Image Analysis Fuzzy System

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Abstract
The fingerprint image quality relies on the clearness of separated ridges by valleys and the uniformity of the separation. The condition of skin still dominate the overall quality of the fingerprint. However, the identification performance of such system is very sensitive to the quality of the captured fingerprint image. Fingerprint image quality analysis and enhancement are useful in improving the performance of fingerprint identification systems. A fuzzy technique is introduced in this paper for both fingerprint image quality analysis and enhancement. First, the quality analysis is performed by extracting four features from a fingerprint image which are the local clarity score (LCS), global clarity score (GCS), ridge_valley thickness ratio (RVTR), and the Global Contrast Factor (GCF). A fuzzy logic technique that uses Mamdani fuzzy rule model is designed. The fuzzy inference system is able to analyse and determine the fingerprint image type (oily, dry or neutral) based on the extracted feature values and the fuzzy inference rules. The percentages of the test fuzzy inference system for each type is as follow: For dry fingerprint the percentage is 81.33, for oily the percentage is 54.75, and for neutral the percentage is 68.48. Secondly, a fuzzy morphology is applied to enhance the dry and oily fingerprint images. The fuzzy morphology method improves the quality of a fingerprint image, thus improving the performance of the fingerprint identification system significantly. All experimental work which was done for both quality analysis and image enhancement was done using the DB_ITS_2009 database which is a private database collected by the department of electrical engineering, institute of technology Sepuluh Nopember Surabaya, Indonesia. The performance evaluation was done using the Feature Similarity index (FSIM). Where the FSIM is an image quality assessment (IQA) metric, which uses computational models to measure the image quality consistently with subjective evaluations. The new proposed system outperformed the classical system by 900% for the dry fingerprint images and 14% for the oily fingerprint images.

Keywords:
Dry fingerprint image; fuzzy Morphology; Oily fingerprint image;Fingerprint image Quality.

1. Introduction

Fingerprint identification is the most widely used biometrics technologies and is used in criminal investigations, commercial applications, and so on. With such a wide variety of uses for the technology, the demographics and environment conditions that it is used in are just as diverse. However, the identification performance of such system is very sensitive to the quality of the captured fingerprint image. Fingerprint image quality analysis and enhancement is useful in improving the performance of fingerprint identification systems.

In many systems it is preferable to substitute low quality images for better ones. Therefore, image quality analysis and enhancement takes an important part in image processing. The quantification of image quality allows to tune a system and to evaluate measurement accuracy of a given input image (Li, Z., Han, Z., & Fu, B. 2009).

Various factors can affect the quality of fingerprint images such as dryness/wetness conditions, non-uniform and inconsistent contact, permanent cuts and so on. Many of these factors cannot be avoided. Therefore, assessing and enhancing the quality and validity of the captured fingerprint image is necessary and meaningful. Many papers in biometric literature address the problem of enhancement and assessing fingerprint image quality. But these methods still have some problems and can't be suitable for all conditions (Li, Z., Han, Z., & Fu, B. 2009).

Alexey Saenko et al. (Saenko, A., Polte, G., & Musalimov, V. 2012) have proposed a technique to analysis image quality that uses two different methods. The first is a crisp method that uses matrix norm which is a scalar that gives some measure of the magnitude of the elements of the matrix. The second is a fuzzy logic method which evaluates the image quality by using IF-THEN-RULES with the following parameters: Sharpness, Noise, Contrast, Vignetting and Field curvature.

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All of these parameters are linguistic variables and have three possible linguistic values "bad", "normal", and "good".

Eun-Kyung Yun et al. (Yun, E. K., & Cho, S. B. 2006) proposed a method to analysis and enhance image quality by extracting five features from a fingerprint which are as follows: Mean, Variance, Block directional difference, Ridge valley thickness ratio, and Orientation change. According to these features images then can be clustered by using ward's clustering algorithm which is a hierarchical clustering method. The method initially assigns an independent cluster to each sample, then it seeks the most similar pairs of clusters and merges them into one cluster. Then an adaptive pre-processing method is performed, according to their characteristic enhancement.

Taru Mahashwari and Amit Asthana (Mahashwari, T., & Asthana, A. 2013)have proposed a fuzzy method, which was applied on a greyscale image by converting the image data into fuzzy domain using Gaussian function and have modified membership function by using if then rules as follow: "If pixel intensity is dark then output is darker", or "if pixel intensity is grey then output is grey", or "if pixel intensity is bright then output is brighter". The last stage was defuzzification, which is the inverse of fuzzification where the defuzzification algorithm maps the fuzzy plane back to grey level intensities.

Selvi, M., and Aloysius George (Selvi, M., & George, A. 2013)have proposed a method which was designed to identify the noisy area and have enhanced that portion a lone by using a fuzzy based filtering technique and adaptive thresholding. The method was applied in four stages. The first stage was the pre-processing, which cropped the original database images into specified size. The second stage was a fuzzy filtering technique, which was done by replacing the central pixel in the window of the image by that one which maximizes the sum of similarities among all its neighbours. The third stage was adaptive thresholding, which determined the threshold value. This value was applicable to use with the image having different types of noise. The last stage was the morphological operation, which did perform two operation; the dilation process and the erosion process, which was used to eliminate all pixels in regions that are too small to contain the structuring image.

Chen et al (Chen, Y., Dass, S. C., & Jain, A. K. 2005, July)have proposed two quality indices, global (Qf) and local (Qs), for fingerprint images. They have compared the two in a generic evaluation framework and have observed the following: (1) Qf has better predictive capabilities at the image enhancement stage than Qs. This is because the image enhancement algorithm they have used was based on Gabor filtering in the frequency domain, and is therefore directly related to Qf. (2) Qs is slightly more effective than Qf at the feature extraction stage. This is because feature extraction concentrates on local details which was measured directly by Qs. (3) Both Qf and Qs were effective in predicting and improving the matching performance.

Zahedi et al(Zahedi, M., & Ghadi, O. R. 2015)have proposed a method by combining the Gabor filter and fast Fourier transform (FFT). The Gabor filter has improved the clarification of ridge and valley structures, where it adapted to the local ridge orientation and ridge frequency, and then fingerprint images were enhanced based on the fast Fourier transform. The experiment results have shown that the whole finger print was enhanced, andconsequently, it did lead to a better recognition rate.

The paper is organized as follows: section 2 presents the Fingerprint image quality; section 3 presents the new proposed fingerprint image quality analysis and enhancement system that analysis and enhancement oily, neutral and dry fingerprint image. Section 4 presents the experimental results using the DB_ITS_2009 database which is a private database collected by the Department of Electrical Engineering, Institute of Technology Sepuluh Nopember Surabaya.

1.1 Fingerprint Image Quality

In general, the fingerprint image quality relies on the clearness of separated ridges by valleys and the uniformity of the separation. Although the change in environmental conditions such as temperature, humidity and pressure might influence a fingerprint image in many ways, but the condition of skin still dominate the overall quality of the fingerprint (Saenko, A., Polte, G., & Musalimov, V. 2012). Dry skin tends to cause inconsistent contactof the finger ridges with the scanner's platen surface, causing broken ridges and many white pixels replacing ridge structure as shown in Figure 1 (c). 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 as shown in Figure 1 (a). Figure 1 shows examples of oily, neutral and dry images, respectively

(Yun, E. K., & Cho, S. B. 2006). The three image types are as follows:

Fig.1. Examples of fingerprint Images (Yun, E. K., & Cho, S. B. 2006)

- Oily image: Even though the separation of ridges and valleys is clear, some parts of valleys are filled up causing them to appear dark. Ridges tend to be very thick (Yun, E. K., & Cho, S. B. 2006).
- Neutral image: In general, neutral images have no special properties such as oily and dry. It does not have to be filtered (Yun, E. K., & Cho, S. B. 2006).
- Dry image: The ridges are scratchy locally and there are many white pixels in the ridges (Yun, E. K., & Cho, S. B. 2006).

2. The Proposed Method

The proposed method to analysis and enhance fingerprint image was done in three steps; the first step is the fingerprint image quality analysis, the second step is the dry fingerprint image enhancement, and last step is the oily fingerprint image enhancement.

2.1. Fingerprint Image Quality Analysis

Figure 2 shows the flowchart of the proposed method. The method starts by extracting four features from the fingerprint image for image quality assessment using Fuzzy Inference System to determine the type of the fingerprint image quality. The feature extraction stage is given as follows:

2.1.1.Features Extraction

In this stage four features were extracted which are the Local Clarity Score (LCS), Global Clarity Score (GCS), Ridge_Valley Thickness Ratio (RVTR), and the Global Contrast Factor (GCF), to analysis the fingerprint image quality using a fuzzy inference system. The following subsections will present few fingerprint image scores that will be used in analysing fingerprint images:

2.1.1.1.Ridge-Valley Clarity Scores for 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 (Syam, R., Hariadi, M., & Purnomo, M. H. 2010).

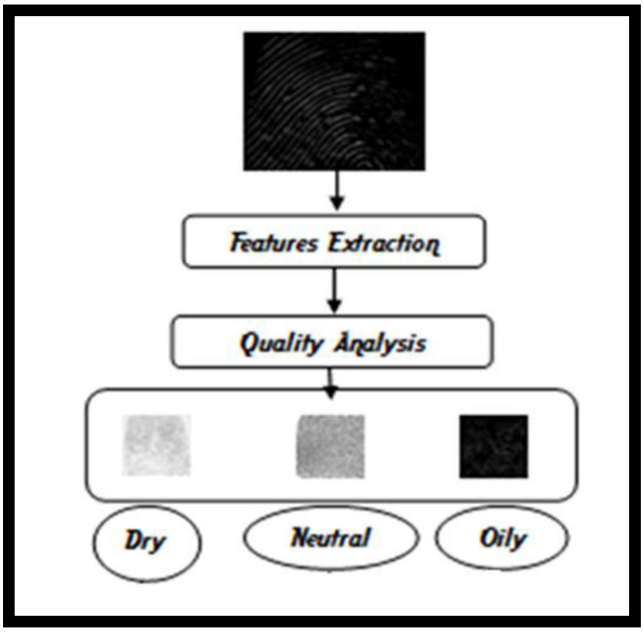

Fig.2. Proposed Method Flowchart for quality analysis

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 2-D vector V_1 (slanted square shown in Figure 3) with size 32x13 pixels can be extracted and transformed into a vertical aligned 2-D Vector V_2. Equation (1) is a 1-D Vector V_3, which is the average profile of V_2(Syam, R., Hariadi, M., & Purnomo, M. H. 2010).

$$\mathbf{V_3(i)} = \frac{\sum_{j=1}^{m} \mathbf{v_2}}{\mathbf{m}}, \mathbf{i = 1 \ldots 32} \quad (1)$$

Where m is the block height (13 pixels) and *i* is the horizontal index. Once V_3 is calculated as in (1), then linear regression can be applied to V_3 to find the Determine Threshold (DT1). Figure 4 shows the method of regional segmentation. DT1 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 DT1 are classified as the ridges and the others are as valleys. Hence, the regions of ridges and valleys can be separated in the 2-D vector V_2 by the 1-D average profile V_3 with the DT1 shown as the dotted straight line in Figure 4. As ridges and valleys are separated, a clarity test can be performed in each segmented 2-D rectangular regions. Figure 5 shows the gray level distribution of the segmented ridges and valleys. The overlap area is the region of misclassification, which is the area of failing to determine ridge or valley accurately by using DT1. Hence, the area of the overlap region can be an indicator of the clarity of ridge and valley. For thecalculation of the clarity score refer to equations (2), (3), and (4) (Syam, R., Hariadi, M., & Purnomo, M. H. 2010).

$$\boldsymbol{\alpha} = \frac{\boldsymbol{V_B}}{\boldsymbol{V_T}} \quad (2)$$

$$\boldsymbol{\beta} = \frac{\boldsymbol{\Re_B}}{\boldsymbol{\Re_T}} \quad (3)$$

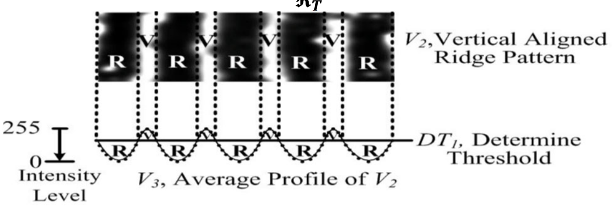

Fig.3. Region Segmentation of vector V_2 (Syam, R., Hariadi, M., & Purnomo, M. H. 2010).

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

Where V_B is the number of bad pixels in the valley that the intensity is lower than the DT_1, $V_T$is the total number of pixels in the valley region, $\Re_B$ is the number of bad pixels in the ridge that the intensity is higher than the DT_1 and $\Re_T$ 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 both α and β.

For ridges with good clarity, both distributions should have a very small overlap area. The following factors affect the size of the total overlap area (Syam, R., Hariadi, M., & Purnomo, M. H. 2010):

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 effect of directional noise.
5. Highly curved ridge.
6. Minutiae, bifurcation, delta point or core.

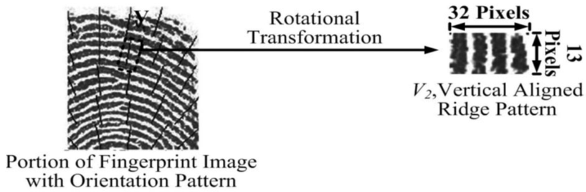

Fig.4. Extraction of a local region and transformation to vertical aligned ridge pattern (Syam, R., Hariadi, M., & Purnomo, M. H. 2010).

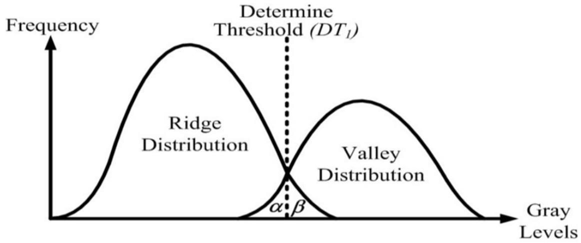

Fig.5. Distribution of ridge and valley (Syam, R., Hariadi, M., & Purnomo, M. H. 2010).

Factors 1 to 4 are physical noise found in the image. Factors 5 and 6 are actual physical 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* (Syam, R., Hariadi, M., & Purnomo, M. H. 2010) as can be seen in equation (5).

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

Where $$\boldsymbol{E}(.) = \sum_{i=1}^{H}\sum_{j=1}^{v}(.) \quad (6)$$

LCS (i, j) is the Clarity Scores which is calculated according to equations (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 blocks, respectively. The GCS can be used to describe the general ridge clarity of a given fingerprint image.

2.1.1.2.The ratio for ridge thickness to valley thickness is computed in each block.

Furthermore, the thickness of ridge and valley is obtained using the gray level values for one image block in the direction normal to the flow ridge. The ratio of each block is computed and the average value of the ratio is obtained over the whole image (Syam, R., Hariadi, M., & Purnomo, M. H. 2010).

2.1.1.3.Global Contrast Factor (GCF)

Contrast in image processing is usually defined as a ratio between the darkest and the brightest spots of an image. The Global Contrast Factor (GCF) corresponds closer to the human perception of contrast. GCF uses contrasts at various resolution levels in order to compute overall contrast (Matkovic, et al 2005).

The contrast of any (small) part of an image is called the local contrast. The global contrast is defined as the average local contrast of smaller image fractions (Matkovic, et al 2005).

First compute the local contrast factors at various resolutions, and then build a weighted average based on human perception method which it can be approximated with the square root of the linear luminance, which it gamma corrected luminance using a gamma of 2.2 for standard displays (Matkovic, et al 2005).

Let us denote the original pixel value with k, k $\in$ {0, 1… 254, 255}. The first step is to apply gamma correction with g=2.2, and scale the input values to the [0, 1] range. We will denote the scaled and corrected values of the linear luminance with L (Matkovic, et al 2005).

$$\boldsymbol{L} = \left(\frac{\boldsymbol{K}}{\boldsymbol{255}}\right)^{\boldsymbol{Y}} \quad (7)$$

The perceptual luminance L is now

$$\boldsymbol{L} = \boldsymbol{100} * \sqrt{\boldsymbol{L}} \quad = \boldsymbol{100} * \sqrt{\left(\frac{\boldsymbol{K}}{\boldsymbol{255}}\right)^{\boldsymbol{Y}}} \quad (8)$$

Once the perceptual luminance is computed, thenthe local contrast will have to be computed. For each pixel the average difference of L between the pixel and the four neighboring pixels will be computed (Matkovic, et al 2005). By assuming the image is w pixels wide and h pixels high, and the image is organized as a one dimensional array of row-wise sorted pixels, the local contrast Lc_i for pixel i is computed as follows (Matkovic, et al 2005):

$$\boldsymbol{Lc_i} = \frac{|L_i - L_{i-1}| + |L_i - L_{i+1}| + |L_i - L_{i-w}| + |L_i - L_{i+w}|}{4} \quad (9)$$

The average local contrast for the current resolution C_i is computed now as the average local contrast Lc_iover the whole image (Matkovic, et al 2005).

$$\boldsymbol{C_i} = \frac{1}{w*h} * \sum_{i=1}^{w*h} \boldsymbol{LC_i} \quad (10)$$

Now since the average local contrasts $C_i$was computed, the weigh factors $w_i$needs to be found, which will be used to compute the global contrast factor

$$\boldsymbol{GCF} = \sum_{i=1}^{N} \boldsymbol{W_i} * \boldsymbol{C_i} \quad (11)$$

2.1.2.Quality Analysis - Fuzzy Inference System

Fingerprint image quality analysis has been developed and implemented using fuzzy inference system (FIS). FIS has been developed using five stages. The stages are as follow:

2.1.2.1.The Fuzzy Inference System Editor

This stage shows the fuzzy inference system editor which displays the general information about the proposed method as show in Figure 6 which shows the four inputs LCS, GCS, RVTR and GCF with their membership functions. It also shows the three different outputs; one for oily, dry, and neutral.

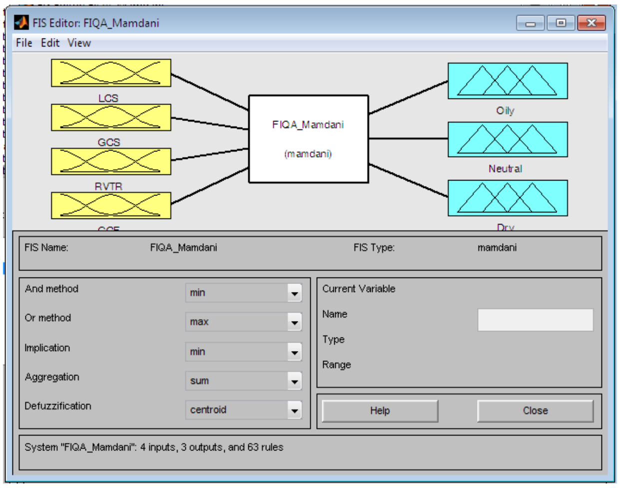

Fig. 6.FIS Editor for image quality Classification

2.1.2.2.The Membership Function Editor

This stage shows the membership function for each of the four inputs. Figures 7, 8, 9, and 10 shows the membership functions for GCF, LCS, GCS, and RVTR respectively.

The Figures also display the range of feature values for the three types of fingerprint images (Dry,Neutral, and Oily).

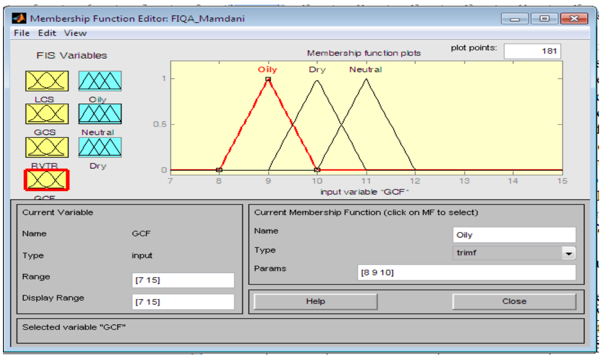

Fig. 7. FIS Membership Functions for GCF

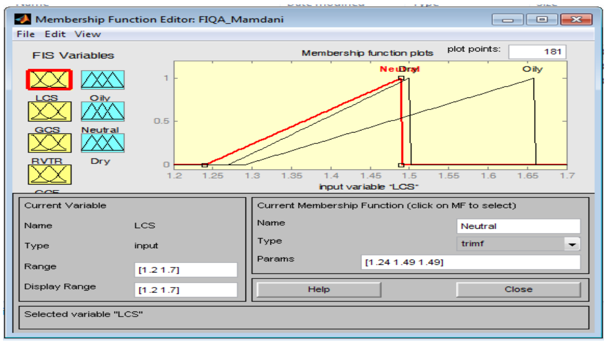

Fig.8. FIS Membership Functions for LCS

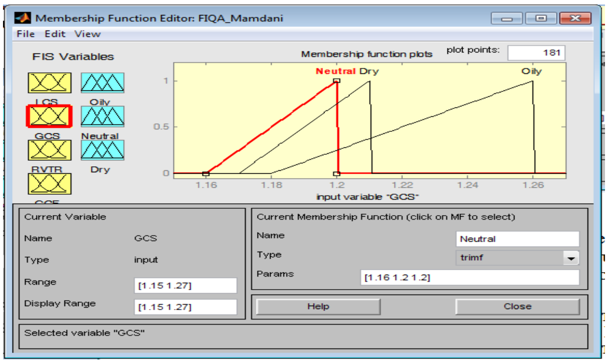

Fig.9. FIS Membership Functions for GCS

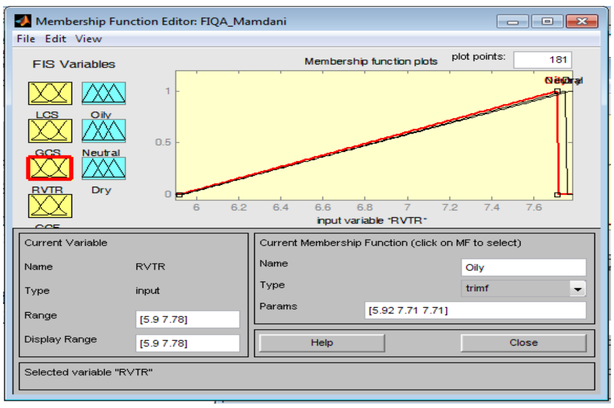

Fig. 10. FIS Membership Functions for RVTR

2.1.2.3.The Rules Editor

This stage shows the construction of the rule base for four inputs and three outputs FIS. Figure 11 shows the rule base editor where 63 rules were created. Each output has two linguistic values. For example, the linguistic values for DRY fingerprints are S.Dry (Strong Dry) and M.Dry (Moderate Dry).

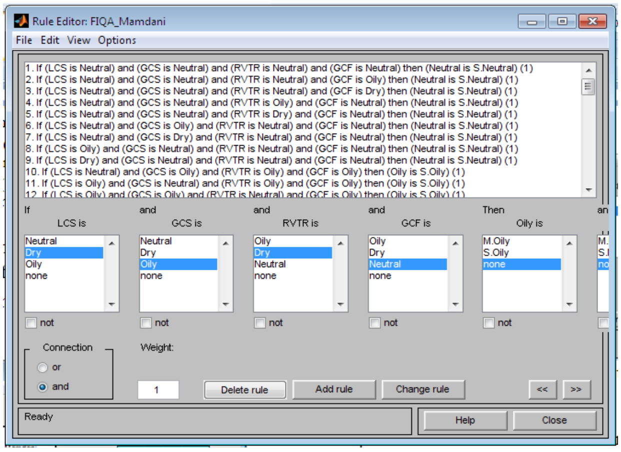

Fig. 11. FIS Rule Editor

2.2.Dry Fingerprint Image Enhancement

Figure 12 shows the flowchart for the method used to enhance dry image. The method is divided into three subsections. First, we inputted smoothing image using low pass filter. Secondly, we employed fuzzy morphology on the smoothed image. Afterward, the union operation is utilized to display results.

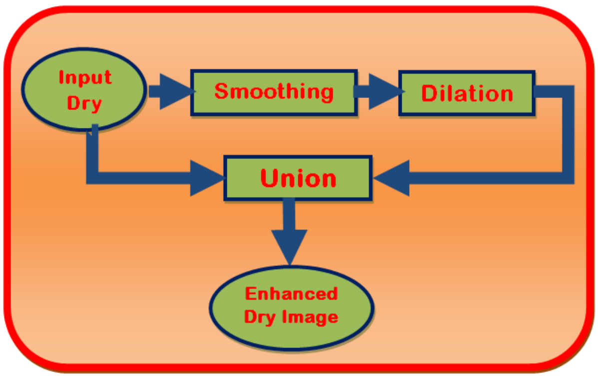

Fig. 12. Proposed Method Flowchart for dry image enhancement

Finally, performance evolution is conducted to measure the quality of the enhanced image compared with previous studies using the Feature Similarity index (FSIM).

Smoothing is applied to reduce noise in an image and to decrease the disparity between pixel values by using winner filter. Figure13 shows a smoothed fingerprint image.

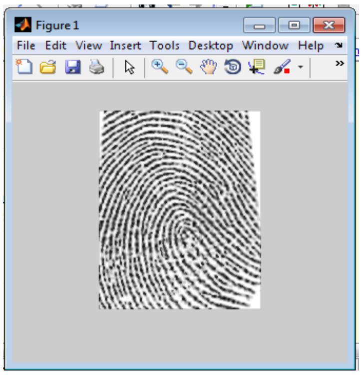

Fig.13. Smoothing image

Fuzzy Morphology uses the concepts of fuzzy set theory. Fuzzy mathematical morphology is the extension of greyscale morphological operations to fuzzy sets (Bloch, I. 2009).

The performance of fuzzy morphological operation depends on the size of the structuring element. The fuzzy structuring element (SE) itself is a function or image, which has greater capability to affect the image through size (Bloch, I. 2006).

Structuring element is selected as a3x3 mask matrix to cover the whole image boundaries. Generally, in image processing odd sized mask shows a pixel values neighboring pixels. As the size of the mask increases, the detailed results of the operations decrease. For this reason it is better to have a small odd sized structuring element mask for better performance. The values used inside the structuring element are the pixel values. These pixel values are randomly selected values so that a user can define different elements for the mask (Pahsa, A. 2006). Table1 show the fuzzy structuring element used in this paper.

Table1. Structuring Element Mask

0.3	0.8	0.3
0.8	1	0.8
0.3	0.8	0.3

Fuzzy morphological operations are sensitive to details within an image allowing to fine tune standard morphology operations. The basic fuzzy morphological operations are dilation and erosion which are defined as follows:

$$\mathbf{[g(x) \oplus \mu\ (x)]\ \alpha(x)=supmin[g(x-y),\mu(x)]} \tag{12}$$

Where y ∈X for Dilation.

$$\mathbf{[g(x) \ominus \mu\ (x)]\ \alpha(x)=inf\ max[1-g(x-y),\mu(x)]} \tag{13}$$

Where y ∈X for Erosion.

Figure14 shows an example of fuzzy morphology dilation calculation.

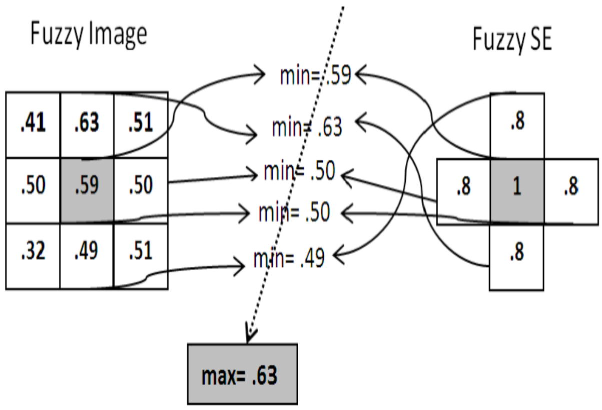

Fig.14. An example of a fuzzy morphology operation(Dilation)(Pahsa, A. 2006).

Figure 14 shows the fuzzy dilation which takes two pieces of fuzzified data as input where the first is the image which is to be dilated and the second is set of coordinate points known as structuring element (ES). The fuzzy dilation determines the precise effect of the dilation on the input image (Pahsa, A. 2006).

Fuzzy dilation is applied on smoothing fingerprint image in stages. The first stage is to fuzzify the input image. The second stage is to apply the α-cut dilation and the third stage is to defuzzify which is the inverse of fuzzification. For image fuzzification normalized membership functions are employed, where the membership values lie between 0 and 1. The selection of membership function depends on the application and experience. In image processing, heuristic membership functions are widely used to define certain properties (such as lightness or darkness of a pixel value). S-function is the most prominent heuristic membership function. The shape of S-function has three parameters a, b, and c which are specified to ensure the membership function maximizes the information contained in the image

(Sivanandam,et al 2007). In this study we will apply the S-membership function as shown below:

$$\mu(x) = \begin{cases} 0 & x<a, \\ 2\,[(x-a)/(c-a)]^2 & a<x<b, \\ 1-2\,[(x-c)/(c-a)]^2 & b<x<c, \\ 1 & x>c, \end{cases} \qquad (14)$$

where, b is any value between a and c. Figure 15 shows the membership function plot for a = Xmin = 50, c = Xmax = 250, for normalized set.

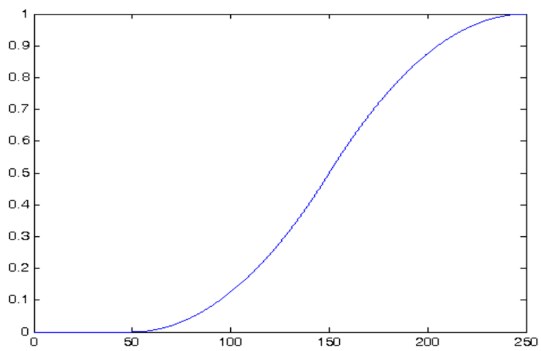

Fig. 15.S-membership functions

The fuzzified image can be created from the S-membership function with improved quality. The membership function μ = 1 represents the maximum brightness. This study used the S-membership function to improve the quality of image.

Fuzzy dilation is applied by probe the structuring element to scan the whole image, and replace the center pixel in each probe of structuring element with the pixel that satisfy the equation number (12). Figure 16 shows an example of a dilated fingerprint image using fuzzy morphology.

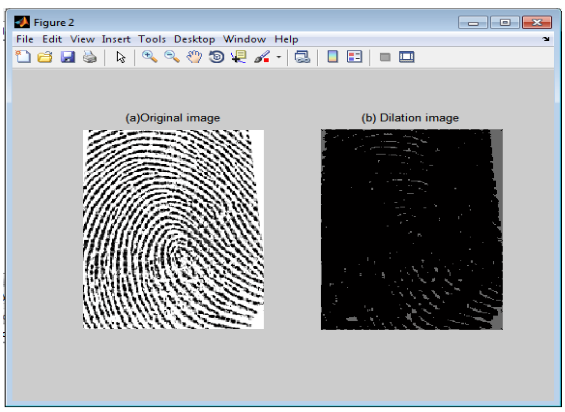

Fig.16. Fuzzy dilated image

The final step, the union operation step, where a logical operation exist that extracts the union of black pixels in the original image (input dry image) and the dilated image. In this step the white pixels in the ridges are removed and enhanced image with good ridges was obtained as shown in Figure 17.

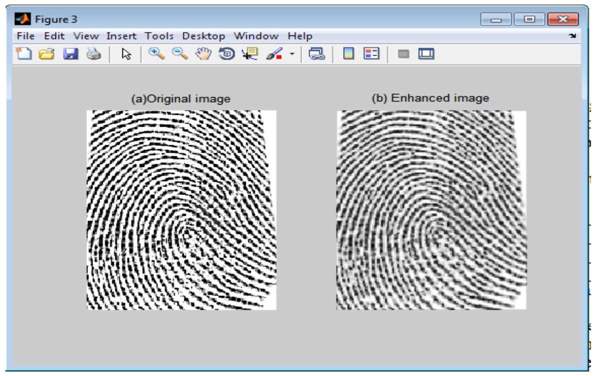

Fig.17. An enhanced image

2.3.Oily Fingerprint Image Enhancement

Figure 18 shows the flowchart for the new proposed oily fingerprint enhancement method. The method is made of five steps. The steps are as follows:

Step 1: Input an image to a low pass filter to smooth the image. Then employ a fuzzy morphology dilation on the smoothed image and lastly perform the intersection operation between the original image and dilated image.

Step2: Employ fuzzy morphology erosion on the original image.

Step3: Come up with the inverse of the dilated image.

Step4: Take the intersection operation between the output of second step and third step.

Step5: Perform the union operation between the output of first step and fourth step to display results.

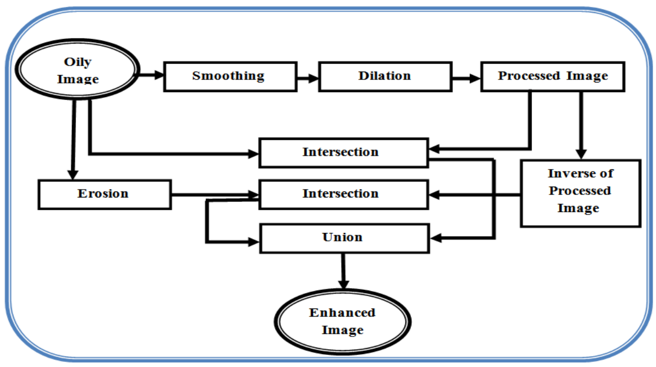

Fig.18. The flowchart of the proposed method to enhancement oily image

Finally, performance evolution is conducted to measure the quality of the enhanced image compared with previous studies using feature similarity index metric (FSIM) (Zhang, et al2011). Smoothing is applied to reduce noise in an image and to decrease the disparity between pixel values by using winner filter (Das, et al 2015). Figure19 showsa smoothed fingerprint image.

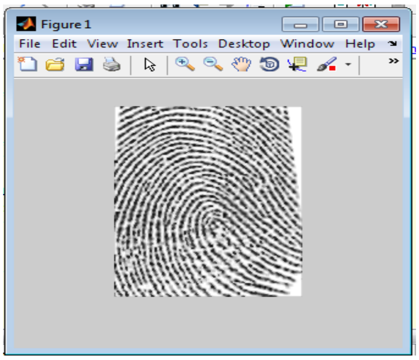

Fig.19. A smoothed image

Figures 20 and 22 shows an examples of a dilated and eroded fingerprint image using fuzzy morphology, respectively.

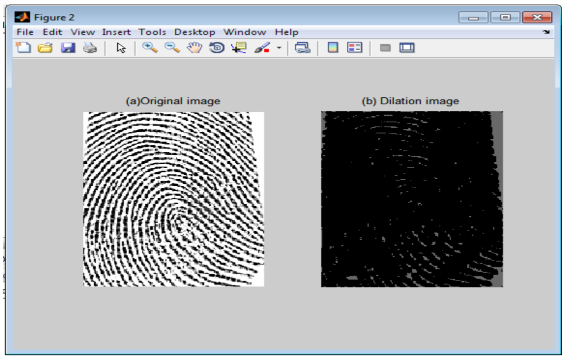

Fig. 20. Fuzzy dilated image

Fuzzy dilation and erosion operations are dual operations. Dilation is applied on smoothing fingerprint image, where erosion is applied on oily image (input image). When input images need to be fuzzified then both the α-cut dilation equation to dilate the images and the α-cut erosion equation to erode the images are applied. Fuzzification is applied to transfer the image back to greyscale image. S-function is used to fuzzify images.

Inverse of an image is obtained from dilated image using mathematical function which is the subtraction operation between the maximum value in the image and the image pixels as shown in Figure 21.

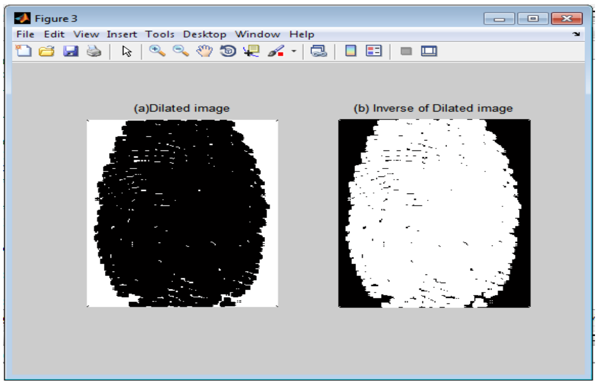

Fig.21. The inverse of dilated image

Fuzzy erosion is applied by probe the structuring element to scan the whole image and replace the center pixel in each probe of structuring element with pixel that satisfy equation (13).

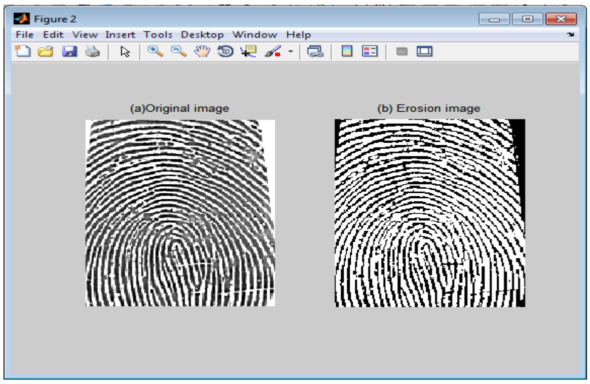

Fig.22. Fuzzy eroded fingerprint image

The logical operations intersection and union are usedto extracts the intersection and union of black pixels, as shownin Figure23. Figure23(C) shows the intersection between the eroded image and the inverse of the dilated image.

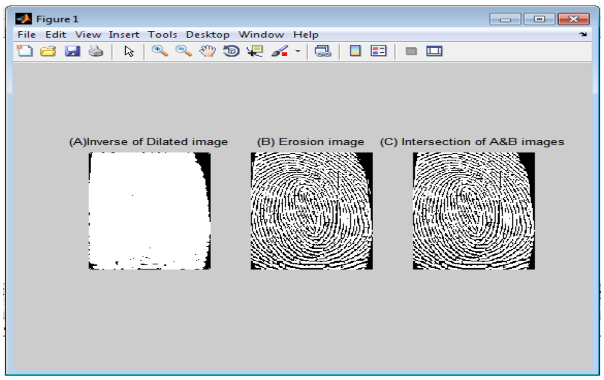

Fig.23. Intersection operation

Finally, the union operation between the two intersection operations presented in Figure18 is performed, then an enhanced image is derived as shown in Figure24.

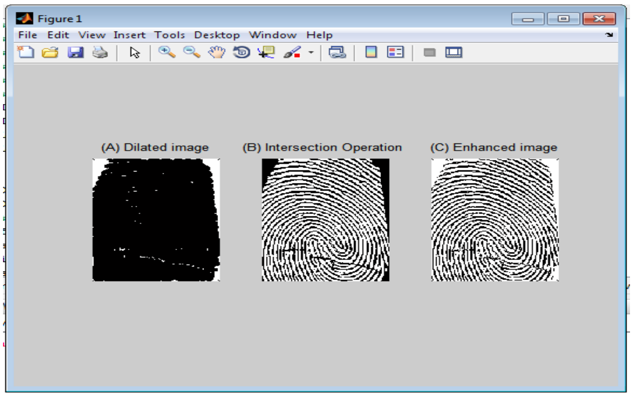

Fig.24. An enhanced image

3. Experimental Results

Experiment was done using the DB_ITS_2009 database, which is a private database collected by the Department of Electrical Engineering, Institute of Technology SepuluhNopember Surabaya. It was collectedwith great caution because the image quality considerations. The DB_ITS_2009 database was collectedusing 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: The fingerprint images are classified into three types the finger conditions (dry, neutral and oily). Each type of finger condition consists of 568 fingerprint images sourced from 71 different fingers, each of these fingerprint images 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, baby-oil was smeared on the fingertips before the image was taken (Syam, R., Hariadi, M., & Purnomo, M. H. 2010). The experiment was done in three stage quality analysis, dry image enhancement, and oily image enhancement.

First, the quality analysis. Where the implementation of a FIS was done using MATLAB. A code was written to extract the four features LCS, GLS, RVTR, and GCF as shown in Table2 and then run this code after saving it as an .m file in MATLAB workspace. Then 63 fuzzy if-then rules were developed and implemented.Table2 shows some of the results of feature extractions.

Table2. Experimental data samples for features

NO	LCS	GCS	RVTR	GCF
1	1.1539e+004	1.1482e+004	6.6246e-005	10.8909
2	1.1267e+004	1.1537e+004	6.2187e-005	10.6000
3	1.1518e+004	1.0982e+004	6.6594e-005	9.9507
4	1.1038e+004	1.1477e+004	6.2016e-005	8.6157
5	1.1649e+004	1.1479e+004	6.2943e-005	10.0419
6	1.1557e+004	1.1498e+004	6.7557e-005	11.2489
7	1.0978e+004	1.1425e+004	6.6096e-005	10.0785
8	1.1499e+004	1.1525e+004	7.2351e-005	10.2556
9	1.1043e+004	1.1577e+004	7.2182e-005	11.3194
10	1.1119e+004	1.1564e+004	7.1498e-005	10.4392
11	1.1581e+004	1.1537e+004	7.3957e-005	10.3576
12	1.1986e+004	1.1535e+004	7.0347e-005	10.4759

The best analysis for fingerprint image was derived by using FIS which uses five GUI tools for building, editing, and observing fuzzy inference systems. The rules described in Figure 11 were tested in our FIS with DB_ITS_2009 database feature values. Tables 3, 4 and 5, as well as Figures25, 26, and 27 show the performance of our FIS, which determined the fingerprint image quality according to their features extracted values. Tables 3,4, and 5 show the values of features when the image is oily, neutral, and dry, respectively.

Table3. Oily fingerprint image features values

LCS	GCS	RVTR	GCF
1.58	1.21	6.95	9

Table4. Neutral fingerprint image features values

LCS	GCS	RVTR	GCF
1.39	1.17	6.66	11.1

Table5. Dry fingerprint image features values

LCS	GCS	RVTR	GCF
1.41	1.19	7.78	10

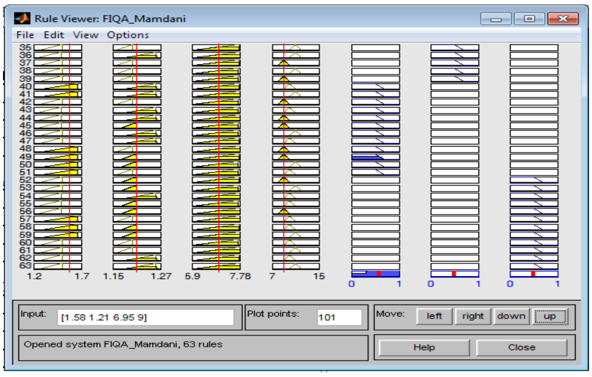

Fig. 25. Rule viewer for Oily fingerprint Image

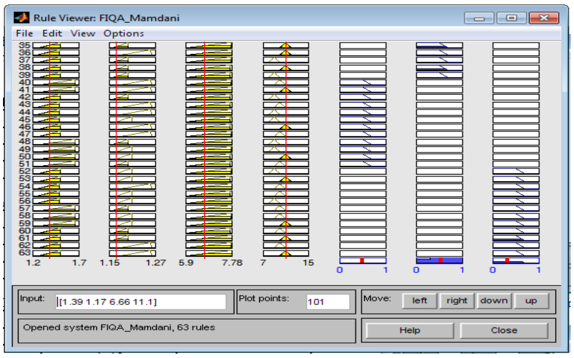

Fig. 26. Rule viewer for Neutral fingerprint Image

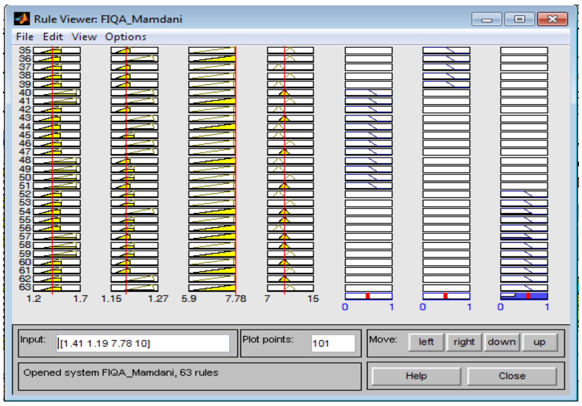

Fig. 27. Rule viewer for Dry fingerprint Image

The rule viewer, which display a roadmap of the whole fuzzy inference process, shows the values of input variables and their output. It also has the ability to change inputs and observe output changes. Figures 25, 26, and 27 shows the rule viewer for Neutral, Oily and Dry fingerprint image, respectively.

The surface viewer presents three dimensional curve that represent two input features and the image quality type. Figures 28, 29, and 30 shows the three surface viewer for Dry, Neutral and Oily fingerprint image respectively, which presents the two important features GCS and RVTR with image quality type.

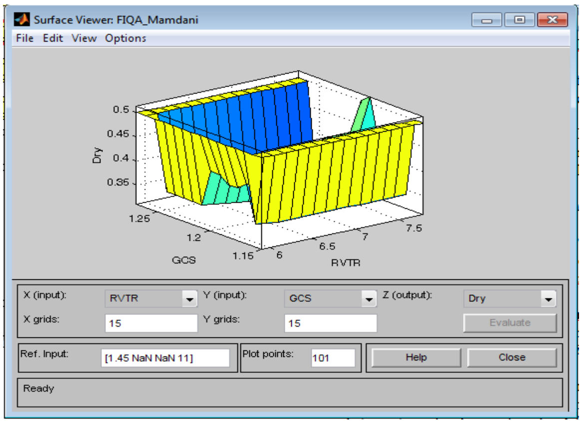

Fig. 28. Surface viewer for Dry fingerprint image

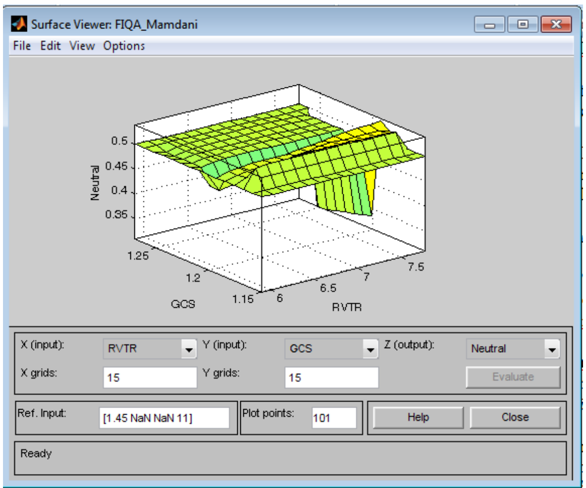

Fig. 29. Surface viewer for Neutral fingerprint image

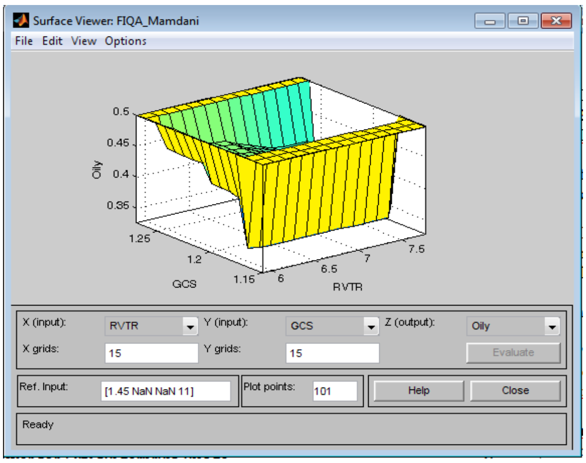

Fig. 30. Surface viewer for Oily fingerprint image

To measure the performance of the proposed method used to analysis fingerprint image quality, we inputted the extracted feature values for the four features extraction (LCS, GCS, RVTR, and GCF) to the FIS which can determined the type of fingerprint image. Figure 31 shows the number of detected and not detected fingerprint image for each type.

For oily fingerprint images the detected number is311 images, and not detected is257 images. For neutral fingerprint images the detected number is 389 images, and not detected is 179 images. For dry fingerprint image the detected is 462 images, and not detected is 106 images.

The percentage of detected for each type is given as follow: For dry fingerprint the percentage is 81.33, for oily the percentage is 54.75, and for neutral the percentage is 68.48.

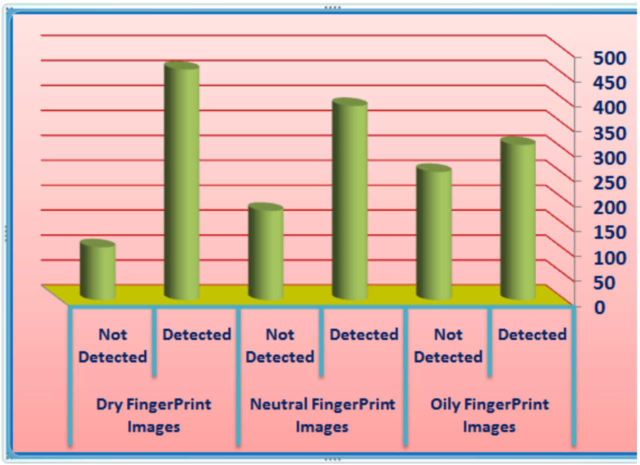

Fig. 31. Fingerprint image Quality analysis

For the dry image enhancement, the image smoothing is done using Winner filter, then fuzzy morphology operations are performed. A greyscale image is fuzzified with the use of the S-fuzzy membership functions. Then a fuzzy structuring element is traversed on the whole image to process dilation operations. Figure 17 shows an example of an enhanced image through the proposed method.

The Feature Similarity index (FSIM) is applied to evaluate the performance of the proposed method. The FSIM (Zhang, et al 2011) is an image quality assessment (IQA) metric, which uses computational models to measure the image quality consistently with subjective evaluations. The FSIM is a full reference IQA which is based on the fact that human visual system (HVS) understands an image mainly according to its low-level features. Specifically, the following low-level features: the phase congruency (PC) and the gradient magnitude (GM), which represent the complementary aspects of the image visual quality. The PC, which is a dimensionless measure of the significance of a local structure, is used as the primary feature in FSIM. Considering that PC is contrast invariant while the contrast information does affect HVS' perception of image quality, and the image GM is employed as the secondary feature in FSIM.

The computation of FSIM index consists of two stages. In the first stage, the local similarity map is computed, and then in the second stage, the similarity map is pooled into a single similarity score, as in the following equation (15):

$$\mathbf{FSIM} = \frac{\sum_{x\in\Omega} S_L(x).PC_m(X)}{\sum_{x\in\Omega} PC_m(X)} \qquad (15)$$

Where

Ω means the whole image spatial domain.

SL is the similarity between two images

PC is Phase congruency

The proposed dry fingerprint enhancement method using fuzzy morphology gives high FSIM when compared to the existing enhancement method by Eun-Kyung Yun et al. (Yun, E. K., & Cho, S. B. 2006)that uses an adaptive pre-processing method based on binary morphology image processing. The FSIM for the existing method and the proposed method are described in tables 6 and 7, respectively.

Table6. The FSIM values for Yun et al. Method (Yun, E. K., & Cho, S. B. 2006)

Finger# / Person #	1	2	3	4	5	6	7	8
1.	0.0687	0.0641	0.0660	0.0601	0.0681	0.0693	0.0654	0.0818
2.	0.0724	0.0696	0.0719	0.0723	0.0720	0.0692	0.0695	0.0731
3.	0.0466	0.0600	0.0512	0.0604	0.0613	0.0593	0.0470	0.0518
4.	0.0640	0.0613	0.0599	0.0594	0.0665	0.0543	0.0670	0.0541
5.	0.0770	0.0748	0.0730	0.0614	0.0728	0.0704	0.0604	0.0714
6.	0.0747	0.0738	0.0782	0.0747	0.0679	0.0647	0.0684	0.0679
7.	0.0606	0.0610	0.0523	0.0524	0.0608	0.0649	0.0618	0.0580
8.	0.0598	0.0597	0.0557	0.0511	0.0472	0.0504	0.0524	0.0476
9.	0.0621	0.0606	0.0642	0.0647	0.0674	0.0638	0.0603	0.0621
10	0.0582	0.0540	0.0546	0.0603	0.0556	0.0566	0.0580	0.0599

Table7. The values of FSIM for proposed method

Finger# / Person #	1	2	3	4	5	6	7	8
1.	0.8330	0.8332	0.8318	0.8706	0.8551	0.8380	0.8272	0.8403
2.	0.8482	0.8543	0.8566	0.8510	0.8575	0.8522	0.8560	0.8526
3.	0.8805	0.8678	0.8940	0.8827	0.8719	0.8748	0.8880	0.8718

4.	0.8488	0.8467	0.8474	0.8419	0.8435	0.8592	0.8512	0.8703
5.	0.8488	0.8544	0.8487	0.8508	0.8480	0.8495	0.8640	0.8531
6.	0.8533	0.8573	0.8571	0.8591	0.8547	0.8602	0.8627	0.8547
7.	0.8745	0.8599	0.8719	0.8781	0.8663	0.8639	0.8690	0.8733
8.	0.8140	0.8143	0.8239	0.8211	0.8134	0.8278	0.8277	0.8168
9.	0.8640	0.8588	0.8596	0.8736	0.8621	0.8660	0.8660	0.8673
10	0.8571	0.8606	0.8811	0.8658	0.8617	0.8736	0.8658	0.8599

Figure 32 shows the comparison between Eun-Kyung Yun et al. (Yun, E. K., & Cho, S. B. 2006) method and the proposed method. Eun-Kyung Yun et al. method is an adaptive pre-processing method which is based on binary image morphology.

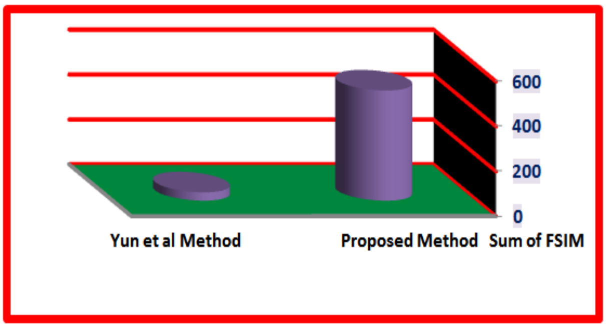

Fig. 32. Comparison of Yun et al method and proposed method for dry fingerprint images.

From Table6, Table7 and Figure 32, it is clear that the proposed method is better than the Eun-Kyung Yun et al. method. The percentage improvement between the proposed method and Eun-Kyung Yun et al. method is 900% (calculated for all the database). Therefore, the value of FSIM for the proposed method as in Table7 is higher than the value of FSIM for the Eun-Kyung Yun et al. method as in Table6.

For the oily image enhancement, the image smoothing is done using Winner filter, then fuzzy morphology operations are performed. A greyscale image is fuzzified with the use of the S-fuzzy membership functions. Then a fuzzy structuring element is traversed on the whole image to process dilation and erosion operations.

The logical operations, union and intersection, are done using mathematical function as well as inverse of dilated image. Figure 24 shows an example of an enhanced image through the proposed method.

The proposed oily fingerprint enhancement method using fuzzy morphology gives high FSIM when compared to the existing enhancement method by Eun-Kyung Yun et al. (Yun, E. K., & Cho, S. B. 2006) that uses an adaptive pre-processing method based on binary morphology image processing. The FSIM for the existing method and the proposed method are described in tables 8 and 9, respectively.

Table8. Samples of FSIM values for Eun-Kyung Yun et al. method (Yun, E. K., & Cho, S. B. 2006)

Finger# / Person #	1	2	3	4	5	6
1.	0.5616	0.5807	0.5616	0.5829	0.5928	0.5967
2.	0.6084	0.6082	0.6122	0.5884	0.5925	0.5924
3.	0.6013	0.6030	0.5938	0.5997	0.5925	0.6033
4.	0.5900	0.6087	0.5857	0.5990	0.6244	0.6060
5.	0.5538	0.5442	0.5723	0.5713	0.5361	0.5759
6.	0.5928	0.5755	0.5792	0.5942	0.5827	0.5716
7.	0.5983	0.6157	0.6174	0.6167	0.6164	0.6166
8.	0.6002	0.5917	0.6112	0.6033	0.5707	0.6020
9.	0.6247	0.6163	0.6151	0.6163	0.6190	0.6085
10.	0.6024	0.6161	0.6303	0.6291	0.6112	0.6234

Table. 9. Samples of FSIM values for proposed method

Finger# / Person #	1	2	3	4	5	6
1.	0.7291	0.6977	0.7291	0.7038	0.6884	0.7126
2.	0.7201	0.7192	0.7137	0.6996	0.6969	0.6977
3.	0.7032	0.7084	0.7042	0.7091	0.7157	0.7092
4.	0.7356	0.7179	0.7466	0.7393	0.7339	0.7344
5.	0.6561	0.6531	0.6599	0.6716	0.6498	0.6836
6.	0.6983	0.6689	0.6769	0.6784	0.6902	0.6859
7.	0.7064	0.6978	0.7300	0.7203	0.7101	0.7239
8.	0.7551	0.7550	0.7484	0.7443	0.7273	0.7198
9.	0.7323	0.7086	0.7234	0.7232	0.7179	0.7298
10.	0.7181	0.7314	0.7348	0.7343	0.7251	0.7163

Figure33 shows the comparison between Eun-Kyung Yun et al. (Yun, E. K., & Cho, S. B. 2006) method and the new proposed method. Eun-Kyung Yun et al. method is an adaptive pre-processing method which is based on binary image morphology. Figure 33 shows that the proposed method enhanced the quality of fingerprint image and increased the fingerprint identification rate from 82% to 96%.

From Table8, Table9 and Figure33, it is clear that the proposed method has performed better than the Eun-Kyung Yun et al. method. The FSIM difference between the proposed method and Eun-Kyung Yun et al. method is 14.2308% (calculated for all database). Therefore, the values of FSIM for the proposed method as in Table9 is higher than the values of FSIM for the Eun-Kyung Yun et al method as in table8. The new proposed method has an FSIM value of about 96% as an identification rate and Eun-Kyung Yun et al. method has an FSIM value of about 82%as an identification rate.

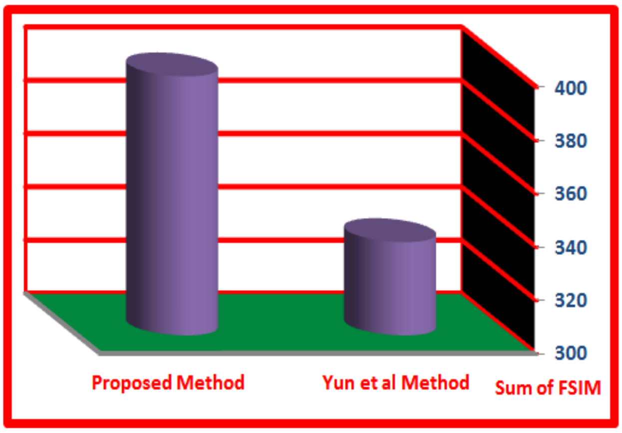

Fig.33. Comparison of Yun et al method and proposed method for oily fingerprint images

4. Conclusion

The performance of fingerprint identification system relies heavily on the image quality. Hence, images quality analysis and enhancement make the system performance more robust. However, it is usually very difficult to obtain good quality images. To overcome this problem, image enhancement is needed.

In this paper, a fuzzy inference system was proposed to analyze fingerprint image quality and a fuzzy morphology method to enhance dry and oily fingerprint images was also proposed.

The fuzzy inference system method used to analyze fingerprint image quality using four extracted features LCS, GCS, RVTR and GCF. The fuzzy inference system has four input variables and three output variables with sixty three rules. The results obtained using the FIS were successful. The FIS has the ability to determine the fingerprint image quality (Oily, Neutral, or Dry) according to their input features.The percentages of test fuzzy inference system for each type as follow. For dry fingerprint the percentage is 81.33, for oily the percentage is 54.75, and for neutral the percentage is 68.48.

The fuzzy morphology method used to enhance dry and oily fingerprint images. For dry image the method includes three steps; smoothing with low pass filter then fuzzy dilation, which is applied on smoothing fingerprint image by fuzzification input image with S-Membership function, then apply α -cut dilation then defuzzification which is the inverse of fuzzification and finally the union between the dilated image the input image. The result obtained using the method were successful. It gave better result than Eun-Kyung Yun et al method where the percentage improvement was900%. The performance evaluation was performed using FSIM. For oily images, the method applied was as follow: smoothing with low pass filter then fuzzy dilation and erosion. Fuzzy dilation was applied on smoothing the fingerprint image and fuzzy erosion was applied on oily image (the input image). Both operations were done by fuzzifying the input image using theS-Membership function. The α-cut dilation or erosion was applied, then defuzzification was performed which was the inverse of fuzzification. Using logical operation to extract the union and intersection of black pixels from processed images, as well inverse of dilated image to get lost information in image. This way, the valleys of oily fingerprint images were enhanced. The result obtained using the method was better than the result from using Eun-Kyung Yun et al method. The performance evaluation was performed using FSIM. The new proposed method has an FSIM value of about 96%as an identification rate and Eun-Kyung Yun et al. method has an FSIM value of about 82%as an identification rate which uses an adaptive pre-processing method based on binary morphology image processing.

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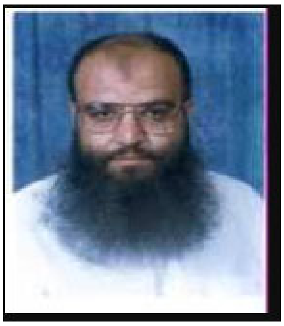

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