\mathrm{x}(\mathrm{r},\theta), \mathrm{y}(\mathrm{r},\theta)\big) \rightarrow I(\mathrm{r},\theta) \quad (3)$$

Where $x(r,\theta)$, $y(r,\theta)$ are lines between pupil boundary $(x_p(\theta), y_p(\theta))$ and iris boundary$(x_i(\theta), y_i(\theta))$ as shown in the Figure 3.

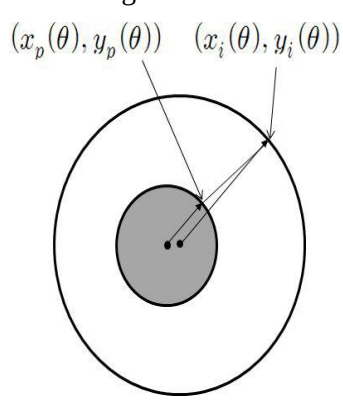

Figure 3. Polar Transformation

Where $I(\mathrm{r}, \theta)$ denotes the gray value for the pixel position in the iris region, r and θ

respectively represent the thickness and the angle of the sampled iris. In addition, $(x_p(\theta), y_p(\theta))$ represents the point present between the pupil and iris boundary, $(x_i(\theta), y_i(\theta))$ represents the point present between the iris and the sclera boundary.

3. Proposed Method

The overall process of recognition is shown in Figure 4, where the entered iris image is processed to find the registered class in the database by using the rotation invariant property of Zernike moment.

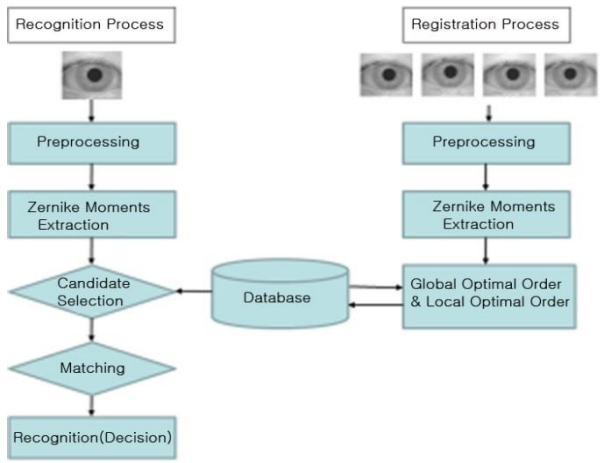

Figure 4. Flow Chart of the Proposed Method

The proposed method is divided into an offline registration process and online registration process. The procedure of registering the multiple images obtained from one iris, that is the various images from one class, extracts the Zernike moments with the local optimum order, and updates the global minimum order on the database.

Thus, the recognition process is to determine which input iris image matches with the registered iris class by using a local optimum order and the global minimum order of Zernike moments obtained during the registration process.

The global optimal order Zernike moments are used to filter the candidate iris classes from the database. The candidate classes selected from the above process can be matched by using the local optimal order which is optimized for each class to compare the measured distance between the input of an iris and the candidate classes.

The number of Zernike moments up to 15 degrees is 72, but not all of the values are used. Because each degree moment shows a different performance of expressing characteristics of the iris[12]. The specific frequency components can have key information even though the iris patterns have the random characteristics of the inherent textures.

In addition, the reason of dividing the selected order to the global optimum and local optimum order is as follows. The global optimum order is used for selecting candidate classes because it shows the best result on the average for the registered classes in the database. The local optimum order is used for determining the similarity between classes because it shows the best result on each specific class.

3.1. Zernike Moment Extraction

Zernike moments are complex orthogonal moments whose absolute values are rotation invariant. Cho-Huak Teh compared various moments with the sensitivity to image noise, the redundancy information and image representation ability[13]. In this study, the Zernike moment is superior to geometric moment, Legendre moment, inertia moment, and the complex moment. Zernike moment is defined within the unit circle, the radiation polynomial $R_{nm}(\rho)$ is defined as equation (4).

$$R_{nm}(\rho) = \sum_{s=0}^{(n-|m|)/2} (-1)^s \frac{(n-s)!}{s!\left(\frac{n+|m|}{2}-s\right)!\left(\frac{n-|m|}{2}-s\right)!}\rho^{n-2s} \quad (4)$$

Where n, m are non-negative integers, and $\mathrm{n}-|m|$ are to be of an even number, must satisfy $|m| \leq \mathrm{n}$. And the Zernike moments of the two-dimensional image $\mathrm{f}(\rho,\theta)$ is defined as formula (5) in the polar coordinate system.

$$Z_{nm} = \frac{n+1}{\pi} \int_{unit} \int_{disk} V_{nm}^{*}(\rho,\theta) f(\rho,\theta) \quad (5)$$

Where $V_{nm}(\rho,\theta)$ is the basis function of Zernike moment in equation (6), and V^* is a complex conjugate.

$$V_{nm}(\rho,\theta) = R_{nm}(\rho)\exp(jm\theta), \qquad \rho \leq 1 \quad (6)$$

The absolute value of the Zernike moment has the same value for the rotated images [14]. This feature can be derived as follows. If the image $\mathrm{f}(\rho,\theta)$ rotated by α, then the image is defined as in equation (7).

$$f^r(\rho,\theta) = f(\rho,\theta+\alpha) \quad (7)$$

When this is applied to the equation (5), we can get as follows.

$$Z_{nm} = \frac{n+1}{\pi}\int_0^{2\pi}\int_0^1 V_{nm}^{*}(\rho,\theta) f(\rho,\theta+\alpha)\rho d\rho d\theta \quad (8)$$

$$Z_{nm}^r = Z_{nm} e^{jm\alpha} \quad (9)$$

$$\left| Z_{nm}^r \right| = |Z_{nm}| \quad (10)$$

Therefore, the absolute value of the Zernike moment has the same value for the rotated image as shown in equation (10).

3.2. Filtering Zernike Moments (Filtering Stage)

The number of Zernike moments up to 15 degrees is 72, which can reconstruct the original picture to substantially the same form [15]. But in iris recognition, it is only necessary to keep the moment coefficients that have high discrimination for features. The discrimination index (discriminability d') is used for the selection of the moment coefficients as shown in Figure 5.

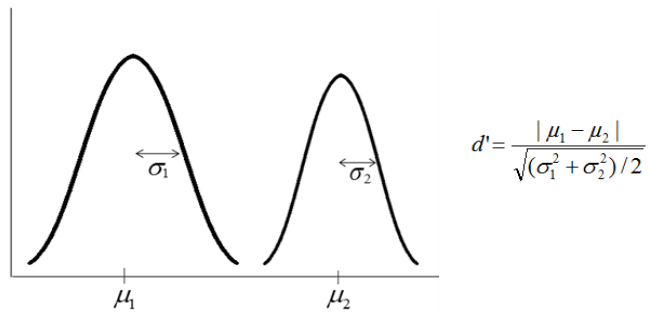

Figure 5. Discrimination Indices for the Two Classes d'

The procedure is as follows. The discriminability d' can be obtained by calculating the Zernike moments up to 15 degrees for all images in the database and take the mean and the variance into account for each degree. Zernike moment degree whose d' has the top 12% in descending order is used for filtering. Namely, the mean and variance within class, and the mean and variance between class are used for calculating discriminability d' to sort in descending order. The top 9 Zernike moment degrees are employed for future matching.
Suppose that the database is in Figure 6 composed of N number of classes, and each class C_j (where j 1, 2, ..., N) has N^{C_j} images. The class corresponds to one of the iris. If the absolute value of the Zernike moment is $|Z_{nm}|$, one iris image can be represented by Zernike moment vectors $x$which are composed of 72 elements, like in Figure 7.

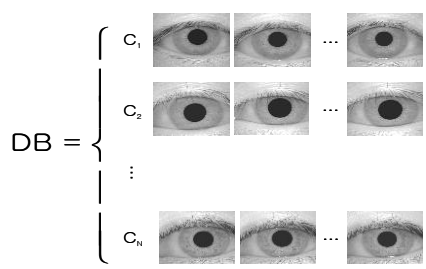

Figure 6. Iris Classes Comprising the Database

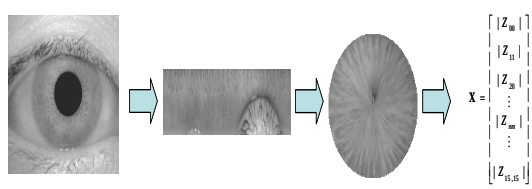

Figure 7. Zernike Moments Vector Extraction Process

Therefore, class C_j may be composed of the N^{C_j} vectors ($C_j = \{\mathbf{X}_1, \mathbf{X}_2, \cdots, \mathbf{X}_{N^{C_j}}\}$). When each component of the vector $\mathbf{X}(n,m)$ has the absolute value $|Z_{nm}|$ of the Zernike moment degree (n,m), the absolute value of Zernike moment of degree (n,m) of class C_j's i' the image can be expressed as $\mathbf{X}_i^{C_j}(n,m)$.

Let's assume that the average of the absolute value of each Zernike moment degree of class

C_j is $\mu_{nm}^{C_j}$, then $\mu_{nm}^{C_j}$ can be calculated like follows.

$$\mu_{nm}^{C_j} = \frac{\sum_{i=1}^{N^{C_j}} \mathbf{X}_i(n,m)}{N^{C_j}} \quad (11)$$

The standard deviation of absolute value of each Zernike moment degree $\sigma_{nm}^{C_j}$ can be calculated like follows.

$$\sigma_{nm}^{C_j} = \sqrt{\frac{1}{N^{C_j}} \sum_{i=1}^{N^{C_j}} (\mathbf{X}_i(n,m))^2 - (\mu_{nm}^{C_j})^2} \quad (12)$$

Therefore, the mean μ_{nm}^{DB} and standard deviation σ_{nm}^{DB} of degree (n,m) for the database can be represented by formula (13) and (14).

$$\mu_{nm}^{DB} = \frac{\sum_{j=1}^{N} \mu_{nm}^{C_j}}{N} \quad (13)$$

$$\sigma_{nm}^{DB} = \sqrt{\frac{1}{N \cdot N^{C_j}} \sum_{j=1}^{N} \sum_{i=1}^{N^{C_j}} (\mathbf{X}_i^{C_j}(n,m))^2 - (\mu_{nm}^{DB})^2} \quad (14)$$

And discrimination index $\varsigma_{nm}^{C_j}$ of each degree (n,m) of class C_j becomes the formula (15).

$$\varsigma_{nm}^{C_j} = \frac{|\mu_{nm}^{C_j} - \mu_{nm}^{DB}|}{\sqrt{(\sigma_{nm}^{C_j})^2 + (\sigma_{nm}^{DB})^2}} \quad (15)$$

In order to select Zernike moment degree (n,m) that has a good discrimination filtering for the entire class, the mean value of each class discrimination index can be calculated by using formula (16).

$$\varsigma_{nm}^{DB} = \frac{1}{N} \sum_{j=1}^{N} \varsigma_{nm}^{C_j} \quad (16)$$

For selecting the good discrimination filtering, ς_{nm}^{DB} is sorted in descending order to select top nine values.

Filtering takes place through the following process. The Zernike moment is calculated from the given the iris image. For the selected nine discrimination filtering degrees, the mean Zernike moment of each candidate class having values between $-\sigma$ and $+\sigma$ passing given criteria from at least eight discrimination filtering can be qualified for next level decision stage.

This filtering process can be made faster when using the indexing method. That is because only sorted filtering degree can be tested in sequence to select classes whose Zernike moments have values between $Z(n,m) - \sigma$ and $Z(n,m) + \sigma$.

3.3. Screening of Zernike Moments (Decision phase)

The decision phase uses a multi-class SVM for candidates that have passed the filtering stage to determine which class it belongs by using Zernike moment degree that best reflect the characteristics of each class. The degrees that were used for selecting

the good discrimination filtering is superior on average but not for each individual class. It does not have the best discriminability d' for some classes. Thus in decision phase, the higher-order 10 degrees which indicate the best performance for each class can be used to classify classes. The top 10 largest value of the discrimination indices $C_{nm}^{C_i}$ is used for training the SVM for C_i class.

3.4. Recognition Using SVM

The selected Zernike moment order is used for recognizing class from large scale database. The recognition process uses SVM which is widely used in pattern matching and recognition area.

If there are N number of classes in the database (N people), then we use N number SVM. The learning method uses the 10-order Zernike moments that best reflect the characteristics of each class for each SVM. For example, SVM uses top ten Zernike moment degrees sorted in descending order, whose value is obtained from the formula (16).

The maximum value of the trained SVM is selected as the matching class when the Zernike moment order is applied for each iris input. However, the predefined threshold is employed to prevent an unregistered class from being matched. If the maximum value of SVM is below the threshold, the class is classified as unknown class.

4. Experimental Results and Discussion

In this paper, we use the CASIA database [16] for conducting the performance evaluation of our proposed method.

4.1. Performance Evaluation

This paper uses the formula (17) to evaluate the recognition performance for the recognition rate.

$$Recognition\ Rate(\%) = \frac{(N_{total} - N_{err})}{N_{total}} \times 100 \tag{17}$$

Where N_{total} is the number of total tested images and N_{err} is the number of misclassified classes that has occurred.

4.2. Experimental Methods

Most of the information for the iris recognition that is contained in the surrounding of the pupil and farther from the pupil boundary is likely to be affected by the eyelids and eyebrows. It shows a better performance when using only a portion of the pupil boundary side than to use the whole area of the iris. In this paper, we use the region in the figure 8 for iris recognition.

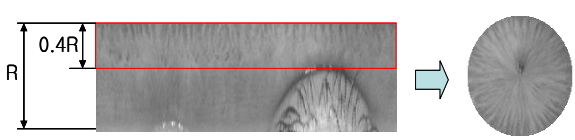

Figure 8. The used Region of Iris Recognition and unit Circle Mapping

In addition, because the Zernike moments are defined only on the unit circle, the area of interest is to be mapped as in the Figure 8, where we mapped the pupil boundary side to the outside of the unit circle. This is to reflect that the information is contained more on the side pupil boundary.

4.3. Experiment Results

4.3.1 Performance Evaluation According to the Number of Zernike Moments used for Filtering

The proposed method can be affected by the number of Zernike moments used for filtering. It is expected that if we reduce the number of Zernike moments, then there is more possibility that the class is missing. If we increase the number of Zernike moments then there are more candidate classes filtered that increase the recognition processing time.

Table 1 shows the mean and the probability that the class is missing according to the number of Zernike moments used for filtering.

Table 1. The Mean of the Number of Candidate Classes and the Missing Probability According to the Number of Zernike Moments

Zernike moment number	Mean of the number of candidate class	Likely to be missed probability (%)
5	24.98	0
6	21.32	0
7	18.24	0
8	14.39	0
9*	12.23	0
10	10.86	0.13
11	9.91	0.22
12	9.16	0.35
13	8.53	0.51
14	8.14	0.64
15	7.72	0.73
16	7.58	0.86
17	7.31	1.15
18	7.25	1.42

The number of the moments used by the filtering step should be determined so as to minimize the number of candidates which should include the true matching class. From the experiment, the number of moments used for filtering may be determined that the optimum number is 9. The number of classes passing through the filter stage at this condition is 11%.

Table 2 shows the Zernike moment degree in descending order of ς_{nm}^{DB} discrimination index.

Table 2. Zernike Moment Degree and Discrimination Indices for Filtering

Zernike Moment Degree	Discrimination Index
Z(14,0)	3.621733
Z(2,0)	3.542077
Z(6,0)	3.031972
Z(4,0)	2.820777
Z(6,2)	2.81767
Z(10,4)	2.76081
Z(7,3)	2.759701
Z(8,0)	2.732673
Z(8,2)	2.527476

4.3.2 Performance According to the Number of Zernike Moments used by the Decision Step

In decision step using a multi-class SVM, the evaluation, which is based on the number of Zernike moments, is made in the correct recognition accuracy on the test images by varying the number of Zernike moments used in the training of the SVM.

We divided seven iris image data set per class into two groups, which are the training group and the test group. We chose four randomly selected images per each class for training the SVM, and the remaining three images were used to test the trained SVM.

The SVM was implemented by using LIBSVM [17], and the kernel was implemented by using RBF (Radial Basis Function). Gamma value of 0.6 was used as RBF, and the penalty factors for misclassification (penalty parameter), the value of C, was set to 20. Table 3 shows the performance and recognition results using the parameters.

Table 3. Recognition Performance of the Multi-class SVM

Number of Zernike moments	Success	Failure	Recognition rate
3	262	62	80.86
4	283	41	87.35
5	299	25	92.28
6	311	13	95.99
7	317	7	97.84
8	320	4	98.77
9	321	3	99.07
10	322	2	99.38
11	322	2	99.38
12	322	2	99.38

Table 4. Feature Extraction Time

	Proposed method	Daugman method
Feature Extraction(msec)	62	47

Table 5. Recognition Time According to the Number of Images Per Class

Recognition time(sec)	Proposed method	Daugman method
108 images (1/class)	0.23	0.20
216 images (2/class)	0.23	0.39
324 images (3/class)	0.23	0.59

Table 6. Recognition Time According to the Rotational Angle Correction

Recognition time(sec)	Proposed method	Daugman method
-5 ~ 5 degree	0.23	0.45
-10 ~ 10 degree	0.23	0.59
-15 ~ 15 degree	0.23	0.73

The proposed method takes more time for feature extraction from Table 4, but the feature extraction time is not a problem because only one execution is performed on an input image.

The comparison result of the recognition time between the proposed method and the Daugman method are shown in Table 5.

It clearly reveals the difference between the conventional method and the proposed method. In the case of the conventional method, the recognition time is increased in proportion as the increasing number of images, but the proposed method is not increased in recognition time even when the number of registered images per class is increased. In most cases, to increase the correct rate of iris recognition system, more than one image per class is registered per person. As a result, the recognition time becomes slow. But the proposed method is not affected because it uses the statistical properties of the Zernike moments.

Next, the result of the recognition time of the rotational angle correction from Table 6 shows that the time is increased as the rotational angle is bigger in the Daugman method. This is due to the increased comparison time which the extracted feature values are compared in proportion to the rotation range as mentioned in earlier chapter. In contrast, the proposed method does not change the recognition time. The additional processing is not necessary for the image rotation because of Zernike moment using a rotation invariant property.

5. Conclusion

In this paper, we proposed a new method using the Zernike moments which makes use of filtering the candidate class in the iris database and using a multiple SVM for recognizing iris.

The proposed method confirmed that no additional processing time was required for the rotation using the characteristics of Zernike moment. In addition, only the candidates that pass through the filter undergo the recognition process using the multi-SVM. So, it is possible to match fast because the search process did not match one to one feature data like conventional methods. Therefore, the proposed method could be effectively applied to the mass iris recognition system.

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