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# Fingerprint Pattern Feature Extraction for Loop Fingerprint Pattern Identification by Zhang-Suen and Stentiford Thinning Method

Faiza Alif Fakhrina and Muhammad Fakhry

***Abstract*—Every fingerprint that a human possesses must have a fingerprint pattern and must be unique. Each pattern has a ridge pattern that will not change as long as there is no change due to an accident or injury. This ridge pattern can be used as biometric recognition. Based on the ridge pattern owned, the fingerprint pattern is divided into 4 patterns, including the tented arch pattern, the whorl pattern, the loop pattern (ulnar loop and radial loop). The stage of fingerprint pattern recognition begins by looking for minutiae (termination and bifurcation) points on the fingerprint using the Crossing Number (CN) method. Before searching for CN, the fingerprint image must be processed using the Otsu and Zhang-Suen or Stentiford Thinning methods. Thinning is used to facilitate the extraction of minutiae in fingerprint images. The last stage in obtaining the minutiae point is classified by the Linear Discriminant Analysis (LDA) method. The results obtained from the test data were 30 images, 24 images could be classified correctly, and 4 images could not be recognized. The accuracy rate of the fingerprint pattern identification system is 80%.**

***Index Terms*— crossing number, fingerprint, thinning, LDA**

## I. INTRODUCTION

BThe reproduction of the outer appearance of the fingertips is called the fingerprint, where the fingerprint has structural characteristics called ridges and valleys (Ashbaugh, 1999), when viewed from the fingerprint image, the ridge line is a ridge line that is dark in color, while the light-colored one is called valleys (figure 3.1).[1]

Fingerprints consist of ridge and valley patterns located on the surface of human fingertips. The uniqueness level of fingerprints can be divided into 3 levels of features, including: Level 1 features are global features, ridge orientation, frequency fields, and singular points. The level 2 feature refers more to minutiae points in local regions (i.e. ridge endings and bifurcation are types of minutiae that often appear). Level 3 features include all attribute dimensions at a good scale, such as width, shape, curvature, and edge contours of ridges, pores, incipient ridges, and other details. The collection of minutiae points or minutiae is the most common feature and is often used for fingerprint matching. [2]

The advantage of using a fingerprint initial selection algorithm is to reduce the difficulty in performing fingerprint matching. The method used to match a fingerprint to one or more predefined fingerprints is called Fingerprint Grouping (see Figure 1.13). Research on fingerprint pattern grouping conducted by Henry [3] It has produced 5 patterns, namely the Whorl pattern, the Left Loop pattern, the Right Loop pattern, the Arch pattern, and the Tended Arch pattern. At the time of conducting the research, if the fingerprint pattern is entered into the database and fingerprint grouping is carried out, the primary and secondary classes with high accuracy results are produced. In fact, the distribution process of fingerprints grouped into 5 types of fingerprint patterns is not uniform and some fingerprints look vague (see Figure 10) so that they cannot be accurately grouped by experts.

Minutiae is one of the frequently used fingerprint features. Forensic experts often use minutiae to match 2 fingerprint images. It turns out that 150 different types of minutiae were found [4], among the types of minutiae there are ridge endings and ridge bifurcations which are commonly used for the combination of ridge endings and ridge bifurcations, as shown in Figure 1 below. [1]

The part that reproduces the outer appearance of the fingertip is called the fingerprint, where the fingerprint has structural characteristics called ridges and valleys (Ashbaugh, 1999), when viewed from the fingerprint image, the ridge line is a ridge line that is dark in color, while the light-colored one is called valleys. The fingerprint consists of a ridge and valley pattern located on the surface of a human fingertip [1]. The uniqueness level of fingerprints can be divided into 3 levels of features, including: Level 1 features are global features, ridge orientation, frequency fields, and singular points. The level 2 feature refers more to minutiae points in local regions (i.e. ridge endings and bifurcation are types of minutiae that often appear). Level 3 features include all attribute dimensions at a good scale, such as width, shape, curvature, and edge contours of ridges, pores, incipient ridges, and other details. The collection of minutiae points or minutiae is the most common

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feature and is often used for fingerprint matching.[5]

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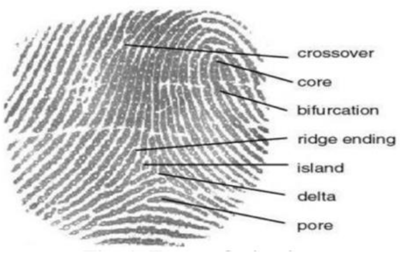
One example of a case is that in the NIST 4 special database of 4000 stored fingerprint images, there are 17% of images that have 2 actual label differences. In general, even though fingerprint grouping has been carried out, it is not helpful if the fingerprint search process is carried out on a large number of databases. The Thinning algorithm is particularly suitable for use in fingerprint images to reduce noise and improve the minutiae extraction algorithm. The result obtained is that some minutiae can be generated and only a few minutiae cannot be detected [2]. Where, this algorithm can improve the capabilities of the AFIS system. [6]

The quality of the fingerprint images used greatly affects the use of fingerprint extraction and classification algorithms. One example of the algorithm used is the Gabor Filter in improving the quality of the fingerprint image so that it gives good results. For the minutiae extraction process, you can use the Rutovitz Crossing Number (CN) to be able to detect all minutiae (either wrong or correct) after the thinning process. The performance results have been evaluated using FAR and FRR calculations. The results of the calculation produced a high level of accuracy, namely FAR 0% and FRR 0.23%.

Minutiae is one of the frequently used fingerprint features. Forensic experts often use minutiae to match 2 fingerprint images. It turns out that 150 different types of minutiae were found [4], among the types of minutiae there are ridge endings and ridge bifurcations which are commonly used for combinations of ridge endings and ridge bifurcations, such as Picture 1 below:




Picture 1. Types of minutiae [7]

Therefore, the author wants to create a loop-type fingerprint pattern recognition system, namely *ulnar loop* and *radial loop* using the *Zhang-Suen and* Stentiford *thinning method* to determine the extraction of minutiae (*ridge ending* and *bifurcation*). In the process of processing fingerprint images, feature segmentation is used, namely *thinning*, to facilitate the recognition of fingerprint patterns. The next step is to find *the minutiae* and count the number of *minutiae* for each fingerprint image. Group the number of *minutiae* of each fingerprint image based on the Loop fingerprint pattern. The next step is to classify the fingerprint image pattern based on the number of *ridge endings* using the *Linear Discriminant Analysis* (LDA) method. LDA is *a class-specific linear* method that can perform dimensional reduction transformations of elements that are members of a class grouped together in a low-dimensional space [5].

The expected result of this study is that the system can recognize the pattern of radial *loop* fingerprints, and *ulnar loops* based on the extraction of minutiae (*ridge ending* and *bifurcation*).

## II. MATERIALS

A. Algorithm Thinning

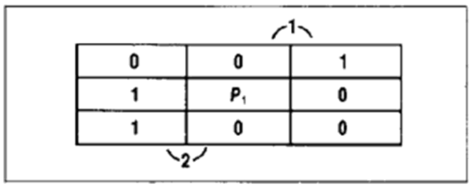
Thinnning is particularly suitable for use in fingerprint images to reduce noise and improve minutiae extraction algorithms [2].

1. Zhang-Suen Thinning

Zhang-Suen thinning is used for extracts the image frame by removing all the point of the image contour except the point that is connected to the frame. Thinning will divide the iteration into 2 sub-iterations to maintain the connection on the skeleton. In the first sub-iteration, the P1 contour point is removed from the digital pattern if it meets the conditions below [8]:

a. $2 \leq B(P1) \leq 6$
b. $A(P1)=1$
c. $P2 \times P4 \times P6 = 0$
d. $P4 \times P6 \times P8 = 0$

Where A(P1) is the number of pattern 01 then determines P2, P3, ... P8 is 8 neighbors of P1 as in Picture 2.




Picture 2. Picture of Zhang-Suen's thinning pattern

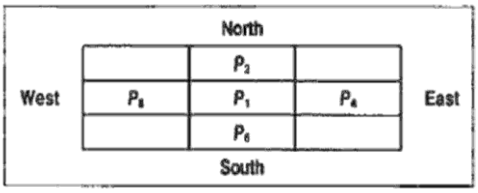
The value of B(P1) is the number of non-zero neighbors of P1, is: [8]

$$B(P1) = P2 + P3 + P4 + ... + P8 + P9 \quad (1)$$

The values P2, P3, P4, ..., P9 are A(P1) = 2, and P1 is not removed from the image if all conditions are met.

In the second iteration only conditions (c) and (d) change as in Picture 3 By: [8]

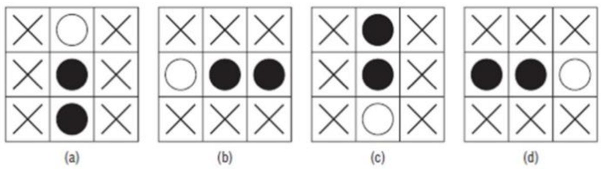
c. P2 x P4 x P8 = 0
d. P2 x P6 x P8 = 0




Picture 3. Conditions for points to be removed

All of the above steps are repeated until no more points are deleted. That only removing the points in the south-east boundary point and the north-west corner of the point is not an ideal framework if you look at conditions (c) and (d) in the first subiteration.

2. Stentiford Thinning
The Stentiford algorithm was invented in 1983, which uses a 3x3 template. Where in the appropriate template in the image will be deleted to white for the image pixel in the middle. Examples of templates used on Stentiford are Picture 4 below: [9]




Picture 4. Template for pixel identification to be removed

Picture 4 shows the template used for Stentiford's algorithm. The process of determining black and white pixels is adjusted to pixels that are identical to the color of the image.
Below is a basic explanation of the Stentiford algorithm used:
1. Find the pixel location (i, j) as in Figure 4 that corresponds to the M1 template (Figure 5).

| | | |
|---|---|---|
| $P_4$ | $P_3$ | $P_2$ |
| $P_5$ | P | $P_1$ |
| $P_6$ | $P_7$ | $P_8$ |

Picture 5. 3x3 pixel window

2. If the center pixel is not an endpoint, and *connectivy number* = 1 then mark this pixel for subsequent removal
3. Repeat steps 1 and 2 for all pixel locations that fit the *M1* template
4. Repeat steps 1 through 3 for *M2, M3 and M4* templates
5. If any pixels are already marked for deletion, then delete them by making them white
6. If any of the pixels were removed in step 5, then repeat the previous process from step 1; until it stops.

The system must read the fingerprint imagery for each template must match in a specific order for each template. The pixels removed around the edges of the object are the purpose of the M1 Template. Then, the pixels from the left side of the object will be matched by the M2 template. The way M2 templates work is to move the image from the bottom to the top. The final step is that the M4 template is matched from top to bottom, right to left to find the pixels on the right side of the object. [9]

B. Minutiae Extraction
The extraction process is carried out in general, namely the fingerprint image object is converted to a grayscale image and then converted to a binary image accompanied by a thinning process, then the ridge line on the fingerprint is converted into a skeleton. Where, the representation of minutiae characteristics has a unique orientation position so that it can reduce the problem of fingerprint pattern classification. Therefore, to find out the location of the minutiae point effectively and accurately, a minutiae detection algorithm can be used.
The minuatiae detection algorithm used is Crossing Number, where the pixels that correspond to the minutiae are based on the difference in crossing number from 2. *The crossing number* (cn(p)) of pixel p in a binary image is half the sum of the difference between the pixel parts in the 8-neighbor of p:

$$\mathrm{Cn}(p) = \sum \mathrm{i}=1 \ldots 8\ |\mathrm{val}(\mathrm{Pi}) - \mathrm{val}(\mathrm{pi}+_1)| \qquad (2)$$

where:
$p0, p_1, \ldots, p_7$: the pixel that defines the 8-neighbor of p
Val(p) ε € {0.1}: pixel value

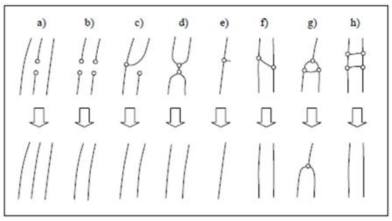



Figure 6. General structure *of false minutiae* (top row) and structure of *minutiae* after deletion (bottom row)

From Figure 6 it is obtained that pixel p with val(p) = 1: [10]
- The intermediate *ridge* point if cn(p) = 2
- Corresponds to *the minutiae ridge ending* if cn(p) = 1
- Corresponds to *minutiae bifurcation* if cn(p) = 3

C. Linear Discriminant Analysis (LDA)
Generally, the LDA method handles cases when the frequencies in the classes are not the same and when the test checks the randomly generated performance. LDA maximizes the ratio of variants between classes to variants in a certain class of data sets so that they are separated to the maximum. The difference between

PCA and LDA is that PCA has more feature classification and LDA is more inclined to data classification. In PCA, the shape and location of the data authenticity change when transformed into a different form, while LDA does not change the location but makes the classes separate and depicted according to the decision area between the given classes. [10]

The following is the formulation of the LDA classification: [10]

a. The formulation of test set data and training set data is below:

$$\text{set 1}=\begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \\ \dots & \dots \\ a_{m1} & a_{m2} \end{bmatrix} \qquad \text{set 2}=\begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \\ \dots & \dots \\ b_{m1} & b_{m2} \end{bmatrix}$$

b. Calculate the mean of each training and test data. $\mu_1$ and $\mu_2$ are the mean of set 1 and set 2, while $\mu_3$ is the mean of the entire data, obtained from combining set 1 and set 2.

$\mu_3 = p1 \times \mu_1 + p2 \times \mu_2$ (3)

P1 and P2 are a priori classes of probabilities. At

The case of two simple classes, assume the probability is 0.5.

c. In LDA, within-class and between-class distributions use formulation criteria for class separators. The within-class distribution is the expected covariance of each class. Spread measurements using formulas (4) and (5) below:

$Sw=\Sigma_j \text{ pj x (covj)}$ (4)

For two classes:

Sw=0.5 x cov1+0.5 x cov2 (5)

All covariate matrices are symmetrical. COV1 and Cov2 is a covariant of set 1 and set 2. Matrix Covariance is calculated using formulations in below:

$\text{covj} = (xj-\mu_j)(x_j-\mu_j)^T$ (6)

The between-class spread is calculated using Formulation below:

$Sb=\Sigma_j(\mu_j-\mu_3)x(\mu_j-\mu_3)^T$ (7)

Optimization factors for dependent class types can be calculated with the formulation below:

criterionj= inv(covj) x Sb (8)

optimizations used below:

$\text{criterion} = \text{inv}(S_{in}) \text{ x Sb}$ (9)

d. In LDA, the transformation to obtain the eigenvector matrix is with formulas (18) and (19).

e. After obtaining the matrix transformation, we change the test data using LDA. From these results, it can be observed that the transformation of all data on one axis provides a limit for data classification. For LDA dependent class,

$\text{transform}_{\text{set}_j}$ = transform_jT x set_j (10)

For the LDA independent class,

transformedset=transformspecTxdata_setT (11)

f. One transformation is completed using LDA, euclidean distance or RMS is used for data point classification. The Euclidean distance is calculated using the formulation (12), where for the class, the Euclidean distance is obtained for each test.

$$\text{distn} = \left(transform_{n_{spec}}\right)^T \text{ x x - } \mu_{\text{ntrans}} \qquad (12)$$

g. The smallest Euclidean distance among n-distances classifies the test vector as belonging to class n.

D. Extraction Minutiae with Crossing Number [11]

The Crossing Number (CN) method is generally used for minutiae extraction. The Rutovit definition of the crossing number for pixel P is

| | | |
|---|---|---|
| P4 | P3 | P2 |
| P5 | P | P1 |
| P6 | P7 | P8 |

Figure 7. The 3x3 pixel window that CN will do

$$CN = 1/2 \sum_{i=1}^{8} |p_i - p_{i+1}| \qquad (13)$$

Pi is the value of a binary pixel neighboring P with Pi=(0) or (1) and $P_{1=P9}$ .

The image of the fingerprint skeleton is scanned and all the little things are detected using the CN property, as in Figure 4. In general, the width of the fingerprint frame should be exactly one pixel. However, this is not always true as Figure 5 shows some examples, where the skeleton is two pixels wide in some bug pixel locations.

A bug pixel is defined as a pixel that has more than two of the 4 connected neighbors (marked with bold italics 1 and 0). In the branching region there is a bug pixel and the branching should be detected, but the pixel has CN=2. There are several effects caused by the existence of bug pixels, including: 1) destroying the integrity of bridges and spurs, 2) changing the type of minutiae points, 3) incorrectly detecting the actual branching as shown in Figure 6.

Therefore, before extracting the little things, we developed a validation algorithm to eliminate bug pixels while maintaining skeleton connectivity at fork points. gion. By scanning the fingerprint image frame line by line from top left to bottom right, we remove the first bug pixel found and then check again the next bug pixel to find out the number of 4 neighbors connected. If the number of 4 neighbors connected after the deletion of the previous bug pixel is still more than two, then the pixel will also be deleted; otherwise, the pixel will be retained and treated as a normal pixel. Some examples are shown in Figure 5.

After this validation process, all pixels in the framework meet the CN property. Thus we can extract all the little things including the real little things and the little things that are wrong. The little things that go wrong can be eliminated in the post-processing stage.

## III. METHODS

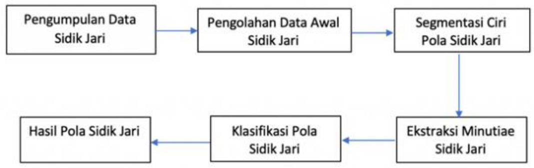


Figure 8. Fingerprint Pattern Classification Research Flow

Below are the steps to conduct fingerprint pattern classification research as shown in Figure 8:

a. Data acquisition

The initial process carried out includes cleaning the fingers to be scanned using the Fingerspot tool. The criteria for fingers to be scanned are fingers that have full ridges due to the limitations of the tool used. The pixel resolution value of Fingerspot is 512 dpi, and the fingerprint scan area is 14.6 mm.

b. Pre-processing

The stage is that the digital image is processed using the Otsu thresholding method to obtain the image result of one pixel. The thresholding results obtained will be used for the process of extracting features from fingerprint patterns. The image of Otsu's result has a clean background so that the fingerprint minutiae can be seen clearly.

c. Feature segmentation

The stage to select and separate an object from the entire image is the stage of feature segmentation. Determining the accuracy of the system in the fingerprint pattern recognition process is an important stage in feature segmentation. The data used is an image of the result of initial processing, namely Otsu thresholding.

Thinning Zhang-Suen and Stentiford is important because this method helps to remove all outer points that are not included in the frame and thin out the parts that are included in the frame. From this process, it is easier to perform calculations for the extraction of fingerprint pattern characteristics using the Zhang-Suen and Stentiford thinning methods.

The method used is the Zhang-Suen thinning method with a 3x3 mask and the number of iterations used is 500. The determination of the number of iterations used in this system affects the computing speed of the computer used.

d. Minutiae Extraction

Minutiae extraction is used to find minutiae points in each fingerprint image and then group them based on a predetermined fingerprint pattern. The initial stage is that the fingerprint image is processed by the Otsu method and then Zhang-Suen thinning is carried out. The minutiae point is obtained from the image of the preprocessing result that is added by the filter using a 3x3 window. The minutiae points used are termination and bifurcation.

Termination is if the center is 1 and has only 1 neighbor, whereas bifurcation is if the center is 1 and has 3 neighbors. A normal pixel is when the center is 1 and has 2 neighbors. After determining the termination and bifurcation, then the red mark is marked for termination and the green mark is marked for bifurcation.

Figure 9 is an image showing the minutiae obtained from the fingerprint image.


Figure 9. Specified minutiae sign

e. Fingerprint pattern data classification process

The LDA method is used for fingerprint pattern classification. LDA has 2 different approaches by which the dataset can be transformed and the test vector can be classified in space, namely: [10]

1. Class-dependent transformations:
   This approach focuses on maximizing the ratio of variance between classes and variance within classes so that adequate class separation is obtained. The use of two criteria is involved to optimize for data set changes independently.
2. Independent class transformation:
   This approach focuses on maximizing the ratio of overall variance to variance in the classroom. The optimal criterion used is only 1 and then the dataset is transformed because all data points regardless of their class identity are transformed using this transformation. Each class used in the LDA method is considered a separate class against all other classes.

The LDA classification process uses minutiae data from each fingerprint pattern that has been grouped according to the specified pattern. Data processed using LDA is data on the number of minutiae (termination and bifurcation) obtained from whorl and ulnar loop fingerprint patterns. Each minutiae obtained from each pattern will be stored in the form of a .txt file. Before testing the system, the learning stage is needed. This stage is done by determining the type of fingerprint pattern based on the minutiae pattern, then saving the number of minutiae obtained.

The specified fingerprint pattern is the whorl fingerprint pattern and ulnar loop. Minutiae data are grouped and stored in the form of .txt files and then processed by the LDA method. The results of LDA method are minutiae data for each pattern (whorl pattern and ulnar loop pattern) grouped according to minutiae data groups (grouped based on the number of terminations and the number of bifurcations of each whorl pattern and ulnar loop pattern).

The output of the LDA classification process is in the form of a distribution diagram of data classification, minutiae data, fingerprint patterns. The results obtained are the Limits of the termination and bifurcation values of each fingerprint pattern.

f. Fingerprint pattern recognition

Fingerprint pattern recognition is the process of processing fingerprints that are known by classifying the number of terminations and bifurcation on each fingerprint image that has been determined by the previous fingerprint pattern.

## IV. RESULT AND DISCUSSION

### A. Processing input data

At this stage, the initial data processing process is carried out to input the fingerprint pattern classification system. The input data used is fingerprint image data. The type of data used is primary data, where this data is taken directly from the subject to be researched. The fingerprint data collection was taken from each finger of the right hand and the finger of the left hand. The fingers to be scanned have several provisions, including that the palm of the finger is not torn, not injured, does not bleed, and there are fingerprint ridges. Because fingerprint ridges can be identified based on their patterns.

### B. Initial processing stages of the image

At this stage, the fingerprint image data processing process is carried out using the enhancement method (sharpening image quality). The method used in this process is thresholding otsu. This method is used to sharpen the minutiae in the processed fingerprint image. Before the otsu thresholding process, a filter will be carried out using Unsharp Masking. This filter is used to reduce the blurriness of the original image. The original image has been refined and then combined with the image that has been unsharpened to get a sharper image than the original.

(a) (b)

Figure 10. (a) Original image of the fingerprint and (b) Image of the result of preprocessing

### C. Feature Segmentation

The feature segmentation stage begins after the fingerprint image is filtered by Otsu thresholding as shown in Figure 11. The results of the Otsu stage will be continued with the next segmentation process, namely using the Zhang-Suen and Stentiford thinning method.

Figure 11. Fingerprint image of the result of Binerize

In this process, 2 stages are carried out, including:

a. The fingerprint image was initially processed using the Otsu method followed by processing using the Zhang-Suen or Stentiford Thinning method.
b. The thinning method is carried out to make it easier to determine the characteristics of fingerprints by thinning the fingerprint image and can reduce the time of the computing process.

In Figure 12. Showing the results of the fingerprint image process that has been processed using the Thinning method.

Figure 12. Fingerprint image of Zhang-Suen's thinning processing

### D. Minutiae Extraction

The function of the minutiae extraction stage is to obtain the position of the minutiae point on the fingerprint image that has been processed by the Zhang-Suen Thinning method. Steps that can be implemented include:

a. Obtain the minutiae points on the fingerprint image using the resulting values from crossing number termination and bifurcation
b. Removing incorrect minutiae points by calculating the euclidian distance between termintions and between bifurcations
c. Determine the Region of Interest (ROI) value
d. Determining the orientation value of each minutiae point (termination and bifurcation)
e. Convert the minutiae (termination and bifurcation) point values on file type .txt.

In Figure 13. Explain the stages of the minutiae extraction process (termination and bifurcation) on fingerprint images.

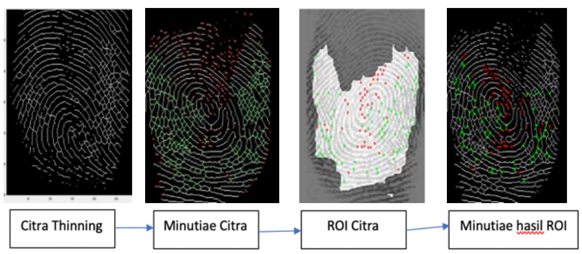



Figure 13. Stages of minutiae extraction

E. Fingerprint Pattern Classification Results

The characteristic extraction carried out in this study was to obtain minutiae points, namely termination and bifurcation. The stages that need to be carried out include:

1. Group the fingerprint images that have been obtained based on the fingerprint pattern to be classified
2. Find the termination and bifurcation values present in each fingerprint image pattern
3. Obtain and group termination and bifurcation values according to fingerprint patterns
4. Perform the minutiae classification process based on the existing termination and bifurcation values using the Linear Distance Analysis (LDA) method. The LDA method was used to see the distribution of minutiae data on the fingerprint image.

Figure 14 shows the pattern of fingerprint imagery to be classified as below:

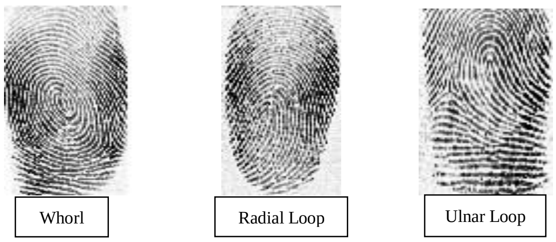



Figure 14. Fingerprint image pattern grouping

Based on Figure 13, it can be explained that:

a. The image to be classified using LDA must complete the stages to determine the ROI on the fingerprint image.
b. If the fingerprint image has blurring in the image, the image is not used as classification data.
c. The fingerprint pattern data used is only 3 patterns (whorl pattern, ulnar loop pattern, and radial loop pattern).
d. The results of the classification using LDA can be used to group minutiae based on the value of minutiae in a predetermined fingerprint pattern.
   Figure 15 shows the results of fingerprint pattern classification using the LDA method as below:

F. Fingerprint Pattern Recognition

This stage is the final stage of the research, namely how the system can recognize fingerprint patterns based on fingerprint image input. The fingerprint pattern system can correctly recognize as many as 24 fingerprint images. And the system cannot recognize the fingerprint pattern as many as 6 fingerprint images. Fingerprints that cannot be detected are usually caused by finger minutiae ridges that are damaged (for example, there are scars from knife scratches) so that when scanned, the minutiae ridges are not clearly visible. The next problem could be because there are 1 or several humans who do not have a fingerprint pattern. So, when the scan is done on that finger, the minutiae ridges are not visible at all. Table 1 below shows the acquisition of the accuracy level of the fingerprint pattern recognition system obtained from:

Table 1. Fingerprint Pattern Recognition Results

| No. | Nama Citra Sidik Jari | Minutiae | | Pola Hasil Uji Sistem | Pola Sesungguhnya |
|---|---|---|---|---|---|
| | | Termination | Bifurcation | | |
| 1 | A.jpg | 41 | 87 | Ulnar Loop | Ulnar Loop |
| 2 | B1.jpg | 101 | 102 | Whorl | Whorl |
| 3 | H5.jpg | 77 | 71 | Whorl | Whorl |
| 4 | G3.jpg | 27 | 74 | Radial Loop | Radial Loop |
| 5 | E5.jpg | 24 | 139 | Radial Loop | Radial Loop |
| 6 | S2.jpg | 77 | 120 | Whorl | Whorl |
| 7 | R4.jpg | 33 | 90 | Radial Loop | Radial Loop |
| 8 | Q1.jpg | 69 | 118 | Whorl | Whorl |
| 9 | A2.jpg | 76 | 114 | Whorl | Whorl |
| 10 | C2.jpg | 48 | 91 | Whorl | Whorl |
| 11 | C1.jpg | 17 | 108 | Radial Loop | Radial Loop |
| 12 | B3.jpg | 67 | 69 | Whorl | Whorl |
| 13 | D2.jpg | 43 | 69 | Ulnar Loop | Ulnar Loop |
| 14 | N1.jpg | 34 | 67 | Radial Loop | Radial Loop |
| 15 | M4.jpg | 27 | 63 | Radial Loop | Radial Loop |
| 16 | P4.jpg | 61 | 100 | Whorl | Whorl |
| 17 | G2.jpg | 27 | 89 | *Pola Tidak Dikenali* | *Radial Loop* |
| 18 | U5.jpg | 64 | 48 | Whorl | Whorl |
| 19 | C4.jpg | 26 | 126 | Radial Loop | Radial Loop |
| 20 | N3.jpg | 82 | 56 | Whorl | Whorl |
| 21 | D5.jpg | 35 | 89 | *Radial Loop* | *Whorl* |
| 22 | M1.jpg | 38 | 94 | *Ulnar Loop* | *Whorl* |
| 23 | Z1.jpg | 45 | 72 | Ulnar Loop | Ulnar Loop |
| 24 | Z4.jpg | 55 | 85 | Ulnar Loop | Ulnar Loop |
| 25 | X5.jpg | 25 | 134 | *Whorl* | *Ulnar Loop* |
| 26 | J3.jpg | 21 | 103 | *Pola Tidak Dikenali* | *Ulnar Loop* |
| 27 | K1.jpg | 12 | 23 | *Pola Tidak Dikenali* | *Radial Loop* |
| 28 | O1.jpg | 85 | 45 | Whorl | Whorl |
| 29 | P3.jpg | 23 | 120 | Radial Loop | Radial Loop |
| 30 | H4.jpg | 48 | 80 | Ulnar Loop | Ulnar Loop |

Based on Table 1, it can be seen that:

1. Number of correct fingerprint images = 24 images
2. Total images tested = 30 images
3. System accuracy value = $\frac{24}{30}$ x 100% = 80%

It can be concluded that the accuracy level of the whorl, ulnar loop, and radial loop fingerprint pattern recognition system is 80%. Zhang-Suen and Stentiford's thinning method is an important step to help make computation faster and more accurate. The accuracy value obtained is greater than the results of research conducted by Raditiana Patmasari by 60% [12].

## V. CONCLUSION

From the results of the fingerprint pattern recognition system, it can be concluded that it is as follows:

1. The fingerprint pattern identification system achieved an accuracy rate of 80%.
2. The test data used in the system is 30 fingerprint images. 24 fingerprint images can be recognized by fingerprint patterns and 6 fingerprint images are not recognized or misidentified.
3. The method used for feature segmentation, namely Zhang-Suen and Stentiford Thinning, is the most

important stage in this study because this method greatly determines the accuracy of the system in recognizing fingerprint patterns.

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