Fingerprint Recognition

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Fingerprint

- A fingerprint is the reproduction of the exterior appearance of the fingertip epidermis.
- There are two types of skin on the human body:
  - smooth skin and
  - friction ridge skin.
- The friction ridge skin is observed to have a pattern of ridges interspersed with valleys.
- The pattern of friction ridges on each finger is unique and immutable, enabling its use as a mark of identity.
- Even identical twins can be differentiated based on their fingerprints.
- Superficial injuries such as cuts and bruises on the finger surface alter the pattern in the damaged region only temporarily.

Applications of Fingerprint

- The use of fingerprints as a biometric identifier
  - the oldest mode of automated person identification and
  - the most widely deployed biometric identifier.
- Because of the distinctiveness and permanence properties, fingerprints have been successfully employed in law enforcement applications.
- Another important application of fingerprints in law enforcement is to establish the identity of a suspect based on partial fingerprints left at a crime scene. These are called latent prints, i.e., poor image quality prints.

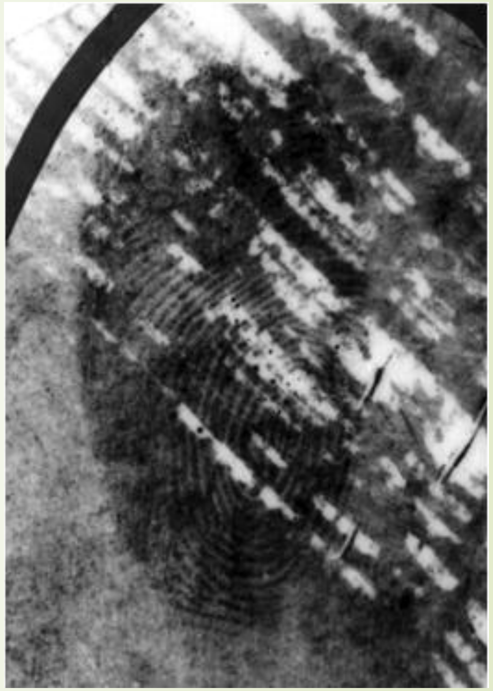
Why fingerprint impressions are recorded?

- to identify repeat offenders who often use an alias to hide their identity and
- to perform background checks for employment or licensing.

Fingerprint Impressions

Rolled Fingerprint

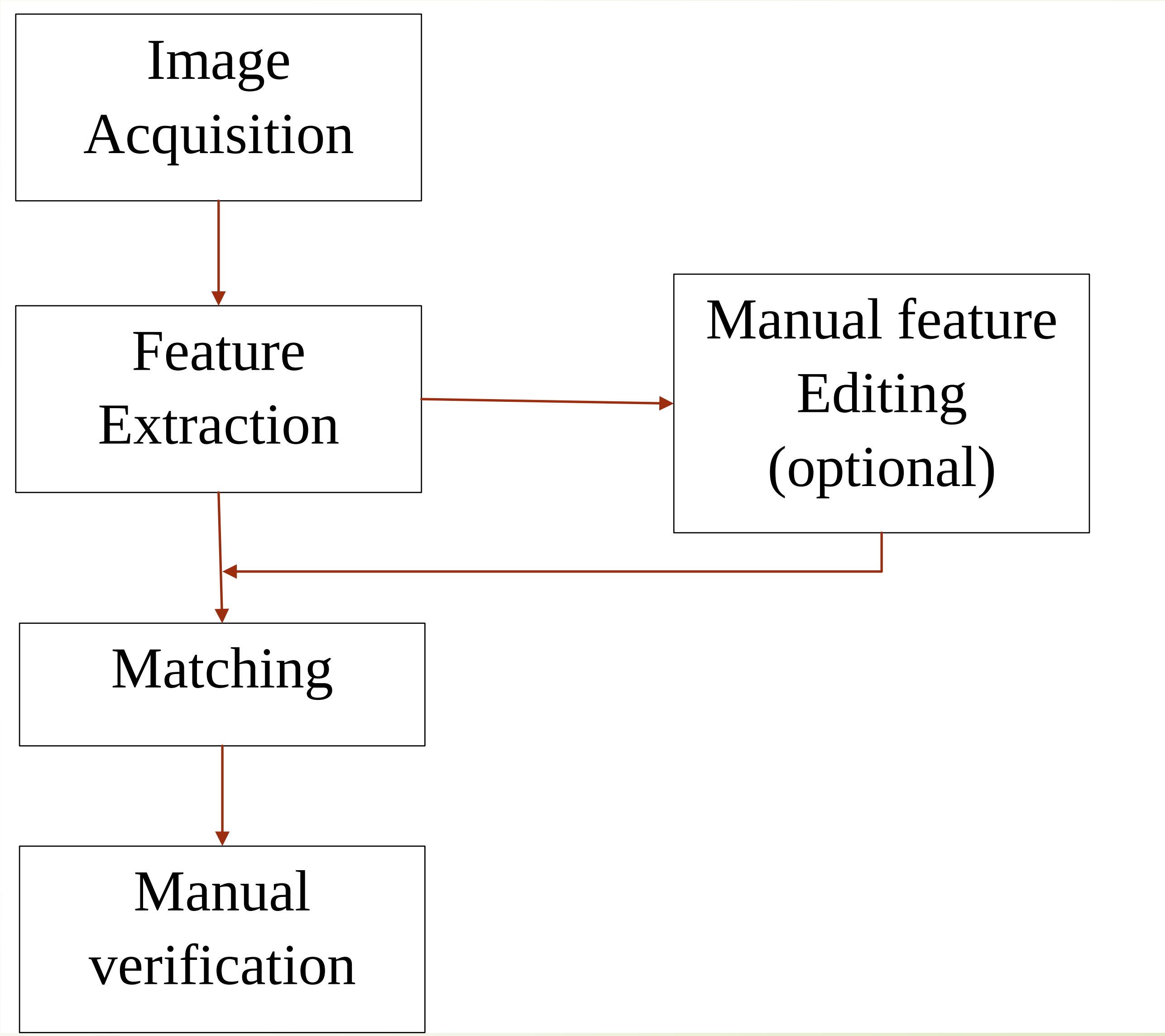
Plain fingerprint



Latent fingerprint

Automated Fingerprint Identification Systems (AFIS)

- Developed by NEC to improve the efficiency and accuracy of fingerprint matching.
- The AFIS was originally used by the U.S. Federal Bureau of Investigation (FBI) in criminal cases.
- It has gained favor for general identification and fraud prevention.



Fingerprint Features

- Feature should have the following desirable properties:
  - Retain the discriminating power (uniqueness) of each fingerprint at several levels of resolution (detail).
  - Easily computable.
  - Amenable to matching algorithms.
  - Stable and invariant to noise and distortions.
  - Efficient and compact representation.

Feature Extraction

- The raw biometric data is required to be pre-processed before features are extracted from it.
- Commonly used pre-processing steps
  - quality assessment,
  - Segmentation

    to separate the required biometric data from the background noise
  - Enhancement

    to clarify image's edge and also known as an edge sharpening

    enhancement algorithms like smoothing or histogram equalization may be applied

    to minimize the noise introduced by the camera or illumination variations.

Fingerprints scanned using different sensors

Using 1000 ppi fingerprint sensor

500 ppi sensor

Fingerprint – Pre-processing

- Segmentation
- Normalization
- Enhancement
- Binarization
- Thinning

Segmentation

- Process of separating the foreground regions in the image from the background regions
- Foreground regions

  The clear fingerprint area containing the ridges and valleys, which is the area of interest.

  It exhibits high grey-scale variance value.
- Background region

  the regions outside the borders of the fingerprint area, which do not contain any valid fingerprint information.

  It exhibits a very low variance

Segmentation: Process

- Divide the image into blocks ($W \times W$).
- Calculate the grey-scale variance for each block in the image.
- If the variance is less than the global threshold, then the block is assigned to be a background region;
- otherwise, it is assigned to be part of the foreground.

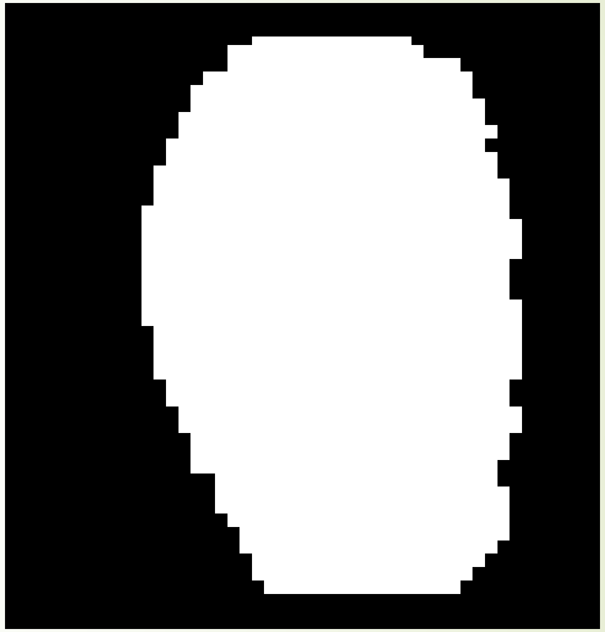
Grey-level variance for a block of size $W \times W$ is defined as:

$$V(k) = \frac{1}{W^2} \sum_{i=0}^{W-1} \sum_{j=0}^{W-1} (I(i,j) - M(k))^2$$

where $V(k)$ is the variance for block k, $I(i, j)$ is the grey-level value at pixel (i, j), and $M(k)$ is the mean grey-level value for the block k.

Segmentation

Input Image



Segmentation Boundary

Normalization

- To standardize the intensity values in an image by adjusting the range of grey-level values so that it lies within a desired range of values.
- Let $I(i, j)$ represent the grey-level intensity value at pixel (i, j), and $N(i, j)$ represent the normalized grey-level value at pixel (i, j).

$$N(i,j) = \begin{cases} M_0 + \sqrt{\dfrac{V_0(I(i,j) - M)^2}{V}} & \text{if } I(i,j) > M \\ M_0 - \sqrt{\dfrac{V_0(I(i,j) - M)^2}{V}} & \text{otherwise} \end{cases}$$

where M and V are the estimated mean and variance of the image I respectively, and M_0 and V_0 are the desired mean and variance values, respectively.

Mean & variance of image

- Fingerprint image I is $N \times N$ matrix.
- Mean of the grey-level fingerprint image is

$$M = \frac{1}{N^2} \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} I(i,j)$$

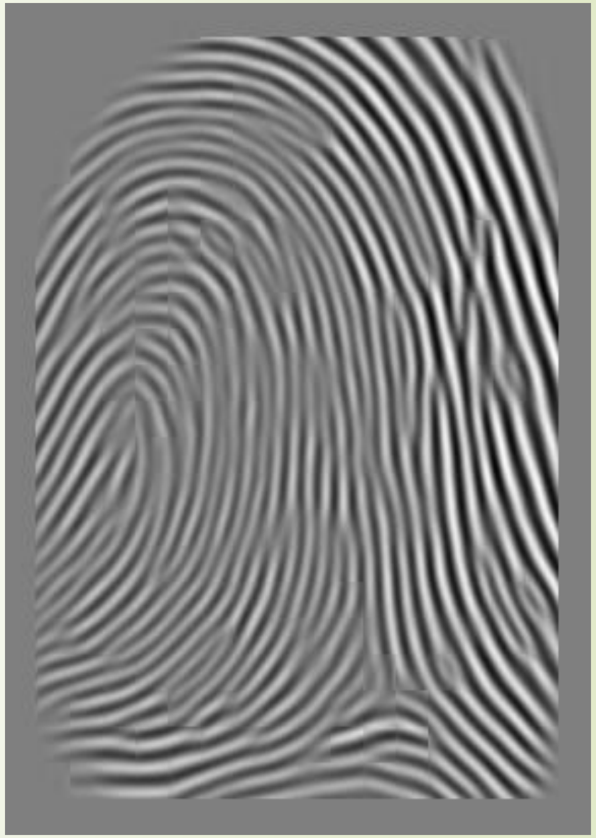
- Variance of the image I is

$$V = \frac{1}{N^2} \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (I(i,j) - M)^2$$

Enhancement

- To connect broken ridges and separate joined ridges.
- This requires filtering the image with the real part of a 2D complex Gabor filter whose orientation and frequency are tuned to the local ridge orientation and frequency.

Fingerprint



Enhanced image

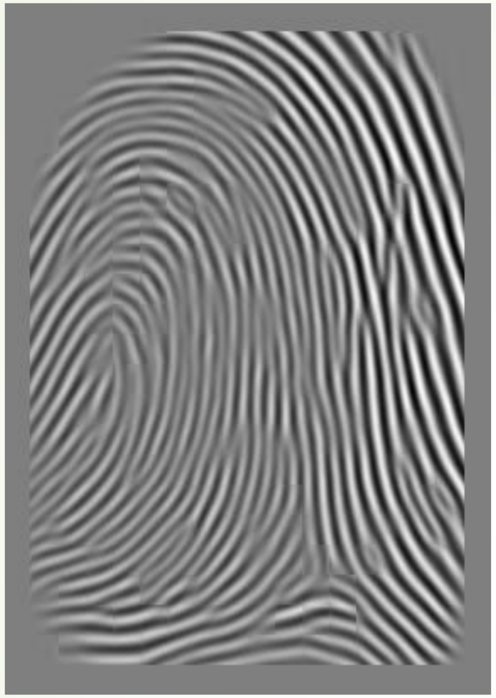
Binarization

- Fingerprint binarization is the process of converting an 8-bit gray-scale fingerprint image into a 1-bit ridge image.
- Otsu's thresholding method can be used
- Otsu's thresholding is based on the linear discriminant criteria.
- It finds the threshold that minimizes the weighted within class variance and maximizing the between class variance

Fingerprint Ridge Thinning

- Thinning is the process of reducing the thickness of each line of patterns to just a single pixel width
- The requirements of a good thinning algorithm with respect to a fingerprint are
  - The thinned fingerprint image obtained should be of single pixel width with no discontinuities.
  - Each ridge should be thinned to its centre pixel.
  - Noise and singular pixels should be eliminated.
  - No further removal of pixels should be possible after completion of thinning process.

Fingerprint image



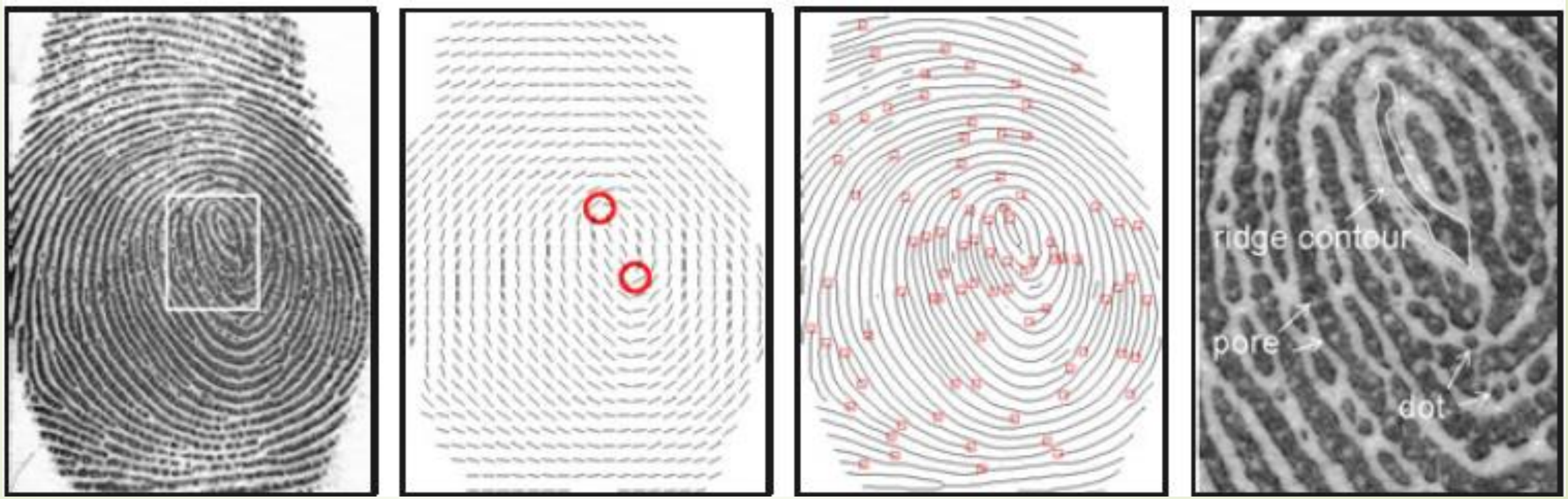
Enhanced image

Binarized image

Thinned ridge image

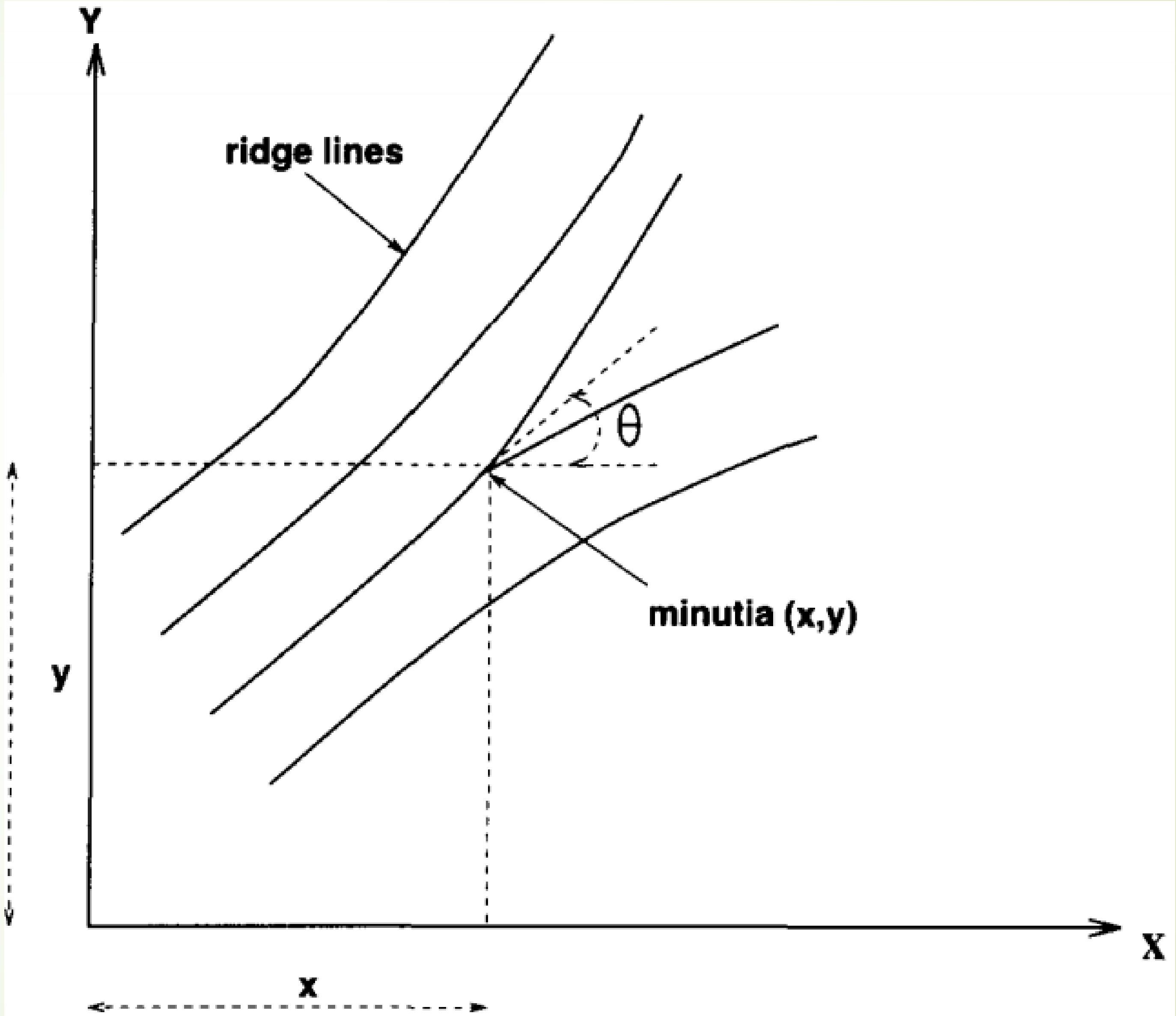
Fingerprint Features

- Level 1: Ridge orientation field
- Level 2: Minutiae
- Level 3: Inner holes (sweat pores) and outer contours (edges) of the ridges

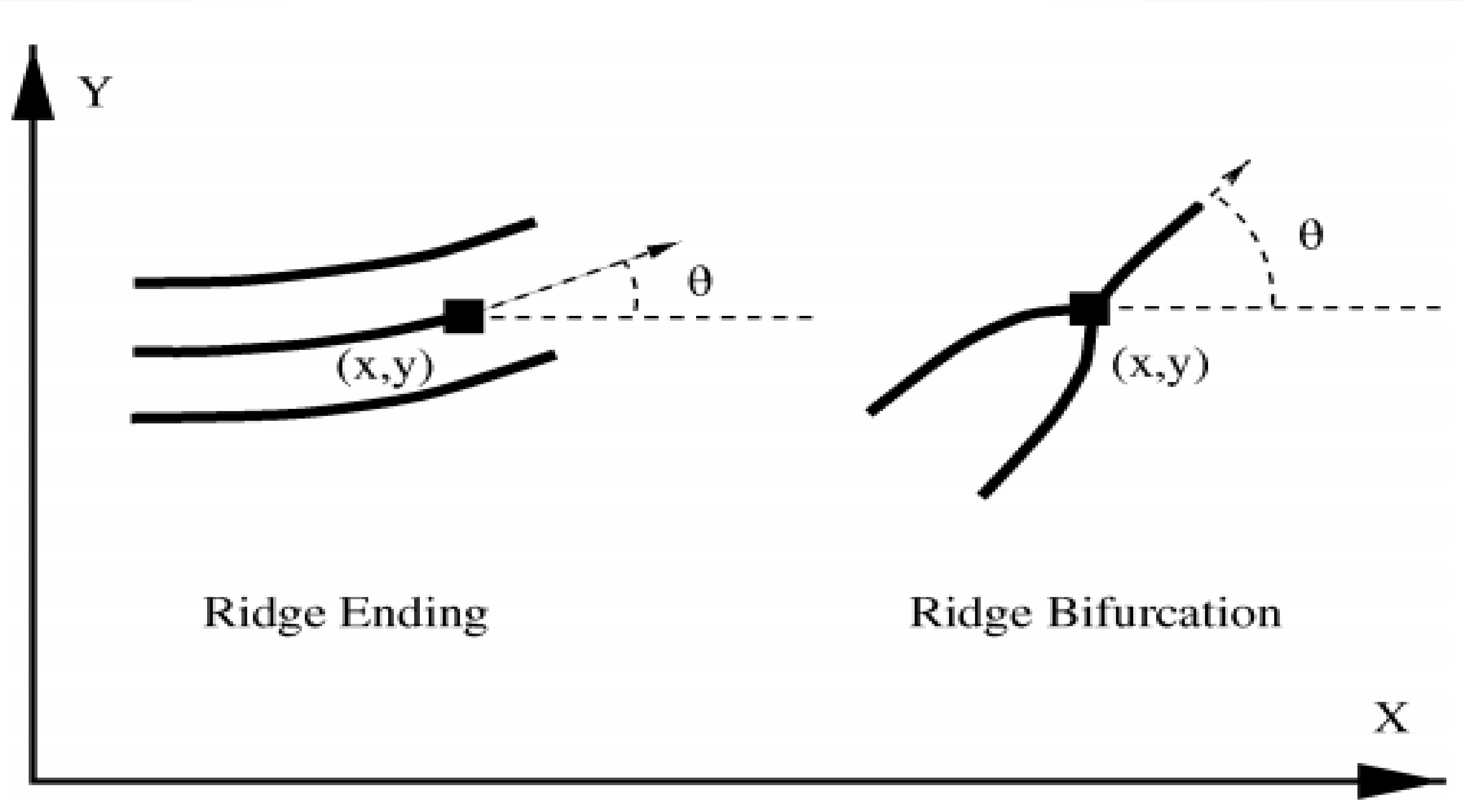


Ridge Orientation Field

- The local ridge orientation at a pixel (x, y) represents the tangential direction of ridge lines passing through (x, y).
- The ridge orientation is a unit-length vector whose direction lies between 0 and π.



Ridge Orientation

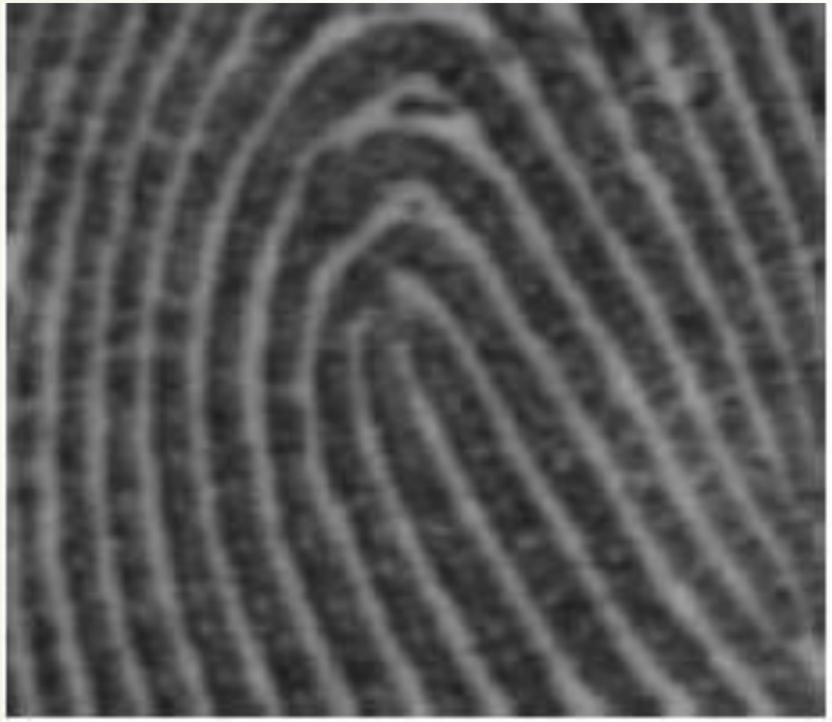


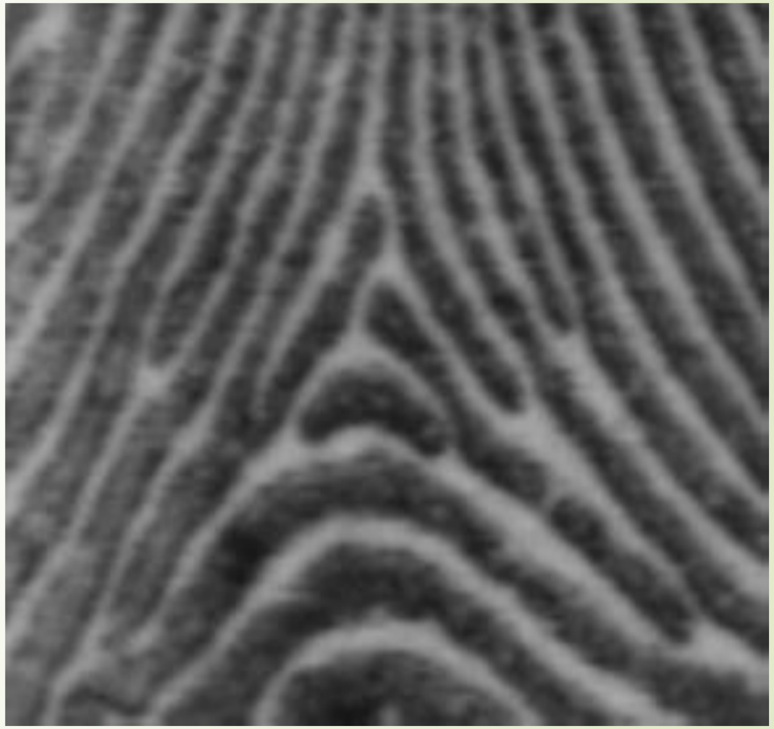
Ridge Singular Points

- A ridge orientation map typically contains some salient locations where the ridge orientations change abruptly - such locations are termed as singular points.
- There are two basic types of singular points, visually distinctive
  - Loop, also called core: the northmost point of maximum ridge curvature

    Loop in a fingerprint can be used as a landmark point to align the fingerprint.
  - Delta (triangle type)

Singular points: Loop and Delta





Finding fingerprint Orientation Fields- gradient based method

- A fingerprint field orientation map is represented in the form of a matrix $\{\theta_{xy}\}$, θ is the orientation direction of ridge flows at (x, y).
- The gradient vectors $[G_x, G_y]^T$, where G_x and G_y are the partial derivatives of image intensity at (x, y) in cartesian coordinates.
- The gradient vectors point to the highest variation of gray intensity which is perpendicular to the edge of ridge lines.
- The gradient phase angle φ denotes the direction of the maximum intensity change. Therefore, the orientation direction θ is orthogonal to the dominant gradient phase angle φ.
- Orientation direction$\{\theta_{xy}\}$ at point (x, y) of image I, lies in $[0, \pi]$.

Finding fingerprint Orientation Fields

- $G_x = G\cos\varphi$ and $G_y = G\sin\varphi$
- Problem: Averaging gradients

  A ridge line has two edges, the gradient vectors at both sides of a ridge are opposite to each other. Therefore, If the average of gradient angles is zero.

- Kass and Witkin proposes an idea of doubling the gradient angles before finding the average gradient angle.
- In practice, 2φ are the angles of squared gradient vectors $[G_{sx}, G_{sy}]^T$

  $G_{sx} = G^2(\cos 2\varphi) = G_x^{\,2} - G_y^{\,2}$ and $G_{sy} = G^2(\sin 2\varphi) = 2\,G_x\,G_y$

2φ the angles of squared gradient vectors $[G_{sx}, G_{sy}]^T$?

- Doubling the angle and squaring the length of a vector is squaring a complex number

$$
\begin{aligned}
(G_{sx} + i\,G_{sy}) &= (G_x + i\,G_y)^2 \\
&= G_x^{\,2} - G_y^{\,2} + i\,(2G_x\,G_y) \\
&= G^2\,(\cos 2\varphi) + i\,G^2\,(\sin 2\varphi)
\end{aligned}
$$

$$\begin{bmatrix} G_{sx} \\ G_{sy} \end{bmatrix} = \begin{bmatrix} G_x^2 - G_y^2 \\ 2G_xG_y \end{bmatrix}$$

- The average squared gradient $\left[\bar{G}_{sx}, \bar{G}_{sy}\right]$ in a window W is

$$\begin{bmatrix} \bar{G}_{sx} \\ \bar{G}_{sy} \end{bmatrix} = \begin{bmatrix} \sum_W G_{sx} \\ \sum_W G_{sy} \end{bmatrix} = \begin{bmatrix} \sum_W (G_x^2 - G_y^2) \\ \sum_W 2G_xG_y \end{bmatrix} = \begin{bmatrix} G_{xx} - G_{yy} \\ 2G_{xy} \end{bmatrix}$$

Where $G_{xx} = \sum_W G_x^2, \quad G_{yy} = \sum_w G_y^2, \quad G_{xy} = \sum_W G_xG_y$

These are the average variance and covariance of G_x and G_y over the window W.

$2\bar{\varphi} = tan^{-1}\left(\frac{2G_{xy}}{G_{xx} - G_{yy}}\right)$, $2\varphi \in [-\pi, \pi)$ which corresponds to the squared gradients.

$$\bar{\varphi} = \frac{1}{2} tan^{-1}\left(\frac{2G_{xy}}{G_{xx} - G_{yy}}\right)$$

- The average ridge-valley direction θ, with $-\frac{\pi}{2} < \theta < \frac{\pi}{2}$, is perpendicular to φ.

$$\theta = \begin{cases} \varphi + \frac{\pi}{2} & for\ \varphi \leq 0 \\ \varphi - \frac{\pi}{2} & for\ \varphi > 0 \end{cases}$$

- If the input fingerprint image is divided into equal-sized blocks of $N \times N$ pixels. The direction of orientation field $\theta_B \epsilon [0, \pi)$ in a block B is

$$\theta_B = \frac{1}{2} tan^{-1}\left(\frac{\sum_{i=1}^{N}\sum_{j=1}^{N} 2G_x(i,j)G_y(i,j)}{\sum_{i=1}^{N}\sum_{j=1}^{N}\left(G_x^2\ (i,j) - G_y^2(i,j)\right)}\right) + \frac{\pi}{2}$$

Algorithm: Estimation of Orientation

- Divide the input fingerprint image into blocks of size $N \times N$.
- Compute the gradients G_x and G_y at each pixel in each block.
- Estimate the local orientation of each block using the formula:

$$\theta_B = \frac{1}{2} tan^{-1}\left(\frac{\sum_{i=1}^{N}\sum_{j=1}^{N} 2G_x(i,j)G_y(i,j)}{\sum_{i=1}^{N}\sum_{j=1}^{N}\left(G_x^2\,(i,j) - G_y^2(i,j)\right)}\right) + \frac{\pi}{2}$$

Reliability of estimation for orientation angle

- The coherence of the squared gradients can be expressed as

$$Coh_B = \frac{\left|\sum_W G_{sx}, G_{sy}\right|}{\sum_W \left|G_{sx}, G_{sy}\right|} = \frac{\left|\sum_{i=1}^{N} \sum_{j=1}^{N} G_{sx}(i,j) G_{sy}(i,j)\right|}{\sum_{i=1}^{N} \sum_{j=1}^{N} \left|G_{sx}(i,j) G_{sy}(i,j)\right|}$$

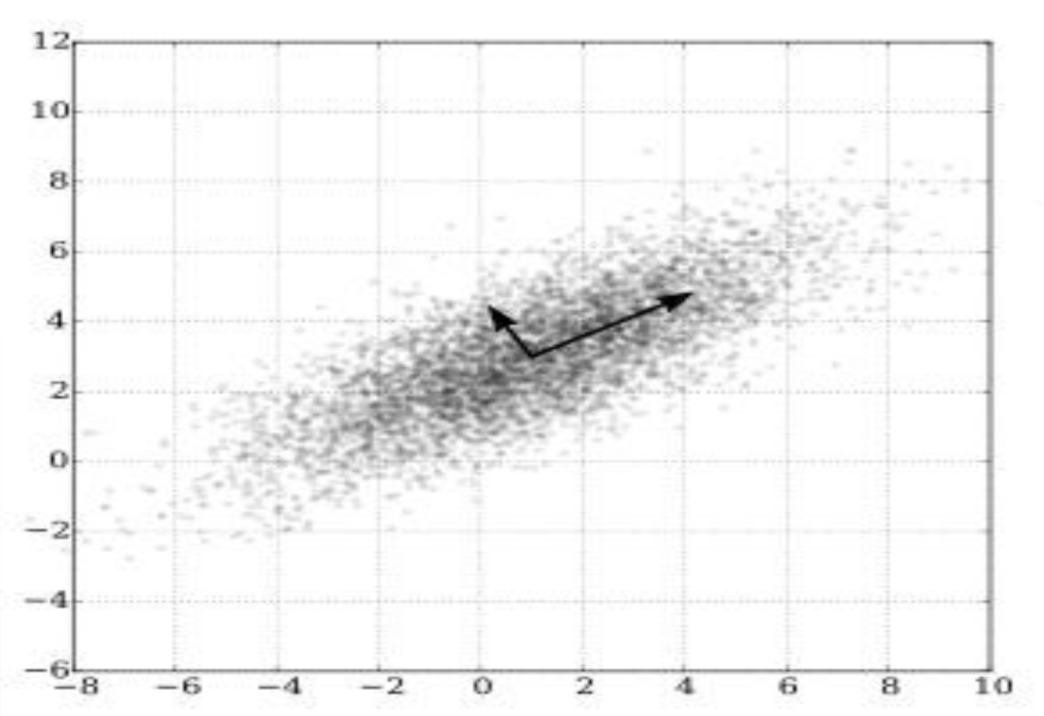
- Coherence of any block *B* lies in [0, 1].
- If all squared gradient vectors are pointing in the same direction, then coherence is 1.
- If the squared gradient vectors are equally distributed in all directions, then coherence is 0.
- Coherence estimates the strength of the average gradient.

Coherence of Gradient

- It indicates strength of the averaged gradients
- The coherence value is low at the high curvature regions, the core points are mainly high curvature regions hence this property is very useful to find the location of core point

Principal Component Analysis (PCA)

- Discrete version of Karhunen-Loeve Transform (KLT)
- Goal: to identify the most meaningful basis to re-express a data set.



Change of Basis

- Let X be matrix of original k-dim data points.

  X is a $k \times n$ matrix.

  P is a $k \times m$ matrix that transforms X into Y. $m \leq k$
- Y: $m \times n$ matrix is a new representation of that data set i.e. $Y = P^T X$
- Geometrically, P is a rotation and a stretch which transforms X into Y.

Principal Component Analysis

- An eigenvalue of covariance matrix is a number, tells how much variance there is in the data in the direction of eigenvector of the eigenvalue.
- The eigenvector with the highest eigenvalue is therefore the principal component.

Finding fingerprint Orientation Fields based on Principal Component Analysis

- PCA computes a new orthogonal base given a multidimensional data set s.t. the variance of the projection on one of the axes of this new base is maximal, while the projection on the other one is minimal.
- The base is formed by the eigenvectors of the autocorrelation matrix of the data set.
- Find the variance covariance matrix C of the gradient vector pairs

$$C = \begin{bmatrix} G_{xx} & G_{xy} \\ G_{xy} & G_{yy} \end{bmatrix} = \sum_{W} \begin{bmatrix} G_x^2 & G_x G_y \\ G_x G_y & G_y^2 \end{bmatrix}$$

Finding fingerprint Orientation Fields based on Principal Component Analysis

- In this estimate, the assumption is made that the gradient vectors are zero-mean, in a window w in the given fingerprint. i.e.,

$$E[G_x] = E[G_y] = 0$$

- The longest axis v_1 is given by the eigenvector of the variance covariance matrix that belongs to the largest eigenvalue say λ_1.
- This axis corresponds to the direction in which the variance of the gradients is largest, and so to the "average" gradient orientation.

Finding fingerprint Orientation Fields based on Principal Component Analysis

- The ridge-valley orientations are perpendicular to this axis therefore, it is the shortest axis v_2.
- Vector v_2 is the direction of the eigenvector that belongs to the smallest eigenvalue λ_2.
- The average ridge valley orientation θ is $\angle v_2$.
- The strength of the orientation can be defined

$$S = \frac{\lambda_1 - \lambda_2}{\lambda_1 + \lambda_2}$$

Strength of the orientation

- The strength of the orientation

$$S = \frac{\lambda_1 - \lambda_2}{\lambda_1 + \lambda_2}$$

- If all gradients are pointing in the same direction,

  then $\lambda_2 = 0$ & $S = 1$.
- If the gradients follow uniform distribution over all angles,

  then $\lambda_1 = \lambda_2$ and $S = 0$.

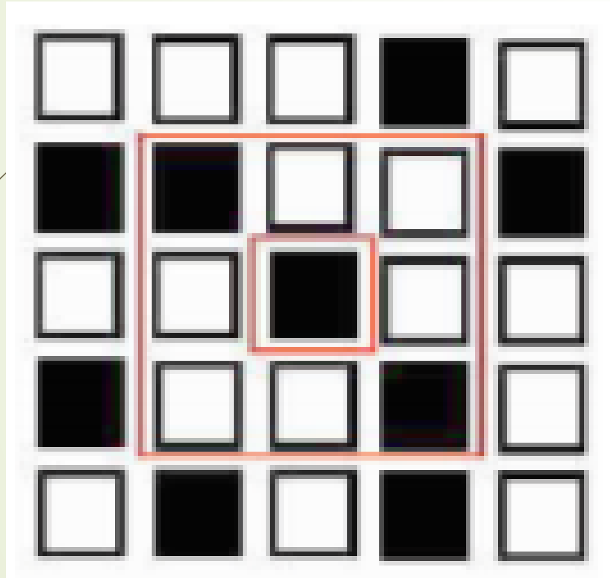
Minutiae Extraction

- The minutiae are extracted by scanning the local neighborhood of each ridge pixel P in the image using a 3×3 window.

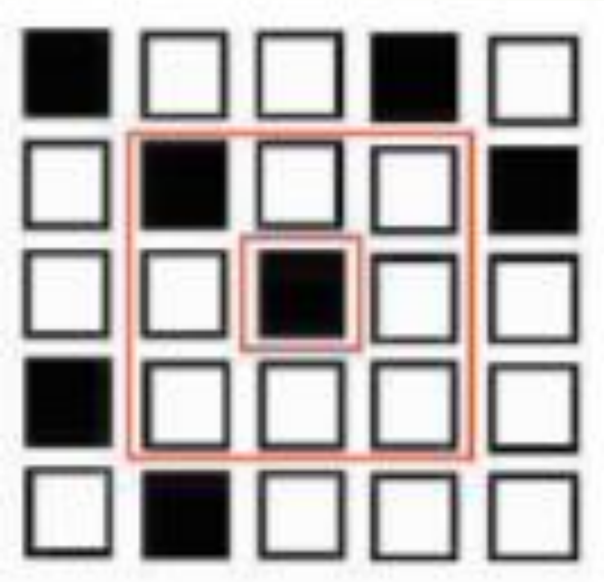
P_4	P_3	P_2
P_5	P	P_1
P_6	P_7	P_8

- Pixel P is classified as
  - a ridge ending if it has only one neighbouring ridge pixel in the window.
  - a bifurcation if it has three neighbouring ridge pixels in the window.

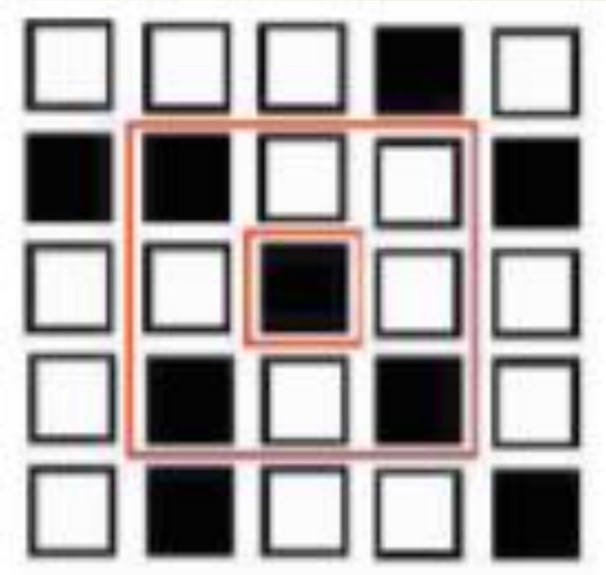
Minutiae Extraction



Normal Ridge Pixel



Ridge Termination



Ridge Bifurcation

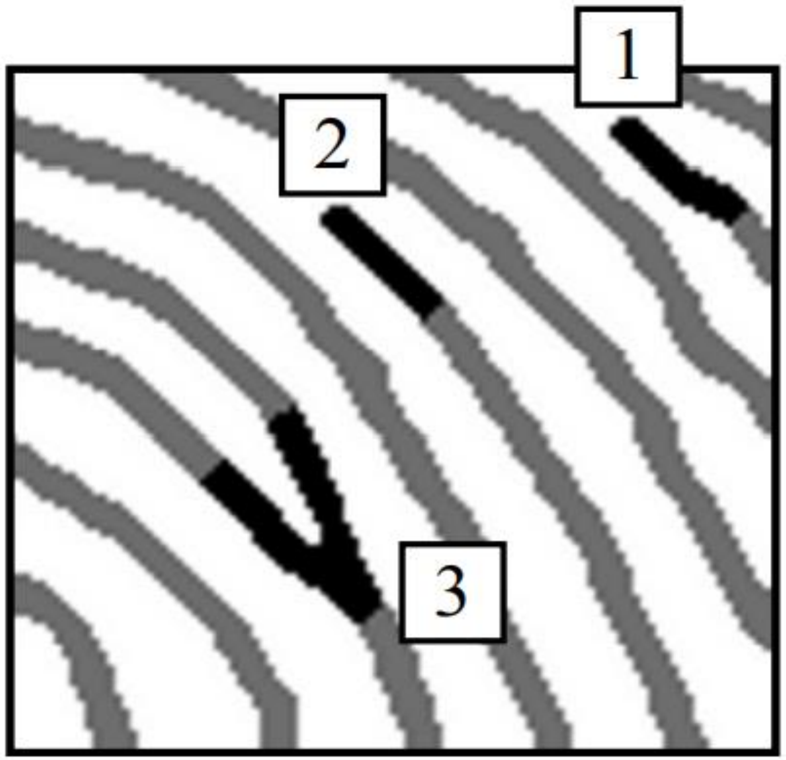
False Minutia Removal: Algorithm

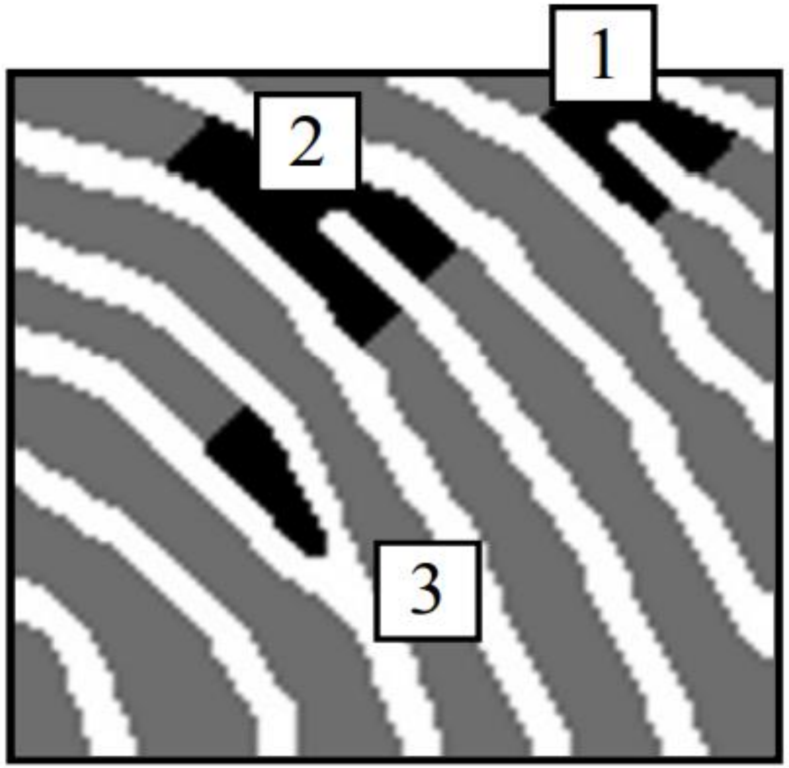
- If several minutiae form a cluster in a small region, then remove all of them except for the one nearest to the cluster center
- All the minutiae points near the border and within a certain fixed distance from it are removed.
- If two ridge ending minutiae are located close enough, facing each other, but no ridges lie between them, then remove both of them.
- If the distance from the ridge ending to the ridge bifurcation is less than certain fixed distance then remove both of them.

Matching

- Given the query minutiae set $\{x_i^Q, y_i^Q,\ \theta_i^Q\}_{i=1}^M$ and template minutiae set $\{x_i^T, y_i^T,\ \theta_i^T\}_{i=1}^N$.
- Steps
  - Alignment
    - Geometrically aligning both the minutiae sets
  - Forming pairs of corresponding minutiae
  - Computing match score

Ridge-ending/bifurcation duality





Binary image its negative image

Alignment

- Requirement: Spatial transformation model
- In a spatial transformation each point (x, y) of image A is mapped to a point (u, v) in a new coordinate system.

$$u = f_1(x, y)$$

$$v = f_2(x, y)$$

- Generalized Hough transformation can be used for estimating the spatial transformation between the two sets.
- For fingerprint alignment the transformation parameters $\Delta\theta, \Delta x, \Delta y$

Generalized Hough Transform: Algorithm

Input : Two minutiae sets $\{x_i^Q, y_i^Q,\ \theta_i^Q\}_{i=1}^{M}$ and $\{x_i^T, y_i^T,\ \theta_i^T\}_{i=1}^{N}$.

Initialize accumulator array A to 0

for i = 1 to M

for j = 1 to N

$\Delta\theta = \theta_i^T - \theta_j^Q$

$\Delta x = x_i^T - x_j^Q \cos\Delta\theta - y_j^Q \sin\Delta\theta$

$\Delta y = y_i^T + x_j^Q \sin\Delta\theta - y_j^Q \cos\Delta\theta$

$A(\Delta\theta, \Delta x, \Delta y) = A(\Delta\theta, \Delta x, \Delta y) + 1$

return location of peak in A

Pairing of corresponding minutiae

Input : Two minutiae sets $\{x_i^Q, y_i^Q,\ \theta_i^Q\}_{i=1}^M$, $\{x_i^T, y_i^T,\ \theta_i^T\}_{i=1}^N$ and transformation parameters $\Delta\theta, \Delta x, \Delta y$

Initialize Set flag arrays f^T and f^Q as 0. count = 0, list as empty

for i = 1 to M

for j = 1 to N

if ($f^T(i) = 0$ & $f^Q(j) = 0$ & $d(i, j) = 0$ & $rot(i, j) = 0$)

f^T (i) = 1, $f^Q(j) = 1$

count = count + 1

list(count) = $\{i, j\}$

return list

- Here $d(i, j)$ is distance between minutiae i and minutiae j
- $rot(i, j)$ is rotation between minutiae i and minutiae j.

Computing match score

- The number of paired minutiae in the fingerprint
- The number of paired minutiae in overlapped area
  - For genuine match the percentage of paired/matched minutiae is greater than threshold
  - For imposter match the percentage of paired minutiae is less than threshold