Ordinal Measure of Discrete Cosine Transform Blocks for Iris Identification

[1,2]Fitri Arnia, [1]Fery Irianda,[3]Siti Aisyah, [1,2]Khairul Munadi

[1]Department of Electrical Engineering, Syiah Kuala University, Banda Aceh 23111, Indonesia; [2]Master of Electrical Engineering Program, Syiah Kuala University, Banda Aceh 23111, Indonesia; [3]Department of Electrical Engineering, Batam Polytechnic, Batam 29461, Corresponding Author: fitriarnia@elektro.unsyiah.ac.id

Abstract. Currently, a common method for identifying a person is by means of an identity card (ID) or combination of an ID and password. The approaches are not very reliable, since the ID can be stolen and password can be forgotten. A more reliable identification system is required. In the last decades, identification systems based on biometrics have been gaining attention, since they are more reliable. Biometrics-based devices identify people based on their physical or psychological characteristics, such as palmprints, fingerprints, gait and iris. Unlike fingerprints or palmprints, irides features distribute randomly, and the features were unique; the features between right and left eyes are different, as well as between twins. Therefore, in addition to reliability, the use of irides can enhance identification accuracy. Purpose of the paper was to improve identification rate of an iris identification method, using ordinal measure of Discrete Cosine Transform (DCT) coefficient. The input iris image was tiled into blocks of 8x8 pixels, then the DCT was applied to each blocks. The AC coefficients of each block were sorted from the smallest to the largest values, in which the sorted values were referred to as ordinal measures. Identification was accomplished by measuring a distance between the ordinal measure of the input images with the ones of the existing images in the database using Minkwoski distance metric. Proposed method increased the averaged identification rate as compared to the previous method by nearly twice from 33% to 61.4%.
Keywords: Ordinal measure of DCT coefficients, iris identification, Minkowski distance.

Introduction

Currently, a common method for identifying a person is by means of an identity card (ID) or combination of an ID and password. The approaches are not very reliable, since the ID can be stolen or copied without the authorized owner being realized, and password can be forgotten. To solve this issue, a biometrics-basedidentification system, in which the identification was based on physical characteristics of an individual such as fingerprints, palmprints, gait and iris, has been developed. Identification systemsthat based on biometrics were claimed more reliable, since each person has a unique biometric characteristic. Amongst the biometrics mentioned above, iris was reportedto have the highest reliability, since iris texture was randomly distributed; the texture betweenleftand right eyes are different, as well as between the twins.

In the last two decades, many iris identification methods have been developed (Wildes, 1997; Daugman, 2002; Miyazawa etal., 2005; Arnia etal., 2011). Moreover, recent year developments attempt to identify iris in more complicated conditions, such as identifyingnoisy iris image that has been captured from a distance and/or in different lighting conditions. Previously, ordinal measure of *Discrete Cosine Transform* (DCT) was applied to detect copies of an image. In this case, image's copies were originated from a single image, and experienced several kinds of changes/attacks, including lighting and gamma changing and noise addition (Kim, 2003). Ordinal measure of DCT coefficient implemented for identifying iris image wasa relatively new method (Arnia *et al*., 2012).

This paper proposedthe use of ordinal measure of DCT for identifying iris. Input iris image was normalized and then tiled into blocks of 8x8 pixels. Furthermore, the DCT transform was applied to each block. Then the AC coefficients of each block were sorted by their absolute values,which were referred to as ordinal measure. Identification was accomplished by measuring a distance between ordinal measuresof an input image with those of the existing images in the database, using Minkowski distance metric. Compared to the previous method (Arnia etal., 2012), the proposed method increasedaveraged identification by nearly twice, from 33% to 61.4%.

Materials and Methods

The proposed method was evaluated on the basis of simulation results. This section represented simulation conditions and simulation steps of the proposed method.

Simulation condition

Iris image used in the simulation was the iris images from CASIA (Chinese Academy of Sciences. 2003)–IrisV1 database. The databaseconsisted of 756 iris images, taken from 108 persons (classes). Each person (class)consisted of seven images, which taken by two types of cameras in different times. For convenience, images in CASIA-IrisV1 database was renamed into Casia-1 to Casia 756 (abbreviated withC-1 to C-756). From the database, 10 query images (also referred to as test image or input image) were randomly selected. To analyse the proposed method, we compared it with the method in (Arnia etal., 2012). As many as 10 query images (which correspond to 10 persons/classes) were used.The query images were the same images as the ones used in (Arnia etal., 2012). Table 1 listed the query images and all images from each query image's class. In the next sections, the term of query images, input images and test images will be used interchangeably.

Simulation steps of the proposed method

The proposed method was simulated based on the sequence illustrated in Figure 1 and was described as follows:

1. Normalized image (size 240 x 20 pixels) was tiled into blocks of8x8 pixelsto produce 60 blocks in one iris image.
2. All 60 blocks werethen transformed using discrete cosine transform (DCT) resulting in DCT coefficients of each block.
3. Ordinal measureswere generated by sorting the absolute values of AC part of the DCT coefficients. As many as 60 ordinal measures were produced from 60 blocks of DCT coefficients. Steps 1 to 3 wereperformed on the input image and the database image.
4. Calculating Minkowski distance between ordinal measure of input images and ordinal measure of database images, which resulted in 60 distances.
5. Averaging the distances.
6. Identify the images based on the average distance.

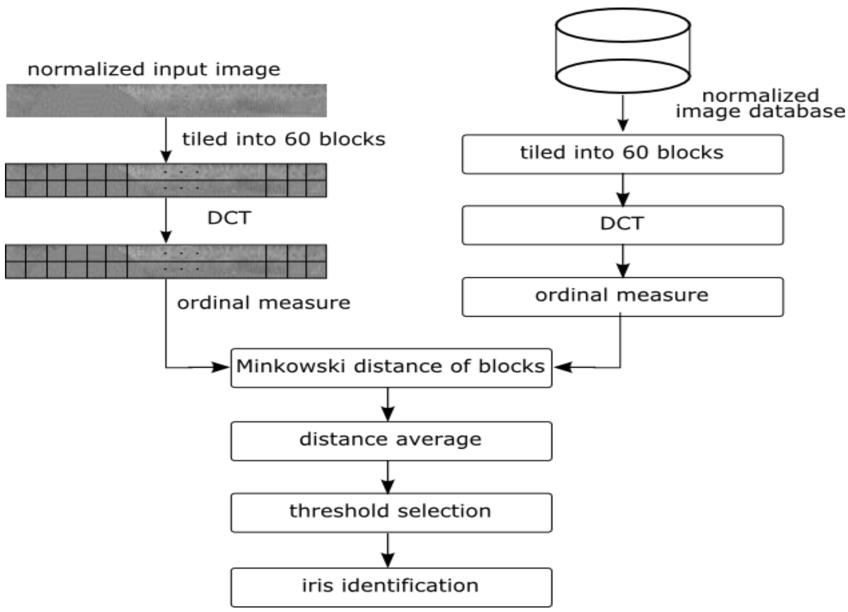


Figure 1. Simulation diagram of the proposed method

Table 1. Query images and images in the same class with query image

Query Image	Images of Query Image's class
C-2	C-1 until C-7
C-64	C-64 until C-70
C-207	C-204 until C-210
C-273	C-273 until C-279
C-343	C-343 until C-349
C-420	C-420 until C-426
C-484	C-481 until C-487
C-556	C-551 until C-557
C-625	C-622 until C-628
C-691	C-691 until C-697

7. If the distance between the input images and one of the database imageswas less than a specified threshold value, the image was identified and vice versa.

The distance between two block images according to Minkowski equation is defined as,

$$d(m,d) = \sum_{l=1}^{N=63} |m_l - d_l|$$

where*m* represents blocks of input image
*d*represents blocks of database image

Performance of the proposed method was measured by calculating an identification rate, i.e. number of images in one class that has the closest distance to the input iris image (measured in percentage). Here, 100% identification rate indicated that all images in a class identified with the closest distance to the input iris image. It is worth noting that when an image had been selected as an input, it has six other image versions in the database. The distances of two identical images were "zero". In implementation, a threshold value to separate images in one class fromimages of other classes has to be determined.

Results and Discussions

Simulation results are shownin Table 2 to 11. Each table represents one input image. In the second column of each table, names of iris image with the closest distance to the input image were listed. The image's names that were printed in bold were images of the same class with the input image. In general, the identification rate ranged between 14% (Table 4) and 86% (Tables 2, 3 and 9), with averaged identification rate 61.4%. For identification rate of 86%, the input image had the closest distance to the images in its own class, as shown in Tables 2 and 3. Meanwhile, foridentification rate less than 86%, the input image did not always have the closest distance to the images in its own class. The smallest identification rateof 14% occurred when the input image C-207 was used (Table 4).

Lists of identification rate of the proposed method as well as method in (Arnia etal., 2012) were given in Table 12. Both methods usedapproximately the same iris area of normalized iris image. However, the proposed method tiled the iris image region into blocks, in which the size of each block was 8x8 pixels. Although both methods used a comparable iris region, averaged identification rate of the proposed method increasedby nearly twice from 33% to 61.4%.

Commonly, characteristics of the identification rate follow three trends. First, the identification rates of both methods were fixed, for example identification of C-2. Second, the identification rates of the proposed method were significantly improved, for example the identification rate of C-64, C-273, C-343, C-420, C-484, C-556, C-625 and C-691. Third, the identification rate of the two methods remain low, i.e.the identification rate of C-207.

Table 2. Rank dan distance of input iris image C-2

Rank	Image	Normalized Distance
1	C-2	0.000
2	C-4	0.1786
3	C-7	0.1786
4	C-3	0.1834
5	C-1	0.1923
6	C-5	0.2018
7	C-394	0.2034

Table 3. Rank dan distance of input iris image C-64

Rank	Image	Normalized Distance
1	C-64	0.000
2	C-65	0.2275
3	C-66	0.2735
4	C-67	0.3435
5	C-69	0.3447
6	C-70	0.3487
7	C-57	0.3530

Table 4. Rank dan distance of input iris image C-207

Rank	Image	Normalized Distance
1	C-207	0.000
2	C-649	0.2350
3	C-663	0.2364
4	C-232	0.2413
5	C-669	0.2420
6	C-664	0.2459
7	C-668	0.2533

Table 5. Rank dan distance of input iris image C-273

Rank	Image	Normalized Distance
1	C-273	0.000
2	C-274	0.3506
3	C-278	0.3518
4	C-275	0.3600
5	C-245	0.3638
6	C-276	0.3711
7	C-247	0.3773

A result of the proposed method with the input image C-2 suggests that the use of the entire image either at once or per block did not affect the identification rate value. This could mean that parts of the iris image in this class were very consistent between one imageto another. Irisimage of this class was shown in Figure 2a. Meanwhile, a significant improvement in identification rate of the proposed method can be explained as follows. Method in (Arnia *et al*., 2012) calculated the DCT coefficients of the overall normalized iris images (20x240 pixels) at once, sorted them into ordinal measure, and then measured the distance between two iris images. As known, the DCT compress the most important part of information into only the first few coefficients. Therefore, from the DCT coefficients of 20x240, only the first few coefficients (low frequency) holds the characteristics of the iris image which its represent, the rest can be treated as noise (high frequency). The use of all coefficients, including the high-frequency coefficients, can expand a distance between the images in the same class due to noise part in high frequency.On the other hands, the proposed methoddivided the iris image into blocks of size 8x8 pixels. Effect of using all frequency components, including high frequency of these blockswas less significant. In the future, extended experiments and deep analysis are required to quantify the results.

For most input images, the identification rate of the proposed method tended to rise. However, it is not the case whenthe input image was C-207. For the image, there was no improvement in identification rate. This can be due to variances of iris position and lighting differences between one image andothers in the corresponding class. The images of this group were shown in Figure 2.b.

Normalized distances listed in Table 2 and Table 11 showed that there was a variation ofdistance interval between image's classes. For example, in Table 2, the furthest distance of the images within the same class was about 0, 2. While in Table 3, the furthest distance of the images within the same class was about 0.35. These values can result in difficulties when a threshold that will be used for the whole systemhadto be determined.In the future, approaches to minimize those variations would be required.

Table 6. Rank dan distance of input iris image C-343

Rank	Image	Normalized Distance
1	C-343	0.000
2	C-344	0.2221
3	C-348	0.2354
4	C-347	0.2471
5	C-346	0.2656
6	C-78	0.2973
7	C-709	0.2992

Table 7. Rank dan distance of input iris image C-420

Rank	Image	Normalized Distance
1	C-420	0.000
2	C-421	0.2754
3	C-422	0.3026
4	C-424	0.3112
5	C-107	0.3170
6	C-423	0.3175
7	C3-90	0.3209

Table 8. Rank dan distance of input iris image C-484

Rank	Image	Normalized Distance
1	C-484	0.000
2	C-481	0.2707
3	C-637	0.3303
4	C-485	0.3651
5	C-65	0.3817
6	C-64	0.3843
7	C-752	0.3843

Table 9. Rank dan distance of input iris image C-556

Rank	Image	Normalized Distance
1	C-556	0.000
2	C-553	0.2999
3	C-554	0.3316
4	C-552	0.3371
5	C-145	0.3576
6	C-557	0.3588
7	C-551	0.3693

Table 12. Identification rate of the proposed method, compared with the method in (Arnia. *et al*. 2012); measured in percentage

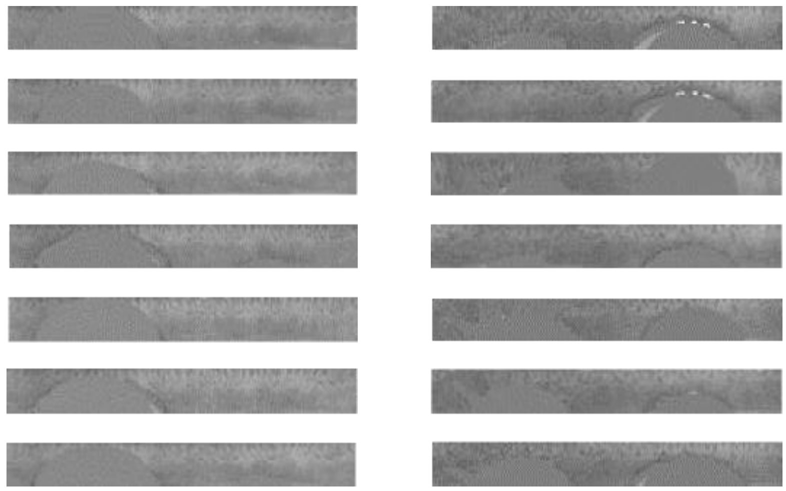
Used AC Coefficients	Input Iris Image										
	C-2	C-64	C-207	C-273	C-343	C-420	C-484	C-556	C-625	C-691	Average
Proposed Method	86	86	14	71	71	71	43	86	57	57	61.4
Method in (Arnia. et.al. 2012) with all coefficients	86	43	14	14	57	14	14	43	14	29	33

Table 10. Rank dan distance of input iris image C-625

Rank	Image	Normalized Distance
1	C-625	0.000
2	C-624	0.2749
3	C-564	0.2784
4	C-558	0.2871
5	C-626	0.2885
6	C-319	0.2960
7	C-622	0.3038

Table 11. Rank dan distance of input iris image C-691

Rank	Image	Normalized Distance
1	C-691	0.000
2	C-692	0.3309
3	C-158	0.3792
4	C-693	0.3816
5	C-388	0.4020
6	C-658	0.4078
7	C-695	0.4081



(a). Iris image C- 2 (2nd column) and images in its class

(b). Iris image C- 207 (5th column) and images in its class

Figure 2. Examples of two iris image classes used in the simulation

Conclusions

This paper proposed the use of ordinal measure for iris identification, in which the ordinal measure was calculated from blocks of *Discrete Cosine Transform (DCT)* coefficients. Identification was accomplished by measuring the distance between ordinal measure of input iris image andthose of the existing iris imagesin the database, using the Minkowski distance. The proposed method increased averaged identification rate by nearly twice, as compared to the previous method, from 33% to 61.4%. However, it is necessary to develop a method to minimize the variation of distance interval of image's class, thus a global thresholdcan be determined correctly.

References

Arnia F., Pramita N. 2011. Enhancement of Iris Recognition System Based on Phase Only Correlation.Telkominika, Vol.9, No.2, pp. 387-394.

Arnia F., Munadi K., Fujiyoshi M., Kiya H. 2012. Iris recognition method based on ordinal measure of discrete cosine transform coefficients. 2012 IEEE Symposium on Computers & Informatics (ISCI), pp. 203-207.

Chinese Academy of Sciences. 2003. Institute of Automation. Database of 756 Greyscale Eye Images. [Online] Available: http://www.sinobiometricss.com Version 1.0.

Daugman J. 2002. How iris recognition works. IEEE Conference on Image Processing. Rochester, New York(1): 33-36.

Kim. C. 2003. Content-based image copy detection. Sig. Proc.: Image Comm. 18(3). pp. 169-184.

Miyazawa K, Ito K, Aoki T, Kobayashi K, Nakajima H. 2005. A Phase-Based Iris Recognition System. In: D. Zhang, A.K. Jain, Editors. Lecture Notes in Computer Science (LNCS) 3832. Berlin Heidelberg: Springer Verlag. pp. 356-365.

Wildes R. 1997. Iris Recognition: An Emerging Biometrics Technology. Proceedings of the IEEE. 1997; 85: pp. 1348-1363.