CHAPTER 4

MINUTIAE EXTRACTION

Identifying an individual is precisely based on her or his unique physiological attributes such as fingerprints, face, retina and iris or behavioral attributes such as gait and signature characteristics known as biometrics. Biometrics is intrinsically more consistent and more skilled in distinguishing an endorsed person and a forged imposter than conventional token-based or knowledge-based methods. Fingerprint recognition is one of the most trustworthy and optimistic personal identification techniques in the midst of all the biometrics technologies. Amongst all other distinctive physiological traits, fingerprint biometrics is the most extensively used and accredited by all.

4.1 MINUTIAE EXTRACTION – A PART OF AFIS

The purpose of minutiae extraction is to identify the diplomat features called minutiae and to extract them from the input fingerprint images. It is very complicated to opt for the prominent and accurate demonstration of the input images for AFIS. This demonstration must incorporate the following properties (Hong et al 2008).

(i) Retain the discriminating power of raw digital fingerprint images
(ii) Compactness
(iii) Amenable to matching algorithms
(iv) Robust to noise and distortions and
(v) Easy to compute

The first property says that the individuality of fingerprints should be maintained by demonstration, i.e. the demonstration can be established by the identity alone. The second property insists that the demonstration should be represented concisely and clearly. In the third property, it is given that the demonstration should be appropriate for a matching algorithm. The fourth property postulates that the demonstration should be strong enough to tolerate noise and distortions, i.e. it represents the quality of fingerprint images. The final property reveals that the demonstration should not be too complex in computation.

A fingerprint recognition system involves many processes and stages. Figure 4.1 shows the general process to identify the fingerprint. The scopes for this chapter are shown by dashed box in the figure below.

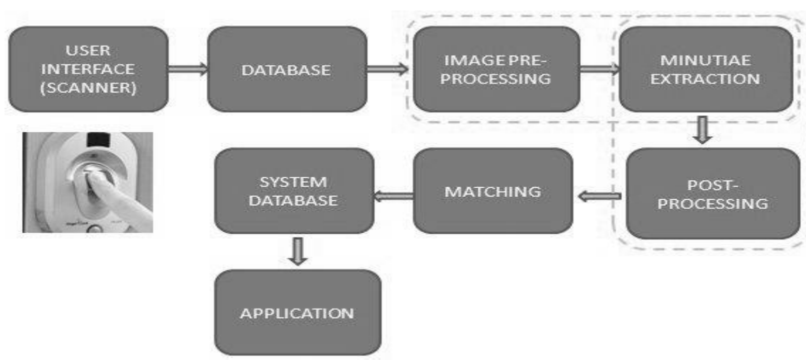


Figure 4.1 General process of fingerprint recognition

Fingerprint extraction consists of three main steps, and they are

- Preprocessing.
- Minutiae extraction.
- Post-processing.

The pictorial representation of the various processes and their intermediate stages are depicted in Figure 4.2.

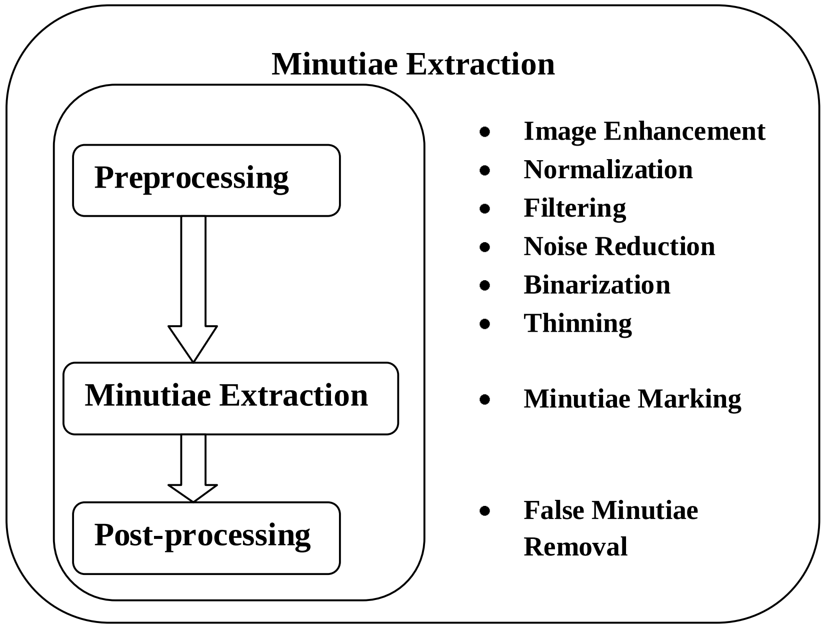


Figure 4.2 Minutiae extraction and its stages

4.2 PREPROCESSING

A fingerprint image consists of lot of redundant information when it is captured. To get an acceptable image, the problems such as images with scars, too dry or too moist fingers, or incorrect pressure must be overcome (Ratha et al 1995). And hence, the input fingerprint images need to be preprocessed. The steps that are present in almost every process are

- Image enhancement
- Normalization
- Filtering
- Noise reduction
- Binarization
- Thinning

Image Enhancement : The fingerprint is first converted into grayscale (Douglas 1993). For contrast expansion, local histogram equalization is used. Mapping of gray levels 'q' into gray level 'p' is made so that the distribution of gray level 'p' is uniform and thus defines histogram equalization. The range of gray levels is expanded near the histogram maxima. The detectability of the image features is improved since the contrast is expanded for most of the image pixels. The probability density function of a pixel intensity level l_k is given by

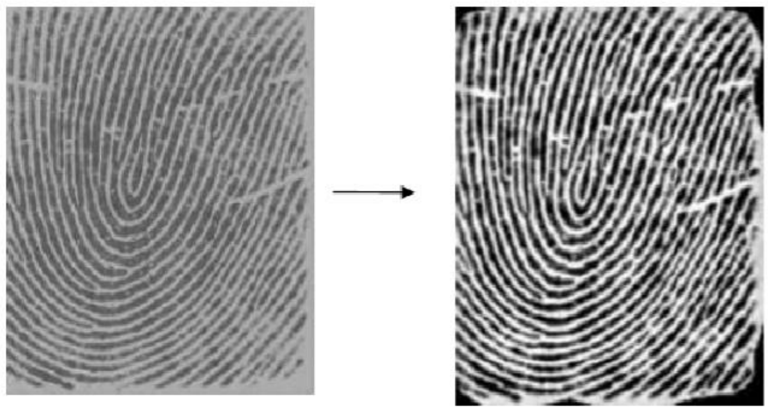
$$P_k(l_k) = \frac{m_k}{m} \tag{4.1}$$

where $0 \leq l_k \leq 1, k = 0,1, \ldots \ldots 255, m_k$ is the number of pixels at intensity level l_k and m is the total number of pixels.

Normalization : Normalization of an image means to spread the gray scale evenly and fill all available values instead of a part of the available gray scale (Almansa and Lindeberg 2000). By means of histogram, the distribution of pixels with a certain amount of gray has been plotted. To normalize an image, the area which is to normalize has to be known. The highest and the lowest pixel values of the current image have to be identified and this is the foremost thing. Along this scale, each and every pixel is then evenly spread out. The following equation represents the normalization process:

$$Inorm\,(x,y) = \frac{I(x,y)-Imin}{I\text{max}-Imin}\, X\, M \tag{4.2}$$

where I is the intensity (gray level) of the image. I_{min} is the lowest pixel value found in the image, I_{max} is the highest one found. M represents the new maximum value of the scale, mostly M = 255, resulting in 256 different gray levels, including black (0) and white (255). $I_{norm}(x, y)$ is the normalized value of the pixel with coordinates x and y in the original image $I(x,y)$. The normalized images are much easier to evaluate and determine quality since the spread now has the same scale. Without the normalization it would be impossible to use a global method for comparing quality. Figure 4.3 shows a sample normalized image.



Raw image from sensor **Normalized image**

Figure 4.3 Sample normalised image

It is important to filter out image noise coming from finger consistency and sensor noise. For that purpose, the orientation of the ridges can be determined so that it is able to filter the image exactly in the direction of the ridges. Figure 4.4 shows an orientation field overlaid on a fingerprint.

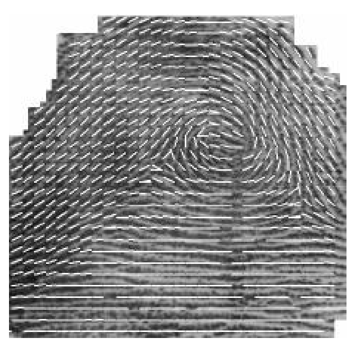
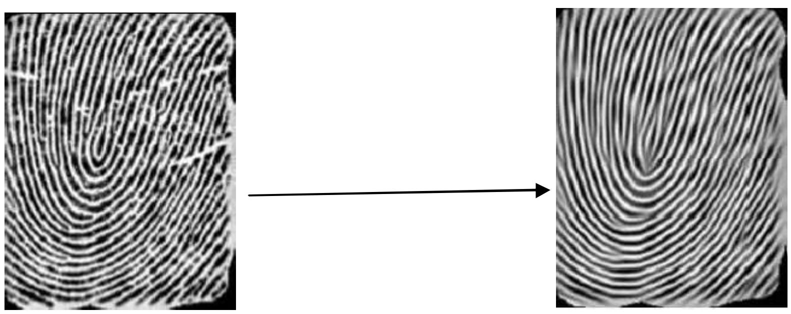


Figure 4.4 An orientation field overlaid on a fingerprint

Filtering : By this filter method, without affecting the ridge structure itself, the ridge noise is greatly reduced. One approach to ridge orientation estimation depends upon the local image gradient. A gray scale gradient is a vector whose orientation indicates the direction of the steepest change in the gray values and whose magnitude relies on the amount of change of the gray values in the direction of the gradient (Yang et al 2003). The pixel gradient orientations of the block can be determined from the local orientation in a block. A sample Filtered Image is shown in Figure 4.5 as below.



Normalized image **Directionally filtered image**

Figure 4.5 Sample directionally filtered image

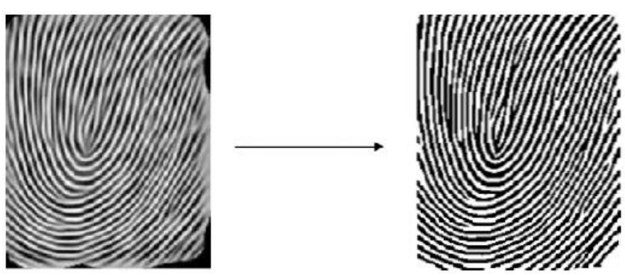
Noise Reduction : In order to reduce the noise, pixel-wise wiener filtering is proposed (Greenberg et al, 2000). The filter is based on the estimated local statistics from a local neighbourhood $'a'$ of size 3×3 of each pixel, and is given by

$$w(m_1, m_2) = \tau + \frac{\mu^2 - \sigma^2}{\mu^2}\left(I(m_1, m_2) - \tau\right) \quad (4.3)$$

where σ^2 is noise variance, τ and μ^2 are local mean and variance, where the gray level intensity is represented $(m_1, m_2) \in a$.

Binarization : The separation of the object and background is known as Binarization. A gray scale picture is turned into a binary picture. A binary picture has two dissimilar values only. The colors black and white are represented by the values 0 and 1 respectively. A threshold value in the gray scale image is picked for binarization of an image. Everything darker than this threshold value is converted to black and everything lighter is converted to white. To find the identification marks in the fingerprints such as singularity points or minutiae, this method is performed. The complexity with binarization lies in finding the accurate threshold value to be able to eliminate insignificant information and improve the significant one. Finding a working global threshold value that can be used on every image is unfeasible. The deviations can be too huge in these types of fingerprint images that the background in one image can be darker than the print in another image. Therefore, algorithms to find the optimal value must be applied separate on each image to get a functional binarization. There are a number of algorithms to perform this; the simplest one uses the mean value or the median of the pixel values in the image. This algorithm is based on global thresholds. Nowadays local thresholds are often used. The image is separated into smaller parts and threshold values are then calculated for each of these parts. This enables adjustments that are not possible with global calculations. Local thresholds demand a lot more calculations but mostly compensate it with a better result (Greenberg et al, 2000). The binarization process is carried out using the following adaptive threshold, and a sample binarized image is given in Figure 4.6.

$$I_{new}(m_1, m_2) = \begin{Bmatrix} 1 \; if \; I_{old}(m_1, m_2) \geq Local\ Mean \\ 0 \; otherwise \end{Bmatrix} \tag{4.4}$$



Directionally filtered image **Binarized image**

Figure 4.6 Sample binarized image

Thinning : One way to make a skeleton is through thinning algorithms. The technique takes a binary image of a fingerprint and makes the ridges that appear in the print just one pixel wide without changing the overall pattern and leaving gaps in the ridges creating a sort of “skeleton” of the image. The form ✣ is used as structural element, consisting of five blocks and each block representing a pixel. The center pixel of that element is called the origin. When the structural element overlays the object pixels in its entirety, only the pixels of the origin remain. The others are deleted. Figure 4.7 shows the example of thinning process. Thinning makes it easier to find minutiae and removes a lot of redundant data.

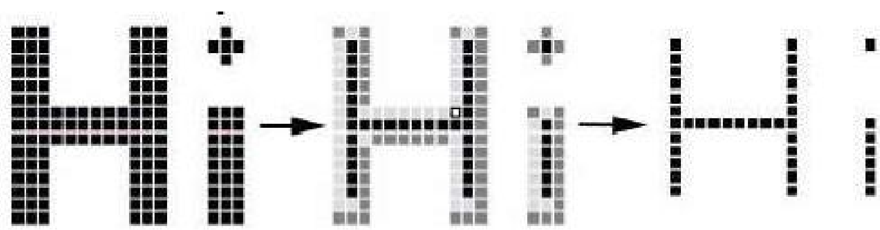
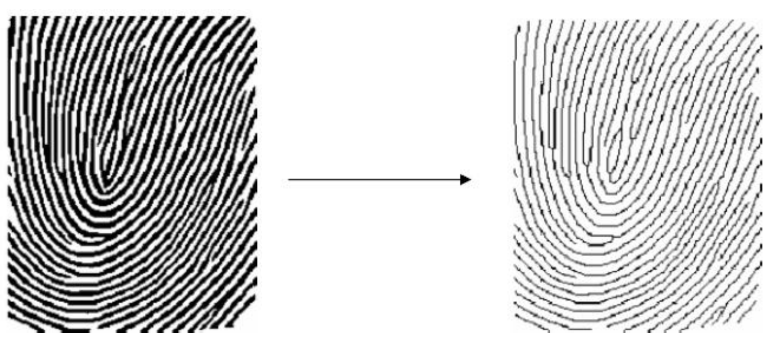


Figure 4.7 An example of thinning

Thinning makes it easier to find minutiae and removes a lot of redundant data, which would have resulted in longer process time and sometimes different results (Tico et al 2005). A sample thinned image is depicted in Figure 4.8.



Binarized image **Thinned image**

Figure 4.8 Sample thinned image

4.3 MINUTIAE EXTRACTION

A valid demonstration of a fingerprint is the pattern of the minutiae details of the fingerprint. It satisfies the basic properties like compactness, agreeable to matching algorithms, robust to noise and distortions and is easy to compute (Ravi et al 2009). A total of 150 diverse local ridge characteristics, called minutiae details, have been identified. Most of them are not enduring and cannot be consistently recognized, and they depend deeply on the impression conditions. The seven most prominent ridge characteristics are shown in Figure 4.9

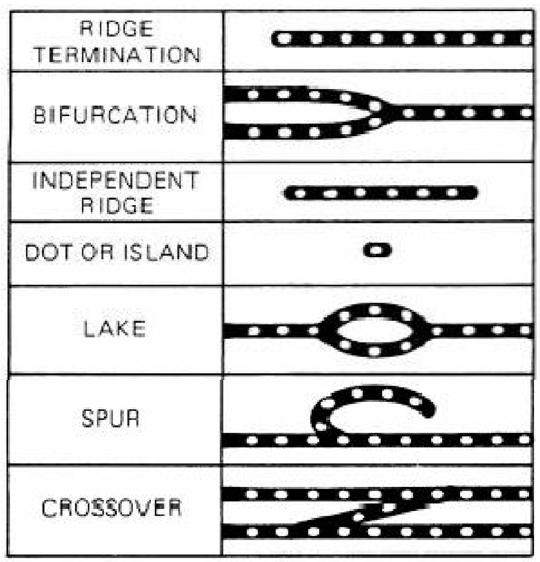
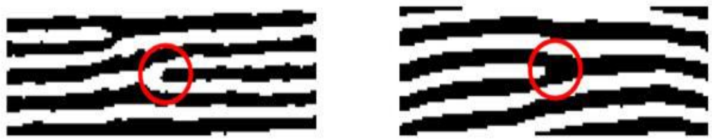


Figure 4.9 Minutiae details

Only two most prominent types of minutiae details are used in AFIS because of their stability and robustness. They are ridge endings and bifurcations. Ridge endings are the points where the ridge curve terminates, and bifurcations are where a ridge splits from a single path to two paths at a Y-junction (Amengual et al 1997). Figure 4.10 illustrates an example of a ridge ending and a bifurcation. In this example, the black pixels correspond to the ridges, and the white pixels correspond to the valleys.



Ridge ending Ridge bifurcation

Figure 4.10 Ridge ending and ridge bifurcation

Accurate minutiae detection is an essential component for all minutiae-based fingerprint recognition systems (Venu et al 2003). Without accurate minutiae detection, the results and performance of a system are not reliable.

4.3.1 Types of Minutiae Extraction

There are a lot of minutiae extraction techniques available in the literature. There are generally four categories of detection algorithms based on image detection domain. They are

i) Direct level minutiae extraction
ii) Binary image - based minutiae extraction
iii) Machine learning method and
iv) Skeletonization -based minutiae extraction.

In the first category, minutiae are extracted directly from the gray-level image without using binarization and thinning processes. The second category of method extracts minutiae from binary image profile patterns. The third category of method extracts minutiae via machine learning methods. The final category of method extracts minutiae from binary skeletons.

Gray-level minutiae extraction algorithm works well only for good quality fingerprint images (Otsu 1979). Thinning-based minutiae detection algorithms are time-consuming, and the position of detected minutiae shifts by the ridge width. In the machine learning method, various techniques like

Neural Networks, Genetic Programming, Reinforcement Learning and fuzzy logic are used to extract the minutiae points. It has been concluded that the traditional skeletonization – based Minutiae extraction method is more satisfactory than Genetic Programming and Reinforcement Learning. And hence the Skeletonization – based Minutiae Extraction is selected for implementation. In particular, the crossing –number concept is used for the implementation.

4.3.2 Minutiae Extraction Using Crossing - Number Concept

A minutiae extraction algorithm is said to be a good one if and only if it satisfies the following requirements. The first and foremost thing comprises the non-creation of the spurious minutiae. Next, the genuine minutiae should not be missed. And finally, it should be accurate in localization of the minutiae portion and computation of minutiae orientation (Shi et al 2006). And thus a reliable and efficient minutiae extraction algorithm is defined.

Crossing-Number Concept: The Crossing-Number (CN) concept is the most commonly employed technique of minutiae extraction. The skeleton image where the ridge flow pattern is eight-connected is used in this method. By scanning the local neighborhood of each ridge pixel in the image using a 3x3 window, the minutiae are extracted. The value of CN, which is defined as half the sum of the differences between pairs of adjacent pixels in the eight-neighborhood, is then computed.

The ridge pixel can then be classified as a ridge ending, bifurcation or non-minutiae point, using the properties of the CN as shown in Table 4.1. For example, a ridge pixel with a CN of one corresponds to a ridge ending, a CN of two corresponds to a connective point and a CN of three corresponds to a bifurcation.

Table 4.1 Properties of the crossing number

CN	Property
0	Isolated point
1	Ending point
2	Connective point
3	Bifurcation point
4	Crossing point

4.3.3 Methodology

To extract the minutiae points, the Crossing Number (CN) method is used. By examining the local neighborhood of each ridge pixel using a 3x3 window, this method extracts the ridge endings and bifurcations from the skeleton image. The concept of Crossing Number (CN) is widely used for extracting the minutiae (Jain *et al*., 1997). The crossing number for a pixel P is

$$CN = \frac{1}{2} \sum_{i=1}^{8} | \mathrm{Pi} - \mathrm{Pi} + 1| \qquad (4.5)$$

where, P_i is the binary pixel value in the neighborhood of P with P_i = (0 or1) and $P_9 = P_1$. For a pixel *P*, its eight neighboring pixels are scanned in an anti-clockwise direction as follows:

$$\begin{array}{ccc} P_4 & P_3 & P_2 \\ P_5 & P & P_1 \\ P_6 & P_7 & P_8 \end{array}$$

Then the pixels are classified according to the property of their CN value. As shown in Figure 4.11, a ridge pixel with a CN of one corresponds to a ridge ending, and a CN of three corresponds to a bifurcation.

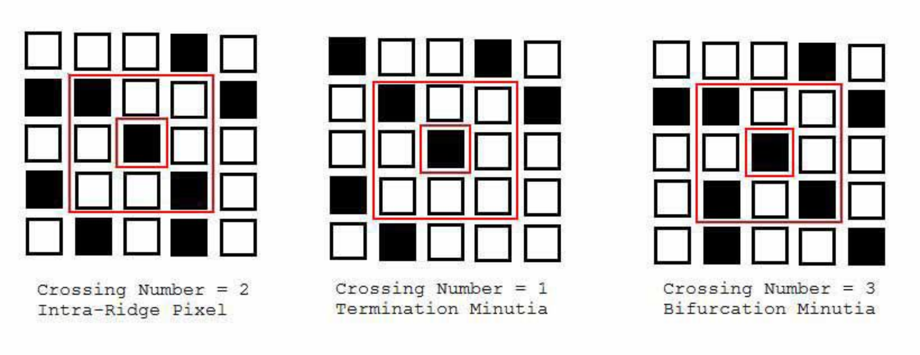


Figure 4.11 Examples of a ridge ending and bifurcation pixel

Depending upon the finger and the sensor area, the measured fingerprint consists of an average of about thirty to sixty minutiae points. After performing the image processing step, these can be extracted from the image. The point at which a ridge ends, and the point where a bifurcation begins are the most basic minutiae and are used in most applications. After obtaining the thinned ridge map, the ridge pixels with three ridge pixel neighbors are identified as ridge bifurcations, and those with one ridge pixel neighbor are identified as ridge endings (Sharat et al 2005).

The absolute position (x,y), the direction (θ), and if necessary, the scale(s) are stored for each and every extracted minutia. The position of the minutiae are generally indicated by the distance from the core, with the core serving as the (0,0) on an x,y-axis. Some authors use the far left and bottom boundaries of the image as the axes, correcting for misplacement by locating and adjusting from the core. The angle of the minutia is normally used in addition to the placement of the minutia. When a ridge ends, its direction at the point of termination establishes the angle. This angle is taken from a horizontal line extending rightward from the core.

At the very superior level, intra-ridge details can be detected. These are essentially the finger sweat pores whose position and shape are considered extremely unique (Robert 2007). Extracting pores is usable only in high-resolution fingerprint images of good quality, and hence this kind of representation is not practical for most applications.

4.4 POST-PROCESSING

A post-processed image is the starting point of minutiae extraction (Lu et al 2002). Though it is a much defined image, it will have deformations and forged minutiae that required to be filtered out. Since minutiae are very rarely adjacent, an algorithm may abolish one of two adjacent minutiae. Scars, sweat or dirt may cause irregular minutiae that appear as false minutiae when acquiring the fingerprint image. Algorithms should trace any points or patterns that do not produce sense, such as a spur on an island which maybe a false minutia (Tico and Kuosmanen 2000). In addition to that, they have to identify a ridge crossing at right angles to two or three others that maybe a scar or dirt (Zhao and Tang 2002). By this post-processing stage, an outsized proportion of false minutiae are abandoned.

Figure 4.12 is an evidence for several examples of false minutiae. In clockwise order, interrupted ridges, forks, spurs, structure ladders, triangles and bridges are portrayed in the figure. Two very close lines with the same direction create the interrupted ridges. A fork is produced by two lines connected by a noisy line (Greenberg et al 2000). The short lines whose direction is orthogonal to ridges' direction are known as spurs. The pseudo - rectangle between two ridges composes ladders. A genuine bifurcation with a noisy line between two ridges produces the triangles.

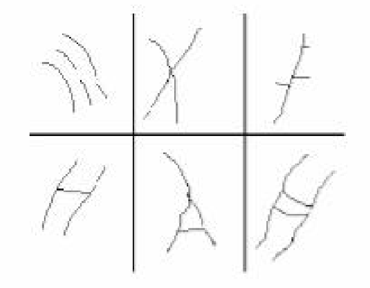
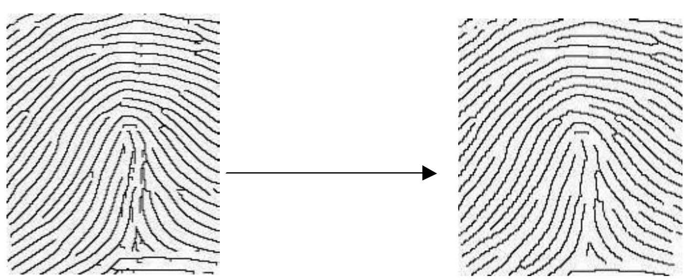


Figure 4.12 False minutiae: interrupted ridges, forks, spurs, structure ladders, triangles and bridges in clockwise order

At last, a noisy line between two ridges constitutes the bridge. By means of all these characteristics, a number of false minutiae are generated. In the algorithm first the spurs are being eliminated, the endpoints are being merged, the bridges are being excluded, the triangles are being eradicated and the ladder structures are being abolished. Thus the algorithm is arranged in an order and is executed in that sequence to remove the several false minutiae. Figure 4.13 denotes a sample post-processing image where its false minutiae are removed.



Thinned image with spur **Thinned image after removal of spur**

Figure 4.13 Impact of removing spurs

4.5 EXPERIMENTATION AND RESULTS

Prior to the implementation of the minutiae extraction algorithm, the database repository has to be created. The image acquisition and the creation of image database are discussed in the following sections.

4.5.1 Image Acquisition and Database Creation

The selection of training examples is very significant for any supervised learning algorithm like SVM, Neural Networks etc. as well as for traditional minutiae extraction. It has a massive impact on classification accuracy, stability of the model and simplification to novel samples. For this purpose, the available databases in the internet are investigated. But these databases are not adequate as they contain only the fingerprint images. They do not have the particulars about the gender and the age. As a result, a classifier is left confused because of various examples that look alike in the database. The absence of varied sets in the database is a major hindrance to the classifier. To overcome this problem, a new database of images with unique fingerprints should be prepared. This database should contain sets of fingerprints varied in terms of number of fingers, gender and age.

For the database, a set of nearly 3000 unique fingerprint images were collected from the 250 male and 250 female of the public. The fingerprints of 6 numbers for each person were collected. The fingerprint images collected were in the range of age from 1 to 90 years. As these are real time images, they have reasonable variability in the number of images, gender and age.

Figure 4.14 Digital persona U.are.U 4500 fingerprint reader

Figure 4.14 shows the optical device known as Digital Persona U.are.U 4500 Fingerprint Reader which is used to capture the fingerprint images. Its pixel resolution is 512 dpi. The captured image will be of the size 14.6x 18.1 and it is an 8 – bit grayscale image.

4.5.2 Data Distribution

The male and female images from all ages and both genders are included to attain good simplification and solidity of the classifier. The database was divided into nine age groups 1 to 10, 11 to 20, 21 to 30, 31 to 40, 41 to 50, 51 to 60, 61 to 70, 71 to 80 and 81 to 90 years. People from age of 1-90 were used in this thesis. Figure 4.15 and Figure 4.16 show a break-up of the data according to gender and age groups.

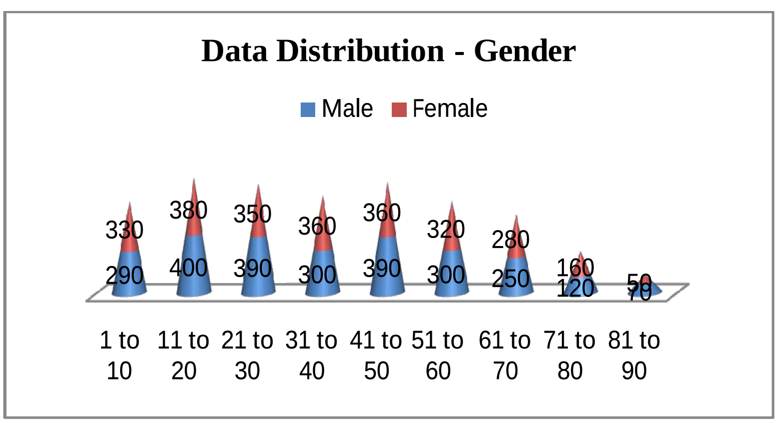


Figure 4.15 Data distribution based on gender

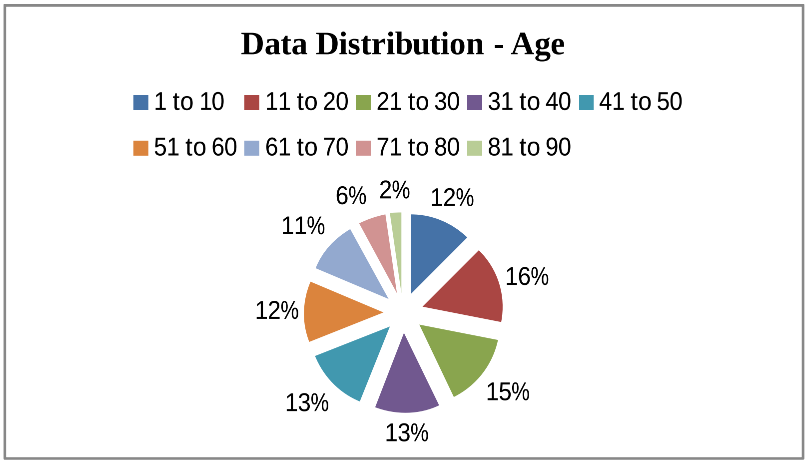


Figure 4.16 Data distribution based on age groups

Figure 4.17 shows the input image for minutiae extraction – Preprocessing. The experimental results of Minutiae Extraction - reprocessing – filtering, binarization, thinning and minutiae extraction are presented as shown in Figures 4.18, 4.19, 4.20 and 4.21 respectively.

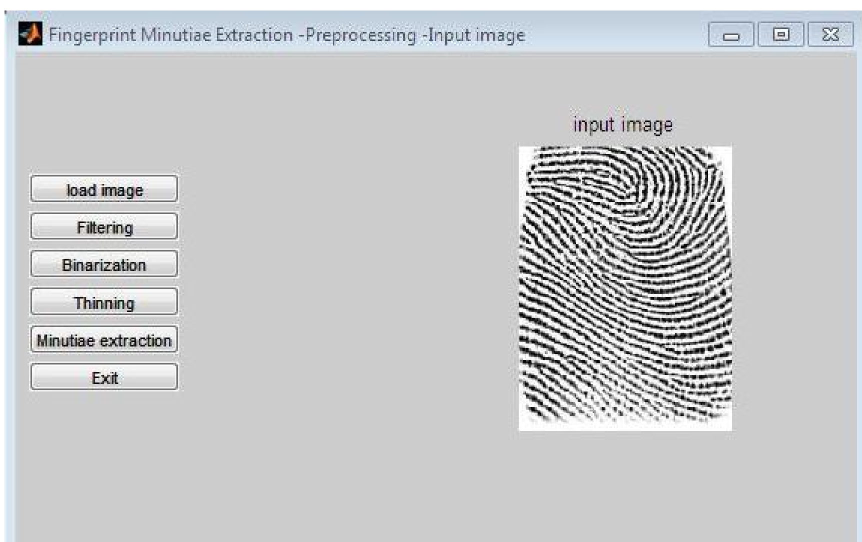


Figure 4.17 Input image for minutiae extraction

Figure 4.18 Filtered image for minutiae extraction

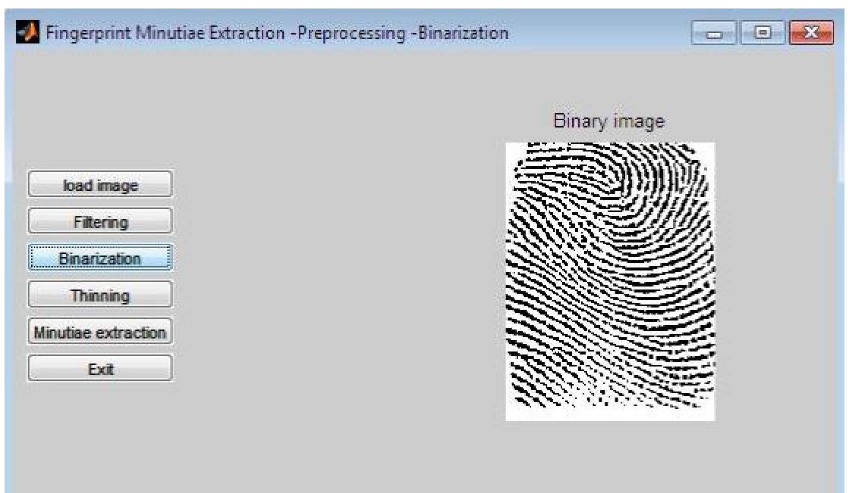


Figure 4.19 Binarized image for minutiae extraction

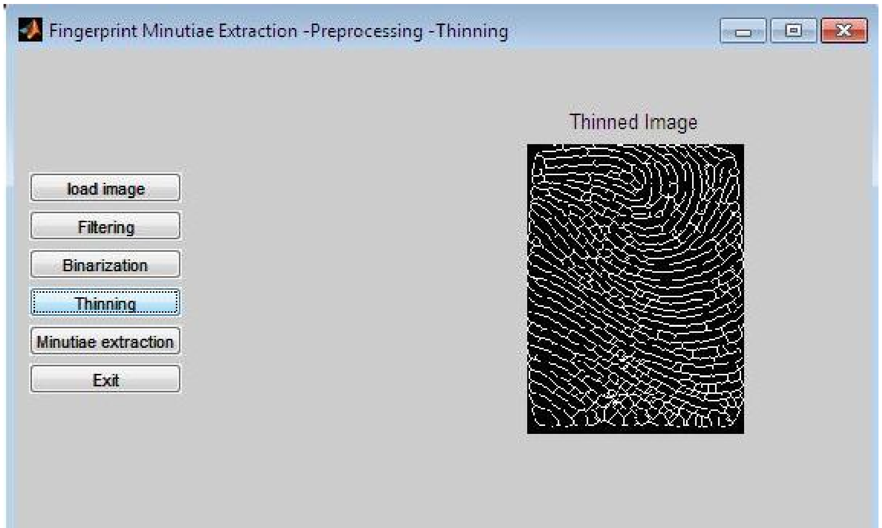


Figure 4.20 Thinned image for minutiae extraction

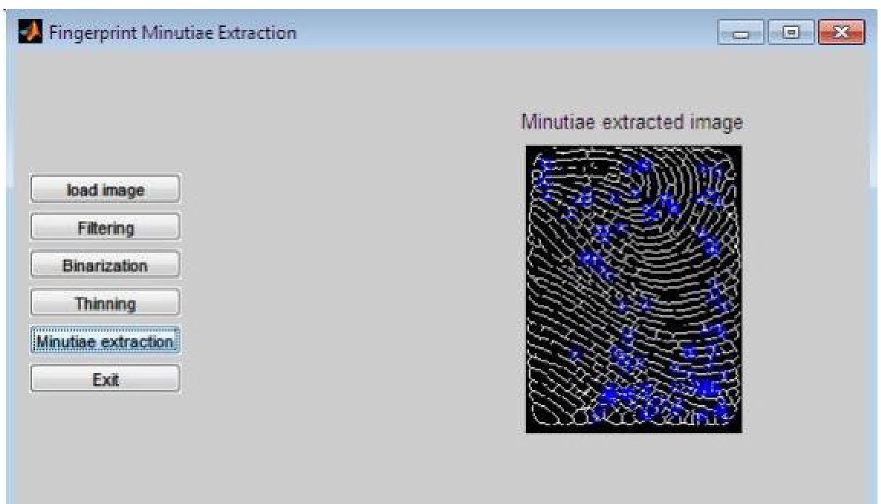


Figure 4.21 Minutiae extraction

The entire process of minutiae extraction including the various stages are depicted in Figure 4.22.

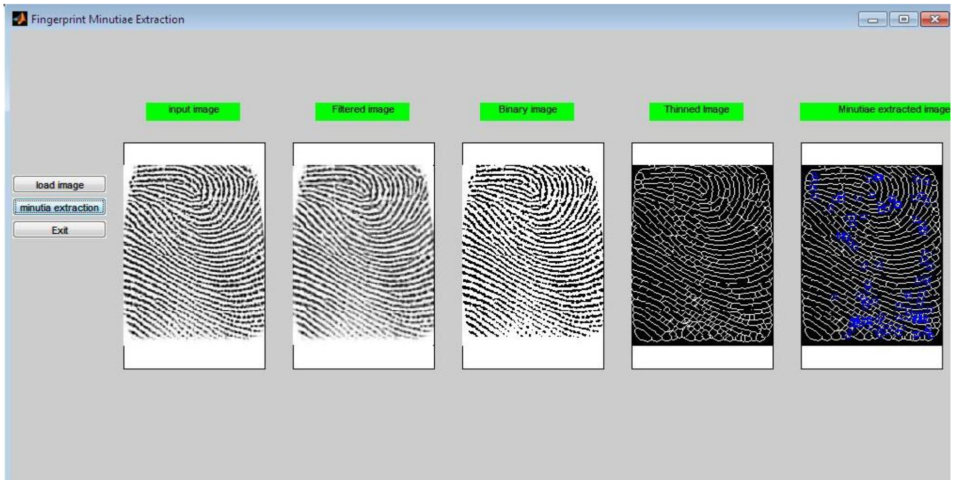


Figure 4.22 All the stages of fingerprint minutiae extraction

Though minutiae extraction using crossing numbers method is used to extract minutiae points, the preprocessing techniques are adopted from various algorithms. And hence the execution time for this entire process is reduced considerably. The time taken for the minutiae extraction stages are given in Table 4.2.

Table 4.2 Execution time for minutiae extraction

Stages	**Time (Seconds)**
Preprocessing	0.54
Minutiae Extraction	0.53
Post-processing	0.2
Total	1.27

4.6 SUMMARY

Minutiae extraction finds diplomat features, called minutiae from the input fingerprint images. A strong as well as computationally efficient minutiae extraction algorithm should be formed. If the quality of the fingerprint image is poor, it can be either rejected or enhanced before minutiae extraction. The corrupted ridge structures that degrade the image quality should be processed by a good minutiae extraction algorithm so that the image quality is enhanced. A minutiae extraction algorithm which is both fast and reliable has been devised. The various stages that an input fingerprint image is passed through are image enhancement, normalization, filtering, noise reduction, binarization, thinning and post-processing and these are very useful to extract the correct and concise minutiae points. As the preprocessing steps are appropriately chosen, the overall time taken to extract the minutiae points is reduced. From the experimental results, it is clearly shown that this algorithm not only performs well but also fast. The overall execution time for the preprocessing, minutiae extraction and the post-processing includes 1.27 seconds. Moreover, it extracts clear and concise minutiae points. The various steps implemented in that algorithm are chosen from different literatures. When this minutiae extraction algorithm is executed on the whole, it is a novel one. This algorithm helps to extract the minutiae points and other parameters like ridge count, whitelines count etc., in a short span of time. Though minutiae extraction is incorporated in this research work, the main objective is to classify the gender and age from fingerprints.