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Ordinal Measure of Discrete Cosine Transform (DCT) Coefficients And Its Application to Fingerprint Matching

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ABSTRACT

Recently, the identification system is not limited in using an ID and personal identification number (PIN) but also in using biometriccharacteristics.One of biometric characteristics that has been widely used is fingerprint.This paper proposes a fingerprint matching algorithms using ordinal measure of DCT coefficient. The ordinal measure of DCT coefficient is generated from DCT blocks with size 8x8 pixels. Matching level was determined by computing the Minkowski distance between features of input fingerprint image and fingerprint images in the database. The simulations were accomplished using 128 fingerprints that have been normalized, from which as many as 1024 genuine attempts and 15360 impostor attempts were generated. The proposed algorithms achievedan Equal Error Rate (EER) at threshold 0.3. At the EER, it resulted in FAR value of 0.82%, and FRR value of 78.41% respectively. The low value of FAR showed that the system wasconsiderably secure.

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1. INTRODUCTION

The rapid growth of technology has enforced the development in all aspects including identification technology. Recently, the identification system is not limited in using an ID and personal identification number (PIN) but also in using biometriccharacteristics. Biometric characteristics is an individual biologic characteristic that identifies a person.One of the biometric characteristic that has been widely used is fingerprint. This identification system is applied mostly for security system and authentication system [1]. The system has two stages, the first stage is capturing fingerprint features and the second deciding the matching level of the input fingerprint featureto the features saved in the database.

The fingerprint feature is usually categorized into three levels. The first level is macro feature of the fingerprint such as ridge flow and pattern type. The second feature level is known as Galton feature (minutiae) such as ridge bifurcations and endings. The third feature level or shape includes all attributes of ridges such as ridge path deviation, width, shape, breaks, scars and other permanent details [2]. The performance enhancement of the fingerprint recognition is investigated in [2] where second and third feature levels are used. It is found that there is an improvement around20% in terms of EER if both of the features are employed. The work in [3] proposes a combination of texture features and minutiae for fingerprint matching. It is argued that features (descriptors) instead of the minutiae itself are required to increase the matching rate of a fingerprint system. The correspondent between two individual features is established by an alignment-based greedy matching algorithm. The features are implied in order to carry out the deficiency of minutiae in the orientation matching.

One of the features that resists to the changing of orientation and lighting is ordinal measure of DCT coefficient [4]. This feature has been used for image matching in image retrieval application. Particularly for biometric, the ordinal measure of DCT coefficient was also applied as a feature to identify iris biometric [5, 6, 7]. It was reported that the ordinal measure of DCT coefficient was able to reach the iris identification rate of more than 60%.

This paper proposeda fingerprint matching algorithmusing ordinal measures of DCT coefficient asfeatures. The ordinal measure was calculated by ordering the absolute value of AC components of DCT coefficients of each image’s block with size 8x8 pixels. Matchingwas determined by computing the Minkowski distance between features of input fingerprint image and fingerprint images in the database. Furthermore, a threshold value that provided a trade-off between FAR and FRR values, wasselected. The simulation wasaccomplished using 128 fingerprints that have been normalized, from which as many as 1024 genuine attempts and 15360 impostor attempts were generated. The proposed algorithms achieved an Equal Error Rate (EER) at threshold 0.3. On the EER, the value of FAR and FRR were 0.82% and 78.41% respectively. The low value of FAR shows that the system wasconsiderably secure because the possibility that the system receives the fingerprint from unregistered individual was small. On the other hand, high FRR value shows that the system was very selective, means that there was no guarantee that the registered users will be accepted by the system.

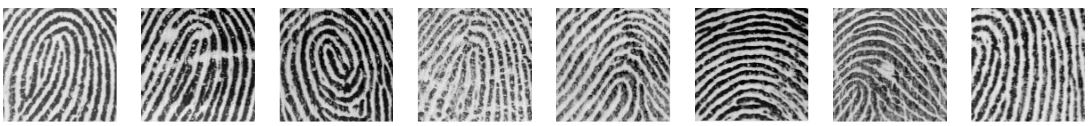
2. RESEARCH METHOD

The fingerprint matching algorithm proposed in this paper was evaluated based on simulation results. Initial step in this research was the preparation of fingerprint image database, followed by designing the identification algorithm. Finally, the algorithm was implemented and evaluated using fingerprint images saved in the database.

The database of fingerprint imageswas obtained from UPEK Fingerprint Database [8]. The images in the database were taken from 16 individuals (classes), in which each class consisted of 8 image versions; thus the total image in the database was 128. The actual size of each image in the database was 338 x 248 pixels. These images were first normalized with regard to size and its relative spatial position. The size of the normalized image was 128 x 128 pixels while the center of the fingerprint was set manually so that it was located in the centre of the image. Several original images in the database and their normalized versions are shown in Figure 1.

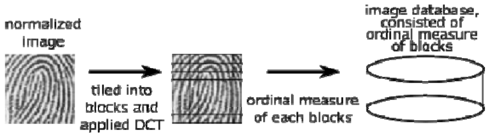
The proposed matching algorithm was divided into two stages and illustrated in block diagrams as shown in Figure 2. The first stagewas the process of building fingerprint image database, which is illustrated in Figure 2(a). The second stagewas fingerprint image matching process as shown in Figure 2(b). The building of database was initiated with normalizing the size of the images in the database into 128 x 128 pixels. Furthermore, the normalized images were tiled into blocks with size 8 x 8 so that the total block was 256. Then, each block was transformed using discrete cosine transform (DCT) so that each block haditsDCTcoefficients. Finally, the absolute value of the AC component of DCT coefficientof each block was sorted in order to obtain the ordinal measure. All of these ordinal measures were stored in the database for subsequent matching process. In this case, ordinal measure of DCT coefficient is the feature of the proposed algorithm.

a. Original fingerprint images with size of 338 x 248 pixels

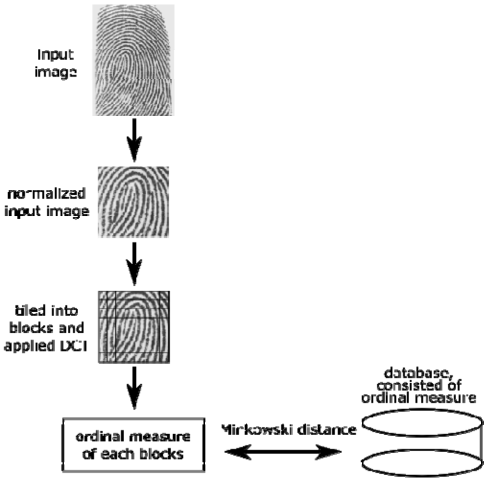


b. Normalized fingerprint images with size of 128 x 128 pixels

Figure 1. Original fingerprint images and their normalization



a. Image database generation process



b. Diagram of the proposed matching technique

Figure 2. Database generation and the proposed matching technique

The proposed matching algorithm was similar to the database building process. The input images were normalized, tiled, and transformed to DCT in order to obtain the ordinal measure. Furthermore; the distance of ordinal measure of the input image and all of ordinal measure in the database were calculated using Minkowski distance based on Eq. 1.

$$d(q,u) = \sum_{l=1}^{N} |q_l - u_l| \quad (1)$$

where *q* dan *u* were ordinal measure of the input image and the database image respectively , and *l*was the total AC components from each 8x8-pixel block, which were 63 coefficients. In the matching process, ideal condition was achieved if the Minkowski distances between the images in a particular class were very small or approaching zero.

Performance of the proposed algorithms was obtained by calculating the distances between all the images in the database. For instance, distances ofthe first image to 128 other images in the database werecomputed, and then distance of the second image to 128 other images in the database were also computed, and so on until 16384 distance values were obtained. From the total distance, 1024 were the genuine attempts and 15360 were impostor attempts. These distance values were used to create two distribution curves named as genuine distribution and impostor distribution. Genuine distribution was a histogram of all image distances from one class, while the impostor distribution was the histogram of all image distances from different classes.

The proposed algorithm performance was measured using two evaluating parameters, which are False Acceptance Rate (FAR) and False Rejection Rate (FRR). FAR is defined as the acceptance error rate in matching process. It happens when the system accepts the input image that supposed to be rejected because it comes from different classes. The FAR is formulated in Eq. 2 as follows

$$FAR = \frac{\text{Total of error acceptance}}{\text{Total of impostor event}} \text{ x } 100\% \quad (2)$$

The FRR denotes the condition if the system is making an error when rejecting the input. This means that the input image that supposed to be accepted by the system because the image has been registered in the database, being rejected by the system. The FRR is given in Eq. 3 as follows

$$FRR = \frac{\text{Total of error rejection}}{\text{Total of genuine event}} \text{ x } 100\% \quad (3)$$

The value of FAR and FRR can be calculated by joining genuine distribution and impostor distribution curves. Then, on the combined curve the value of Equal Error Rate (EER) can be determined.

3. RESULTS AND ANALYSIS

Analysis of simulation results were classified into into three sections. The first section described the Minkowski distance between one input image and other images from different classes that were available in the database. The second section illustrated the distance variability in one image class. The simulation data from the first and the second part were tabulated in Tables1 to 12. These results describedempiric results of the proposed algorithm. The third section discussed the whole performance of the proposed algorithm, indicating by FAR and FRR value as shown in Figure 4.

3.1. Minkowski Distance of Inter Class Images

Table 1 to 12providesevera instances of distances betweenan input image and all images in the database. There are sixteen classes, in which each class consisted of eight versions that were written as 1_1, 1_2, … 2_1, 2_2, … 16_1, … and 16_8. The highlighted data in these tables meant that the data belong to the same class as the input image, and will contribute to genuine distribution. On the other hand, data that were not highlighted are data from different class and give contribution to impostor distribution.

Table 1. Matching rank and Minkowski distance of input image 7_8

Rank	Database's Images	Minkowski distance
1	**7_8**	**0**
2	**7_6**	**0.5483**
3	**7_1**	**0.5971**
4	**7_7**	**0.6035**
5	**7_3**	**0.6043**
6	**7_5**	**0.6277**
7	**7_2**	**0.6307**
8	14_7	0.6443
9	13_4	0.6522
10	13_8	0.6654
11	1_8	0.6672
12	13_2	0.6701
13	9_8	0.6783
14	13_1	0.6791

Table 2. Matching rank and Minkowski distance of input image 8_4

Rank	Database's Images	Minkowski distance
1	**8_4**	**0**
2	**8_3**	**0.4631**
3	**8_6**	**0.479**
4	**8_7**	**0.4874**
5	6_8	0.4903
6	12_7	0.4955
7	**8_8**	**0.4988**
8	6_7	0.5002
9	**8_2**	**0.5018**
10	11_6	0.5021
11	6_3	0.5067
12	6_4	0.5069
13	**8_5**	**0.5075**
14	**8_1**	**0.5122**

Table 3. Matching rank and Minkowski distance of input image 1_1

Rank	Database's Images	Minkowski distance
1	**1_1**	**0**
2	**1_7**	**0.526**
3	**1_5**	**0.5754**
4	13_3	0.5884
5	**1_8**	**0.5959**
6	**1_2**	**0.5989**
7	**1_4**	**0.608**
8	13_2	0.6091
9	13_4	0.6136
10	**1_3**	**0.6206**
11	13_1	0.6222
12	3_3	0.6225
13	14_8	0.6323
14	14_7	0.6328

Table 4. Matching rank and Minkowski distance of input image 15_8

Rank	Database's Images	Minkowski distance
1	**15_8**	**0**
2	5_7	0.2452
3	**15_5**	**0.2456**
4	**15_7**	**0.2468**
5	4_6	0.2501
6	4_8	0.2522
7	16_5	0.2544
8	4_5	0.2598
9	5_8	0.2601
10	4_2	0.263
11	**15_3**	**0.2647**
12	13_7	0.2665
13	5_5	0.2666
14	**15_6**	**0.2728**

Table 1 to 4 present several distance values between input fingerprint images and the images in the database after being sorted from the closest to the furthest. Four samples of input images, namely image 7_8, 8_4, 1_1 and 15_8 were evaluated. These tables contained only fourteen closest distances. Table 1 shows a good matching result, in which seven fingerprint images were being identified as genuine from total eight images that represent one individual (class).At this point, it may be said that the matching rate approaching 82.5%.

Table2 and 3 show poor matching results since the images belong to a particular class did not have the closest distance to the input image of the corresponding class. In Table 2, all of the images from the same classeswererankedfrom number one to fourteen, but not at the highest ranks. The worst condition was illustrated in Table 4, in which only five images from the same class obtained the smallest distance. The distance values given in Tables2 to 4 expose inter-classvariability.

3.2. Minkowski Distance of Intra-class Images

Table 5 to 12 contain matching rank and Minkowski distance from the images in one class. Here, it wasrepresented by class 10. In Table 6 and 9, the matching rate approached 87.5%, while in Table 7, the matching rate was 100%. In other tables, the matching rate varied in the range of 25% to 75%. The distance values in those tables indicated that the intra-class variability wassufficiently high.

To obtain illustration of the relationship between the matching rates and the condition of the images used in the simulation, please refer to Figure 3. Figure 3 shows the images whose distance valuesbetween them provided in Table 5 to 12. Observation to those images related to variation of matching rates resulted in two considerations. The first one is that those images did not go through an image registration process. There was pixel shifting from one imageto another, which was caused by manually cropping the images during the normalization process. The second onewassize of DCT block applied in the process was very small, which was8x8 pixels in this case. Theblock size was not sufficient to represents uniqueness of ordinal measures of DCT coefficients of the corresponding blocks.

Table 5. Matching rank and Minkowski distance of input image 10_1

Rank	Database's Images	Minkowski distance
1	**10_1**	**0**
2	15_2	0.3822
3	16_8	0.3822
4	16_5	0.3829
5	16_7	0.3844
6	16_4	0.3851
7	**10_4**	**0.386**
8	13_5	0.3908
9	15_3	0.3909
10	16_1	0.3944
11	16_3	0.4032
12	15_6	0.4034
13	13_7	0.4041
14	5_6	0.4056

Table 6. Matching rank and Minkowski distance of input image 10_2

Rank	Database's Images	Minkowski distance
1	**10_2**	**0**
2	**10_3**	**0.4736**
3	**10_4**	**0.502**
4	**10_5**	**0.5025**
5	**10_8**	**0.5138**
6	**10_7**	**0.5169**
7	15_2	0.5189
8	16_2	0.5328
9	13_6	0.5331
10	7_2	0.5368
11	16_6	0.5384
12	16_3	0.5386
13	**10_6**	**0.5404**
14	7_7	0.5416

Table 7. Matching rank and Minkowski distance of input image 10_3

Rank	Database's Images	Minkowski distance
1	**10_3**	**0**
2	**10_2**	**0.4729**
3	**10_4**	**0.4832**
4	**10_6**	**0.4937**
5	**10_7**	**0.5004**
6	**10_1**	**0.507**
7	**10_8**	**0.5133**
8	**10_5**	**0.5151**
9	15_2	0.526
10	16_2	0.5301
11	13_6	0.5383
12	15_1	0.5387
13	16_6	0.541
14	7_7	0.5422

Table 8. Matching rank and Minkowski distance of input image 10_4

Rank	Database's Images	Minkowski distance
1	**10_4**	**0**
2	**10_1**	**0.4255**
3	16_2	0.4333
4	16_1	0.4404
5	16_3	0.4419
6	16_7	0.4419
7	**10_3**	**0.4432**
8	15_2	0.4487
9	13_6	0.4521
10	**10_8**	**0.4531**
11	16_4	0.4535
12	16_5	0.4559
13	**10_7**	**0.4565**
14	**10_5**	**0.4579**

Table 9. Matching rank and Minkowski distance of input image 10_5

Rank	Database's Images	Minkowski distance
1	**10_5**	**0**
2	**10_7**	**0.3821**
3	**10_8**	**0.4094**
4	16_2	0.447
5	15_2	0.4532
6	**10_4**	**0.4639**
7	**10_2**	**0.4662**
8	15_1	0.4726
9	16_1	0.4774
10	15_3	0.4778
11	15_4	0.4779
12	**10_3**	**0.4786**
13	16_7	0.4793
14	**10_6**	**0.4815**

Table 10. Matching rank and Minkowski distance of input image 10_6

Rank	Database's Images	Minkowski distance
1	**10_6**	**0**
2	**10_7**	**0.4566**
3	**10_8**	**0.4577**
4	**10_3**	**0.4707**
5	**10_4**	**0.4828**
6	15_2	0.4838
7	15_4	0.4845
8	16_2	0.4893
9	15_3	0.4898
10	15_1	0.4916
11	**10_5**	**0.494**
12	16_6	0.5009
13	16_1	0.5062
14	16_3	0.5065

Table 11. Matching rank and Minkowski distance of input image 10_7

Rank	Database's Images	Minkowski distance
1	**10_7**	**0**
2	**10_8**	**0.3637**
3	**10_5**	**0.3653**
4	16_1	0.4145
5	15_1	0.4175
6	16_3	0.4212
7	15_4	0.423
8	16_2	0.4237
9	15_2	0.4243
10	**10_6**	**0.4254**
11	16_5	0.427
12	15_3	0.4273
13	15_6	0.4285
14	16_6	0.4337

Table 12. Matching rank and Minkowski distance of input image 10_8

Rank	Database's Images	Minkowski distance
1	**10_8**	**0**
2	**10_7**	**0.369**
3	**10_5**	**0.3971**
4	16_1	0.413
5	16_3	0.4163
6	16_4	0.4222
7	15_3	0.423
8	15_2	0.4274
9	16_6	0.428
10	15_5	0.4282
11	16_2	0.4286
12	15_4	0.4296
13	16_7	0.4303
14	16_5	0.4314

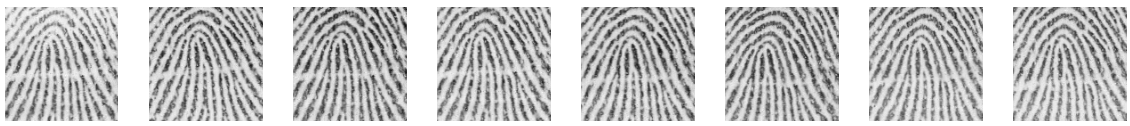
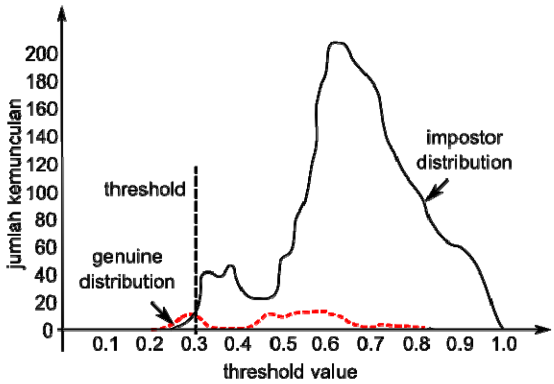


Figure 3. Images of class 10

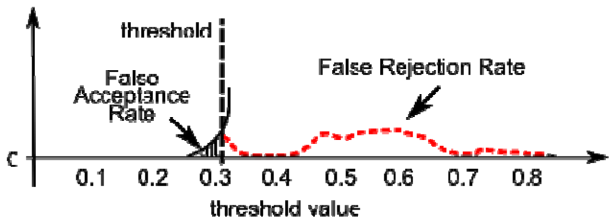
3.3. FAR and FRR of the Proposed Algorithm

Figure 4 illustrates the overall performance of the proposed algorithm using FAR and FRR curves. Histogram of genuine distribution drawn in dash line as shown in Figure 4(a) was generated from 1024 genuine attempts. While an impostor distribution demonstrated by the graph in Figure 4(a) as the solid line was sketch based on as many as 15360 impostor attempts. A better illustration of FAR and FRR values are provided in Figure 4(b). In this figure, it can be observed that the intersection of impostor distribution and genuine distribution curves occured at threshold 0.3. This point is called Equal Error Rate (EER) point. From this EER point, the FAR value of 0.82% was obtained (that is the percentage of impostor occurrence at values less than 0.3), and the FRR value was 78.41% (that is the percentage of genuines occurrence at velues higher than 0.3)

The value of FRR and FAR describesa trade-off between security and ease of the proposed algorithm. The low value of FAR shows that the system wasconsiderably secure because the possibility that the system receives the fingerprint from unregistered individual was small. Based on the data achieved from the simulation, from 100 impostors that trying to access system that less than one individual is success. On the other hand, high FRR value shows that the system was very selective, means that there was no guarantee that the registered users will be accepted by the system.



a. Genuine and impostor distribution of the proposed method



b. False Acceptance and False Rejection Rate

Figure 4. Performance of the proposed method

4. CONCLUSION

This paper proposed a fingerprint matching algorithms using ordinal measure of DCT coefficient. The ordinal measure of DCT coefficient was generated from DCT blocks with size 8x8 pixels. The simulation was accomplished using 128 fingerprint images that have been normalized, from which as many as 1024 genuine attempts and 15360 impostor attempts were generated. The proposed algorithms resulted in an Equal Error Rate (EER) at threshold 0.3. On the EER, it achieved FAR value of 0.82% and FRR value of 78.41% respectively.

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Fitri Arnia received B. Eng degree from Universitas Sumatera Utara (USU), Medan in 1997. She finished her master and doctoral degree from Universsity of New South Wales (UNSW), Sydney, Australia and Tokyo Metropolitan University, Japan in 2004 and 2008 respectively. She has been with the Department of Electrical Engineering, Faculty of Engineering, Syiah Kuala University since 1999. She is a member of IEEE and IAENG. Her research interests include signal, image and multimedia information processing.