

Fingerprint Image Quality Fuzzy System

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Abstract: In this paper, we present a novel technique to analysis fingerprint image quality using fuzzy logic. The quality of fingerprint image greatly affects the performance of minutiae extraction and the process of matching in fingerprint identification system. The system uses the extracted four features from a fingerprint image which are the Local Clarity Score (LCS), Global Clarity Score (GCS), Ridge_Valley Thickness Ratio (RVTR), and the contrast. The proposed fuzzy logic system uses mamdani fuzzy rule model which can analysis and determinate the fingerprint image type (oily, dry or neutral) based on the extracted feature values and fuzzy inference rules.

Keywords: Fingerprint image quality, LCS, GCS, RVTR, contrast, fuzzy inference system.

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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 or assessment 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 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 [11].

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 the quality and validity of the captured fingerprint image is necessary and meaningful. Many papers in biometric literature address the problem of assessing fingerprint image quality. But these methods still have some problems and can't be suitable for all the condition [11].

Saenko *et al.* [9] proposed a technique to analysis image quality that uses two different methods. The first is 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. All of these parameters are linguistic variables and have three possible linguistic values "bad", "normal", and "good".

Eun-Kyung and Cho [2] proposed a method to analysis image quality by extracted five features from a fingerprint as follows: Mean, variance, block directional difference, ridge valley thickness ratio, and orientation change. According to these features they cluster images by using ward's clustering algorithm which is a hierarchical clustering method. It initially assigns an independent cluster to each sample, then it seeks the most similar pairs of clusters and merges them into one cluster.

Rahmat *et al.* [8] proposed a model to determine the standard value used in classifying the type of distortions within fingerprint images based on the image quality. They used the ridge-valley clarity score and ridge-valley thickness ratio score to describe the fingerprint image quality.

Rahmat *et al.* [7] proposed 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.

Li and Xie [5] proposed a method for measuring fingerprint image quality using Fourier spectrum. This method measures fingerprint image quality based on the global characteristics of the image and do not rely on local ridge orientation estimation. The method first search the band frequency which corresponds to the global average period of ridge. Then the quality score of the fingerprint image is computed by measuring relative magnitude of the band frequency components.

Modi and Elliott [6] studied the impact of fingerprint image quality of two different age groups: 18-25, and 62 and above on overall performance using two different matchers. The difference in image quality between the two age groups was analysed and the impact of image quality on performance of fingerprint matchers between the two groups was also analysed. Image quality analysis was performed using NFIQ which is part of NIST Fingerprint Image

Software (NFIS). NeurotechnologijaVeriFinger and bozorth3 NFIS matchers were used to assess the overall performance.

The paper is organized as follows: Section 2 presents the rationale of using fuzzy logic, section 3 presents a brief introduction to fingerprint image quality, section 4 presents the new proposed fingerprint image classification system that classifies the image into one of three types; dry, oily or neutral and section 5 presents the results using the DB_ITS_2009 database which is a private database collected by the Department of Electrical Engineering, Institute of Technology SepuluhNopember Surabaya.

2. Fuzzy Logic

Fuzzy logic is a form of many-valued logic or probabilistic logic, it deals with approximate (rather than fixed and exact) reasoning. It has been extended to handle the concept of partial truth, where the truth value may range between completely true and completely false [10].

Linguistic variables are used to express fuzzy rules, which facilitate the construct of rule-based fuzzy systems. A linguistic variable can be defined as a variable whose values are words or sentences. For example a linguistic variable such as age may have a value such as young, very young, old, very old rather than 30, 36, 18 etc., However, the advantage of linguistic variables is that they can be changed via hedges (fuzzy unary operators) [10].

Fuzzy Inference System (FIS) is a method that interprets the values in the input vectors and based on user defined rules, assigns values to the output vector. Using a GUI editors and viewers in the MATLAB fuzzy logic toolbox, we can build the rules set, define membership functions and analyse the behaviour of a FIS. The editors and viewers are used to edit and view the membership functions and rules for FIS [1].

3. 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 dominates the overall quality of the fingerprint [9]. 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 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 the examples of the oily, neutral and dry images, respectively [2].



Figure 1. Examples of fingerprint Images [2].

- Oily Image: Even though the separation of ridges and valleys is clear, some parts of valleys are filled up causing them to appear dark or adjacent ridges stand close to each other in many regions. Ridges tend to be very thick [2].
- Neutral Image: In general, it has no special properties such as oily and dry. It does not have to be filtered [2].
- Dry Image: The ridges are scratchy locally and there are many white pixels in the ridges [2].

In this paper, the FIS is applied to analyze fingerprint image quality to three types (oily/dry/neutral) based on four features which are the LCS, GCS, Ridge_Valley Thickness Ratio (RVTR), and the contrast, then use mamdani fuzzy rule model to determine each type depend on the extracted feature values and the FIS rule base.

4. Proposed Method

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 FIS to determine the type of the fingerprint image quality.

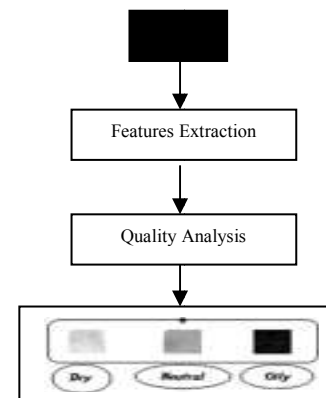


Figure 2. Proposed method flowchart.

4.1. Features Extraction

In this stage we extracted four features which are the LCS, GCS, RVTR, and the Global Contrast Factor (GCF), to analysis the fingerprint image quality using a FIS. The following subsections will present few fingerprint image scores that will be used in analysing fingerprint images.

4.1.1. 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 [8].

To perform local clarity analysis, the fingerprint image is quantized into blocks of size 32×32 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 shown in Figure 3) with size 32×13 pixels can be extracted and transformed to a vertical aligned 2D Vector V_2 . Equation 1 is a 1D Vector V_3 , which is the average profile of V_2 [8].

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

Where m is the block height (13 pixels) and i is the horizontal index. Once V_3 is calculated as in Equation 1, then linear regression can be applied to V_3 to find the Determine Threshold (DT_1). Figure 4 shows the method of regional segmentation. 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 classified as the ridges and the others are as valleys. Hence, the regions of ridges and valleys can be separated in the 2D vector V_2 by the 1D average profile V_3 with the DT_1 shown as the dotted straight line in Figure 4. As ridges and valleys are separated, a clarity test can be performed in each segmented 2D rectangular regions. Figure 5 shows the gray level distribution of the segmented ridges and valleys. 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. For the calculation of the clarity score refer to Equations 2, 3, and 4 [8].

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

$$\beta = \frac{\mathcal{R}_B}{\mathcal{R}_T} \quad (3)$$

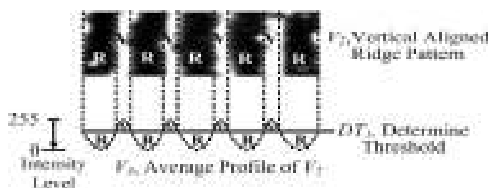


Figure 3. Region Segmentation of vector V_2 [8].

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

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, \mathcal{R}_B is the number of bad pixels in the ridge that the intensity is higher than the DT_1 and \mathcal{R}_T is the total number of pixels in the ridge region. α and β are the portion of bad pixels. Hence, the LCS is the average value of both α and β .

For ridges with good clarity, both distributions should have a very small overlapping area. The following factors affect the size of the total overlapping area [8]:

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.

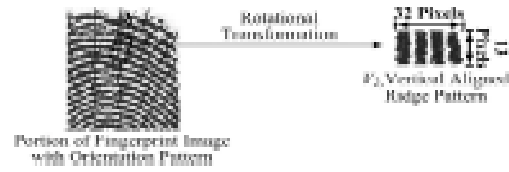


Figure 4. Extraction of a local region and transformation to vertical aligned ridge pattern [8].

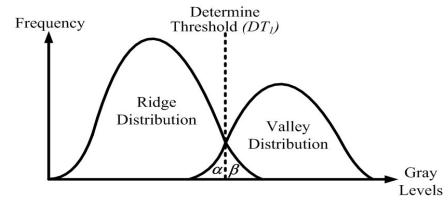


Figure 5. Distribution of ridge and valley [8].

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 32×13 pixels is chosen to minimize the chance of encountering too many distinct features in the same location. The GCS can be computed by the expected value of the LCS [8].

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

Where

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

As seen in Equation 5, $LCS(i, j)$ 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.

4. The Ratio for Ridge Thickness to Valley Thickness is Computed in each Block.

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 [8].

5. 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 newly introduced GCF corresponds closer to the human perception of contrast. GCF uses contrasts at various resolution levels in order to compute overall contrast [3].

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 [3].

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 [3].

Let us denote the original pixel value with k , $k \in \{0, 1, \dots, 254, 255\}$. 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 linear luminance with L [3].

$$L = \left(\frac{K}{255} \right)^y \tag{7}$$

The perceptual luminance L is now:

$$L = 100 * \sqrt{L} = 100 * \sqrt{\left(\frac{K}{255} \right)^y} \tag{8}$$

The square root to compute luminance was used [3]. Once the perceptual luminance is computed we have to compute local contrast. For each pixel we compute the average difference of L between the pixel and four neighboring pixels [3].

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 [3]:

$$Lc_i = \frac{|L_i - L_{i-1}| + |L_i - L_{i+1}| + |L_i - L_{i-w}| + |L_i - L_{i+w}|}{4} \tag{9}$$

The average local contrast for current resolution C_i is computed now as the average local contrast Lc_i over the whole image [3].

$$C_i = \frac{1}{w * h} * \sum_{i=1}^{w * h} Lc_i \tag{10}$$

Now that, we have computed average local contrasts C_i , we need to find the weigh factors w_i , which will be used to compute the GCF .

$$GCF = \sum_{i=1}^N W_i * C_i \tag{11}$$

4.2. Quality Analysis- FIS

Fingerprint image quality analysis has been developed and implemented using FIS. FIS has been developed using five stages. The stages are as follow:

4.2.1. The FIS Editor

This stage shows the FIS 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.

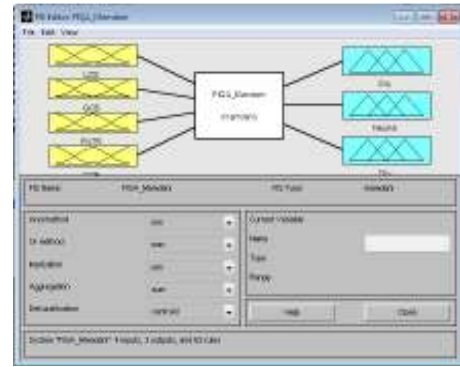


Figure 6. FIS Editor for image quality classification.

4.2.2. 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 function for GCF, LCS, GCS, and RVTR respectively.

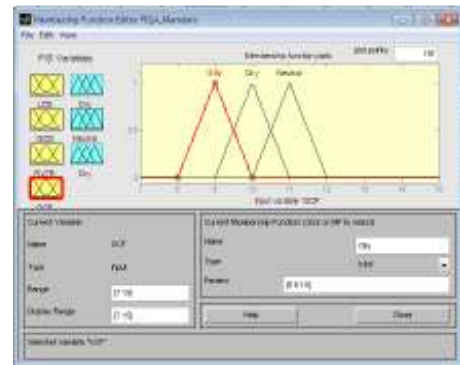


Figure 7. FIS membership function editor for GCF.

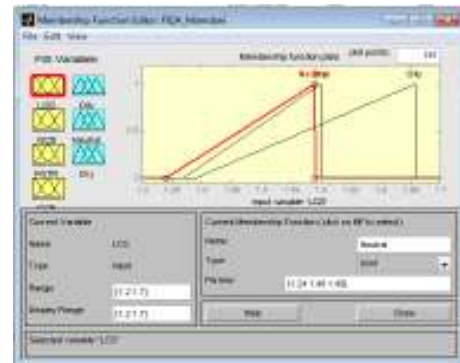


Figure 8. FIS membership function editor for LCS.

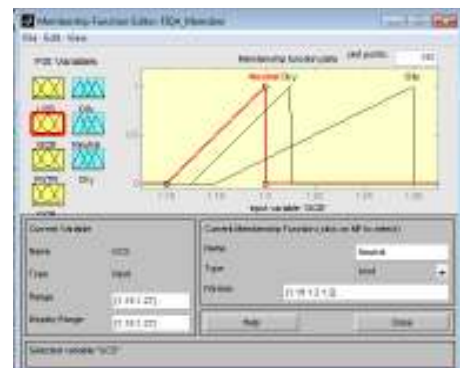


Figure 9. FIS membership function editor for GCS.

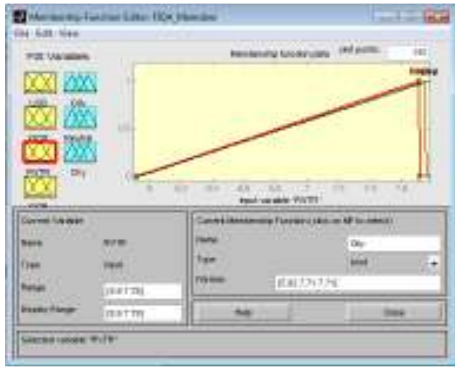


Figure 10. FIS membership function editor for RVTR.

4.2.3. The Rules Editor

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



Figure 11. FIS rule editor.

5. Result

The implementation of our FIS was done using MATLAB. A code was written to extract the four features LCS, GLS, RVTR, and GCF as shown in Table 1 and then run this code after saving it as an .m file in MATLAB workspace. Then Fuzzy if-then rules was developed and implemented with 63 rules.

Experiment 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. It was taken with great caution because the image quality considerations. The DB_ITS_2009 database was 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 154×208 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 3×71×8=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 was taken [7]. Table 1 shows some of the results of feature extractions.

Table 1. 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

We get the best analysis for fingerprint image by using FIS which uses five GUI tools for building, editing, and observing FISs.

The rules described in Figure 11 were tested in our FIS with DB_ITS_2009 database feature values. Tables 2, 3 and 4, as well as Figures 12, 13, and 14 shows the performance of our FIS, which it determine the fingerprint image quality according to their features extracted.

Table 2. Oily fingerprint image.

LCS	1.58	Oily
GCS	1.21	
RVTR	6.95	
GCF	9	

Table 3. Neutral fingerprint image.

LCS	1.39	Neutral
GCS	1.17	
RVTR	6.66	
GCF	11.1	

Table 4. Dry fingerprint image.

LCS	1.41	Dry
GCS	1.19	
RVTR	7.78	
GCF	10	

The rule viewer which displays a roadmap of the whole fuzzy inference process, shows the values of input variables and their output, and has ability to change inputs and see output change. Figures 12, 13, and 14 shows the rule viewer for neutral, oily and dry fingerprint image respectively.



Figure 12. Rule viewer for oily fingerprint image.



Figure 13. Rule viewer for neutral fingerprint image.

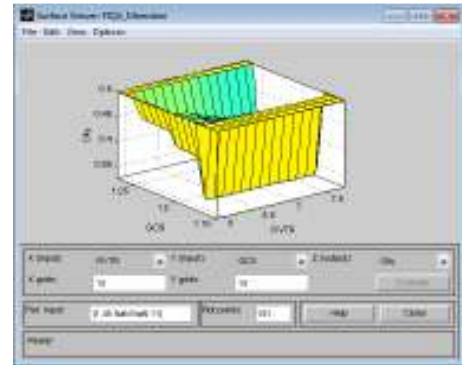


Figure 17. Surface viewer for oily fingerprint image.



Figure 14. Rule viewer for dry fingerprint image.

The surface viewer presents three dimensional curve that represent two input features and the image quality type. Figures 15, 16, and 17 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.

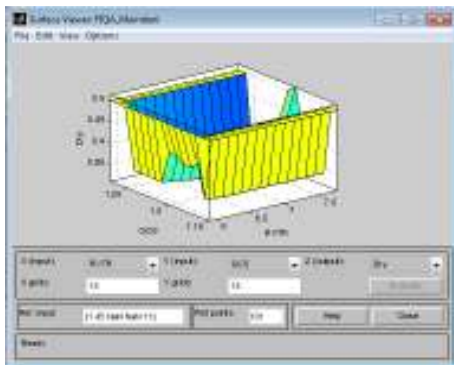


Figure 15. Surface viewer for Dry fingerprint image.

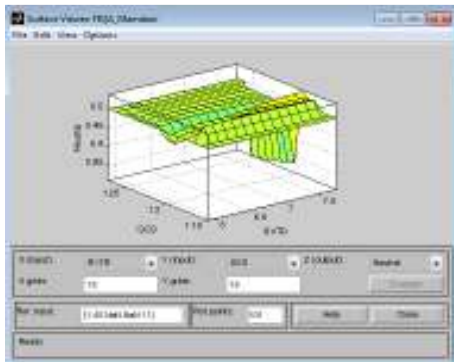


Figure 16. Surface viewer for neutral fingerprint image.

6. Conclusions

In this paper, we have developed a FIS method to analyse fingerprint image quality using four extracted features LCS, GCS, RVTR and GCF. The FIS has four input variables and three output variables with sixty three rules. The result obtained using the proposed FIS were successful. The FIS has the ability to determine the fingerprint image quality (oily, neutral, or dry) according to their input features.

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