# Various Aspects of Minutia As a Fingerprint Feature

Kalyani Mali,
Department of Computer Science & Engineering,
University of Kalyani,
Kalyani, West Bengal, India

Samayita Bhattacharya,
Department of Computer Science & Engineering,
University of Kalyani,
Kalyani, West Bengal, India

***Abstract:-*** **Biometrics is one of the biggest tendencies in human identification. The fingerprint is the most widely used biometric. Extracting minutiae from fingerprint images is one of the most important steps in automatic fingerprint identification and classification. Minutiae are local discontinuities in the fingerprint pattern, mainly terminations or end points and bifurcations.**

***Keywords:-*** **Fingerprint, Minutia, Ridge, Ridge Ending, Bifurcation, Thinning.**

## 1. Introduction

Fingerprints are the graphical flow-like ridges present on human fingers. Finger ridge configurations do not change throughout the life of an individual except due to accidents such as bruises and cuts on the fingertips. This property makes fingerprints a very attractive biometric identifier. Fingerprint-based personal identification has been used for a very long time [9]. Owning to their distinctiveness and stability, fingerprints are the most widely used biometric features. Nowadays, most automatic fingerprint identification systems (AFIS) are based on matching minutiae, which are local ridge characteristics in the fingerprint pattern. Based on the features that the matching algorithms use, fingerprint matching can be classified into image-based and graph-based matching.
Image-based matching [14] uses the entire gray scale fingerprint image as a template to match against input fingerprint images. The primary shortcoming of this method is that matching may be seriously affected by some factors such as contrast variation, image quality variation, and distortion, which are inherent properties of fingerprint images. The reason for such limitation lies in the fact that gray scale values of a fingerprint image are not stable features.
Graph-based matching [10], [11] represents the minutiae in the form of graphs. The high computational complexity of graph matching hinders its implementation. To reduce the computational complexity, matching the minutiae sets of template and input fingerprint images can be done with point pattern matching. Several point pattern matching algorithms have been proposed and commented in the literature [3], [6], [12], [13], [15].
Fingerprint system can be separated into two categories *Verification* and id*entification.*
Verification system authenticates a person's identity by comparing the captured biometric characteristic with its own biometric template(s) pre-stored in the system. It conducts one-to-one comparison to determine whether the identity claimed by the individual is true. A verification system either rejects or accepts the submitted claim of identity. Identification system recognizes an individual by searching the entire template database for a match. It conducts one-to-many comparisons to establish the identity of the individual. In an identification system, the system establishes a subject's identity (or fails if the subject is not enrolled in the system database) without the subject having to claim an identity.
It is now viable for technology to be used in the matching of fingerprints in real time. A fingerprint is often used for biometric identification in criminal investigations. Fingerprints can be used to identify individuals for private and commercial purposes. Personal identification cards or keys could be replaced with a fingerprint scanner system. This will increase security since it is nearly impossible to forge a fingerprint.
Most of the fingerprint recognition systems first detect the minutiae in a fingerprint image and then match the input image set with the template.
A minutia is the unique, measurable physical characteristics scanned as input and stored for matching by biometric systems. For fingerprints, minutiae include the starting and ending points of ridges, bifurcations and ridge junctions among other features.
The most prevalent model for automated fingerprint identification systems are based on minutiae, a fingerprint is also represented in the form of graph whose nodes correspond to ridges and edges represent ridge adjacency information.
It is generally accepted that 8 to 17 distinct minutiae matches between two fingerprints will conclude that the fingerprints match.
The first step in the approach involves binarization: converting the image to black and white pixels whilst still retaining the distinct ridges. It is concluded that a global threshold is inadequate in meeting these requirements. An adaptive threshold retains more information.

Median filtering helps to remove small noise segments present on the binarized image. Without the application of a median filter, the noise would have made minutiae extraction virtually impossible.
The thinning of the median filtered image results in the formation of spurs. These features results in further false minutiae. Minutiae extraction yielded many minutiae resulting from fingerprint irregularities. The noise removal algorithms works particularly well at removing the noise.
Fingerprints are the corrugations formed on the surface of the fingers and thumbs. Their primary evolutionary purpose is to provide friction when grasping objects.
The use of fingerprints as a means of identifying individuals has been used for centuries. The difficulty associated with forging a fingerprint is greater than that associated with forging signatures. The commercially available automatic fingerprint identification systems use ridge bifurcations and ridge endings to identify possible matches. When using large databases, the most likely fingerprint matches are chosen.
Fingerprints recognition has the potential to be used for the identification of unique individuals when accessing, door locks, access control systems, ignition systems, computer access, identity cards, and credit cards.
The purpose of this paper is to discuss the minutia as a fingerprint feature to indentify people from their fingerprints.

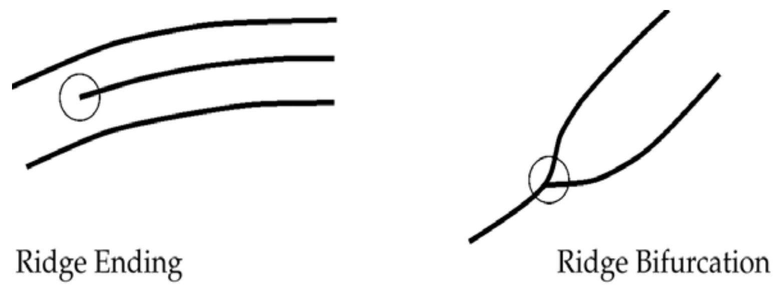


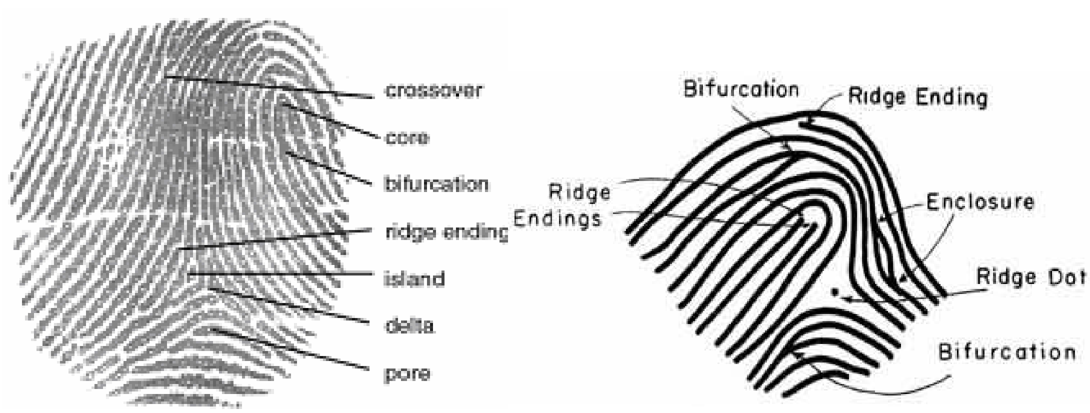

Figure 1. Ridge ending and ridge bifurcation.

**2. Definition and Types of Minutia**

A minutia is the unique, measurable physical characteristics scanned as input and stored for matching by biometric systems.

Minutiae include:

- *Ridge ending* – the abrupt end of a ridge. Looks like this(-)
- *Ridge bifurcation* **–** a single ridge that divides into two ridges
- *Short ridge*, or *independent ridge* **–** a ridge that commences, travels a short distance and then ends
- *Island* – a single small ridge inside a short ridge or ridge ending that is not connected to all other ridges
- *Ridge enclosure* – a single ridge that bifurcates and reunites shortly afterward to continue as a single ridge
- *Spur* **–** a bifurcation with a short ridge branching off a longer ridge
- *Crossover* or *bridge* – a short ridge that runs between two parallel ridges
- *Delta* **–** a Y-shaped ridge meeting
- *Core* **–** a U-turn in the ridge pattern




(a) (b)

Figure 2: Fingerprint image showing Minutiae

**3. Components of Fingerprint Recognition System Using Minutia:**

The following two modules are the main components of fingerprint recognition system using minutia:

- *Minutiae extraction*. Minutiae are ridge endings or ridge bifurcations. Generally, if a perfect segmentation can be obtained, then minutia extraction is just a trivial task of extracting singular points in a thinned ridge map. However, in practice, it is not always possible to obtain a perfect ridge map. Some global heuristics need to be used to overcome this limitation.

- *Minutia matching*. Minutia matching, because of deformations in sensed fingerprints, is an elastic matching of point patterns without knowing their correspondences beforehand. Generally, finding the best match between two point patterns is intractable even if minutiae are exactly located and no deformations exist between these two point patterns. The existence of deformations makes the minutia matching much more difficult.

**4. Fingerprint Enhancement Techniques**

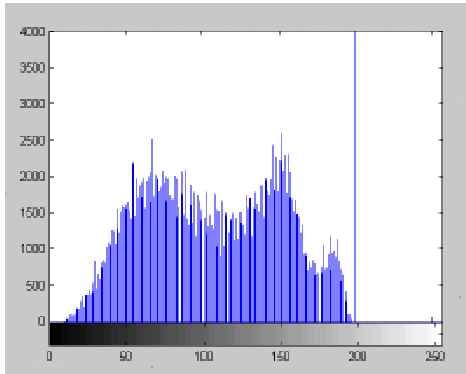
Steps to extract minutiae as a feature are as follows:

**4.1. Binarization**

Binarization is a method of transforming grayscale image pixels into either black or white pixels by selecting a threshold. The process can be fulfilled using a multitude of techniques. Binarization is relatively easy to achieve compared with other image processing techniques.

Unfortunately the global threshold technique sometimes proved to be troublesome in determining appropriate thresholding levels. The resulting images obtained contain large faded and large dark areas. Some globally binarized images are of an adequate standard.

(A)




(B)

Figure 3: (A) binary image resulting from global thresholding. (B) The histogram resulting form the original grayscale image.

Figure 4: An example of a poor image enhancement resulting from global binarization.

If we Binarize using Low pass filter then method retains more of the information present in the fingerprint than global threshold binarization.

**4.2. Thresholding**

The first technique considered focuses on finding the global threshold. The main black and white pixel values of each image is determined. The pixel range in between these pixel values is used to separate the black and white colours. Global binarization involves the formulation of a histogram consisting of the number of pixels versus the pixel value.

Another method experimented with is called contrast enhancement binarization or Adaptive Threshold Binarization. The method involves passing a low pass filter over the image and using the resulting grayscale pixel number to discriminate between a black or white pixel. The low pass filter does not process edges, one pixel wide in the image. Low-pass filtering involves a spatial convolution process within a window.

**4.3. Median Filtering**

Median filters calculate the average of pixel values in a pre-specified window size. The central pixel is then assigned that value.

Median filtering removes a large majority of the noise. Noise is an unwanted perturbation to a wanted signal. Image noise is generally regarded as an undesirable by-product of image capture. The noise (small clusters of black) is averaged with its surroundings. After several passes of the filter, the small clusters of noise disappear.

(a) (b)

Figure 5: The image after the first (a) and seventh (b) median filter

**4.4. Thinning**

The aim of thinning is to reduce the fingerprint to lines one pixel wide. Thinning is a morphological operation performed on binary images. This is achieved by successive deletions of pixels from different sides of each image. (north, south, east, west) Each of the four sides is eroded away according to some set template. Eventually, the image being thinned will no longer possess any points which match the deletion templates. This remaining image will be the thinned representation of the original image.

False minutiae which are included in false minutia structures like spikes, holes, bridges, ladder structures, and spurs are introduced to the fingerprint image after thinning the original image.

(a) (b)

Figure 6: (a) Fingerprint , (b) Image after thinning.

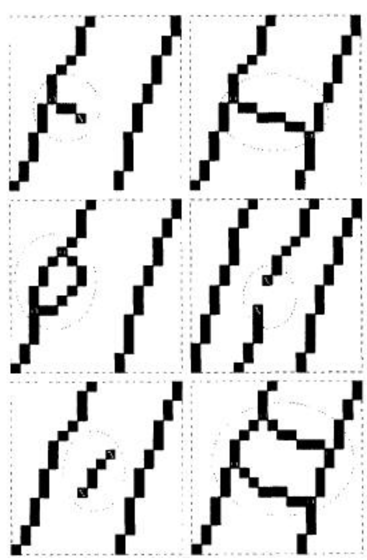


Figure 7: Types of false minutia structures. From left to right and up to bottom we have: spike, bridge, hole, break, spur, and ladder structure. The false minutiae generated by each structure are marked as (x) false ridge ending, and (o) false ridge bifurcation.

### 4.5. Minutiae Detection

The proposed method can only be performed on thinned images. It is known as crossing number or connectivity number. The technique uses a sample window, 3 pixels by 3 pixels wide to detect key features such as endpoints and bifurcation.
Minutia detection is a trivial task. Without a loss of generality, we assume that if a pixel is on a thinned ridge (eight-connected), then it has a value 1, and 0 otherwise.
Let $(x, y)$ denote a pixel on a thinned ridge, and $N0$, $N1$, ..., $N7$ denote its eight neighbors.
A pixel $(x, y)$ is a ridge ending if $(\sum_{i=0}^{7} Ni) = 1$ and a ridge bifurcation if $(\sum_{i=0}^{7} Ni) > 2$
However, the presence of undesired spikes and breaks present in a thinned ridge map may lead to many spurious minutiae being detected. Therefore, before the minutia detection, a smoothing procedure is often applied to remove spikes and to join broken ridges.
If several minutiae form a cluster in a small region, then all of them except for the one nearest to the cluster centre are removed.

The formula for the detection of key points is:

$$CN = 0.5 \sum_{I=1}^{8} |P_i - P_{I+1}| \qquad \text{Where } P_1 = P_9$$

This is applied to the matrix:

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

| CN | Characteristic |
|---|---|
| 0 | Isolated Point |
| 1 | End Point |
| 2 | Continuing Point |
| 3 | Bifurcation Point |
| 4 | Crossing Point |

Table1: Minutiae and the corresponding crossing number

For each surviving minutia, the following parameters are needed to be recorded:
1) x-coordinate,
2) y-coordinate,
3) orientation which is defined as the local ridge orientation of the associated ridge, and
4) the associated ridge.

It is also needed to go through the *Alignment stage*, where transformations such as translation, rotation and scaling between an input and a template in the database are estimated and the input minutiae are aligned with the template minutiae according to the estimated parameters.
Also we need to note that a false minutia is more affecting than missing minutiae.

### 6. Directional Image

The directional image is usually used to derive the average direction of a small segment of the image. The image is divided into 4 sub-directions. If required the image could be sorted into a larger number of bins for greater segmentation.

The technique is used on the unprocessed grayscale images. The darker pixels result in a greater number in the corresponding sub-direction. A test area 16 pixels wide was selected. The actual test area depends on the dimensions of the entire image. The area should include at least 1 ridge (dark area) and 1 valley.

Sub-direction = greatest [ $\sum \left|(\text{pixel\_value-average})\right|$ ] (1)

The technique gives similar results to the dominant ridge direction equation.
The technique for the classification of endpoint directions is easier to implement. The pixel next to the endpoint determines the direction. Unlike the bifurcation direction, endpoint directions are unidirectional.

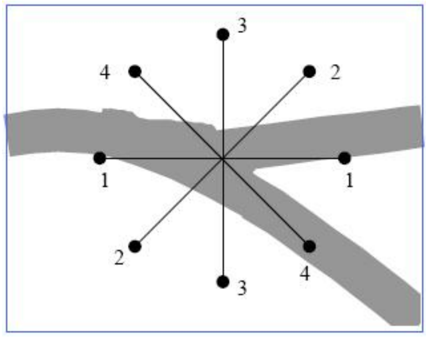


Figure 8: Possible Sub-directions of a bifurcation,

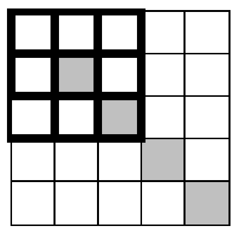


Figure 9: Possible directions of an endpoint

**7. Feature Extraction**
Many features will be extracted from each print. The co-ordinates of each minutia and the type of the minutiae can be determined. The number of total minutiae is also recorded. A fingerprint can have up to 80 minutiae. It is generally accepted as the same print if 8 to 17 points match. Some translation of the fingerprint will be acceptable, however rotation must be minimized since no techniques have been implemented which specifically counteracts rotation.

**8. Spur Removal**
Spur removal helps to remove bifurcations and ends caused by thinning. If these points were not removed, they would result in false endpoints and false bifurcations.
A compromise during spur removal must be met. Although it will remove some noise from the thinned image, it will also move endpoints from their ‘real’ locations. This illustrates the dependency of filtering on the quality of the image. A quality image will require few or no spur removal cycles.
When eroding spurs, normal endpoints are also eroded. This results in small variations of the location of endpoints from their real locations.

**9. Minutia Matching**
Matching is a key operation in the fingerprint identification system. One of the most important objectives of fingerprint systems is to achieve a high reliability in comparing the input pattern with respect to the database pattern. Reliably matching fingerprint images is an extremely difficult problem, mainly due to the large variability in different impressions of the same finger (i.e., large intra-class variations). The main factors responsible for the intra-class variations are: displacement, rotation, partial overlap, non-linear distortion, variable pressure, changing skin condition, noise, and feature extraction errors. Therefore, fingerprints from the same finger may sometimes look quite different whereas fingerprints from different fingers may appear quite similar.

A minutia matching essentially consists of finding the alignment between the template and the input minutiae sets that results in the maximum number of minutiae pairings. In Minutiae based matching the similarity between the input and stored template are computed.
The implementation of a viable technique is quite difficult. Consider the ideal case below. The coordinates of both samples are identical. A simple coordinate matching algorithm would suffice.

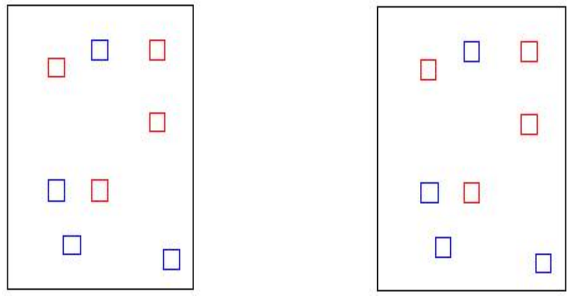


Figure 10. Identical matches of minutia coordinates rarely match perfectly.

Unfortunately, this ideal situation rarely occurs. When a second print is recorded from the same finger it is always misaligned from the original.
The elastic nature of skin means that some features may be stretched or warped, relative to other sections of the print which retain their dimensions.
Noise will most likely occur, caused by applying too much pressure or smudging the print.
Slight rotation of the finger will also cause some features to vary from the origin sample.

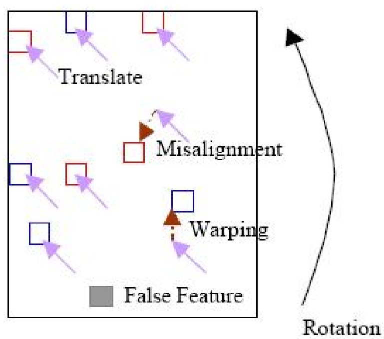



Figure 11. Sources of error in fingerprint recognition.

The searching algorithm must be flexible enough to allow some variance in coordinate position. It must also attempt to distinguish the difference between real and false matches.
The main problem of the matching algorithm is false matches.

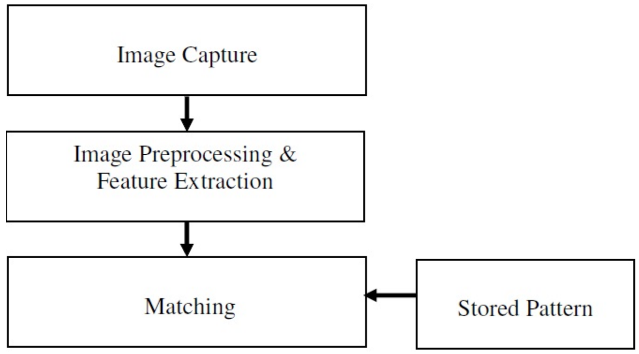



Figure 12: Fingerprint matching steps.

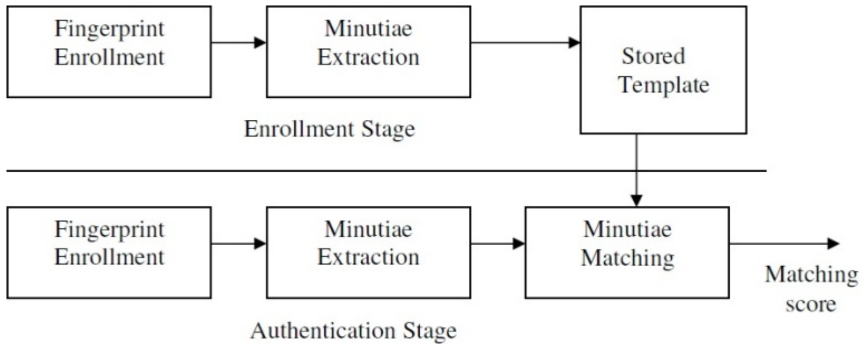



Figure 13**:** Fingerprint authentication steps.

Generally, an automatic fingerprint verification/identification is achieved with point pattern matching (minutiae matching) instead of a pixel-wise matching or a ridge pattern matching of fingerprint images. A number of point pattern matching algorithms have been proposed in the literature [1], [3], [4], [6]. Because a general point matching problem is essentially intractable, features associated with each point and their spatial properties such as the relative distances between points are often used in these algorithms to reduce the exponential number of search paths.

The relaxation approach [6] iteratively adjusts the confidence level of each corresponding pair based on its consistency with other pairs until a certain criterion is satisfied.

Although a number of modified versions of this algorithm have been proposed to reduce the matching complexity [3], these algorithms are inherently slow because of their iterative nature.

The Hough transform-based approach proposed by Stockman et al. [2] converts point pattern matching to a problem of detecting the highest peak in the Hough space of transformation parameters. It discretizes the transformation parameter space and accumulates evidence in the discretized space by deriving transformation parameters that relate two point patterns using a substructure or feature matching technique. Karu and Jain [8] proposed a hierarchical Hough transform-based registration algorithm which greatly reduced the size of accumulator array by a multiresolution approach. However, if the number of minutia point is less than 30, then it is very difficult to accumulate enough evidence in the Hough transform space for a reliable match.

Another approach to point matching is based on energy minimization. This approach defines a cost function based on an initial set of possible correspondences and uses an appropriate optimization algorithm such as genetic algorithm [1] and simulated annealing [4] to find a possible suboptimal match. These methods tend to be very slow.

Recognition by alignment has received a great deal of attention during the past few years [5], because it is simple in theory, efficient in discrimination, and fast in speed.

Alignment-based matching algorithm decomposes the minutia matching into two stages:

1) *Alignment stage*, where transformations such as translation, rotation and scaling between an input and a template in the database are estimated and the input minutiae are aligned with the template minutiae according to the estimated parameters; and

2) *Matching stage*, where both the input minutiae and the template minutiae are converted to polygons in the polar coordinate system and an elastic string matching algorithm is used to match the resulting polygons.

### 9.1. Alignment of Point Patterns

Ideally, two sets of planar point patterns can be aligned completely by two corresponding point pairs. A true alignment between two point patterns can be obtained by testing all possible corresponding point pairs and selecting the optimal one. However, due to the presence of noise and deformations, the input minutiae cannot always be aligned exactly with respect to those of the templates. In order to accurately recover pose transformations between two point patterns, a relatively large number of corresponding point pairs need to be used. This leads to a prohibitively large number of possible correspondences to be tested. Therefore, an alignment by corresponding point pairs is not practical even though it is feasible.

It is well known that corresponding curve segments are capable of aligning two point patterns with a high accuracy in the presence of noise and deformations. Each minutia in a fingerprint is associated with a ridge. It is clear that a true alignment can be achieved by aligning corresponding ridges. During the minutiae detection stage, when a minutia is extracted and recorded, the ridge on which it resides can also be recorded to achieve this.

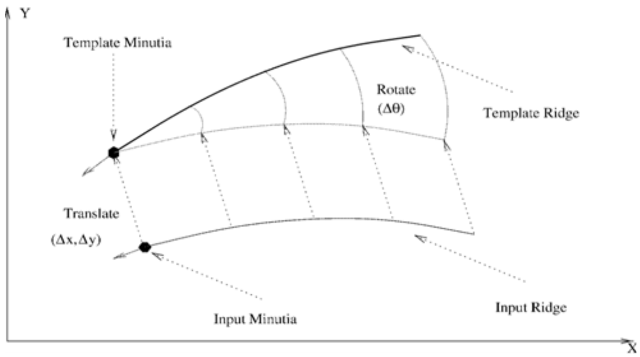



Figure 14. Alignment of the input ridge and the template ridge.

### 9.2. Aligned Point Pattern Matching

If two identical point patterns are exactly aligned with each other, each pair of corresponding points is completely coincident. In such a case, point pattern matching can be simply achieved by counting the number of overlapping pairs.

However, in practice, such a situation is not encountered. On the one hand, the error in determining and localizing minutia hinders the alignment algorithm to recover the relative pose transformation exactly, while on the other hand, alignment scheme mentioned above does not model the nonlinear deformation of fingerprints which is an inherent property of fingerprint impressions. With the existence of such a nonlinear deformation, it is impossible to exactly recover the position of each input minutia with respect to its corresponding minutia in the template. Therefore, the aligned point pattern matching algorithm needs to be elastic which means that it should be capable of tolerating, to some extent, the deformations due to inexact extraction of minutia positions and nonlinear deformations. Usually, such an elastic matching can be achieved by placing a bounding box around each template minutia, which specifies all the possible positions of the corresponding input minutia with respect to the template minutia, and restricting the corresponding minutia in the input image to be within this box [7]. This method does not provide a satisfactory performance in practice, because local deformations may be small while the accumulated global deformations can be quite large.

## 10. Match Probability

The total number of minutia in a sample image can be used to equate a match factor.  The similarity equation is as follows

$$M = \sqrt{((N_m * N_m)/(N_1 * N_2))} \qquad (2)$$

where $N_1$ and $N_2$ are the number of bifurcations in fingerprint 1 and 2 respectively. Nm is the maximum number of matches acquired when the print was compared to all prints in the database set.

A match will have similarity M greater than 0.9 while non-matching pairs will have a similarity measure less than 0.3.

## 11. Approaches may be taken to improve the accuracy

1. Count the number of ridges between each point

-This would be the first task undertaken if this thesis were to continue. It would provide many more constrains with which to limit the amount of false matches.

By implementing this extra small step a security system will be possible.

2. Use another method to align fingerprint images

- A direct match search (same minutia in same coordinates) could be applied to compare images. The centre feature (whirl, loop ect.) of the fingerprint can be found (possibly using the Dominant Ridge Direction) to align the image.

3. Sort fingerprints into classes (whirls, loops ect) then only search through the sample fingerprints category

- This will increase processing time and reduce the probability of a false match.

4. Obtain multiple samples.

- Obtaining multiple samples means the sample print can be judged by the number of picture matches, as well as the number of pixel matches.

5. Reduce search area

-One possible way of reducing the search area is to only look to the left, right, above or below the minutia under analysis. Theoretically it should reduce the amount of false matches (reduction in acceptance area)

## 12. Discussion and conclusion

Recent interest in automatic fingerprint classification system has inspired many groups to conduct researches in this area. All fingerprint images in database need to classify according to the pre-defined classification criteria. This is great importance in order to overcome the accuracy and the identification speed problems. A number of approaches have been applied for about several years that differ in the features used to describe the important of classifying fingerprint image. However, a potential ways to improve the algorithms especially on pre-processing steps still needed to studied.

Different soft computing approaches can be applied for calculating minutiae. By introducing soft computing tools we can add intelligence to the recognition system, so that the system can tell the likelihood of the particular image to be on a particular database and other intelligent features can be introduced.

There have been many algorithms developed for extraction of minutia. Most algorithms found in the literature are somewhat difficult to implement and use a rather heuristic approach.

The reliability of any automatic fingerprint recognition system strongly relies on the precision obtained in the extraction process. Extraction of appropriate features is one of the most important tasks for a recognition system.

## REFERENCES


[1] N. Ansari, M.H. Chen, and E.S.H. Hou, “A Genetic Algorithm for Point Pattern Matching,” Chapt. 13, B. Soucek and the IRIS Group, eds., *Dynamic, Genetic, and Chaotic Programming.* New York: John Wiley & Sons, 1992.

[2] G. Stockman, S. Kopstein, and S. Benett, “Matching Images to Models for Registration and Object Detection via Clustering,” *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 4, no. 3, pp. 229-241, 1982.

[3] J. Ton and A.K. Jain, “Registering Landsat Images by Point Matching,” *IEEE Trans. Geoscience and Remote Sensing,* vol. 27, no. 5, pp. 642-651, 1989.

[4] J.P.P. Starink and E. Backer, “Finding Point Correspondence Using Simulated Annealing,” *Pattern Recognition,* vol. 28, no. 2, pp. 231-240, 1995.

[5] D.P. Huttenlocher and S. Ullman, “Object Recognition Using Alignment,” *Proc. First Int’l Conf. Computer Vision,* pp. 102-111, London, 1987.

[6] A. Ranade and A Rosenfeld, “Point Pattern Matching by Relaxation,” *Pattern Recognition*, vol. 12, no. 2, pp. 269-275, 1993.

[7] N. Ratha, S. Chen, and A.K. Jain, “Adaptive Flow Orientation Based Feature Extraction in Fingerprint Images,” *Pattern Recognition*, vol. 28, no. 11, pp. 1,657-1,672, 1995.

[8] K. Karu and A.K. Jain, “Fingerprint Registration,” Research Report, Michigan State Univ., Dept. of Computer Science, 1995.

[9] A. Almansa and L. Cohen, “Fingerprint image matching by minimization of a thin-plate energy using a two-step algorithm with auxiliary variables,” in *Proc. IEEE 5thWorkshop Applications Computer Vision*, Dec. 2000, pp. 35– 40.

[10] S. Gold and A. Rangarajan, “A graduated assignment algorithm for graph matching,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 18, no. 4, pp. 377–388, Apr. 1996.

[11] D. K. Isenor and S. G. Zaky, “Fingerprint identification using graph matching,” *Pattern Recognit.*, vol. 19, no. 2, pp. 113–122, 1986.

[12] A. K. Jain, L. Hong, and R. Bolle, “On-line fingerprint verification,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 19, no. 4, pp. 302–314, Apr. 1997.

[13] A. K. Jain, L. Hong, S. Pankanti, and R. Bolle, “An identity authentication system using fingerprints,” *Proc. IEEE*, vol. 85, no. 9, pp. 1365–1388, Sep. 1997.

[14] X. Jiang andW. Yau, “Fingerprint minutiae matching based on the local and global structures,” in *Proc. 15th Int. Conf. Pattern Recognition*, vol. 2, Barcelona, Spain, Sep. 2000, pp. 1042–1045.

[15] J. P. P. Starink and E. Backer, “Finding point correspondence using simulated annealing,” *Pattern Recognit.*, vol. 28, no. 2, pp. 231–240, 1995.