Determining the Dry Parameter of Fingerprint Image Using Clarity Score and Ridge-valley Thickness Ratio

Rahmat Syam, *Member, IAENG,* Mochamad Hariadi, and Mauridhi Hery Purnomo

***Abstract*— This paper proposes a novel procedure to determine the parameter values of dry fingerprint images based on the score of clarity and ridge-valley thickness ratio. The parameters are local clarity scores (*LCS*), global clarity scores (*GCS*) and ridge-valley thickness ratio (*RVTR*). Our analysis started by quantizing fingerprint images into blocks with size of 32x32 pixels. The orientation of each block was perpendicularly calculated to the ridge. The middle of the block along the ridge (two-dimensional vector V_1 with the size 32x13 pixels) was extracted and transformed into a two-dimensional vertical vector V_2. Linear regression applied to the one-dimensional vector V_3 which is the average of vector V_2 to produce a Determinant Threshold (DT_1). Less than area of DT_1 is called a ridge, while the opposite is a valley. The tests carried out by calculating the clarity of the image from the overlapping area of the gray-level distribution of ridge and valley that has been separated. The thickness ratio of ridge to valley was then computed for each block based on gray-level value per block of image in the normal direction toward the ridge. Finally, we found the thickness ratio of ridge to valley for all images from which the average value obtained. The results showed that the dry fingerprint could be obtained when the image parameters have *LCS* values between 0.0127 to 0.0149, *GCS* values between 0.0117 to 0.0120, *RVTR* values greater than 7.75E-05.**

***Index Terms*— biometric, dry parameter, fingerprint, ridge-valley, clarity score.**

I. Introduction

FINGERPRINT identification is one of the most popular biometric technologies used in many areas such as criminal investigations, commercial applications, and others [1]. The performance of a fingerprint identification algorithm depends on the quality of input fingerprint images [2]-[3]. If the fingerprint image quality can be classified earlier prior to the identification, the selection of appropriate methods to improve the image quality can be implemented so that the accuracy of fingerprint recognition with the quality of singularity can be improved. In this case producing of high quality images is very important, but in reality it is difficult. In practice, a significant percentage of acquired images are of poor quality due to some environmental factors [4]-[5] such as the temperature or user's body condition such as finger skin of the dry, oily, wet, dirty, scratched or damaged [6]. Determine the parameter values of fingerprint image is necessary to increase the performance fingerprint image quality classifier which might be done by developing a model. However, there has been limited work in modeling parameter values of fingerprint image.

Hong, *et al.* [7] described a method for determinate the quality of fingerprint images. The patterns of ridge and valley modeled as a sine wave. The frequency and amplitude is calculated to determine the quality of fingerprint images. Performance is evaluated in terms of image improvement algorithm using the best indexes based on minutiae and performance verification although this is limited only in checking the quality of picture improvement algorithms performance. A new method for estimation of image quality in wavelet domain was proposed by Ratha and Bolle [8]. They used optimal choice for Wavelet Scalar Quantization (WSQ) compressed fingerprint images, however it is not supported in terms of uncompressed fingerprint images and fingerprint images in general. On the other hand, Lim, *et al.* [1] also develop measurements of global and local quality to estimate the quality as well as validity of a fingerprint image. Orientation certainty is used to certify the localized texture pattern of the fingerprint images while ridge to valley structure is analyzed to detect invalid images. Global uniformity and continuity ensures that the image is valid as a whole. However, this study only determines the quality of fingerprints in the category of good, non-detect, and poor. Bolle, *et al.* [9] introduced a system and method for determining the quality of fingerprint images by divided a fingerprint image into blocks of pixels. The blocks are marked as directional or non-directional. The blocks are also determined to be within the foreground or background of the image. The ratio of all these selected contiguous regions to the total area of fingerprint image (i.e., the foreground) used as a measure of quality. Shen, *et al.* [10] proposed a Gabor-feature based method for determining the quality of the fingerprint images. An image is divided into *w*x*w* blocks. Gabor-features of each block are computed first, then the standard deviation of the *m* Gabor features is used to determine the quality of this block. However, this study only determines the quality of fingerprints in the category of good and poor. Lim, *et al.* [11] developed a method in evaluating fingerprint image quality on a local level. Feature vectors covering directional strength, sinusoidal local ridge/valley pattern, ridge/valley uniformity and core occurrences are first extracted from fingerprint image sub-blocks. Each sub-block is then assigned a quality level through pattern classification. Three different classifiers

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are employed to compare each of its different effectiveness. However, this study only determines the quality of fingerprints in the category of very good, good, bad and very bad. Uchida [12] described a method for fingerprint acceptability evaluation. It computes a spatial changing pattern of gray level profile along with the frequency pattern of the images. The method uses only a part of the image "observation lines" for feature extraction. It can classify fingerprint images into only two categories. Fingerprint image quality is utilized to evaluate the system performance [1], [6], [13], [14], assess enrollment acceptability [12] and improve the quality of databases, and evaluate the performances of the fingerprint sensors.

Until recently the main question of how to classify the type of fingerprint image distorted (dry, normal, and oily) and determine of standard the parameter values of fingerprint image distorted still not fully answered and remain an interesting topic for further research. Therefore, this research aims to propose a novel model to determine the parameter values in the dry fingerprint image based on the score of clarity and the thickness ratio of ridge-valley. To carry out this research, we used DB_ITS_2009 to test the database, which is a private database that collected in the Department of Electrical Engineering, Sepuluh Nopember Institute of Technology, Surabaya. This collection of image is indicated with a better match with great caution because the image quality considerations.

Description about ridge and valley of fingerprint image described in Section II, then determinate value of the parameter of dry fingerprint image in Section III, research analysis and results described in Section IV, and the last Section is conclusion of the research.

II. Ridge and Valley of Fingerprint Images

Fingerprint recognition is one of the most mature biometric technologies and is suitable for a large number of recognition applications [2]. Fingerprints are the oldest biometric identity sign [15]-[16]. On the inside surface of the hand (palm of the hand from the fingertip to the wrist) there is a pattern of lines on the skin along the flow of sweat pores. The pattern of lines on the fingertip is called fingerprint [17].

Within fingerprint, there are two main component usually considered as important factors, ridge and valley. Ridge definition is a single curved section and the valley is the region between two adjacent ridges. In general, black lines mean ridge and white stripes mean valley. Fig. 1. explains that fingerprint comprise with the ridge and valley.

A. Fingerprint Image Quality

Generally, the fingerprint image quality relies on the clearness of separated ridges by valleys and the uniformity of the separation. A fingerprint image might be changed in many ways due to changes in environmental conditions such as temperature, humidity and pressure.

The overall quality of the fingerprint depends greatly on the condition of the skin [11]. Dry skin tends to cause inconsistent contact of the finger ridges with the scanner's platen surface, causing broken ridges and many white pixels replacing ridge structure. To the contrary, the valleys on the oily skin tend to fill up with moisture, causing them to appear black in the image similar to ridge structure. Fig. 2. shows oily/neutral/dry images, respectively.

Type of fingerprint image by environment condition according to [18] definition as:

- Oily fingerprint image: $S_R < S_V$
- Neutral fingerprint image: $S_R = S_V$
- Dry fingerprint image: $S_R > S_V$

Where S_R is ridge scores and S_V is valley scores. Ridge scores is overall ridge area of fingerprint image and valley scores is whole valley area of fingerprint images.

B. Ridge-Valley Clarity Scores of Fingerprint Images

Ridge and valley clarity analysis indicates the ability to distinguish the ridge and valley along the ridge direction. A method of analyzing the distribution of segmented ridge and valley is introduced to describe the clarity of the given fingerprint pattern [18].

To perform local clarity analysis, the fingerprint image is quantized into blocks of size 32x32 pixels. Inside each block, an orientation line, which is perpendicular to the ridge direction, is computed. At the center of the block along the ridge direction, a 2D vector V_1 (slanted square in Fig. 3.) with size 32x13 pixels can be extracted and transformed to a vertical aligned 2-D Vector V_2.

Equation (1) is a 1-D Vector V_3, that is the average profile of V_2, can be calculated.

$$V_3(i) = \frac{\sum_{j=1}^{m} V_2(i, j)}{m}, i = 1 \ldots 32 \tag{1}$$

Where m is the block height (13 pixels) and i is the horizontal index.

Once V_3 is calculated (1), linear regression can be applied to V_3 to find the Determine Threshold (DT_1). Fig. 4. shows the method of regional segmentation [18]. DT_1 is the line positioned at the center of the Vector V_3, and is used to classify the ridge region and valley region. Regions lower than DT_1 are the ridges, otherwise are the valleys. Hence, the regions of ridge and valley can be separated in the 2-D vector V_2 by the 1-D average profile V_3 with the DT_1 as shown as the dotted straight line in Fig. 4. As the ridge and valley have been separated, a clarity test can be performed in each segmented 2-D rectangular regions. Fig. 5. shows the gray level distribution of the segmented ridge and valley [18]. The overlapping area is the region of misclassification, which is the area of failing to determine ridge or valley accurately by using DT_1. Hence, the area of the overlapping region can be an indicator of the clarity of ridge and valley.

Then the calculation of the clarity score refer to (2), (3), and (4).

$$\alpha = \frac{\upsilon_B}{\upsilon_T} \tag{2}$$

$$\beta = \frac{\Re_B}{\Re_T} \tag{3}$$

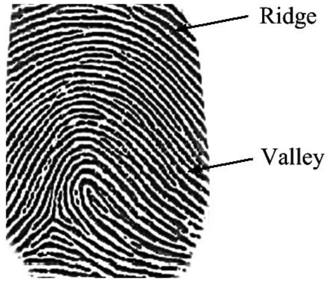


Fig. 1. Ridge and valley of fingerprint

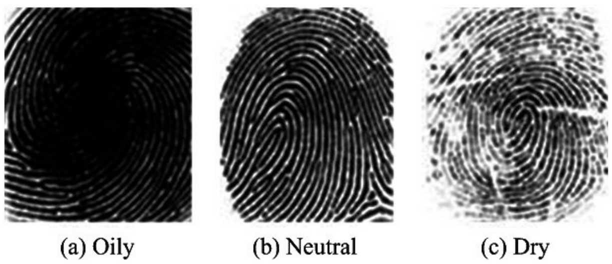


Fig. 2. Various of fingerprint images

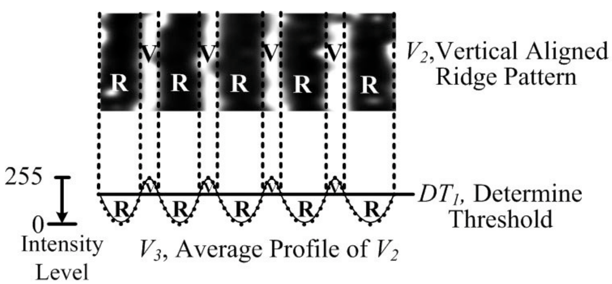


Fig. 3. Region segmentation of vector V_2 [18]

$$LCS = \frac{(\alpha + \beta)}{2} \tag{4}$$

Where υ_B is the number of bad pixels in the valley that the intensity is lower than the DT_1, υ_T is the total number of pixels in the valley region, $\mathfrak{R}_B$ is the number of bad pixels in the ridge that the intensity is higher than the DT_1, $\mathfrak{R}_T$ is the total number of pixels in the ridge region. α and β are the portion of bad pixels. Hence, the Local Clarity Score (*LCS*) is the average value of α and β.

For ridges with good clarity, both distributions should have a very small overlapping area. The following factors affect the size of Total Overlapping Area [18]:

1. Noise on ridge and valley
2. Scar across the ridge pattern
3. Water patches on the image due to wet finger
4. Incorrect of orientation angle due to the affect of directional noise
5. Highly curved ridge
6. Minutiae, bifurcation, delta point or core.

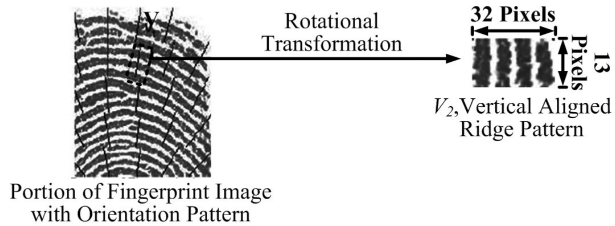


Fig. 4. Extraction of a local region and transformation to vertical aligned ridge pattern [18]

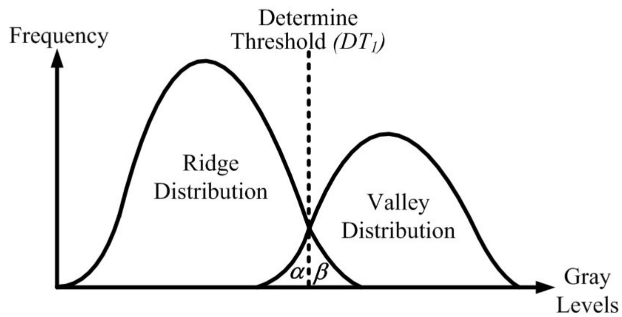


Fig. 5. Distribution of ridge and valley [18]

Factors 1 to 4 are physical noise found in the image. Factors 5 and 6 are physically actual characteristics of the fingerprint. Therefore, a small window with size 32x13 pixels is chosen to minimize the chance of encountering too many distinct features in the same location.

The Global Clarity Score (*GCS*) can be computed by the expected value of the *LCS*.

$$GCS = E(LCS(i, j)) \tag{5}$$

Where:

$$E(.) = \frac{\sum_{i=1}^{H} \sum_{j=1}^{V} (.)}{H.V} \tag{6}$$

As seen in equation (5), *LCS*(*i*,*j*) is the Clarity Scores which is calculated according to (2), (3) and (4) at location (*i*,*j*), where *i* and *j* are horizontal and vertical index of the image block respectively. *H* and *V* are the maximum number of horizontal and vertical block respectively. The *GCS* can be used to describes the general ridge clarity of a given fingerprint images.

C. Ridge-Valley Thickness Ratio (RVTR) of Fingerprint Images

The ratio for ridge thickness to valley thickness is computed in each block [12]. Furthermore, the thickness of ridge and valley are obtained using gray level values for one image block in the direction normal to the flow ridge. Later, the ratio of each block is computed and average value of the ratio is obtained over the whole image.

III. Proposed Model for Determining Dry Parameters of Fingerprint Images

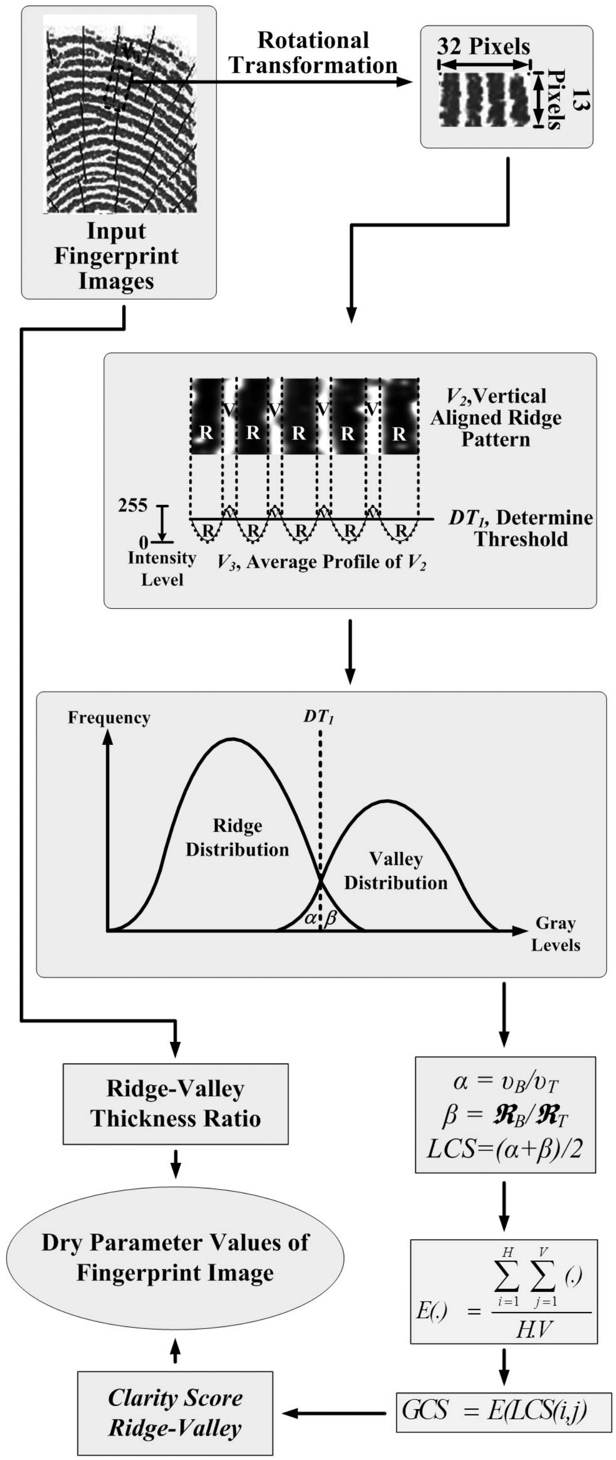


Fig. 6. The proposed model to determine the parameter values of the dry fingerprint images

The proposed model to determine the parameter values of the dry fingerprint images. There are three main steps in this research, namely: clarity scores counting ridge-valley, count ratio ridge-valley thickness, and determining the dry parameter values. The stages conducted in this research described in Fig. 6. as follows:

1. The image input is a fingerprint image taken using a fingerprint sensor type UareU 2000 (type of optical sensor). Before taking a fingerprint image, finger dried using hair dryer for a few seconds to produce a dry fingerprint image. Each finger taken in eight times (positions) which is attributed as *M* and *N* (the number of vertical and horizontal pixels of the image respectively).
2. By applying (7), *Mean* could be calculated which is the average of gray scale intensity values in the image *I* at location (*i*,*j*), where *i* and *j* are vertical and horizontal index of the image respectively for *M* and *N*.
3. *Var* which is the variance of gray scale intensity values in the image *I* is obtained by using (8).
4. Fingerprint image is normalized based on (9) in order to reduce any noises.

$$Mean = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} I(i,j) \tag{7}$$

$$Var = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} (I(i,j) - Mean)^2 \tag{8}$$

$$Norm = \begin{cases} Mean + \sqrt{\dfrac{Var\,(I(i,j) - Mean)^2}{Var}}, & \text{if } I(i,j) > Mean \\ Mean - \sqrt{\dfrac{Var\,(I(i,j) - Mean)^2}{Var}}, & otherwise \end{cases} \tag{9}$$

5. Score clarity ridge-valley is calculated as follows:
   a. Analysis of local clarity fingerprint image is performed by quantizing fingerprint images into blocks of size 32x32 pixels.
   b. Each block calculated an orientation perpendicular to the ridge. In the middle of the block along the ridge, a two-dimensional vector V_1 (squares in Fig. 3. [18]) of 32x13 pixels that can be extracted and transformed into a vertical two-dimensional vector V_2.
   c. Refer to (1), the vector V_3 is calculated from the average profile of V_2.
   d. Linear regression applied to the V_3 to find DT_1. Fig. 4. shows the regional segmentation method [18]. DT_1 is a line that has been positioned in the middle of the vector V_3, and is used to classify the ridge and valley section. Area smaller than the DT_1 is called ridge, otherwise it is a valley. Therefore, the ridge area and the valley can be separated in two-dimensional vector V_2 which is the average profile of vector V_3. In Fig. 4. DT_1 represented by the dotted line perpendicular.
   e. On the ridge and valley that had been separated, clarity trials are conducted in each region of two-dimensional rectangle. Fig. 5 describes the distribution of gray-level ridge and valley that already separated [18]. Instead of both areas, there is also and overlapping area which is not classified. These regions fail to determine the ridge and valley accurately using DT_1.
6. The ratio of ridge-valley thickness is calculated in three steps as follows:
   a. The image is divided into several blocks that do not overlap with the size of *MxN* pixels.

b. Calculate the gray-level value for each block in the direction normal to the ridge.
c. Finally the ratio of each block is calculated and the average value is obtained for the whole image.

7. Setting the parameter value each type of the fingerprint image based on the clarity score and the ridge-valley thickness ratio of fingerprint images, which has been calculated in step 2 to 6. In this step, three parameters are obtained, *LCS*, *GCS*, and *RVTR* of the fingerprint image 568. Each of the parameters for three types (dry, neutral, and oily) of fingerprint image is then calculated to determine the maximum and the minimum value of parameters which represents its range (10)-(14).

$$Val_{\max} = Max\,(Val_{par}) \tag{10}$$

$$Val_{\min} = Min\,(Val_{par}) \tag{11}$$

$$Val_{mid} = \frac{Val_{\max} + Val_{\min}}{2} \tag{12}$$

$$Dist_{top} = \frac{Val_{\max} + Val_{mid}}{2} \tag{13}$$

$$Dist_{bot} = \frac{Val_{\min} + Val_{mid}}{2} \tag{14}$$

Where is:
par = *LCS*, *GCS*, and *RVTR* parameters
Val_{par} = parameter values each type of the fingerprint image
Val_{max} = maximum value of the parameter values
Val_{min} = minimum value of the parameter values
Val_{mid} = middle value of the parameter values
$Dist_{top}$ = upper limit value of the parameter values
$Dist_{bot}$ = lower limit value of the parameter values

IV. Experimental Results

This research used the DB_ITS_2009 database, which is a private database collected by the Department of Electrical Engineering, Institute of Technology Sepuluh Nopember Surabaya. It is taken with great caution because the image quality considerations.

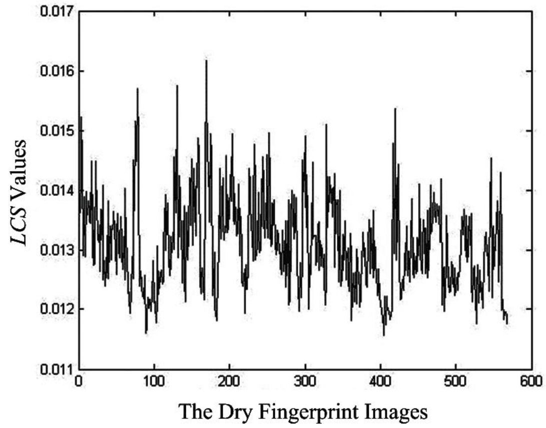
The DB_ITS_2009 database is taken using an optical sensor U.are.U 4000B fingerprint reader with the specifications: 512 dpi, USB 2.0, flat fingerprint, uncompressed. This database has 1704 fingerprint images of size 154x208 pixels. The details are as follows: It is classified into three types the finger condition (dry, neutral, and oily). Each type the finger condition consists of 568 fingerprint images sourced from 71 different fingers, each of these fingerprint image was taken eight times for the three conditions above. As a result, we obtained 3x71x8=1074 fingerprint images. To obtain dry fingerprint images, hair-dryer was used to completely dry the fingertip. Likewise, in order to get oily fingerprint images, we smeared baby-oil on the fingertips before the image taken.

Table 1. Experimental data samples

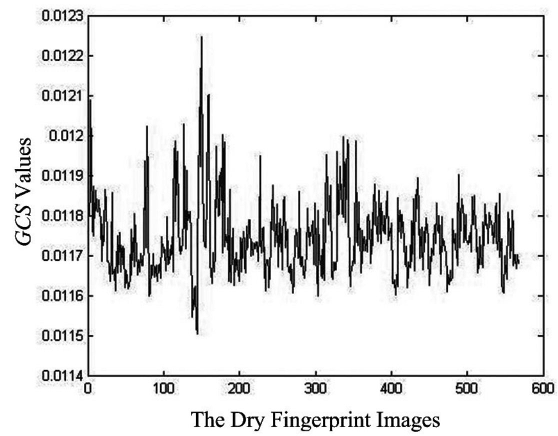
Images	*LCS*	*GCS*	*RVTR*
1	0.01333	0.01179	6.38E-05
2	0.01393	0.01182	6.97E-05
3	0.01400	0.01185	6.82E-05
4	0.01523	0.01209	7.78E-05
5	0.01446	0.01196	6.97E-05
6	0.01291	0.01177	7.06E-05
7	0.01359	0.01175	6.57E-05
8	0.01389	0.01187	6.28E-05
9	0.01288	0.01180	5.67E-05
10	0.01398	0.01183	6.12E-05
11	0.01382	0.01186	6.55E-05
12	0.01359	0.01183	6.02E-05
13	0.01381	0.01181	6.28E-05
14	0.01367	0.01182	6.12E-05
15	0.01348	0.01184	6.00E-05
16	0.01345	0.01180	6.05E-05
17	0.01448	0.01180	6.45E-05
18	0.01287	0.01169	5.99E-05
19	0.01391	0.01178	6.34E-05
20	0.01274	0.01173	5.81E-05
21	0.01276	0.01175	5.82E-05
22	0.01295	0.01177	5.79E-05
23	0.01448	0.01187	6.45E-05
24	0.01353	0.01186	6.28E-05
25	0.01345	0.01174	6.17E-05
26	0.01319	0.01169	6.24E-05
27	0.01313	0.01169	6.16E-05
28	0.01341	0.01168	6.54E-05
29	0.01264	0.01168	5.96E-05
30	0.01367	0.01164	6.47E-05
31	0.01325	0.01171	6.19E-05
32	0.01408	0.01186	6.49E-05
33	0.01250	0.01166	5.76E-05
34	0.01282	0.01166	6.11E-05
35	0.01239	0.01167	5.88E-05
36	0.01287	0.01162	5.86E-05
37	0.01253	0.01167	5.96E-05
38	0.01269	0.01168	5.88E-05
39	0.01381	0.01175	6.47E-05
40	0.01252	0.01166	5.89E-05
41	0.01308	0.01170	6.11E-05
42	0.01340	0.01176	6.20E-05
43	0.01284	0.01166	6.02E-05
44	0.01334	0.01173	6.05E-05
45	0.01335	0.01172	6.27E-05

All fingerprint images were then calculated based on Section III. Table 1 shows the result of data analysis based upon the calculation from points 1 to 7 of Section III. Table 2 shows the experimental results of the three parameter values of fingerprint images, namely *LCS*, *GCS* and *RVTR* by using the equation of 10 to 14. Table 3 shows range interpretation of the parameter values of fingerprint images. Fig. 7 – 9 respectively shows the parameter values graph of the dry, neutral, and oily fingerprint images from Table 1.

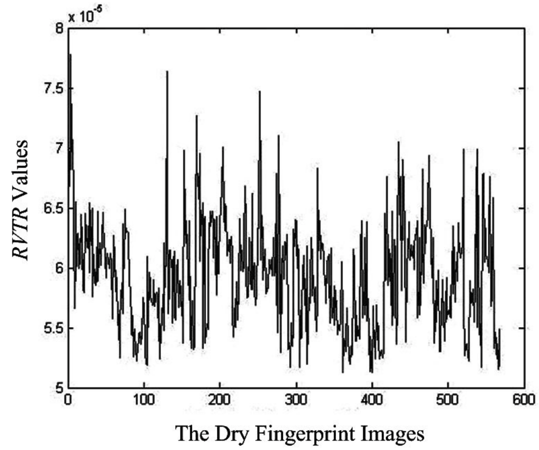
Fig. 7 shows parameter values of the dry fingerprint images. It can be seen in Fig. 7. (a) that the minimum value for *LCS* is approximately 0.0117 while the maximum one is 0.0167. Similarly, Fig. 7. (b) depicts the minimum and the maximum values for *GCS* are 0.0115 and 0.0123 respectively. Also, the minimum and the maximum values for *RVTR* are shown in Fig. 7. (c) of 5.13E-05 and 7.78E-05 respectively.



(a) *LCS*

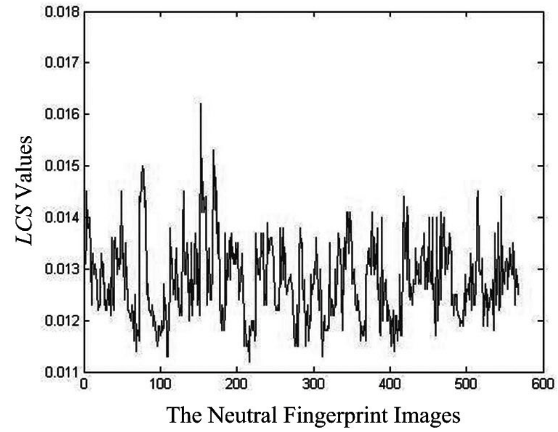


(b) *GCS*

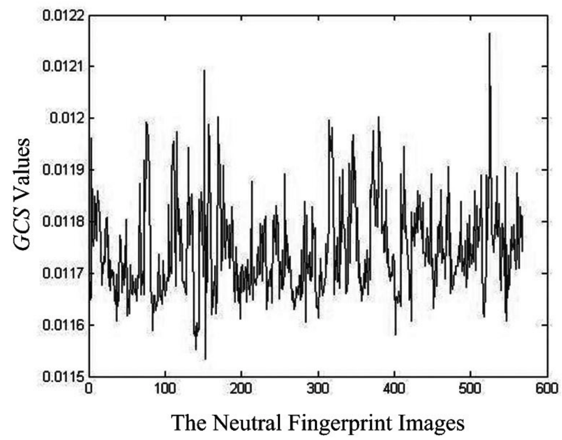


(c) *RVTR*

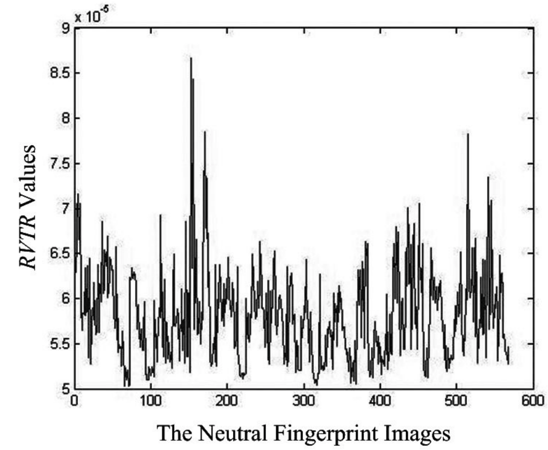
Fig. 7. Parameter values of the dry fingerprint images



(a) *LCS*



(b) *GCS*

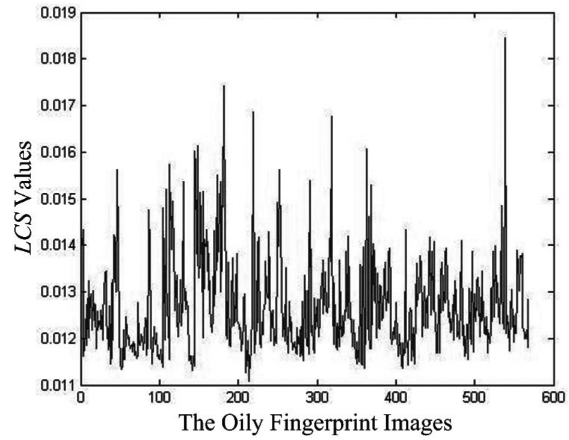


(c) *RVTR*

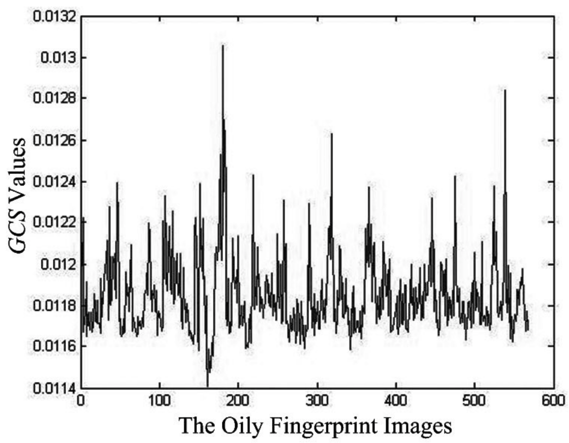
Fig. 8. Parameter values of the neutral fingerprint images

In addition, Fig. 8 shows parameter values of the neutral fingerprint images. As can be seen in Fig. 8. (a), the *LCS* values are fluctuated between 0.0112 (minimum) and 0.0162 (maximum). Likewise, Fig. 8. (b) shows *GCS* values from 0.0115 as the minimum value to 0.0122 as the maximum one. Additionally, it can be seen from Fig. 8. (c) that the value of *RVTR* is ranging from as less as 5.03E-05 to 8.66E-05 as its maximum value.

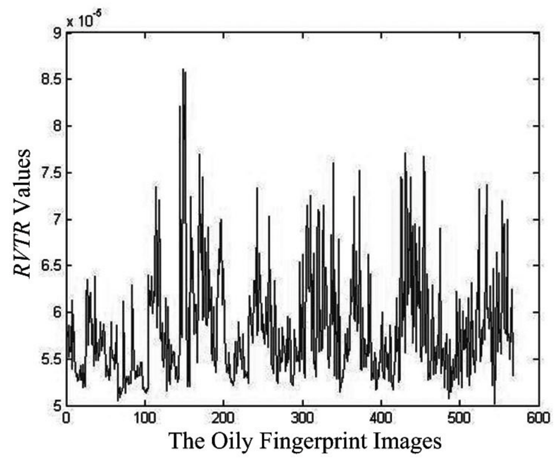
Fig. 9. shows parameter values of the oily fingerprint images. Fig. 9. (a) shows *LCS* values with 0.0110 as the minimum one and 0.0184 as its maximum value. Then, *GCS* values are represented in Fig. 9. (b) that shows the lowest value of 0.0114 and the maximum one of 0.0130. Finally Fig. 9. (c) depicts different *RVTR* values between 5.02E-05 and 8.61E-05 as the minimum and the maximum values.



(a) *LCS*



(b) *GCS*



(c) *RVTR*

Fig. 9. Parameter values of the oily fingerprint images

Then, more details analyses were performed to each type of fingerprint images. Fig. 10 to 12 are the detailed interpretation of data in Table 3. Furthermore, these results are our main findings presented in Table 4 – 5.

Table 2. Experimental results of the parameter values of fingerprint images

Type of the Fingerprint Images		Parameter Values		
		LCS	***LCS***	***RVTR***
Dry	Val_{max}	0.0167	0.0123	7.78E-05
	Dis_{top}	0.0150	0.0121	7.77E-05
	Val_{mid}	0.0137	0.0119	6.45E-05
	Dis_{bot}	0.0127	0.0117	5.92E-05
	Val_{min}	0.0117	0.0115	5.13E-05
Neutral	Val_{max}	0.0162	0.0122	8.66E-05
	Dis_{top}	0.0149	0.0120	7.75E-05
	Val_{mid}	0.0137	0.0118	6.85E-05
	Dis_{bot}	0.0124	0.0116	5.93E-05
	Val_{min}	0.0112	0.0115	5.03E-05
Oily	Val_{max}	0.0184	0.0130	8.61E-05
	Dis_{top}	0.0166	0.0126	7.71E-05
	Val_{mid}	0.0147	0.0122	6.82E-05
	Dis_{bot}	0.0129	0.0118	5.91E-05
	Val_{min}	0.0110	0.0114	5.02E-05

Table 3. Range interpretation of the parameter values of fingerprint images

Type of the Fingerprint Images	Range Interpretation of Parameter Values		
	LCS	***LCS***	***RVTR***
Dry	0.0127-0.0150	0.0117-0.0121	5.92E-05-7.77E-05
Neutral	0.0124-0.0149	0.0116-0.0120	5.93E-05-7.75E-05
Oily	0.0129-0.0166	0.0118-0.0126	5.91E-05-7.71E-05

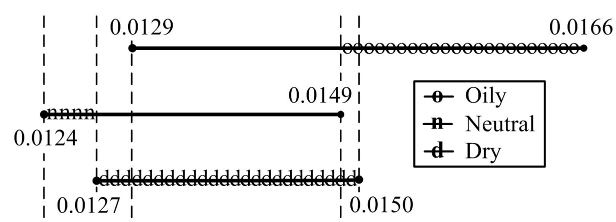


Fig. 10. The illustration to determining of the *LCS* parameter values

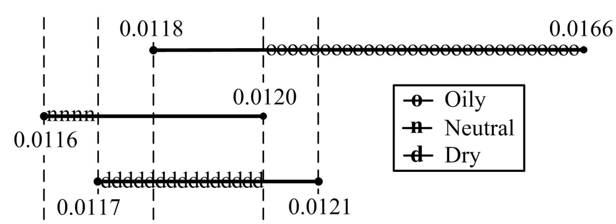


Fig. 11. The illustration to determining of the *GCS* parameter values

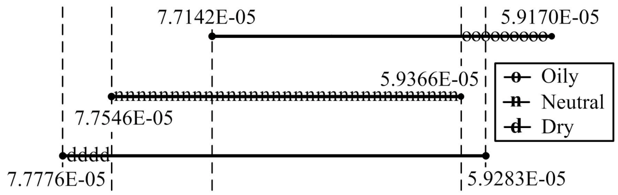


Fig. 12. The illustration to determining of the *RVTR* parameter values

Table 4. Interpretation clarity score (*LCS*, *GCS*) to determining the quality of fingerprint images

Clarity Score		Quality
LCS	***GCS***	
LCS < 0.0127	*GCS* < 0.0117	Neutral
0.0127≤*LCS*≤0.0149	0.0117≤*LCS*≤0.0120	Dry
LCS > 0.0149	*GCS* < 0.0120	Oily

Table 5. Interpretation ridge-valley thickness ratio (*RVTR*) to determining the quality of fingerprint images

RVTR	Quality
RVTR < 5.93E-05	Oily
5.93E-05 ≤ *RVTR* ≤ 7.75E-05	Neutral
RVTR > 7.75E-05	Dry

Based on the experimental results in the Table 4 - 5, it is found that the dry fingerprint image can be obtained if three parameter values are satisfied as follows. First, it should has local clarity scores (*LCS*) between 0.0127 to 0.0149, second the global clarity scores (*GCS*) should be between 0.0117 to 0.0120, and finally the ridge-valley thickness ratio (*RVTR*) must be greater than 7.75 E-05.

V. Conclusion

This study proposes a novel model to determine the parameter values in the dry fingerprint image based on the score of clarity and the thickness ratio of ridge-valley. In addition, the study successfully defines level of dry fingerprint image based on three parameters, *LCS*, *GCS* and *RVTR*.

It is found that a dry fingerprint image is characterized by *LCS* from 0.0127 to 0.0149, *GCS* from 0.0117 to 0.0120, and *RVTR* greater than 7.75E-05.

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References

[1] E. Lim, X. Jiang, W. Yau, "Fingerprint quality and validity analysis", *IEEE International Conference on Image Processing (ICIP)*, Vol. 1, 2002, pp. 22–25.

[2] D. Maltoni, D. Maio, A. K. Jain, S. Prabhakar, *Hand book of Fingerprint Recognition*, London Limited: Springer-Verlag, 2009.

[3] N. K. Ratha, K. Karu, S. Chen, A. K. Jain, "A Real-time Matching System for Large Fingerprint Databases", *IEEE Transaction on Pattern Analysis and Machine Intelligence*, Vol. 18, No. 8, 1996, pp. 799–813.

[4] D. A. Ramli, S. A. Samad, A. Hussain, "A Multibiometric Speaker Authentication System with SVM Audio Reliability Indicator", *IAENG International Journal of Computer Science*, 36:4, IJCS_36_4_08, November 2009.

[5] I. M. El-Emary and S. Ramakrishnan, "A Critical Review of Statistical Modeling of Digital Images", *IAENG International Journal of Computer Science*, 37:1, IJCS_37_1_12, February 2010.

[6] L. C. Jain, U. Halici, I. Hayashi, S. B. Lee, S. Tsutsui, *Intelligent Biometric Techniques in Fingerprint and Face Recognition*, CRC Press, 1999.

[7] L. Hong, W. Yau, A. K. Jain, "Fingerprint Image Enhancement: Algorithm and Performance Evaluation", *IEEE Transaction on Pattern Analysis and Machine Intelligence*, Vol. 20, No. 8, 1998, pp. 777–789.

[8] N. K. Ratha and R. M. Bolle, "Fingerprint Image Quality Estimation", IBM Computer Science Research Report RC 21622, 1999.

[9] R. Bolle, S. Pankanti, Y. -S. Yao, "System and Method for Determining the Quality of Fingerprint Images", US Patent Number US 596356, 1999.

[10] L. L. Shen, A. Kot, W. M. Koo, "Quality Measures of Fingerprint Images". *The 3rd International Conference Audio- and Video-based Biometric Person Authentication (AVBPA)*, 2001, pp. 266–271.

[11] E. Lim, K. Toh, P.N. Suganthan, X. Jiang, W. Yau, "Fingerprint Image Quality Analysis", *IEEE*, Vol. 3, 2004, pp. 1241-1244.

[12] K. Uchida, "Image-based Approach to Fingerprint Acceptability Assessment", *ICBA*, 2004, pp. 294–300.

[13] Y. Chen, S. Dass, A. K. Jain, "Fingerprint Quality Indices for Predicting Authentication Performance", *AVBPA*, 2005, pp. 160–170.

[14] E. Tabassi, C. L. Wilson, "A New Approach to Fingerprint Image Quality". *ICIP*, 2005, pp. 37–40.

[15] G. S. Rao, C. NagaRaju, L.S.S. Reddy, E.V. Prasad, "A Novel Fingerprints Identification System Based on the Edge Detection", *IJCSNS International Journal of Computer Science and Network Security*, Vol. .8, No. 12, 2008, pp. 394-397.

[16] Q. Zhang, H. Yan, "Fingerprint Classification Based on Extraction and Analysis of Singularities and Pseudo Ridges", *the Journal of the Pattern Recognition Society 37*, 2004, pp. 2233-2243.

[17] H. C. Lee, R. E. Gaensslen, *Advances in Fingerprint Technology*, CRC Press, 2001.

[18] T. P. Chen, X. Jiang, W. Yau, "Fingerprint Image Quality Analysis", *IEEE*, Vol. 3, 2004, pp. 1253-1256.

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