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Log-Gabor Orientation with Run-Length Code based Fingerprint Feature Extraction Approach

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Abstract- This paper aims to design and implement Log-Gabor filtering with Run-length Code based feature Extraction technique. Since minutiae extraction is an essential and core process of fingerprint Identification and Authentication systems, the minutiae features are enhanced in each orientation using Log-Gabor filter and features are extracted using the proposed method. Frequency domain is derived using FFT and they are enhanced by Log-Gabor filter for each orientation. In our method six orientations are considered; binarization, thinning are also followed. Fingerprint features are extracted using proposed method which possesses labeling and Run-length Coding technique. Our method is tested with the benchmark Databases and real time images and the results show the better performance and lower error rate.

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Dr. K. Kanagalakshmi [α] & Dr. E. Chandra [σ]

Abstract- This paper aims to design and implement Log-Gabor filtering with Run-length Code based feature Extraction technique. Since minutiae extraction is an essential and core process of fingerprint Identification and Authentication systems, the minutiae features are enhanced in each orientation using Log-Gabor filter and features are extracted using the proposed method. Frequency domain is derived using FFT and they are enhanced by Log-Gabor filter for each orientation. In our method six orientations are considered; binarization, thinning are also followed. Fingerprint features are extracted using proposed method which possesses labeling and Run-length Coding technique. Our method is tested with the benchmark Databases and real time images and the results show the better performance and lower error rate.

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I. Introduction

The accuracy of the Fingerprint matching process firmly depends on the feature extraction phase. The true minutiae alone lead the matching process successfully; and reduce the FRR (False Rejection Rate) and FAR (False Acceptance Rate). The Human fingerprint consists of various types of features that are the ridge patterns, traditionally classified according to the decade's old Hendry system: Left loop, Right loop, Arch, Whorl and Tented arch. Fingerprint features are classified into three levels. Level 1 Features are: Arch, Tented arch, Right loop, Left loop, double loop and Whorl. The Level 2 features are Line-unit, Line-fragment, Ending, Bifurcation, Eye and Hook. The Level 3 features are Pores, line shape, incipient ridges, creases, warts and scars [1]. The statistical analysis shows that the level-1 features are not unique but are useful for fingerprint classifications. The level 2 features are having adequate sharp power, used to establish the individuality of fingerprint [2]. Likewise, the level 3 features are permanent, immutable and unique according to the forensic experts. It also can offer discriminatory information for human identification [1]. Rest of the paper comprises of six sections. Section 2 specifies different feature extraction techniques. In section 3, proposed method is described. Section 4 tabularizes the benchmarks used. Experimental tasks and results are provided in section 5. Section 6 concludes the paper.

II. Background Work

Feature extraction techniques are classified in to different ways; According to image: Direct gray level minutiae extraction, Binary minutiae extraction; According to Levels of features: Level 1 feature extraction, Level 2 feature extraction, Level 3 feature extraction. We desire to extract Binary fingerprint- Level 2 features which posses an adequate and sharp power. Yet other feature extraction techniques are surveyed. They are:

- Orientation or Directional Mapping method
- Gabor-Filter Bank and Orientation method
- Run-Length Coding method
- Chain Code method
- Crossing Number method
- Morphology based method

Run-Length Coding (RLC) method [3, 4] is effective when long sequence of the same symbol occurs. RLC uses the Scan line procedure to extract features. Nalini K. Ratha et al. [5] designed an adaptive flow orientation based feature extraction method to extract binary fingerprint features and also used a waveform projection based ridge segmentation algorithm to locate ridges accurately. Chih-Jen Lee et al. [6] proposed a Gobor-Filter based method for fingerprint recognition. The Gabor-filter based features can also be used for the process of local ridge orientation, core point detection and features extraction. Jain et al. [7] suggested the multichannel approach using Gabor filter for the classification of fingerprints features. Wan S [8] proposed a method based on directional fields of fingerprint image to detect the singular points (cores) and extract features. Neil Yager [9] distinguished the fingerprint features in to different classes. Orientations fields and Gabor-filtering are influential means for classifications of fingerprints features. Classifications and identification of fingerprint features are used for the recognition and features extraction. Sharat Chikkerur et al. [10] proposed an approach of Orientation Map for fingerprint image feature extraction. Feng Zhoo et al. [11] used Crossing Number (CN) method to extract minutiae from the Valley skeleton binary image. The Orientation Maps and Gabor filters are good in fingerprint feature extraction [12]. We

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propose a hybrid approach based on Log-Gabor Orientation with RLC method to get accurate minutiae.

III. Proposed Method

The Proposed method includes three main stages: Image preprocessing, Enhancement and Minutia Extraction and Post processing. The System level design is shown in figure 1.

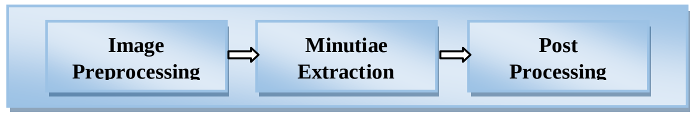

Figure 1 : System Level Design

The flow graph notation of the proposed method is shown in figure 2.

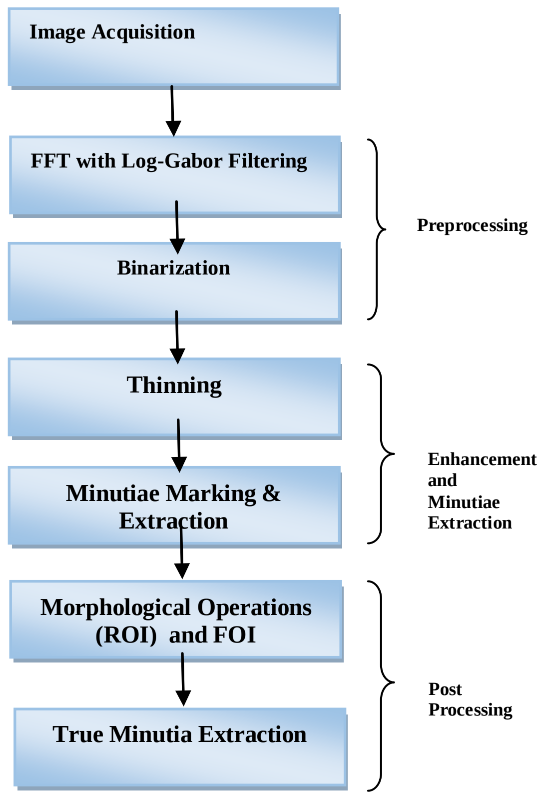

Figure 2 : Algorithm Level design

a) *Preprocessing*

The preprocessing stage includes the Fourier Transformation and the filtering using Log-Gabor Filter followed by Binarization. Steps followed in the first stage are described below.

i. *Image acquisition*

The first step of the algorithm is the image acquisition. The images are acquired from benchmark data sets and also real time fingerprint images.

ii. *FFT and Log-Gabor Filtering*

The image enhancement can be carried out in either spatial or frequency domain. The Log-Gabor can provide a better enhancement on any kind of images with its good smoothening characteristic based on performance and quality measures which were empirically observed [13]. The frequency domain enhancement is carried out for our succeeding work. The frequency values are obtained through the Fast Fourier Transformation. It transforms the image into a frequency image; next the Log-Gabor filter parameters are defined and the Orientations are estimated (six orientations are considered). In this stage, Log-Gabor features and Local ridge orientations are also calculated.

a. *Gabor Features*

The 2-D Gabor filters general format is defined in [14, 15] as follows:

$$G(x, y, \theta_k, f, \theta_k, \sigma_x, \sigma_y) = e^{\left[-\frac{1}{2}\left(\frac{x_\theta{}^2}{\sigma_x{}^2} + \frac{y_\theta{}^2}{\sigma_y{}^2}\right)\right]} \times e^{i2\pi f\, x_{\theta_k}} \quad (1)$$

where $x_{\theta_k} = x\cos\theta_k + y\sin\theta_k$ and $y_{\theta_k} = -x\sin\theta_k + y\cos\theta_k$, f is the frequency of the sinusoidal plane wave, θ_k is the orientation of the Gabor filter, and σ_x, σ_y are the standard deviations of the Gaussian envelop along the x and y axes, respectively.

The complex form of the eqn. (1) can be expressed as follows:

$G = g_{even} + i\, g_{odd}$ where

$$g_{even}\left(x, y, \theta_k, f, \theta_k, \sigma_x, \sigma_y\right) = e^{\left[-\frac{1}{2}\left(\frac{x_\theta 2}{\sigma_x 2}+\frac{y_\theta 2}{\sigma_y 2}\right)^2\right]} \times \cos\left(2\pi f x_{\theta_k}\right) \quad (2)$$

$$g_{odd}\left(x, y, \theta_k, f, \theta_k, \sigma_x, \sigma_y\right) = e^{\left[-\frac{1}{2}\left(\frac{x_\theta 2}{\sigma_x 2}+\frac{y_\theta 2}{\sigma_y 2}\right)^2\right]} \times \sin\left(2\pi f x_{\theta_k}\right) \quad (3)$$

While most local ridge structures of fingerprint images are with the well defined frequency and orientations, *f* can be set by the reciprocal of the average inter ridge distance and *n* as the number of orientations for calculating $\theta_k = \pi(k-1)/n$, k=1, 2,….n; and the cosine and sine form and the sinusoidal shape of the Gabor filter is suitable for modeling ridge structures and smoothing noise, respectively. To reduce the complexity of the Gabor equations and make computation faster, we followed the Log-Gabor method with the modified versions of equation 1. The Log-Gabor expression is given below [13].

$$LGF(f) = LG(f) \times FC \quad (4)$$

where LG(f) is the Log-Gabor Radial Component and FC is the angular component. The radial component controls the frequency band and the angular component controls the orientation.

$$\boldsymbol{LG(F) = e^{\left(-\frac{\log\left(\frac{r}{rf_0}\right)}{2\log\left(\frac{\sigma}{rf_0}\right)}\right)}} \quad (5)$$

$$\boldsymbol{FC = e^{\left(\frac{-d\theta^2}{2\theta\sigma^2}\right)}} \quad (6)$$

where *r* is the normalized radius from centre, rf_o is the normalized radius from centre of frequency plane corresponding to the wavelength and $d\theta$ is an angular distance of sin and cosine. From the product of the eqn. 5 and 6 the Log-Gabor filter is derived.

b. Local Ridge Orientation

The ridge orientation (θ) is computed using the Log-Gabor features as follows:

$$\boldsymbol{\theta = \frac{\sum_{k=1}^{n} LG_{\theta_k} \times \theta_k}{\sum_{k=1}^{n} LG_{\theta_k}}} \quad (7)$$

Where $\theta_k = \pi(k-1)/n$, k=1,2….n, and G_{θ_k} Log-Gabor features.

Log-Gabor Filter is applied on the frequency domain with six orientations (θ_1 – θ_6) in order to eliminate the noise and also enhance the frequency values of an image; and through which even negative frequency values are enhanced [13].

iii. *Binarization*

Binarization is the process of converting the gray-level image [0-255] to binary image [0 or 1]. New value (0 or 1) can be assigned for each pixel according to the intensity mean in a local neighborhood, as follows:

$$I_{new}(p1, p2) = \begin{cases} \boldsymbol{1\ if\ I_{old\,(p1,p2 \geq local\ Mean)}} \\ \boldsymbol{0\ otherwise} \end{cases} \quad (8)$$

The gray-scale transformations do not depend on the position of the pixel in the image. During the binarization process, the low frequency pixels are omitted [16]. For the binarization process, the Log-Gabor filtered image is used.

b) Fingerprint Image Enhancement and Minutiae Extraction

Before extracting minutiae, the fingerprint image is enhanced to get compatible patterns of features. This stage includes three main steps: Thinning, Minutiae Marking (FOI: Feature of Interest) and Extracting minutiae sets.

i. *Thinning*

In order to get skeleton of the fingerprint image, thinning process is followed. A Skeleton is a one-pixel wide ridge [17]. Thinning is a process of translating the thickness of an image into one pixel width representation. From thinning process, thinned and sharp ridges of fingerprint features are derived. It gives a clear structure of the fingerprint image.

The thin operation which we implemented uses the following algorithm [18, 19].

Step 1: Divide the image into two distinct subfields in a checkerboard pattern.

Step 2: Delete pixel p from the first subfield if and only if the conditions G1, G2, and G3 are all satisfied in the first iteration.

Step 3: Delete pixel p from the second subfield if and only if the conditions G1, G2 and G3` are all satisfied during the second sub- iteration.

Condition G1:

$$X_H(P) = 1 \tag{9}$$

where $X_H(P) = \sum_{i=1}^{4} bi$

$$b_i = \begin{cases} 1, if \;\; x_{2i-1} = 0 \; and \; (x_{2i=1} \; or \; x_{2i+1} = 1) \\ 0, \qquad\qquad\qquad otherwise. \end{cases}$$

$x_1, x_2, \ldots, x_8$ are the values of the eight neighbors of p, starting with the least neighbor and numbered n counter-clockwise order. Fig. 3 shows the neighbors of p in a checkerboard format.

x_4	x_3	x_2
x_5	P	x_1
x_6	x_7	x_8

Figure 3 : Pixels of N (P)

Condition G2:

$$2 \le \min\{n1(p), n2(p)\} \le 3 \tag{10}$$

where

$$n1(p) = \sum_{i=1}^{4} x_{2k-1} \vee x_{2k}$$

$$n2(p) = \sum_{i=1}^{4} x_{2k} \vee x_{2k+1}$$

Condition G3:

$$\text{G3: } (x_2 \vee x_3 \vee \overline{x_8}) \wedge x_1 = 0 \tag{11}$$

G3 is in the first sub-iteration.

Condition G3`:

$$G3`: (x_6 \vee x_7 \vee \overline{x_4}) \wedge x_5 = 0 \tag{12}$$

G3`: 180° rotation in the second.

The given two subscriptions together make an iteration of the thinning algorithm. These iterations are repeated until the specified time. We set it as infinite number of iterations (n='inf'). Therefore, the iterations are repeated until the image stops changing. The conditions are all tested using the pre-computed look up tables.

ii. *Minutia Marking*

In our work, Level 2 features: Terminations and Bifurcations are used to extract. Features are marked using labeling technique and also Run-length Coding algorithm [3]. The algorithm to find the minutiae is given below.

Step1: Run-Length Encoding the input image (RLE).

Step 2: Scan the runs; assigning preliminary labels for connected components in binary image.

Step 3: Determine the equivalence classes(c).

Step 4: Concatenate all relevant classes.

Step 5: Re-label the runs based on the determined equivalence classes (LB(c)).

Marking or Labeling of connected components is one of the most main operations in pattern recognition. It is essential when an object gets recognized [20]. The proposed algorithm includes scanning, labeling, and determine the equivalence classes of minutiae in order to group and concatenate the relevant classes. Finally, re-labeling of the scanned runs based on the results determined equivalence classes. Our algorithm uses the skeleton image where the ridge flow is 8-connected. The minutiae which are marked (labeled) by scanning the local neighborhood of each ridge pixels in the fingerprint image using (3×3) non-overlapping windows. Based on the label values LB, the ridge pixels are classified into Terminations and Bifurcations. If the pixel is labeled with 0 then it is determined as Isolation. If the pixel is labeled with 1, 2 then it is determined as Termination and Continuing Terminations respectively; and if the pixel is labeled as 3, 4 then it is determined as Bifurcation, Crossing respectively (see Table 1). The templates of the Termination and bifurcations are shown in fig.4.

Table 1 : Property of the Label

Label (LB)	Property
0	Isolation
1	Termination
2	Continuing Termination
3	Bifurcation
4	Crossing Point

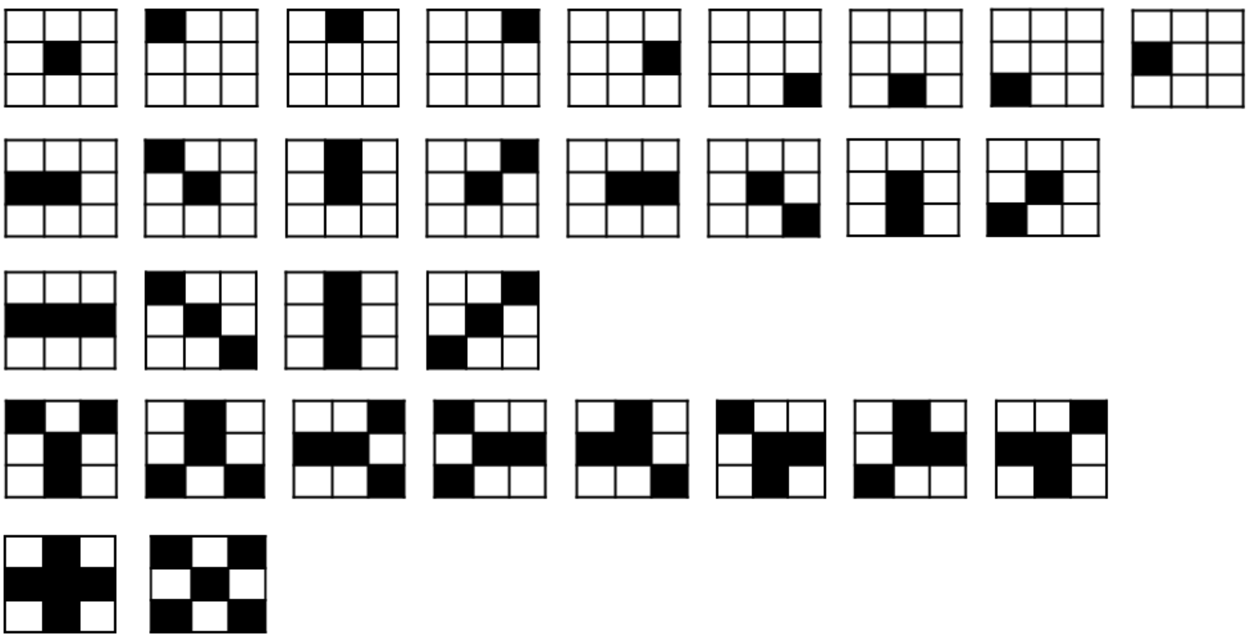

Figure 4 : Templates of Isolation (Row 1), Terminations (Row 2), Continuing Terminations (Row 3), Bifurcations (Row 4), and Crossing (Row 5)

iii. *Minutiae Extraction*

Minutiae extraction depends on the labels and properties of the marked minutiae (as defined in table 1). Based on the properties, the ridge terminations and bifurcations are extracted from the fingerprint image (see fig. 5). The red circle refers the ridge endings and the green square refers the ridge bifurcations.

c) *Minutiae Post-processing*

Post processing of minutiae extraction is a vital process to get true minutiae. Since the image comes across different stages of processing, there exist some spurious points in the image. It causes the inaccuracy of minutiae. Hence, the post processing is essential to remove spurs, H-points, break points, closed and border minutia. The main objectives of post process are to remove false minutiae and retain only true minutiae set. In this part, the morphological operations such as setting Region of Interest (ROI), closing and opening are performed. In addition to that the distance between two endpoints is calculated and compared with the threshold value. If they are equal then it considered as true minutia otherwise false. From the post processing, the true minutia set are extracted.

IV. Benchmarks

In order to check and compare the proposed method, publicly available fingerprint database for FVC in 2000,2002, 2004 and real time data base have been chosen. Each database contains 880(Set A: 100×8, Set B: 10×8)) fingerprints, original from 50 different fingers of untrained volunteers. The same finger is needed to give 5 impressions. Properties of all the selected image databases both public and real time are shown in the table 2.

Table 2 : Bench mark Database and Real Time data sets

Database Name	Sensor Types	Size of the Image	Resolution in dpi
2000 DB1	Low-cost Optical Sensor	300×300	500
2000 DB2	Low-cost Capacitive Sensor	256×364	500
2000 DB3	Optical Sensor	448×478	500
2002 DB1	Optical Sensor	388×374 (142 Kpixels)	500
2002 DB2	Capacitive sensor	296×560(162 Kpixels)	569
2002 DB3	Capacitive Sensor	300×300(88 Kpixels)	500
2004 DB1	Optical Sensor	640×480(45 Kpixels)	500
2004 DB2	Optical Sensor	328×480(100 Kpixels)	500
2004 DB3	Thermal Sweeping Sensor	300×480(56 Kpixels)	500
Real - Time DB	Optical Sensor	300×300	500

V. Experimental Results and Discussions

The proposed algorithm is implemented in MATLAB 7.10 with the standard benchmarks specified in the section 4. The experimental results are shown in fig. 5. The results show the novelty while extracting minutia. From the first step, fingerprint image is captured and then preprocessing stage is carried out; in this stage, the frequency domain enhancement is followed in order to get frequency value. In the second stage, minutia extraction is performed. To eliminate the false minutia, the post processing is also followed thirdly; the extracted minutia set is under the post process. Finally, the true minutiae set are obtained.

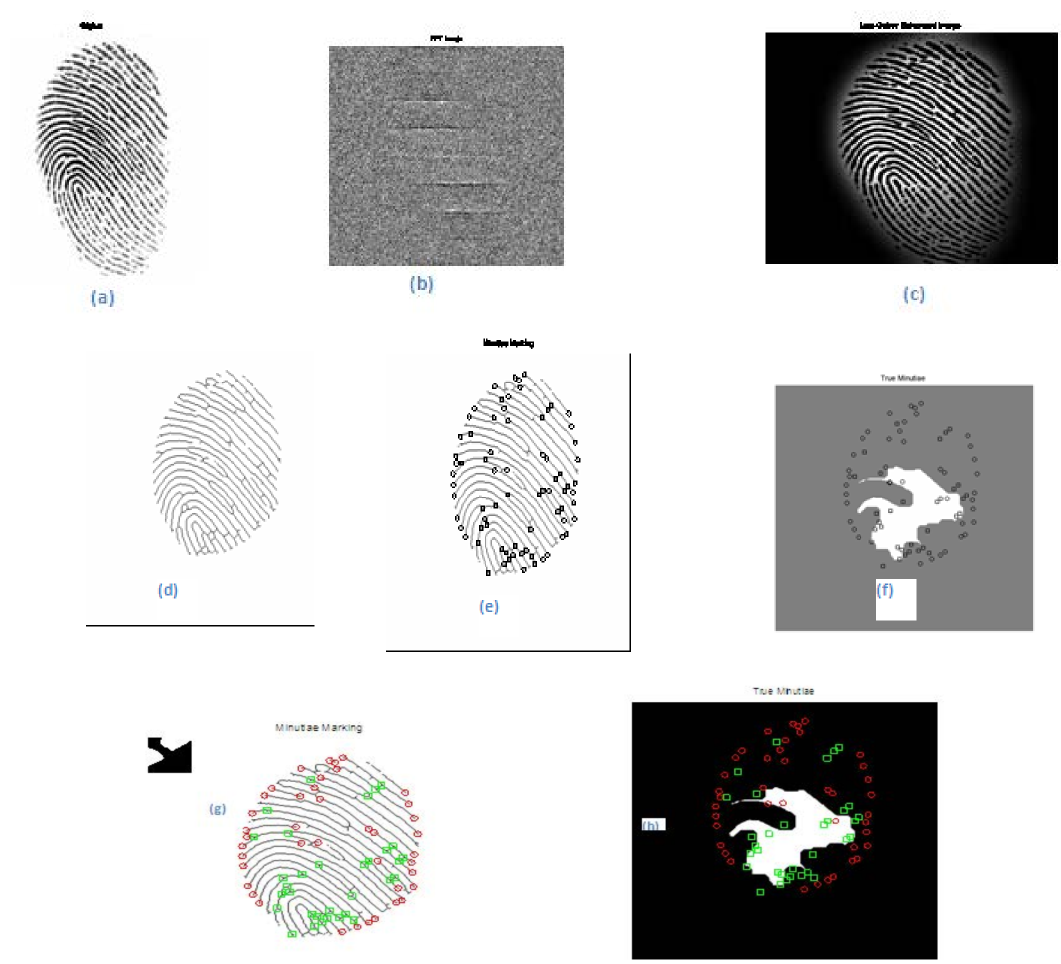

Figure 5 : Minutiae Extraction stages: (a)Origianl image(101_1.tif) (b) FFT Image (c) Log-Gabor filterd image (d) Enhanced cum thinned image (e) Minutiae Marking (before Post Processing) (f) True Minutiae set (after post processing) (g) and (h) are the color versions of the (e),(f) respectively

Table 3 lists the mean noise for each orientation. The accuracy rates of the proposed algorithm on minutiae before and after pre, post processing are reported in table 4, 5, and 6 respectively. In those tables, the accuracy rate of terminations and bifurcations are computed by the Tt /Te and Bt/Be, respectively. The total accuracy rate is also computed using the following formula [11]:

$$\text{Total Accuracy Rate} = \frac{T_t + B_t}{T_e + B_e} \tag{13}$$

where Tt and Bt are the number of true terminations and true bifurcations and Te , Be are the extracted terminations and extracted bifurcations respectively.

Table 3 : Orientations and mean noise

Image #	Mean Noise in each orientation (1-6)					
	θ=0	θ=0.5236	θ=1.0472	θ=1.5708	θ=2.0944	θ=2.6180
01	0.25	0.33	0.6187	0.67	0.41	0.2424
02	0.63	0.46	0.4821	0.62	0.81	0.81
03	0.59	0.53	0.55	0.61	0.61	0.56
04	0.54	0.43	0.59	0.81	0.87	0.74
05	0.86	0.62	0.63	0.78	1.05	1.1629

Table 4 : Accuracy rate of Ridge Minutiae before Pre-Process

Image #	Accuracy rate before Pre-processing		
	Terminations (%)	Bifurcations (%)	Total Rate (%)
01	3.86	20	3.98
02	2.91	64.71	4
03	26.6	3.4	10.95
04	4.04	17.02	4.7
05	3.79	23.26	4.46
06	5.36	2.94	4.21
07	3.31	21.43	3.9
08	3.94	4.35	3.73
09	1.74	60	2.44
10	1.07	14.29	1.4
Average rate	5.662	23.14	4.377

Table 5 : Accuracy rate of Ridge Minutiae after Pre-Process

Image #	Accuracy rate after Pre-processing		
	Terminations (%)	Bifurcations (%)	Total Rate (%)
01	38.1	37.5	38
02	91.67	57.89	76.74
03	83.33	6.49	28.04
04	45.76	24.24	38.04
05	39.71	30.3	32.46
06	93.1	4.62	20
07	77.27	23.08	45.1
08	90	12.5	50
09	50	66.67	53.13
10	80	14.29	31.58
Average rate	68.894	27.758	41.309

Table 6: Accuracy rate of Ridge Minutiae after Post-Proces

Image #	Accuracy rate after Post-processing Terminations (%)	Bifurcations (%)	Total Rate (%)
01	72.73	50.00	67.86
02	84.62	57.89	76.74
03	96.15	7.46	32.26
04	90	44.44	72.92
05	65.85	41.67	47.44
06	79.41	06.19	24.09
07	77.27	24.00	46
08	90	17.39	58.49
09	100	75.00	85
10	80	40.00	60
Average rate	83.603	36.404	57.08

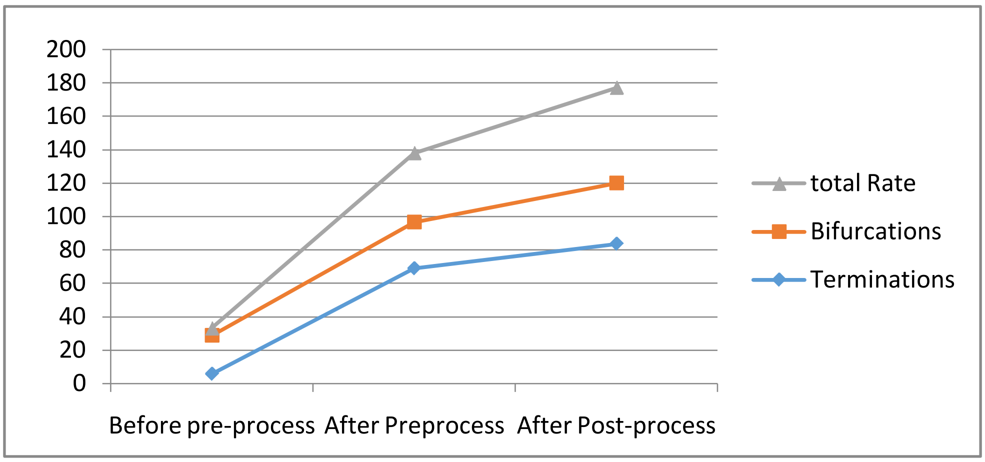

Figure 6 : Accuracy rates of Minutiae

Table 6 shows that the accuracy rates of terminations and bifurcations are increased gradually from preprocessing to post process. The accuracy rates are visualized through chart (see Fig. 6). The performance of the proposed algorithm is compared with other methods proposed by Feng Zhao [11], Maio[21], cheng[22], and Kim[23]. Some attributes are computed to measure the performance. They are:

1. True Minutiae (MT): Minutiae which are marked by a human expert.
2. Extracted Minutiae (ME): Minutiae which are extracted (remained) after post-processing.
3. False Minutiae (MF): Minutiae which are extracted by algorithm that do not coincide with True Minutiae (MT).
4. Dropped (Missed) Minutiae (MD): Minutiae marked by human expert that are not extracted by the algorithm.
5. Type-Exchanged Minutiae (MTE): The minutiae extracted by algorithm coincide with True minutiae (MT) but not the type. That is the exchange of terminations and bifurcations.

Table 7 reports the Average Error Rate (AER) after post processing in terms of average error rates of false minutiae (MF / ME), Dropped Minutiae (MD / MT), and type-exchanged minutiae (MTE / ME). The total error rate can be calculated by summing up them. False Minutiae Rate of the proposed is lesser than the same of Feng Zhao [11] and Kim [23]. Type-exchanged minutiae rate is lesser than results of all the methods except Feng Zhao's result. The results show that our proposed algorithm is better than the other methods in terms of dropped minutiae and total error rates (20.69%). Figure 7 shows the performance of the proposed method according to the Total Error Rate (TER).

Table 7: Average Error Rate (AER) after post processing

	False Minutiae (%)	Dropped Minutiae (%)	Type-Exchanged (%)	Total Error (%)
Proposed	14.61	0.4	5.68	20.69
Feng Zhao[11]	15.3	6.9	5.3	27.5
Maio[21]	11.8	6.5	13.1	31.4
Cheng [22]	9.6	15.9	10.4	35.9
Kim [23]	25.8	13.8	6.3	45.9

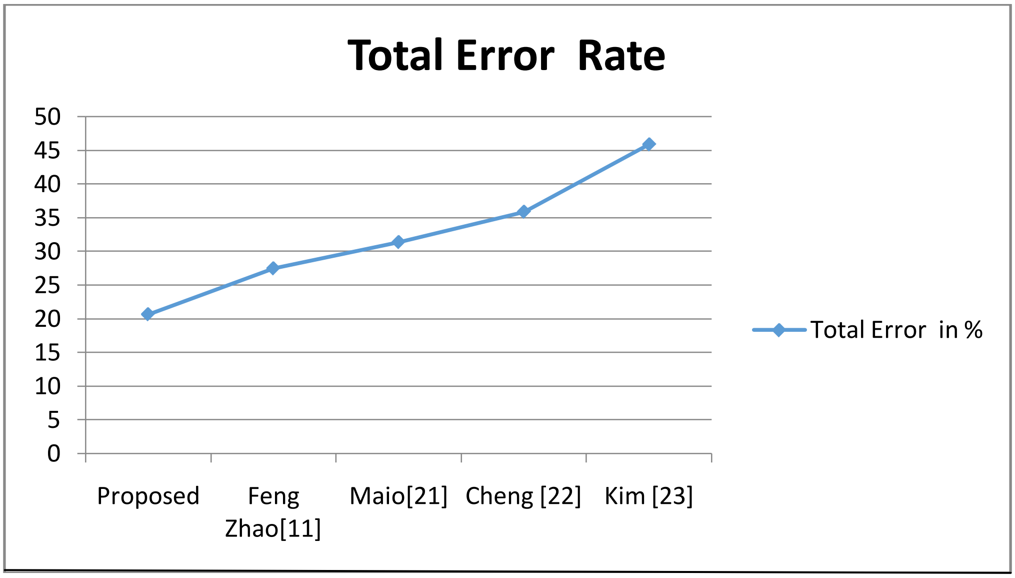

Figure 7: Performance chart

VI. Summary and Conclusion

The proposed algorithm is implemented in order to achieve dual purpose tasks; these are an enhancement cum minutiae feature extraction through the Log-Gabor orientation and RLC methods. Log-Gabor orientation is used to enhance each ridge according to orientation and extract the enhanced minutiae. Enhanced minutiae are extracted for further process. Performance of the proposed method is measured in terms of accuracy rates of minutiae and also average error rates. Those are compared with the existing methods adopted from [11]. Higher the accuracy rate and lower the total error rate advances the performance of our proposed method.

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