

ABSTRACT

FINGERPRINT IDENTIFICATION BY IMPROVED METHOD OF MINUTIAE MATCHING

by Tuo Li

In this study, a new fingerprint identification method based on improved matching algorithm and dual-image template is proposed. While the algorithm is tested with the FVC2002 fingerprint database, which has a large number of fingerprint images with various image sizes, scanned areas of fingers, and different extents of blur and shade, the proposed algorithm demonstrates superior performance compared with a conventional fingerprint matching algorithm. By taking advantage of dual-image template, the proposed matching algorithm also relaxes the requirement on fingerprint image quality for fingerprint matching.

FINGERPRINT IDENTIFICATION BY IMPROVED METHOD OF MINUTIAE
MATCHING

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Chapter I

Introduction

Fingerprint is arguably the most popular biometric information and it is used in different applications requiring identity verification such as entry access control, computer access control, cash withdrawing, etc. The performance of the fingerprint identification system depends on the accuracy of the fingerprint matching algorithm. Matching wrong fingerprints can compromise the security of a system, and failing to match matched fingerprints can cause unnecessary inconvenience.

As a common representative of a citizen's identity, fingerprints' advantages are in the following three aspects: invariance, uniqueness, and accessibility [1]. First, the fingerprint of a person does not change over time. Even if a severe scar or burn happens to a fingertip, in most of the cases, the regenerated fingerprint pattern will maintain the same appearance as one of the old fingerprint. Second, the forming of fingerprint is tightly related to a person's gene. It is virtually impossible that two persons' DNAs have the same permutation and combination of their codons; similarly, it is extremely unlikely, if not impossible, that two persons have identical fingerprints. Third, compared with other biometrics such as DNA and iris image, fingerprint is easier to collect.

In a conventional fingerprint matching system, an individual finger is typically enrolled in a database and the fingerprint matching is conducted between two images: one is the fingerprint enrolled from the database and the other one is the fingerprint to be identified. When image quality is low, the system accuracy sacrifices. The similarity between two fingerprints can be determined based on the numbers of matching fingerprint features known as minutiae between these two images and the result is usually quantified as the similarity score [2].

In this study, we expand the conventional approach by storing two fingerprints from the same finger, referred to the identification template, in the database. The weighted averages of similarity scores between two template images and one image to be identified are calculated according to the information of minutiae on the fingerprint pattern as a new similarity score. In this procedure, the improved matching algorithm is implemented to

further improve the performance of the fingerprint identification. Compared with the conventional fingerprint identification method, the proposed method has a better performance by relaxing the requirement of image quality and increasing the matching accuracy.

Chapter II

Fingerprint

2.1 Fingerprint Identification

Biometrics authentication is a technique of identification, surveillance and access control based on human characteristics. It is widely applied to ensure privacy, maintain security and identify individuals in different places such as airports and hospitals where the security and identification system is required [1].

There are two factors used to assess the performance of biometrics authentication, accuracy and reliability. Among methods of biometrics authentication including fingerprint verification, iris recognition, palm geometry and face recognition, fingerprint identification is a method with the advantage in simplicity and adequate level of accuracy and reliability with the longest implementation history.

The fingerprint identification procedure starts with converting an analog image to a digital image for further processing. Extracting valuable information from the acquired fingerprint image is the main task of the fingerprint identification. At the beginning, recognizing a fingerprint is a time-consuming task done by fingerprint experts. In the late 19th century, the scientific basis for fingerprint identification was established for the first time, and the fingerprint identification was widely used for confirming the appearance of a suspect or victim in a crime scene, or identifying a criminal whose fingerprint is registered in the police database [2].

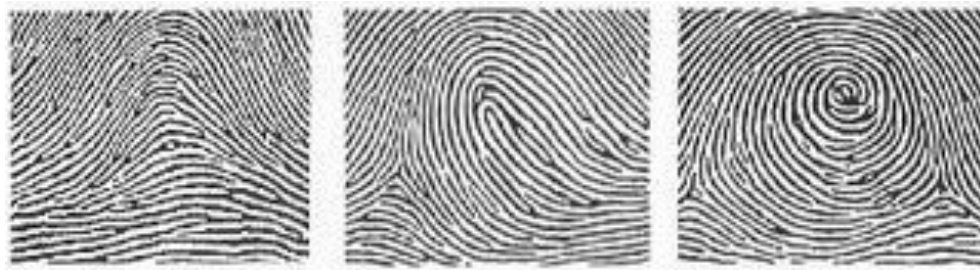
Since 1960's, information technology helped the development of the fingerprint identification technique which is still a very active research topic deserving further research and improvement [3].

2.2 Features of Fingerprint

Generally, there are two kinds of fingerprint features formed by its rugged lines: global features and minutiae [4]. The global feature is the overall characteristic of the fingerprint pattern which can be directly recognized by human eyes. Examples of global features are the arch, loop and whorl [5].

While analyzing the global feature of the fingerprint, the *pattern area*, *core point*, *delta*, and *ridge count* are four key factors used to study the fingerprint type. The *pattern area* is the volar surface where the fingerprint pattern is located and to be identified. Word *vola* derives from ancient Roman term to define the inner surface of hands and feet, which is different from other parts of the body skin [2]. The *core point* is the starting point of lines in a fingerprint. The *delta* is the first point of intersection and the *ridge count* is the number of ridges in the pattern area. After locating a core point, it is not difficult to determine the delta and ridge count in this pattern area. The common way of ridge counting is by connecting the core point and delta, and then counting how many patterns are intersected [6].

Arches, loops and whorls are contained in most fingerprint patterns and they are shown in Figure 2.2.1.



(Arch, Loop and Whorl)

Figure 2.2.1 Three basic fingerprint pattern types [7]

Loops account for about sixty percent of fingerprint patterns and they are commonly generated by asymmetric volar pads that recurve back and form loop-like shapes [2]. There are two sub-classifications of the loop pattern based on their directions, *radial loops* and *ulnar loops*. The *radial loop* points toward the thumb (radius bone); on the contrary, the *ulnar loop* is to the pinky (ulna bone) [7]. Figure 2.2.2 illustrates two different types of loops.

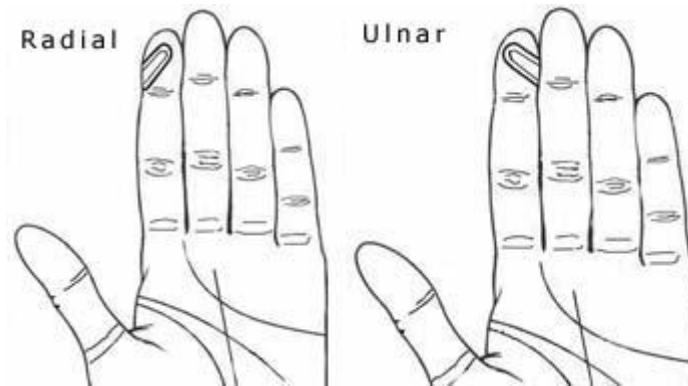


Figure 2.2.2 Radial loop and ulnar loop [8]

Whorls take approximately thirty five percent of fingerprint patterns and they are formed by higher and symmetric volar pads with gyrate appearance that looks like whirlpools. There are four different types of whorls. The *plain whorl* has the feature of concentric circle. The *central pocket whorl* contains a loop where a whorl is at the end. The *double loop* has two loops arranged in an S-shape. The *accidental whorl* is the one with unclassified and irregular shape [9]. Those four types of whorls are presented in Figure 2.2.3.

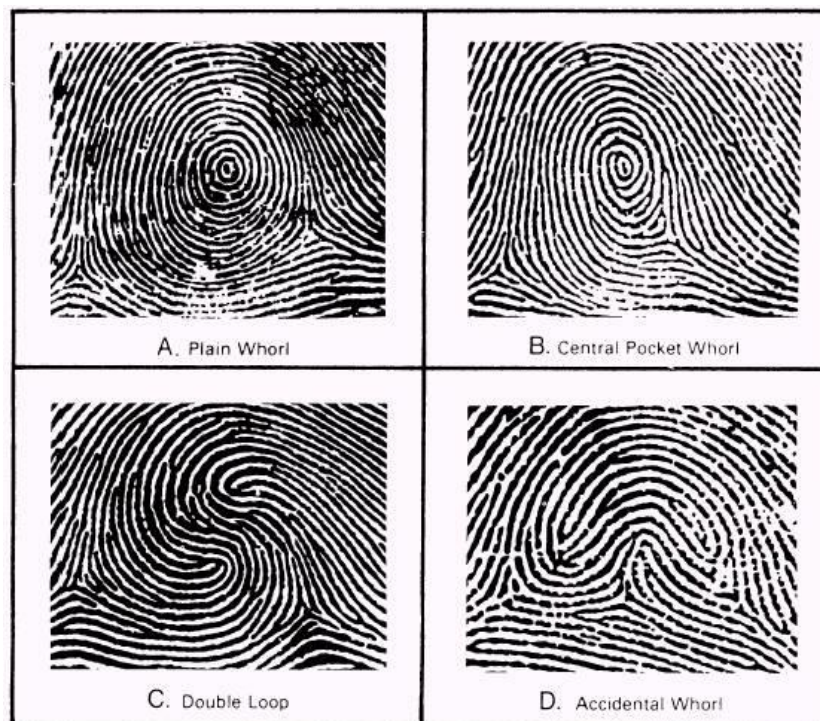


Figure 2.2.3 Different types of whorls [9]

The flatter symmetric volar pads generally produce arches which are less common compared with whorls and loops [2]. Arches take about five percent of fingerprint patterns. The *plain arch* and *tented arch* are two different types of arches. *Tented arches* have a sharper point and *plain arches* have a blunt one. Figure 2.2.4 shows the sample of plain arches and tented arches.

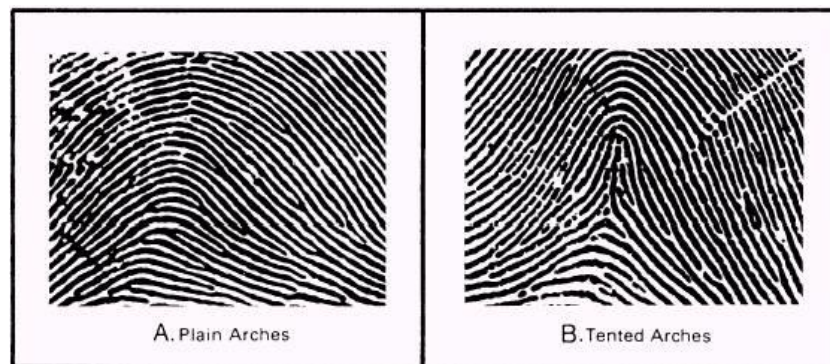


Figure 2.2.4 Plain arch and tented arch [9]

2.3 Minutiae

The minutia is a small local feature of the fingerprint which is also known as Galton detail or point of identity [5]. Minutiae-based matching algorithms which match fingerprints according to the type, orientation and position of minutiae are regarded as the basis of fingerprint identification and widely used in the biometrics field [10]. It requires pre-processing of the fingerprint image and memory space to store extracted minutiae on fingerprint patterns with different image quality. Figure 2.3.1 shows an example of different extracted minutiae labeled on a fingerprint.

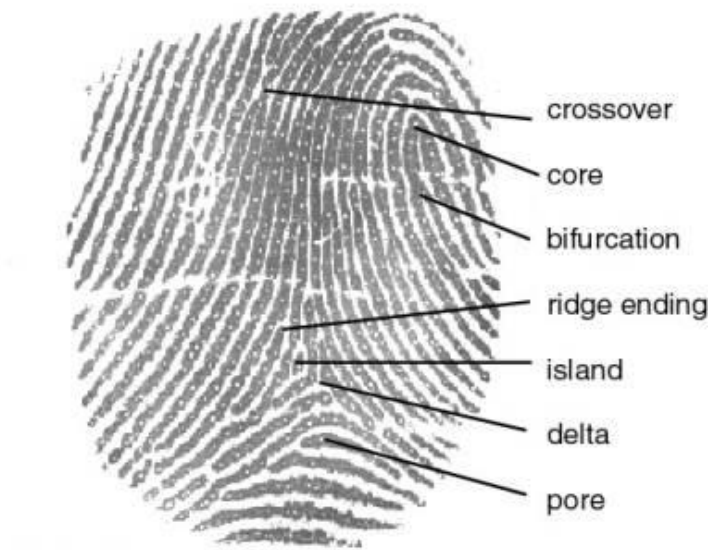


Figure 2.3.1 Minutiae sample [11]

Although there are plenty of different minutiae types, two of them are mostly used for fingerprint matching: the ridge ending and bifurcation. The ridge ending is defined as the end of a ridge which has only one connection from the pixel of the minutia. The bifurcation is on the point where a ridge splits into two ridges, which has three connections to three ridges. Figure 2.3.2 illustrates extracted ridge endings and bifurcations on a scanned fingerprint pattern.

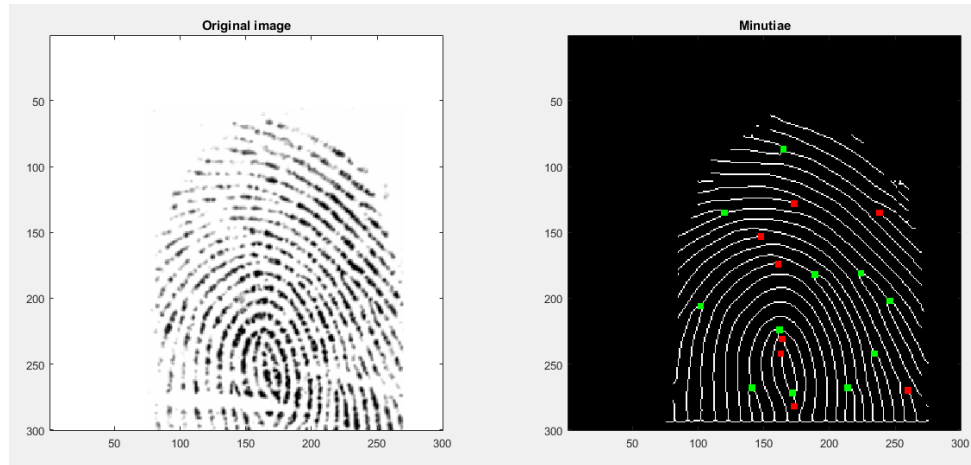


Figure 2.3.2 The ridge ending (red) and bifurcation (green)

Besides ridge ending and bifurcation, some other minutiae are introduced as follows. The *short ridge* is a ridge shorter than other ridges around. The *dot* is an isolated short ridge with approximately identical length and width. The *trifurcation* is a bifurcation with more than two branches from the intersection point. The *ridge crossing* is a point where two ridges intersect to each other. The *enclosure/lake* contains two points where the ridge bifurcates and combines. The *spur/hook* is a bifurcation with one short ridge branching off a longer one. The *bridge* is a ridge that connects two parallel ridges together. Figure 2.3.3 shows the minutiae sample of the *dot* and *lake*.

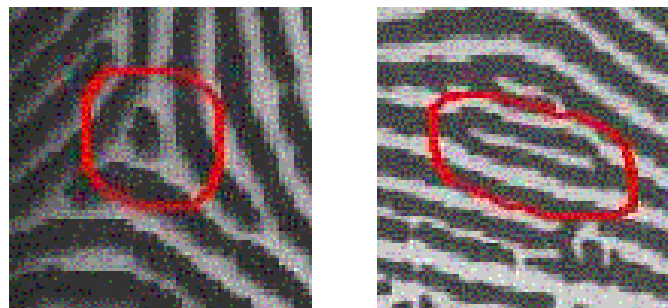


Figure 2.3.3 Dot and lake [5]

Some properties should be taken into consideration while identifying the minutiae from the fingerprint pattern: *Orientation* which stands for the direction of the minutiae, and *position*, including absolute location described as x-y coordinates and relative positions [1].

2.4 FVC2002

Images from Fingerprint Verification Competition (FVC) 2002 databases are used in this study. FVC is a series of international competitions about fingerprint identification [12]. In 2002, the second FVC was organized and results of four databases submitted by 31 industrial and academic participants were presented at the 16th ICPR (International Conference on Pattern Recognition) [12].

FVC2002 was organized in November 2001 and the organizer declared that, instead of an official fingerprint identification system certification, FVC2002 was regarded simply as a technology evaluation to increase the number of participants. As the result, more companies and researched groups participated in FVC2002 compared with FVC2000 [12].



Figure 2.4.1 Samples of FVC2002 images [12]

Sample images of these four databases (referred to as DB1, DB2, DB3, and DB4) are shown in Figure 2.4.1. Fingerprint images of DB1 and DB2 were collected by using optical commercial fingerprint scanners. Fingerprint images of DB3 were collected with capacitive scanners. And fingerprint images of DB4 are synthetically generated by SFinGE software [12]. Properties of FVC2002 fingerprint databases are listed in TABLE 2.4.1.

TABLE 2.4.1 Properties of FVC2002 images [12]

Database	Scanner	Technology	Image Size	Resolution
DB1	Identix TouchView II	Optical	388*374	500 dpi
DB2	Biometrika FX2000	Optical	296*560	569 dpi
DB3	Precise Biometrics 100 SC	Capacitive	300*300	500 dpi
DB4	SFinGE v2.51	Synthetic	288*384	500 dpi

Fingerprint images of FVC2002 are split to two sets: evaluation set A and training set B. In this paper, fingerprints images in set B are used for testing since they are more representative compared with images in set A. In every database of set B (referred to as DB1_B, DB2_B, DB3_B and DB4_B), there are 80 fingerprints collected from 10 different fingers and each finger has 8 images. Figure 2.4.2 illustrates the structure of FVC2002 databases implemented in this study.

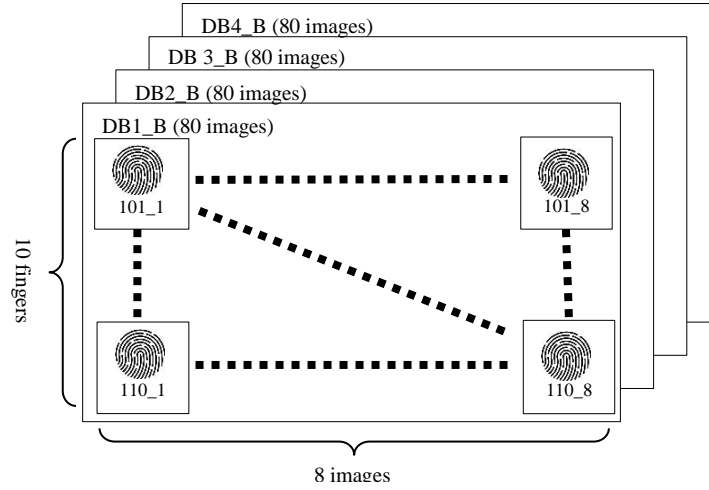


Figure 2.4.2 FVC2002 database

Chapter III

Image Processing

3.1 Image Enhancement

To generate an accurate identification, it is necessary to enhance the quality of fingerprint images by removing the noise, sharpening and brightening after its enrollment [13]. In this study, the fingerprint recognition Matlab® program developed by Vahid K. Alilou [14] is used as the starting point to implement fingerprint image enhancement in this study. To improve fingerprint matching accuracy, the Matlab® program is modified appropriately to lower the error rate.

As a pre-process to improve the image quality, histogram equalization is a method to increase the contrast of an image by changing its intensity values. During the process, the histogram is broadened to make the image clearer [1]. Figure 3.1.1 and 3.1.2 show histograms before and after the processing of equalization and images, and Figure 3.1.3 presents images before and after histogram equalization.

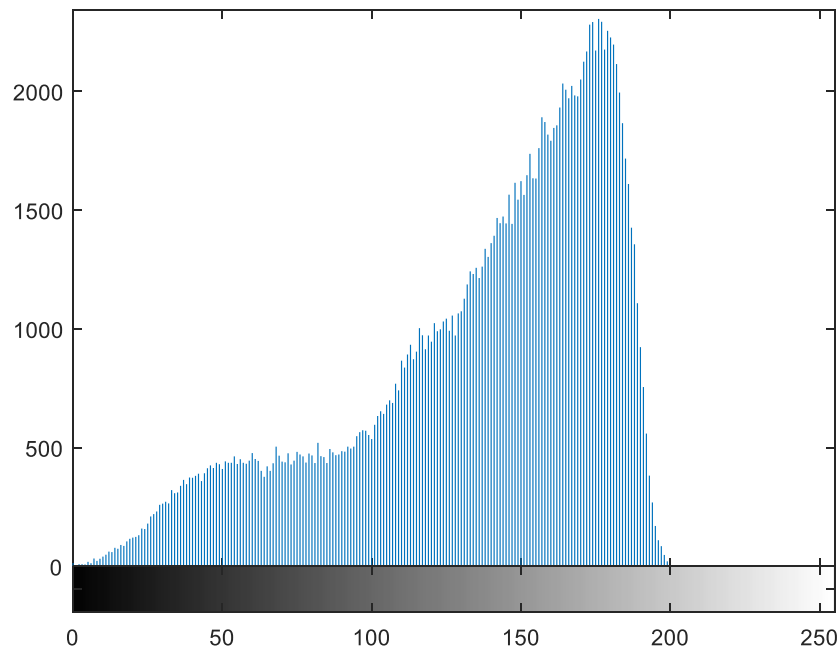


Figure 3.1.1 Original histogram

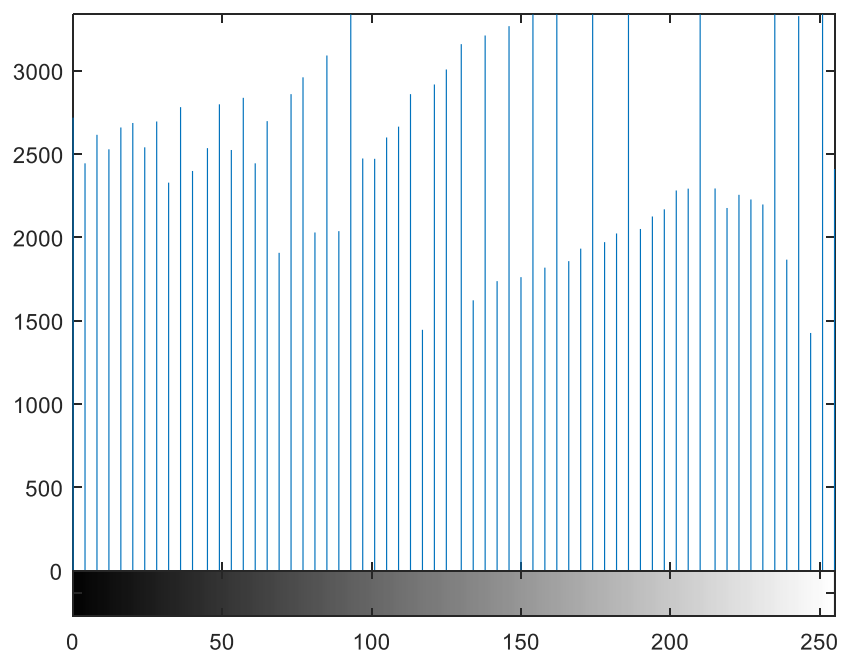


Figure 3.1.2 Equalized histogram



Figure 3.1.3 Images before (left) and after (right) histogram equalization

The step after histogram equalization is normalization. In this step, the magnitude of the data of fingerprint image is balanced to match a pre-defined mean and variance. The result, $N(i,j)$, is the normalized gray scale value at (i,j) [13].

$$N(i,j) = M_0 \pm \sqrt{\frac{V_0(I(i,j)-M)^2}{V}} \quad (3.1.1)$$

where $I(i,j)$ stands for the gray scale of the pixel located at (i,j) coordinate and M_0, V_0 denote the estimated mean and variance.

Ridge orientation estimation is the next step. The local ridge orientation is estimated as an indicator showing the trend of the direction of ridges. The whole image is divided into sub-images, and, for each sub-image, the gradients $\partial_x(i,j)$ and $\partial_y(i,j)$ of each pixel located at (i,j) are calculated with Sobel filter which is a common method to determine the first order gradient [15]. The image's horizontal and vertical gradient ∂_x and ∂_y are calculated as follows:

$$\partial_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \odot A \quad (3.1.2)$$

$$\partial_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \odot A \quad (3.1.3)$$

where A is the original image and the operator, \odot is the convolution operator. The gradient ∂ and angle θ are calculated by using ∂_x and ∂_y :

$$\partial = \sqrt{\partial_x^2 + \partial_y^2} \quad (3.1.4)$$

$$\theta = \arctan\left(\frac{\partial_y}{\partial_x}\right) \quad (3.1.5)$$

The value of local ridge orientation θ of each sub-image centered at (i,j) is deduced as follows [16]:

$$V_x(i, j) = \sum_{u=i-\frac{w}{2}}^{i+\frac{w}{2}} \sum_{v=j-\frac{w}{2}}^{j+\frac{w}{2}} \partial_x(u, v)^2 - \partial_y(u, v)^2 \quad (3.1.6)$$

$$V_y(i, j) = \sum_{u=i-\frac{w}{2}}^{i+\frac{w}{2}} \sum_{v=j-\frac{w}{2}}^{j+\frac{w}{2}} 2\partial_x(u, v) \cdot \partial_y(u, v) \quad (3.1.7)$$

$$\theta(i, j) = \frac{1}{2} \cdot \arctan\left(\frac{V_y(i, j)}{V_x(i, j)}\right) \quad (3.1.8)$$

By doubling local orientation value θ , a pair of new vectors Φ_x and Φ_y is created.

The result of orientation values $O(i, j)$ are shown as follows [16]:

$$\Phi_x(i, j) = \cos(2\theta(i, j)) \quad (3.1.9)$$

$$\Phi_y(i, j) = \sin(2\theta(i, j)) \quad (3.1.10)$$

$$O(i, j) = \frac{1}{2} \cdot \arctan\left(\frac{\Phi_y(i, j)}{\Phi_x(i, j)}\right) \quad (3.1.11)$$

After the ridge orientation is estimated, next step is ridge frequency estimation. Local ridge frequency is the frequency of ridges and furrows appearing in a local neighborhood. Pixels along with ridges and valleys with obvious distinction of gray scale are considered samples of a sinusoidal wave (ridge and valley are peaks of the sinusoidal wave) and the frequency of this sinusoidal wave is defined as the local ridge frequency [13]. Besides local ridge orientation, the frequency is a vital property of the fingerprint image as well. Gabor filter is then implemented for removing noise based on local ridge orientation and local ridge frequency. The definition of an even-symmetric Gabor filter in the spatial domain is shown as follows [13] [17]:

$$G(x, y, : f, \theta) = \exp\left\{-\frac{1}{2}\left[\frac{x_\phi^2}{\delta_x^2} + \frac{y_\phi^2}{\delta_y^2}\right]\right\} \cos(2\pi f x_\phi) \quad (3.1.12)$$

$$x_\phi = x \sin \theta + y \cos \theta \quad (3.1.13)$$

$$y_\phi = x \cos \theta - y \sin \theta \quad (3.1.14)$$

where θ is the orientation and f denotes the frequency of the image. δ_x and δ_y stand for standard deviations of Gaussian envelope in x and y axis respectively.

In the process of image binarization, the original pixel image is converted from gray-scale to black-and-white. After setting up the threshold, the image is converted to 0-1 data format by setting values of pixels whose original values are above threshold to 1 and 0 otherwise. The value of 0 stands for black and 1 represents white. To get an appropriate threshold for binarization, clustering algorithm can be implemented instead of using a fixed threshold value. The image binarization is the basis of segmentation [18]. Figure 3.1.4 shows the fingerprint before and after the process of binarization.



Figure 3.1.4 Image binarization

Because there is only one specific portion of the fingerprint image can provide valid information for the identification which is called ROI (region of interest), in the process of image segmentation, the image is spitted into multiple segments. The area without any valid information is abandoned and the rest area is kept. The procedure of image segmentation includes two steps: direction estimation and ROI extraction [1].

While estimating the direction of the each block, the algorithm calculates the gradient values in x and y directions and uses least square approximation of the block direction as following [1]:

$$\tan 2\beta = 2 \sum \sum (p_x * p_y) / \sum \sum (p_x^2 - p_y^2) \quad (3.1.15)$$

where p_x and p_y represent the gradient values for x-direction and y-direction respectively. The tangent value can be computed based on the above values as showed in the following equation.

$$\tan 2\theta = 2 \sin \theta \cos \theta / (\cos^2 \theta - \sin^2 \theta) \quad (3.1.16)$$

where $\cos \theta$ and $\sin \theta$ are regarded as p_x and p_y respectively.

By using the following equation, the certainty level E can determine whether the block is worthy to be kept or discarded by comparing with the threshold [1].

$$E = \{2 \sum \sum (p_x * p_y) + \sum \sum (p_x^2 - p_y^2)\} / W * W * \sum \sum (p_x^2 + p_y^2) \quad (3.1.17)$$

For ROI extraction, peaks caused by noise and small cavities are removed by inflicting enhancement and shrinking images. The new calculated bound determines the bounded region on the inner area of the fingerprint and abandons the invalid surrounding area [18]. In this step, foreground and background regions of the fingerprint image are separated based on the gray scale variance. The region with higher gray scale variance is regarded as ROI [19]. Figure 3.1.5 shows an example of ROI extraction.

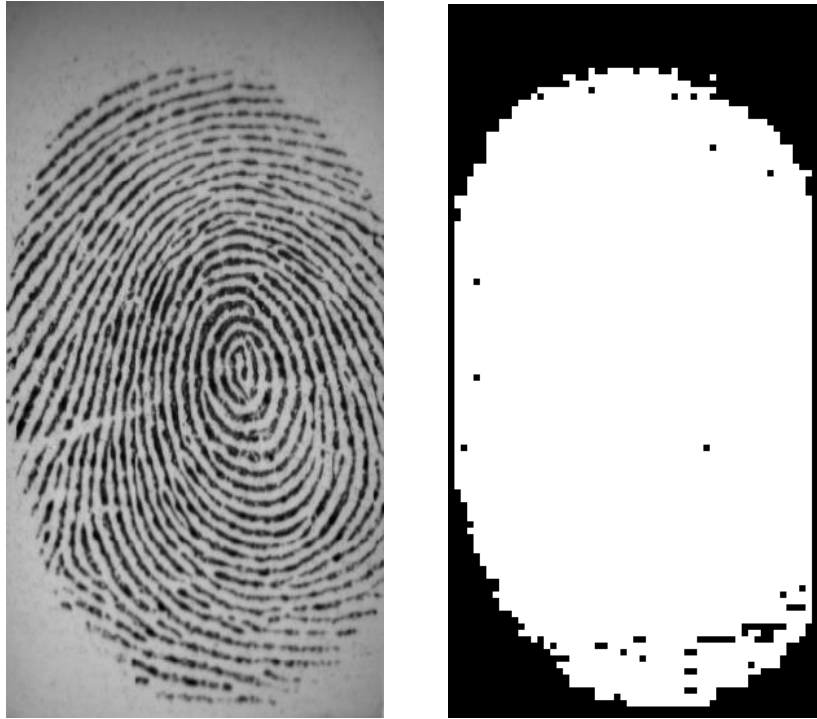


Figure 3.1.5 ROI extraction

Image thinning is the last step of image enhancement before minutiae extraction. It aims to remove repetitive pixels of ridges and make the ridge thinner. During this procedure, the full image is scanned and repetitive pixels are marked by tracing the ridges with highest gray intensity value and removed after several times of scanning by using the small image window [1]. After reducing repetitive pixels, the contrast of ridges is enhanced by implementing image thinning. Figure 3.1.6 shows the thinned fingerprint pattern.



Figure 3.1.6 Image thinning

3.2 Minutiae Extraction

After fingerprint image thinning, minutiae are extracted by using the 3*3 window located on each valid pixel. The crossing number (CN) is used to identify whether there is a valid minutia [20].

$$CN(p) = \frac{1}{2} \sum_{i=1 \text{ to } 8} |val(p_{i \bmod 8}) - val(p_{i-1})| \quad (3.2.1)$$

where p_i stands for the value of pixels surrounding the origin pixel p . If CN equals 1, this pixel will be defined as a ridge ending, and it will be corresponded to bifurcation if CN is 3. Other pixels are not considered as valid minutiae points. Figure 3.2.1 shows the illustration of pixels standing for the ridge, ridge ending and bifurcation.

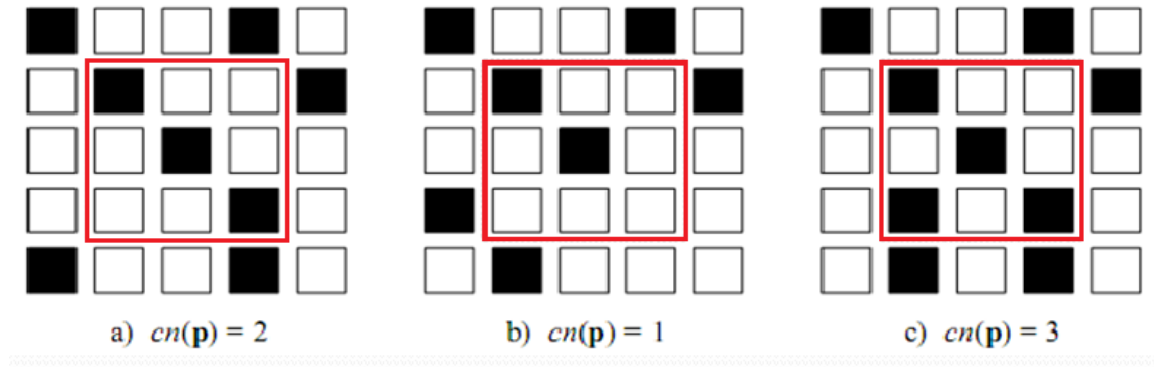


Figure 3.2.1 Ridge, ridge ending and bifurcation [20]

To avoid interference after extraction of ridge endings and bifurcations, unification is implemented to characterize minutiae by using orientation, position and minutiae type. By using above properties, minutiae on the fingerprint images are labeled. All minutiae are stored as (x, y, θ, CN) quadruple [20].

- x and y : spatial coordinates
- θ : orientation
- CN : the Crossing Number.

Chapter IV

Matching Algorithm

4.1 Approach

The procedure of fingerprint matching generally can be divided into four steps: *pairwise similarity comparison*, *alignment*, *corresponding*, and *scoring* [2] as shown in Figure 4.1.1.

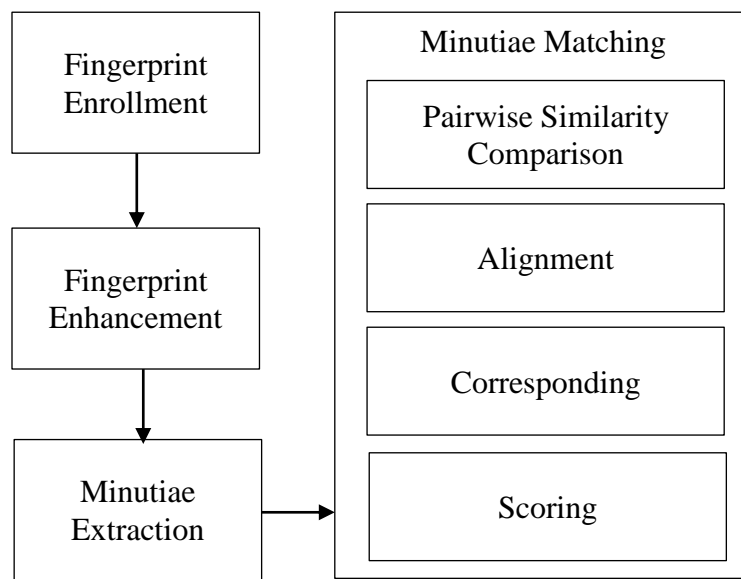


Figure 4.1.1 Procedure of fingerprint pattern matching

- *Pairwise Similarity Comparison*: Two fingerprint images are coarsely aligned based on their local minutiae structures. It is done by translating and rotating two fingerprints so that one minutia from one fingerprint closely overlaps with another minutia of the same kind from the other fingerprint.
- *Alignment*: After two fingerprints are roughly aligned in specific translation and orientation, one of the minutiae sets is rotated to optimize the alignment between two minutiae sets for further minutiae matching.
- *Corresponding*: The correspondence between individual minutiae of two fingerprints is established. Pairs of minutiae with close position and orientation are considered corresponding pairs.

- *Scoring*: A similarity score indicating similarity between minutiae sets of two fingerprints is calculated.

Orientation and position are two properties used to match minutiae extracted from two fingerprints. Orientation represents the direction of the minutia and the position is represented by its x-y coordinates [1]. Minutiae selected from two fingerprints are considered as matched minutiae if their distance and the difference of orientation are less than pre-defined thresholds. Comparisons between distance and difference of orientation and their related threshold values are shown as follows [21].

$$Threshold_{Distance} \geq \sqrt{\Delta x^2 + \Delta y^2} \quad (4.1.1)$$

where Δx is the difference between the x-coordinate of two minutiae and Δy is the difference of two y-coordinates.

$$Threshold_{Orientation} \geq \min(|\Delta\theta|, 360^\circ - |\Delta\theta|) \quad (4.1.2)$$

where $\Delta\theta$ is the difference between orientations of two minutiae.

The fingerprint matching algorithm computes the similarity score between two fingerprints based on the number of matched minutiae. The minutiae extracted from two fingerprints are matched via shifting and rotating fingerprints, and the maximum number of matched minutiae is used to calculate the similarity score as shown below [21].

$$similarity\ score = \frac{(\#\ of\ matched\ minutiae)^2}{(\#\ of\ Image\ 1's\ minutiae) \cdot (\#\ of\ Image\ 2's\ minutiae)} \quad (4.1.3)$$

4.2 Matching Performance Evaluation Methods

Based on different requirements, different measures might be used to evaluate fingerprint matching algorithm performance. Measures used in this study are introduced in this section.

The False Match Rate (FMR) and False Non-Match Rate (FNMR) are the most common indicators used to evaluate fingerprint matching algorithm performance [12]. The FMR is also referred as False Acceptance Rate (FAR), which represents the percentage of impostor/unmatched comparisons which are incorrectly accepted. The FNMR stands for the percentage of genuine/matched comparisons which are incorrectly rejected [22].

When FMR and FNMR are equivalent, the value of the error rate is referred to as Equal Error Rate (EER). The EER is used as the main evaluator in this study. While analyzing FMR and FNMR curves plotting on the same figure, EER is the intersection of FMR and FNMR curves where their values are identical [12].

Besides EER, other indicators are also used in this study and they are listed below:

- FMR100: The lowest FNMR for $FMR \leq 1\%$
- FMR1000: The lowest FNMR for $FMR \leq 0.1\%$
- ZeroFMR: The lowest FNMR for $FMR = 0\%$
- ZeroFNMR: The lowest FMR for $FNMR = 0\%$

Unlike EER, these four indicators give more weight either to FMR (FMR100, FMR1000, ZeroFMR) or FNMR (ZeroFNMR).

4.3 One-to-one Method

In One-to-one Method, there is one image used as the template and similarity score between the template image and image to be identified that determines the matching between two fingerprints is calculated. If the similarity score is higher than the pre-set threshold, a match is declared. Otherwise, it is determined that two fingerprints do not match. It is obvious that the value of threshold for the similarity score affects the FMR and FNMR described in the previous section. In this study, the threshold is set where FMR and FNMR is equivalent, so the EER is used to evaluate fingerprint matching algorithm performance. A standard matching algorithm is used to identify two fingerprints and determine their similarity score. The standard matching algorithm used in this project is listed in TABLE 4.3.1.

TABLE 4.3.1 Standard matching algorithm

<i>Standard Matching Algorithm</i>
Input: Two extracted fingerprint minutiae sets Threshold for distance T Threshold for orientation TT
Output: Similarity score
Step 1: Initialization Calculate the position of minutiae in two sets $\{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$ Calculate the orientation of minutiae in two sets $\{\theta_1, \theta_2, \dots, \theta_n\}$ Record the type of minutiae in two sets $\{type_1, type_2, \dots, type_n\}$
Step 2: Comparison and scoring n1 = size of set 1. n2 = size of set 2. for minutia1=1 to n1 for minutia2=1 to n2 matchedNum=0

```

match minutia1 in set 1 and minutia2 in set 2
(dx=0, dy=0, dθ=0, type(minutia1)=type(minutia2))
rotate set 2 around minutia1 in set 1
  for minutia1'=1 to n1
    for minutia2'=1 to n2
      if(sqrt(dx,dy)<T, dθ<TT, type(minutia1')=type(minutia2'))
        matchedNum= matchedNum+1
        break loop for minutia2'
      end
    end
  end
  end
  similarity score= $\sqrt{\frac{matchedNum^2}{n1*n2}}$ 
  keep the maximum similarity score
end
end

```

To compare two minutiae sets, a coordination transform might need to be applied upon minutiae sets to achieve a meaningful comparison. A coordinate of the minutia can be represented as

$$T = \begin{bmatrix} x \\ y \\ \theta \\ CN \end{bmatrix}^T \quad (4.3.1)$$

where x , y , θ , and CN are the x-axis and y-axis position, orientation, and crossing number which indicates two different types of minutiae including the ridge ending and bifurcation.

Assume that two minutiae sets, Set A and Set B, are to be matched. One specific minutia is chosen as the reference minutia from each set. First, we would like to overlap two reference minutiae. To achieve it, their coordinates need to be transformed.

Assume the coordinates of all minutiae in the same set are $T_i = \begin{bmatrix} x_i \\ y_i \\ \theta_i \\ CN_i \end{bmatrix}^T$ and the

coordinate of the reference minutia is $T_{Ref} = \begin{bmatrix} x_{Ref} \\ y_{Ref} \\ \theta_{Ref} \\ CN_{Ref} \end{bmatrix}^T$. Two reference minutiae of Set

A and Set B should have the same minutiae type, which means their crossing numbers CN_{Ref} are identical; otherwise reference minutiae have to be re-selected. Then the coordinate transformation is done by the following operation:

$$T'_i = \begin{bmatrix} x'_i \\ y'_i \\ \theta'_i \\ CN'_i \end{bmatrix}^T = B_i * R \quad (4.3.2)$$

where T'_i is the minutiae coordinate after transformation,

$$R = \begin{bmatrix} \cos \theta_{Ref} & \sin \theta_{Ref} & 0 & 0 \\ -\sin \theta_{Ref} & \cos \theta_{Ref} & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad (4.3.3)$$

and

$$B_i = \begin{bmatrix} x_i - x_{Ref} \\ y_i - y_{Ref} \\ \theta_i - \theta_{Ref} \\ CN_i \end{bmatrix}^T \quad (4.3.4)$$

By doing so, coordinates of reference minutiae from each set after transformation is

$$T_{Ref}' = \begin{bmatrix} 0 \\ 0 \\ 0 \\ CN_{Ref} \end{bmatrix}^T \text{ thus considered overlapped. All minutiae of Set A and Set B are}$$

transformed by using the same operation.

After Set A and Set B are transformed, they are compared with each other and a similarity score is calculated. This operation will continue until every minutia from Set A has been paired with every minutia of the same kind from Set B and the highest similarity score is recorded as the similarity score between Set A and Set B.

Figures 4.3.1 and 4.3.2 show the minutiae of matched and unmatched fingerprints. Blue and red vectors represent minutiae extracted from two different fingerprints. As shown in Figure 4.3.1, for matched fingerprints, plenty of matched minutiae (shown as green vectors) can be identified. On the other hand, in unmatched fingerprints shown in

Figure 4.3.2, very few matched minutiae can be identified which are represented by overlapped blue and red vectors. To be regarded as matched minutiae, the related minutiae from two sets must have a Euclidean distance and orientation difference lower than thresholds. More matched minutiae compared with unmatched ones means higher similarity score.



Figure 4.3.1 Minutiae from matched fingerprints

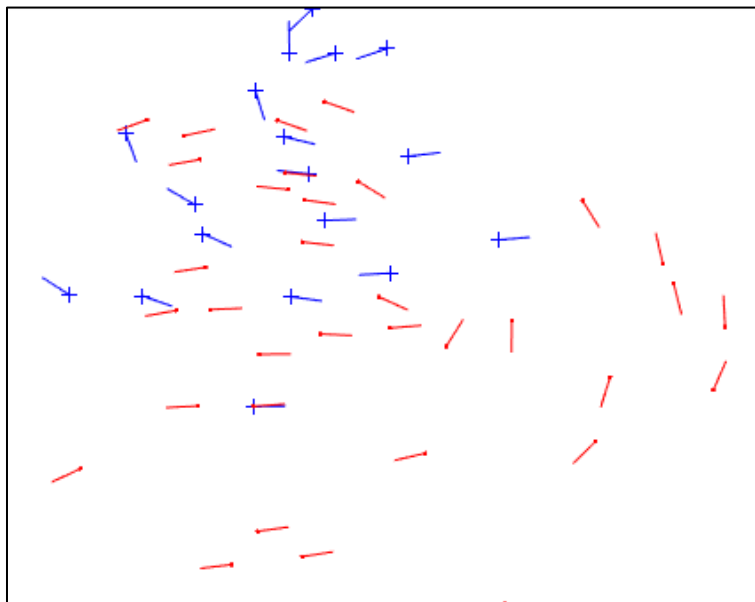


Figure 4.3.2 Minutiae from unmatched fingerprints

4.4 Two-to-one Method

There are two different two-to-one methods to be compared with One-to-one Method in this study:

- *Two-to-one Method 1:* Two images are used as identification templates and the similarity score is the average of the similarity score between the fingerprint to be identified and each fingerprint in the identification template.
- *Two-to-one Method 2:* Two images are used as identification templates and the similarity score is the weighted average of the similarity score between the fingerprint to be identified and each fingerprint in the identification template. An improved matching algorithm is also used in the calculation of similarity score. The proposed algorithm is described in the previous chapter.

As One-to-one Method, the similarity score threshold is set so that FMR and FNMR is equivalent so the EER can be used to evaluate matching algorithm performance. The details of Two-to-one Methods are given below.

A. *Dual-Image Identification Template*

Compared with One-to-one Method, the dual-image identification template consists of two fingerprint images collected from the same finger. While using two template images for fingerprint identification, each fingerprint of the template is compared with the fingerprint to be identified and the mean value of two similarity scores is recorded as the final similarity score of Two-to-one Method 1.

Based on two matchings between the template image and the query image, the Two-to-one Method improves the matching accuracy and relaxes the image quality requirement compared with One-to-one Method which only uses single template.

B. *Improved Matching Algorithm*

To further improve the matching accuracy, an improved matching algorithm is proposed. Differing from the conventional matching algorithm described in the previous section, the proposed algorithm limits the maximum number of minutiae to be matched. Let the maximum number of matched minutiae is defined as N . While matching two

fingerprints, two minutiae with the same type are selected from different sets of minutiae extracted from two fingerprints, and two minutiae sets are matched by transforming to overlap two minutiae selected from different sets. After that, N-1 minutiae which are closest to the chosen minutia from two minutiae sets are selected. Then minutiae selected from different sets are combined as two structures to be identified by each other. In the procedure of calculating the number of matched minutiae and similarity score, differences between two positions and differences of orientations between the first-selected minutia and minutia to be matched in two different sets are two properties used to match minutiae extracted from two fingerprints. Comparisons between distance and difference of orientation and their related threshold values are shown as follows [21].

$$Threshold_{Distance} \geq \sqrt{\Delta(x - x_1)^2 + \Delta(y - y_1)^2} \quad (4.4.1)$$

where (x,y) is the coordinate of the minutia to be matched and (x₁,y₁) is the coordinate of the first-selected minutia.

$$Threshold_{Orientation} \geq \min(|\Delta(\theta - \theta_1)|, 360^\circ - |\Delta(\theta - \theta_1)|) \quad (4.4.2)$$

where θ is orientation of the minutia to be matched and θ_1 is the orientation of the first-selected minutia.

The similarity score is determined based on the similar procedure as described in Section 4.1. By counting the number of matched minutiae from two extracted structures of minutiae, similarity scores based on different minutiae structures are recorded and the highest similarity score between two fingerprints is regarded as the final similarity score. The minutiae extracted from two fingerprints are matched via shifting and rotating fingerprints, and the maximum number of matched minutiae is used to calculate the similarity score as shown below [21].

$$similarity\ score = \frac{(\#\ of\ matched\ minutiae)^2}{(\#\ of\ Image\ 1's\ minutiae) \cdot (\#\ of\ Image\ 2's\ minutiae)} \quad (4.4.3)$$

This pseudocode of this improved matching algorithm can be found in Table 4.4.1. In this study, N is set as 25 since it brings about the best performance.

TABLE 4.4.1 Improved matching algorithm

<i>Improved Matching Algorithm</i>
Input: Two extracted fingerprint minutiae sets Threshold for distance T' Threshold for orientation TT' Minutiae number N
Output: Similarity score
Step 1: Initialization Calculate the position of minutiae in two sets $\{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$ Calculate the orientation of minutiae in two sets $\{\theta_1, \theta_2, \dots, \theta_n\}$ Record the type of minutiae in two sets $\{type_1, type_2, \dots, type_n\}$
Step 3: Comparison and scoring n1 = size of set 1. n2 = size of set 2. for minutia1=1 to n1 for minutia2=1 to n2 matchedNum=0 match minutia1 in set 1 and minutia2 in set 2 (dx=0, dy=0, d θ =0, type(minutia1)=type(minutia2)) create minutiae set 1' and set 2' set minutia1 as the first minutia of set 1' set minutia2 as the first minutia of set 2' add N-1 minutiae from set 1 closest to minutia1 into set 1' add N-1 minutiae from set 2 closest to minutia2 into set 2' rotate whole set 2' around minutia1 for minutia1'=1 to n1 for minutia2'=1 to n2 dDistance=abs(distance(minutia1, minutia1')- distance(minutia2, minutia2'))

```

        dAngle=abs(orientation(minutia1, minutia1')- orientation (minutia2,
minutia2'))
        if(dDistance <T', dAngle <TT', type(minutia1')=type(minutia2'))
            matchedNum= matchedNum+1
            break loop of minutia2'
        end
    end
end
similarity score= $\sqrt{\frac{matchedNum^2}{n1*n2}}$ 
keep the maximum similarity score
end
end

```

C. Similarity Score Weighting Scheme

While implementing two-to-one methods, two fingerprints collected from the same finger are used as a dual-image identification template and the most straightforward way to calculate the similarity score is taking average of two similarity scores based on two different template fingerprints. However, since the fingerprints of the identification template might have different quality, assigning different weights to two similarity scores might be beneficial. The similarity score of the two-to-one method is represented as:

$$Similarity\ Score = \alpha * S1 + (1 - \alpha) * S2 \quad (4.4.4)$$

where α is the weighting parameter. $S1$ and $S2$ stand for the similarity scores calculated based on two different template images. The default value of α is 0.5 which is the value used in Two-to-one Method 1. To determine the value of weighting parameter, here are three factors to be considered:

- *Minutiae number*: For blurred and low-quality fingerprint images, some minutiae are affected and unable to be extracted. The total number of minutiae represents the amount of information included in the fingerprint image. Therefore, if the first template fingerprint has more minutiae than the second template fingerprint, the

weighting parameter α should be larger. The weighting parameter α_1 is calculated as follows:

$$\alpha_1 = \frac{\# \text{ of minutiae on image 1}}{\# \text{ of minutiae on image 1} + \# \text{ of minutiae on image 2}} \quad (4.4.5)$$

- *EER of One-to-one Method:* Since the EER indicates the performance of the fingerprint identification, when the quality of the template image is better, One-to-one Method based on the same image should generate a lower EER. Therefore, if the first template fingerprint generates a smaller EER, the weighting parameter α should be greater. The weighting parameter α_2 can be calculated as follows:

$$\alpha_2 = 1 - \frac{\text{EER of one-to-one method on image 1}}{\text{EER of one-to-one method on image 1} + \text{EER of one-to-one method on image 2}} \quad (4.4.6)$$

- *Mask area ratio:* The mask is the valid fingerprint area of the fingerprint image. If the template fingerprint has larger mask area, the weighting parameter α should be larger. The weighting parameter α_3 is calculated as follows:

$$\alpha_3 = \frac{\text{Mask area ratio on image 1}}{\text{Mask area ratio on image 1} + \text{Mask area ratio on image 2}} \quad (4.4.7)$$

Chapter V

Experimental Results

5.1 Performance Assessment

The images from FVC 2002 are used to evaluate three fingerprint matching algorithms: One-to-One method, Two-to-One method 1, and Two-to-One method 2. To investigate the relation between image quality and algorithm performance, fingerprints are separated into 8 sets based on their image quality (each finger has 8 fingerprints as mentioned previously). The quality of fingerprint is determined by its EER when it is used as a template image. The lower EER it generates, the better quality it possesses. These 8 sets of image are numbered in the order of image quality (the 1st set of image has the best quality).

Two groups of image with good quality and bad quality are used to study the performance of different methods upon fingerprints with different image quality. First three fingerprint sets (1st, 2nd, and 3rd sets) which generate the lowest three EERs are considered to be images with good quality. Last three sets (6th, 7th, and 8th set) which generate the highest three EERs are considered to be images with bad quality. First, we compare the performance of One-to-one Method using images of the 1st set as the template with the performance of Two-to-one Method 1 and 2 using images of the 2nd and 3rd sets as the template. Then, we compare the performance of One-to-one Method using images of the 6th set as the template with the performance of Two-to-one Method using images of the 7th and 8th sets as the template. If Two-to-one Method 1 and 2 outperform One-to-one Method in each comparison, it will be verified that more images in templates not only improve the matching accuracy but the fingerprint image quality requirement can also be relaxed. The process of fingerprint classification and selection is shown in Figure 5.1.1.

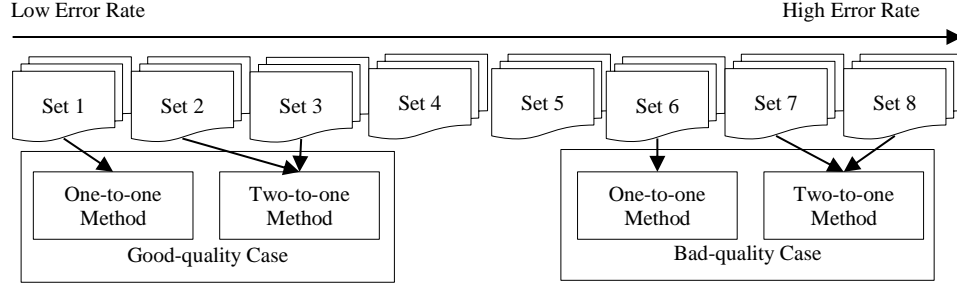
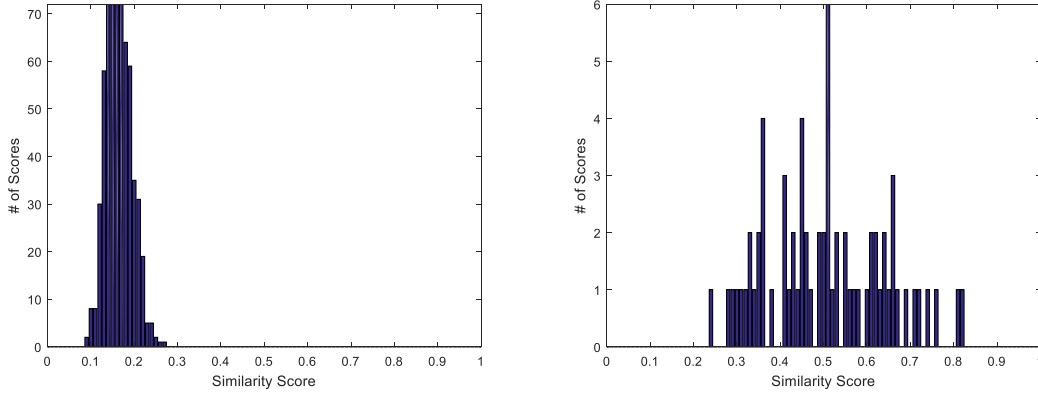


Figure 5.1.1 Fingerprint classification and selection

The total numbers of genuine and impostor tested for One-to-one Method are $C_1^7 * C_1^{10} = 70$ and $C_1^8 * A_2^{10} = 720$. For methods using dual-image template, including Two-to-one Method 1 and 2, the total numbers of genuine and impostor are $C_1^6 * C_1^{10} = 60$ and $C_1^8 * A_2^{10} = 720$.

In order to measure FMR and FNMR of different methods, histograms of similarity score are plotted as the first step. Histograms of good-quality images of DB4_B generated by three methods are shown in Figure 5.1.2 as an example. Histograms of similarity score between unmatched fingerprints are shown in the left column and histograms of similarity scores between matched fingerprints are shown in the right column in Figure 5.1.2.



(a)

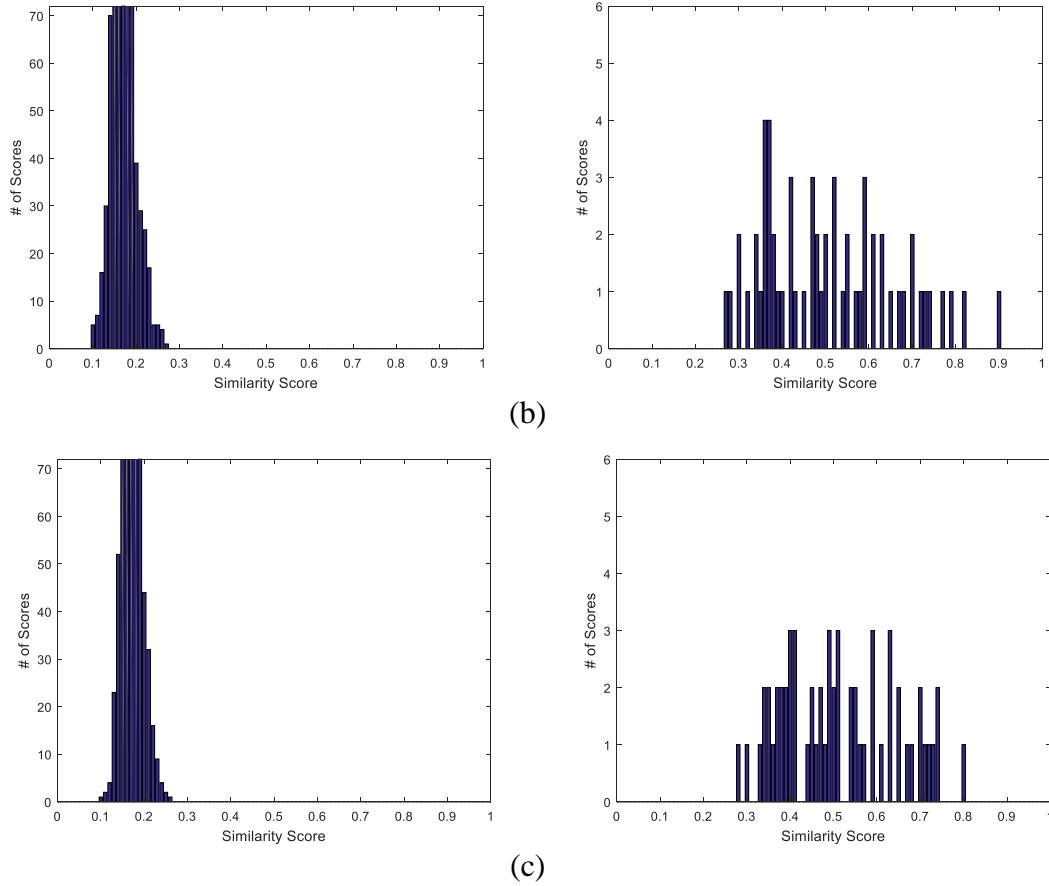
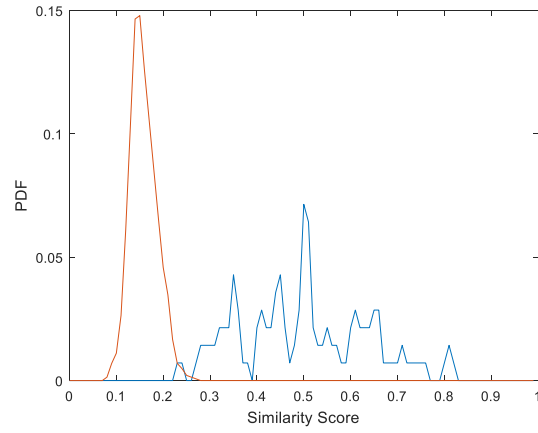
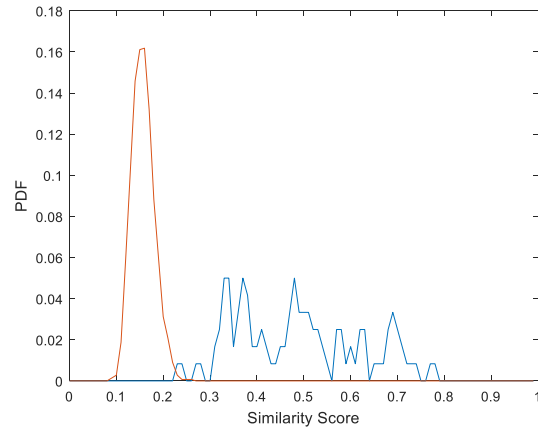


Figure 5.1.2 Similarity score histogram: (a) One-to-one Method (b) Two-to-one Method 1 (c) Two-to-one Method 2 (left: similarity score between unmatched images, right: similarity score between matched images)

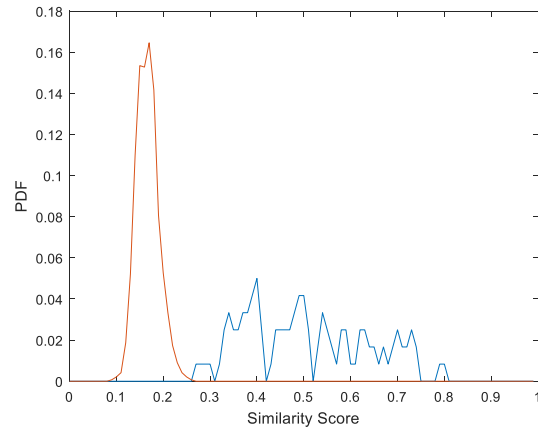
The probability density function (PDF) of similarity scores is calculated and plotted in Figure 5.1.3. In Figure 5.1.3, blue curves are the pdf of similarity score of genuine comparison (the comparison between two matched images) and red curves are the pdf of similarity score of impostor comparison (the comparison between two unmatched images).



(a)



(b)



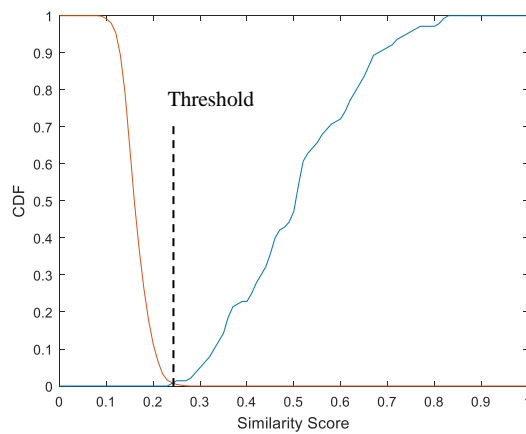
(c)

Figure 5.1.3 Similarity score PDF (blue: genuine red:impostor) (a) One-to-one Method (b) Two-to-one Method 1 (c) Two-to-one Method 2

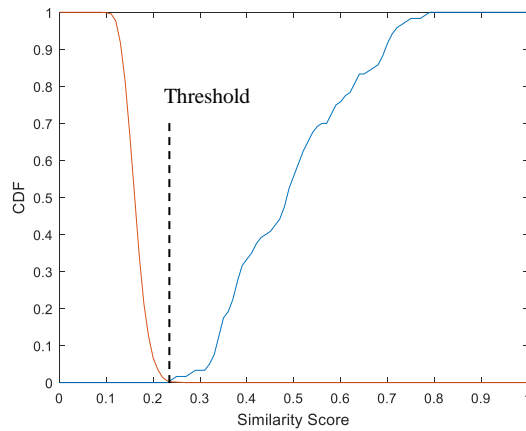
By integrating the PDF of similarity score of genuine and impostor comparisons, the cumulative distribution function (CDF) is plotted in Figure 5.1.4. The CDF curves of

the genuine comparison (in blue) and impostor comparison (in red) can be also be considered as FNMR and FMR curves.

A similarity score threshold is set to determine whether two fingerprints match or not. If the similarity score between two images is higher than the threshold, then these two fingerprints are considered as matched fingerprints. Otherwise, they are considered as unmatched fingerprints. In Figure 5.1.4, if the similarity score threshold is chosen as the similarity score value where FMR and FNMR are equivalent, this threshold generates EER.



(a)



(b)

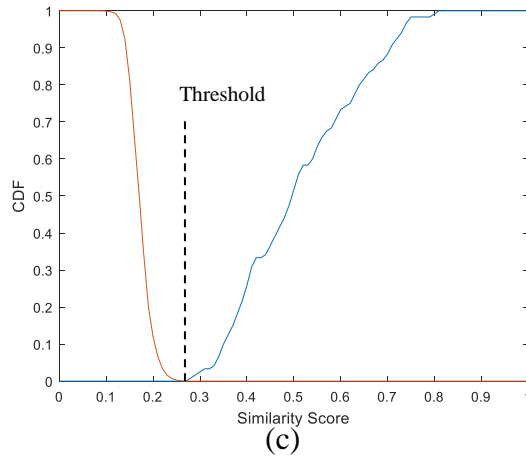


Figure 5.1.4 Similarity score CDF (blue: genuine red:impostor) (a) One-to-one Method (b) Two-to-one Method 1 (c) Two-to-one Method 2

A sample CDF of similarity scores of impostor (in red) and genuine (in blue) comparisons can be used to illustrate performance indicators described in Section 4.2. Five error rates, EER, FMR100, FMR1000, ZeroFMR, and ZeroFNMR, which indicates the performance of fingerprint identification, are labeled in Figure 5.1.5.

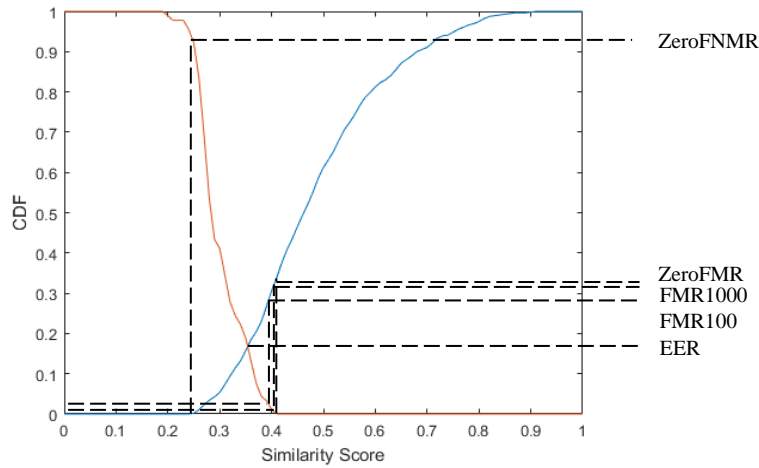


Figure 5.1.5 Error rates and similarity score CDF

5.2 Improvement by Dual-image Template

To analyze the performance improvement brought by the using dual-image template, we compared the EER generated by One-to-one Method and Two-to-one Method 1 upon good-quality and bad-quality images and results are included in TABLE 5.2.1 and 5.2.2 respectively.

TABLE 5.2.1 EER of good-quality for One-to-one Method and Two-to-one Method 1

	One-to-one Method	Two-to-one Method 1
DB1_B	0.51%	0.00%
DB2_B	2.11%	0.73%
DB3_B	6.03%	5.03%
DB4_B	0.83%	0.36%
Average	2.37%	1.53%

TABLE 5.2.2 EER of bad-quality for One-to-one Method and Two-to-one Method 1

	One-to-one Method	Two-to-one Method 1
DB1_B	5.82%	1.67%
DB2_B	6.42%	5.00%
DB3_B	11.30%	10.57%
DB4_B	4.29%	1.67%
Average	5.52%	4.73%

As shown in TABLE 5.2.1 and 5.2.2, with dual-image template, Two-to-one Method 1 definitely outperforms One-to-one Method by lowering the EER upon both good-quality and bad-quality images in all FVC2002 databases, even though the One-to-one Method implemented on the template image with better quality. Comparing the improvement by dual-image template, the average performance is improved more significantly upon good-quality images than bad-quality images.

5.3 Improvement by Improved Matching Algorithm

To investigate the benefit of the improved matching algorithm described in Section 4.4, TABLE 5.3.1 and 5.3.2 show the EER generated by One-to-one Method, Two-to-one Method 1 and Two-to-one Method 2 (without using weighting scheme) upon good-quality and bad-quality images respectively.

TABLE 5.3.1 EER of good-quality for One-to-one Method, Two-to-one Method 1 and Two-to-one Method 2 (No weighting scheme)

	One-to-one Method	Two-to-one Method 1	Two-to-one Method 2 (No weighting scheme)
DB1_B	0.51%	0.00%	0.07%
DB2_B	2.11%	0.73%	1.67%
DB3_B	6.03%	5.03%	3.69%
DB4_B	0.83%	0.36%	0.00%
Average	2.37%	1.53%	1.36%

TABLE 5.3.2 EER of bad-quality for One-to-one Method, Two-to-one Method 1 and Two-to-one Method 2 (No weighting scheme)

	One-to-one Method	Two-to-one Method 1	Two-to-one Method 2 (No weighting scheme)
DB1_B	5.82%	1.67%	1.67%
DB2_B	6.42%	5.00%	4.95%
DB3_B	11.30%	10.57%	8.34%
DB4_B	4.29%	1.67%	1.67%
Average	5.52%	4.73%	4.16%

According to TABLE 5.3.1, Two-to-one Method 2 (without weighting scheme) only outperforms Two-to-one Method 1 in 2 out of 4 databases, yet the Two-to-one Method 2 (without weighting scheme) reduces the average EER from 1.53% to 1.36% (an 11% improvement). As shown in TABLE 5.3.2, compared with Two-to-one Method 1, the Two-to-one Method 2 (without weighting scheme) deliver either a better or an equivalent performance in all database and it reduced the average EER from 4.73% to 4.16% (a 12% improvement). Based on TABLE 5.3.1 and 5.3.2, it can be stated that the proposed improved matching algorithm generates a noticeable overall performance improvement.

5.4 Improvement by Weighting Scheme

When a dual-image template is used, similarity scores between two template fingerprints and the fingerprint to be identified are used to generate the overall similarity score. The default setting assigns equal weight to each similarity score. We would like to investigate whether a more sophisticated weighting scheme can improve the performance of Two-to-one Method 2 or not. The α_1 , α_2 , and α_3 are the weighting parameters for the similarity score based on characteristics of two template images as described in Section 4.4. The EER generated by Two-to-one Method 2 using different weighting scheme upon good-quality images and bad-quality images are presented in TABLE 5.4.1 and 5.4.2 respectively.

TABLE 5.4.1 EER of good-quality with different weights

	0.5	α_1	α_2	α_3	Mean($\alpha_1, \alpha_2, \alpha_3$)
DB1_B	0.07%	0.00%	0.12%	0.07%	0.06%
DB2_B	1.67%	1.67%	1.67%	1.77%	1.67%
DB3_B	3.69%	3.68%	3.65%	3.60%	3.67%
DB4_B	0.00%	0.00%	0.00%	0.00%	0.00%
Average	1.36%	1.34%	1.36%	1.36%	1.34%

TABLE 5.4.2 EER of bad-quality with different weights

	0.5	α_1	α_2	α_3	Mean($\alpha_1, \alpha_2, \alpha_3$)
DB1_B	1.67%	1.67%	2.37%	1.67%	1.67%
DB2_B	4.95%	4.27%	4.35%	4.26%	4.27%
DB3_B	8.34%	8.00%	7.81%	7.78%	7.85%
DB4_B	1.67%	1.67%	1.67%	1.67%	1.67%
Average	4.16%	3.90%	4.05%	3.85%	3.87%

Based on TABLE 5.4.1 and 5.4.2, more sophisticated weighting schemes can bring about a moderate performance improvement. If the average of α_1 , α_2 , and α_3 are used as the value of weighting parameter, the EER is reduced by 1.5% for good-quality images and reduced by 7% for bad-quality images. It appears that the weighting scheme has a bigger advantage when the image quality is worse. One possible explanation is that the

characteristic difference between 7th and 8th sets is more significant than the characteristic difference between 2nd and 3rd sets.

TABLE 5.4.3 and 5.4.4 listed EERs generated by One-to-one Method, Two-to-one Method 1, and Two-to-one Method 2 (without and with weighting scheme) upon good-quality and bad-quality images respectively. As shown TABLE 5.4.3 and 5.4.4, both Two-to-one Method 1 and 2 outperform One-to-one Method. Two-to-one Method 2 with improved matching algorithm and weighting scheme further improves the matching accuracy compared with Two-to-one Method 1. For good-quality images, Two-to-one Method 2 with weighting scheme reduces EER by 43%. For bad-quality images, Two-to-one Method 2 with weighting scheme reduces EER by 30%.

TABLE 5.4.3 EER of good-quality for One-to-one Method, Two-to-one Method 1 and Two-to-one Method 2

	One-to-one Method	Two-to-one Method 1	Two-to-one Method 2 (No weighting scheme)	Two-to-one Method 2
DB1_B	0.51%	0.00%	0.07%	0.06%
DB2_B	2.11%	0.73%	1.67%	1.67%
DB3_B	6.03%	5.03%	3.69%	3.67%
DB4_B	0.83%	0.36%	0.00%	0.00%
Average	2.37%	1.53%	1.36%	1.34%

TABLE 5.4.4 EER of bad-quality for One-to-one Method, Two-to-one Method 1 and Two-to-one Method 2

	One-to-one Method	Two-to-one Method 1	Two-to-one Method 2 (No weighting scheme)	Two-to-one Method 2
DB1_B	5.82%	1.67%	1.67%	1.67%
DB2_B	6.42%	5.00%	4.95%	4.27%
DB3_B	11.30%	10.57%	8.34%	7.85%
DB4_B	4.29%	1.67%	1.67%	1.67%
Average	5.52%	4.73%	4.16%	3.87%

5.5 Overall Performance

Besides EER, other error rates which indicate the fingerprint identification performance are also used to evaluate three methods investigated in this study, and all error rates based on different cases of four FVC2002 databases are presented in TABLE 5.5.1.

As shown in TABLE 5.5.1, for bad quality images, compared with One-to-one Method, the Two-to-one Method 2 reduces every error rate. For good quality images, the Two-to-one Method 2 reduces majority of error rates compared with One-to-one Method.

TABLE 5.5.1 Performance comparisons by all indicators

		One-to-one Method		Two-to-one Method 1		Two-to-one Method 2	
		Good quality test	Bad quality test	Good quality test	Bad quality test	Good quality test	Bad quality test
DB1_B	EER	0.51%	5.82%	0.00%	1.67%	0.06%	1.67%
	FMR100	0.00%	6.66%	0.00%	1.67%	0.00%	1.67%
	FMR1000	1.82%	6.66%	0.00%	2.42%	0.00%	2.73%
	ZeroFMR	2.86%	6.66%	0.00%	3.33%	0.83%	3.33%
	ZeroFNMR	0.76%	66.53%	0.00%	34.17%	0.07%	44.45%
DB2_B	EER	2.11%	6.42%	0.73%	5.00%	1.67%	4.27%
	FMR100	3.80%	9.00%	4.92%	5.00%	1.67%	5.00%
	FMR1000	5.93%	10.39%	6.47%	7.25%	3.67%	7.17%
	ZeroFMR	6.43%	11.43%	6.67%	9.17%	5.00%	8.33%
	ZeroFNMR	60.40%	97.36%	1.53%	97.64%	12.50%	67.99%
DB3_B	EER	6.03%	11.30%	5.03%	10.57%	3.67%	7.85%
	FMR100	7.76%	22.57%	9.17%	19.53%	6.00%	15.00%
	FMR1000	13.93%	41.11%	11.67%	27.50%	13.33%	25.00%
	ZeroFMR	16.43%	42.86%	12.50%	30.00%	16.67%	28.33%
	ZeroFNMR	41.71%	97.29%	82.78%	84.17%	69.31%	94.72%
DB4_B	EER	0.83%	4.29%	0.36%	1.67%	0.00%	1.67%
	FMR100	0.61%	8.57%	0.00%	1.67%	0.00%	1.67%
	FMR1000	1.43%	9.49%	1.67%	2.08%	0.00%	2.91%
	ZeroFMR	2.14%	10.00%	1.67%	4.17%	0.00%	3.33%
	ZeroFNMR	1.60%	96.46%	0.49%	68.89%	0.00%	34.17%
Average	EER	2.37%	6.96%	1.53%	4.73%	1.35%	3.87%
	FMR100	3.04%	11.70%	3.52%	6.97%	1.92%	5.84%
	FMR1000	5.78%	16.91%	4.95%	9.81%	4.25%	9.45%
	ZeroFMR	6.97%	17.74%	5.21%	11.67%	5.63%	10.83%
	ZeroFNMR	26.12%	89.41%	21.20%	71.22%	20.47%	60.33%

Chapter VI

Conclusion and Future Works

A fingerprint identification method based on features of dual-image template, weighting scheme and improved matching algorithm is proposed in this thesis. The proposed method improves matching accuracy by collecting two fingerprints from the same finger as the template, using the information from structures of extracted minutiae, and optimizing the performance of dual-template by weighting scheme. Based on test results by using FVC2002 databases, the performance of fingerprint identification is improved by using two images as the template instead of using one image. Results also show that, when two images are used as the template, the requirement on image quality can be relaxed. Improving matching algorithm and a more sophisticated weighting of similarity scores further improve the identification performance.

The improved matching algorithm and weighting scheme bring about some noticeable matching accuracy improvement. Further improving the matching algorithm and weighting scheme can further enhance the performance of the proposed fingerprint identification method.

Enhancing the fingerprint image after enrollment can be another way to improve the identification accuracy. For example, image filters can abate the low-quality part of the image and strengthen the contrast between ridges and furrows to identify more valid minutiae. Therefore, developing better image enhancement algorithm will be a logical next step of this research project.

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