Chapter 3

Research Methodology

This research uses experimental approach to solve the interoperability issue in fingerprint recognition systems and uses Equal Error Rate (EER) as a measure of system performance. We compare images from different sensors and analyse their effect on fingerprint system performance. Increase in EER value when images from two different sensors are compared vs. when images from the same sensor are compared, indicates that interoperability issue exists between the sensors.

To overcome the interoperability issue, we have devised two novel algorithms, one at the fingerprint image level and another at the fingerprint matcher level. The effectiveness of our algorithms is determined on the basis of the improvement in EER.

This chapter outlines our research methodology, including methods used for fingerprint feature extraction, matching algorithms, fingerprint database management, data analysis and data pruning procedures.

3.1 Fingerprint Feature Extraction

In this section, we explain the feature extraction methods such as extraction of minutiae points, core point identification, line or axis of symmetry identification and newly defined ‘base point’ identification. All these methods are used for both the algorithms proposed in this research.

3.1.1 Fingerprint Pre-processing and Minutiae Extraction

In order to extract reliable minutiae points, some preprocessing needs to be performed on raw fingerprint images. Fig.3.1. illustrates the common procedure for minutiae
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Figure 3.1: Minutiae extraction process: (a) Gray scale image (FVC2002 DB1 19.1) (b) Phase image (c) Skeleton image (d) Minutiae image [16]

extraction. Each minutia point is expressed in the form of \( \{X, Y, \theta\} \). Where, \( \{X, Y\} \) are the spatial co-ordinates of the minutiae points and \( \theta \) is the orientation angle as per the ISO 19794-2 format. We extract \( \{X, Y, \theta\} \) feature using short-time Fourier transform (STFT) fingerprint enhancement technique and chain code minutiae extraction as explained by J. Abraham et al [119]. NIST’s mindtct algorithm [17] extracts minutiae features in \( \{X, Y, \theta, Q\} \) format. Where, \( Q \) is the quality of the minutiae point.

3.1.2 Core Point Identification

Core point is defined as the northern most singularity point in fingerprint image [6]. Accurate core point identification is still a challenging task for biometric research community. Review of some of the existing core point identification techniques is given in Section 2.4.3. We have developed an algorithm for core point identification and the same algorithm is used in both solutions proposed in this research. Steps involved in our core point identification algorithm are as below:

1. Calculate orientation field \( O(i, j) \) from fingerprint image as per the method explained by L. Hong et al [9]. The value of the orientation field, \( O(i, j) \), varies from 0 to \( \pi \). Fig.3.2(b) shows the orientation image.

2. Apply gradient filter to the orientation image \( O(i, j) \) as shown below:

\[
O_f(i, j) = \begin{cases} 
1, & \left| O(i, j) - O(i, j + 1) \right| \geq Th \\
0, & \text{Otherwise}
\end{cases}
\]
This step is used to find sudden intensity changes in the orientation image. As shown in Fig.3.2(c), The value of Th is set to a very small number like 2 or 3 to extract continuous trace of sudden orientation changes in the gradient filtered image.

3. Remove noise in gradient filtered image. As shown in Fig.3.3(a), gradient filtered image $O_f$ has some false traces of high gradient regions, highlighted with circles. These false high gradient regions are filtered using Physical ROI. Calculation of Physical Region of Interest(ROI) is explained in detail in section 3.2 step 1. Here, we eliminate the region outside the physical ROI as shown below:

$$O_{fRoi}(i, j) = \begin{cases} O_f(i, j), & \text{if } pROI(i, j) = 1 \\ 0, & \text{if } pROI(i, j) = 0 \end{cases}$$

4. Remove discontinuities in ROI filtered gradient image. As shown in Fig.3.3(b), the ROI filtered gradient image $O_{fRoi}$ may have some discontinuities because of the noise. These minute discontinuities are smoothen by the morphological operations. Fig.3.3(c) shows the smooth ROI filtered gradient image $O_{fRoiS}$.

5. Trace the continuous line in the $O_{fRoiS}$ in the vertically downward direction till the discontinuity is identified. The first discontinuity identified from vertically downward trace is a core point. Fig.3.4 illustrates the identified core point from the given input fingerprint image.

**Figure 3.2:** Input image (FVC2002 Db1 a 6.2.tif) is enhanced and orientation image is calculated using [9] approach
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(a) Filtered gradient of Orientation Image $O_f$
(b) ROI filtered gradient image $O_{fRoi}$
(c) Smoothed ROI filtered gradient image $O_{fRoiS}$

**Figure 3.3:** Process of identification of smoothed ROI filtered gradient image $O_{fRoiS}$

(a) Tracing of smooth ROI filtered gradient image $O_{fRoiS}$ in the vertically downwards direction
(b) Identified discontinuity in smooth ROI filtered gradient image $O_{fRoiS}$ image
(c) Identified core point

**Figure 3.4:** Process of identification of core point

Our algorithm for core point identification is tested on FVC2002 Db 1a with manual inspection method. Out of 800 images, this algorithm could find accurate core point for 748 images. Thus the accuracy of this algorithm is 93.5% for the given database.

### 3.1.3 Line(axis) of symmetry identification

Importance and the usage of line or axis of symmetry in fingerprint image has received limited attention in fingerprint biometrics literature. Cho et al [28] defines fingerprint symmetry axis as a line which provides the largest symmetry measure
between ridge range directions. We propose that, fingerprint minutiae points have a natural directional flow and their distribution is roughly symmetrical about virtual line. Line of symmetry is a virtual line which passes through the core and divides fingerprint image into two parts maximizing the symmetry between them. Fig.3.5 illustrates the concept of line of symmetry in all basic types of the fingerprint images. We have developed an algorithm to calculate line or axis of symmetry of fingerprint image and use it to extract some extra information about each minutiae point.

![Figure 3.5: Illustration of line of symmetry in all six basic classes of the fingerprints](image)

Steps involved in line of symmetry extraction algorithm are as below:

1. Calculate orientation image $O(i,j)$ as per the method explained by L. Hong et al [9].

2. Calculate core point as explained in section 3.2.1.

3. Select the core point as a starting node and draw a small line segment with fixed distance 'd' at core point with angle equal to the ridge orientation at core point i.e. $O(\text{Core}_x, \text{Core}_y)$.

4. Select the next node as the end point of the previous line segment and draw next line segment of fixed distance 'd' with angle equal to the ridge orientation at that point.

5. Follow the above procedure till end of image is reached.
6. The line joining the core point and last node is called as line of symmetry (Refer Fig. 3.6).

Pseudo code to calculate line of symmetry is illustrated in Fig.3.7. Fig.3.8 illustrates the line of symmetry detection for various fingerprint images from MCYT-100 database.
\textbf{Require:} \textit{len} be the constant length of ridge orientation lines

\begin{itemize}
  \item $FirstNode_x = Core_x$ \text{X co-ordinate of Core point}
  \item $FirstNode_y = Core_y$ \text{Y co-ordinate of Core point}
  \item $O_{ij}$ be the local ridge orientation image
\end{itemize}

\textbf{Ensure:} Physical ROI is estimated

\begin{itemize}
  \item $NextNode_x = FirstNode_x$
  \item $NextNode_y = FirstNode_y$
\end{itemize}

\textbf{while} $ROI(NextNode_x, NextNode_y) \neq 0$ \textbf{do}

\begin{itemize}
  \item $x_{offc} = \frac{ln}{2} \times \cos\{O(NextNode_x, NextNode_y)\}$
  \item $y_{offc} = \frac{ln}{2} \times \sin\{O(NextNode_x, NextNode_y)\}$
  \item $\Delta_x = x_{offc} \times 2$
  \item $\Delta_y = y_{offc} \times 2$
  \item $NextNode_x = NextNode_x + \Delta_x$
  \item $NextNode_y = NextNode_y + \Delta_y$
\end{itemize}

\textbf{end while}

Draw line joining $C(Core_x, Core_y)$ and $\textbf{EndNode}(NextNode_x, NextNode_y)$

\textbf{Figure 3.7:} Pseudo code to calculate line of symmetry
Figure 3.8: Illustration of line of symmetry detection for various fingerprint images from MCYT-100 database [1]
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The manual inspection of the line or axis of symmetry extraction algorithm shows that this method is able to extract line of symmetry for good quality fingerprint images where fingerprint ridge structure is consistent.

3.1.4 Base Point Identification

We define a new term called ‘base point’ B which is a point where line of symmetry intersects with the base line of the image. Fig.3.9 illustrates the process of identification of base point. Pseudo code for detection of base point is mentioned in Fig.3.10. Base point is used as an additional reference point in both of the solutions in this research along with the core point.
Figure 3.9: Examples of base point detection
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Figure 3.10: Pseudo code to calculate base point

3.2 Quality of fingerprint images

To study the interoperability between fingerprint images captured from different sensors, it is important to eliminate the effect of image quality. The most popular fingerprint quality estimation algorithm is NIST’s NFIQ [4]. It generates discrete quality scores ranging from 1 to 5. According to [4] NFIQ Score-1 corresponds to the excellent quality fingerprint image and NFIQ Score-5 corresponds to the poor quality image. However, we observe that, in some cases NFIQ score 1 doesn’t corresponds to the excellent quality fingerprint image. Fig.2.10 shows some of the poor quality fingerprint images but their NFIQ score is 1. Thus, for our interoperability study, we couldn’t use NFIQ as an estimator to classify fingerprint images based on their quality. We designed our new fingerprint quality estimation algorithm.

We observed that, NFIQ has a poor co-relation with Bozorth3 matching algorithm (Refer. Fig.3.17) i.e. we cannot predict performance of matching algorithm from the quality score given by NFIQ. One of the limitations of NFIQ is to estimate quality score of partial fingerprint images. It doesn’t consider location of core point while estimating the quality score. Our newly designed quality estimator identify effective fingerprint region which has significant impact in the matching process. Our estimator
is based on measure of continuity and smoothness of ridge structure. Detailed steps of our novel quality estimation algorithm are as below.

**Step 1. Identification of Physical Region of Interest**

- Given image is enhanced using the Gabhor filters [9] and then converted into a binary image (Refer Fig.3.11(b)).

- The Region of Interest (ROI) is obtained by using morphological operations (closing and erosion) on the binary image (Refer Fig.3.11(c)).

- The ROI is fixed inside a bounding rectangle by tracing the first occurrence of white pixel from all four directions to determine physical centre (Refer to Fig.3.12(a)). Physical centre is a point where the two imaginary diagonals of the bounding rectangle intersect each other (Refer to Fig.3.12(b)).

- The physical ROI is then calculated by the following procedure:

  As shown in Fig.3.11(c), the ROI obtained from morphological operations is not in uniform shape. Let $r$ be the width of the bounding rectangle then we consider Physical ROI as a circular region around the physical centre with a radius of $(r/2) \times 0.8$. Multiplying factor 0.8 is an arbitrary constant selected so as to capture entire fingerprint area with minimum effect of spurious minutiae points near the edges of fingerprint image. Fig.3.12 (c) shows the physical ROI of the input image shown in Fig.3.11 (a).

![Image](a) Input image  | ![Image](b) Processed binary image  | ![Image](c) ROI of binary image

**Figure 3.11:** Input image (FVC2002 Db1 a 6_2.tif) is enhanced using Gabhor filters [9] and ROI is obtained using morphological operations
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Step 2: Identification of Core Point

As per the algorithm explained in section 3.1.2.

Step 3: Identification of Biometric Region of Interest

We defined a term called 'Biometric ROI' which is a circular region around the core point with a constant predefined radius. We set the radius of Biometric ROI as \((r/2) \times 0.8\). Fig. 3.13 illustrates the Biometric ROI and Physical ROI centered at core point and physical centre respectively. We define overlapping area between the two ROIs as the Platinum Region, as it is the most influential region in the fingerprint image. Platinum Region has high impact on fingerprint matching and thus, it is most important region for quality assessment.

\[
Overlap \ Factor(OL) = \frac{(\text{Biometric ROI} \cap \text{Physical ROI})}{\text{Physical ROI}}
\]

Step 4: Calculation of Reliability

Reliability is a measure of continuity and smoothness of fingerprint ridges [6]. We use reliability as a parameter to estimate fingerprint image quality. The process of identification of reliability is as follows [6].

1. Calculate orientation angle \(\theta_{ij}\) as per the method proposed by Jain et al [70]

2. Calculate the reliability \(r\) as
Figure 3.13: Identification of Biometric ROI and overlapping Platinum Region

\[
ri_j = \text{coherence}(\theta_{ij}) = \frac{\sqrt{(G_{xx} - G_{yy})^2 + 4G_{xy}^2}}{G_{xx} + G_{yy}}
\]

reliability ‘r’ varies from 0 to 1. We propose that, the minutiae features are accurately calculated only when the reliability ‘r’ value is more than 0.5.

3. Classify the fingerprint image into two parts, reliable and non-reliable based on the following filtering rule:

\[
r_f(i, j) = \begin{cases} 
1(\text{Relible}), & \text{if } r(i, j) \geq 0.5 \\
0(\text{Non-relible}), & \text{Otherwise}
\end{cases}
\]

Fig.3.14 shows filtered reliability images of best quality, dry impression and wet fingerprint impression respectively.

**Step 5: Calculation of Quality Score**

In the proposed quality estimation approach, higher importance is given to the pixels in platinum region than those in the rest of Physical ROI because minutiae points laying in platinum region has significant impact on matching process. Thus, having less reliable pixels inside the platinum region is not at all desirable for a good quality
fingerprint image. While designing the quality estimator, we assign different weights for pixels in platinum region than those in rest of Physical ROI. Less reliable pixels in *platinum region* should drop the quality score of entire fingerprint image with large extent. Similarly, the high reliable pixels in *platinum region* correspond to very good quality image. In our approach, pixels outside the physical ROI are not considered in the quality score calculation.

Let,

- $Q_{cHigh}$: number of pixels in *platinum region* with Reliability ‘$r’ \geq 0.5$
- $Q_{High}$: number of pixels in Physical ROI but not in *platinum region* with Reliability ‘$r’ \geq 0.5$
- $Q_{cLow}$: number of pixels in *platinum region* with Reliability ‘$r’ \leq 0.5$
- $Q_{Low}$: number of pixels in Physical ROI but not in *platinum region* with Reliability ‘$r’ \leq 0.5$

$$\text{Quality Score}(Q) = \left( \frac{A \ast (Q_{cHigh}) + (Q_{High})}{(A \ast (Q_{cHigh}) + (Q_{High}) + (B \ast (Q_{cLow}) + A \ast (Q_{Low}))} \right) \ast \text{Overlap Factor} \ast 100$$

As shown in the above formula, globally we calculate ratio of number of reliable pixels with all the pixels in fingerprint image. The role multiplying factor $A$ is to boost the quality score if number of reliable pixels in platinum region are more. The role multiplying factor $B$ is to bring down the quality score if number of non-reliable pixels in platinum region are more. As explained above, having non-reliable pixels in platinum region is not at all desirable for a good quality fingerprint image. Thus, $A$ and $B$ are the weights in the quality estimation formula such that $B \gg A$.

Fig.3.15 illustrates the complete procedure of quality estimation.
Figure 3.14: Analysis of best quality fingerprint image. Most of the fingerprint area is reliable (green) and very small area near singularities is non-reliable (blue)
Figure 3.15: Quality estimation of best quality fingerprint image

Figure 3.16: Proposed quality measure overcomes the limitations of NIST’s NFIQ quality measuring software, scores are, 1 for best and 5 for worst
Comparison with Benchmark Algorithm NFIQ

Limitations of NFIQ algorithm have already been reported by many researchers (Refer Fig.2.10). The primary issue of the NFIQ is that, sometimes it assigns best quality score to very poor quality images. Fig.3.16 shows the image wise comparison of the proposed quality estimation algorithm with NFIQ. Efficiency of the quality estimating algorithm is rightly tested by it’s correlation with matching score.

Fig.3.17 shows the performance comparison of NFIQ and proposed quality estimation algorithm on FVC 2002 Db1 a. Here, the genuine match scores are plotted against quality scores ( e.g. quality 1 image is matched with quality 1 only and quality 2 image is matched with quality 2 only and so on). As shown in the figure, there is no correlation of NFIQ scores with genuine match scores. Whereas, proposed quality estimation algorithm gives fair correlation with the genuine match scores. In other words, if the proposed quality estimation algorithm suggests image quality is excellent then chances of false reject are very low (interoperability scenario is not considered here).
Figure 3.17: Performance comparison of NFIQ and Proposed quality estimation algorithm on FVC 2002 Db1 a
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3.3 Fingerprint Database Management

Fingerprint interoperability has received limited attention in biometrics literature. Hence, non-availability of a standard database was the biggest hurdle in our research. Some researchers have reported their fingerprint interoperability related work using in-house private databases which are not openly accessible for research community. For example, Jain et al [15] and Ross et al [114] used Michigan State University (MSU) private database with one optical and one solid-state fingerprint sensor. S.K. Modi has given statistical analysis of interoperability of matching algorithms [118] on a private database with nine fingerprint sensors (optical, capacitive and thermal). Marasco et al [120] used private database of four optical sensors. Gafurov et al [121] have published in-house semipublic multi-sensor fingerprint database having six different sensors.

Few multi-sensor fingerprint databases (Chinese Academy of Science Database, MCYT-100 database etc.) are freely available for the academic research community, but they are not identified as standard benchmark databases. They contain some images which are of bad quality (Refer to Fig.3.19). As performance of fingerprint recognition systems also decreases because of the bad quality fingerprint images, in order to study the effect of interoperability issue, bad quality images should pruned out.

In this research, we have used the Chinese Academy of Science database and MCYT-100 database. We performed fingerprint image quality analysis on both of these databases and chose best quality images for interoperability study. We have also used our in-house private database with two optical sensors (1. single finger scanner 2. Multi-finger scanner). Detailed information of these databases is given in the following sub-sections.

3.3.1 Chinese Academy of Science database

Chinese Academy of Science Multi-Sensor fingerprint database [18] consists of around eighty thousand fingerprint images from ninety subjects. There are nine different sensors using optical or capacitive technology. Nine subsets are created (one per sensor) with the same eight fingers (thumb, index finger, middle finger and ring finger of both hands) by 90 people and 12 impressions per finger \((90 \times 8 \times 12 \times 9 = 77,760\) images). Table 3.1 gives detail information about the database.
Figure 3.18: Sample fingerprint images from: a) Chinese Academy of Science database b) MCYT-100 database c) University of Pune database
### Table 3.1: Chinese Academy of Science Multi-Sensor fingerprint database

<table>
<thead>
<tr>
<th>Sub Database</th>
<th>Sensor Name</th>
<th>Sensing Technology</th>
<th>Interaction Type</th>
<th>Image Size</th>
<th>Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>DB1</td>
<td>FX3000</td>
<td>Optical Press</td>
<td>400x560</td>
<td>569dpi</td>
<td></td>
</tr>
<tr>
<td>DB2</td>
<td>V300</td>
<td>Optical Press</td>
<td>640x480</td>
<td>500dpi</td>
<td></td>
</tr>
<tr>
<td>DB3</td>
<td>URU4000B</td>
<td>Optical Press</td>
<td>500x550</td>
<td>700dpi</td>
<td></td>
</tr>
<tr>
<td>DB4</td>
<td>AES2051</td>
<td>Optical Unfix</td>
<td>500dpi</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DB5</td>
<td>ATRUA</td>
<td>Capacitive Sweep</td>
<td>124x400</td>
<td>250dpi</td>
<td></td>
</tr>
<tr>
<td>DB6</td>
<td>SW6888</td>
<td>Capacitive Sweep</td>
<td>288X384</td>
<td>500dpi</td>
<td></td>
</tr>
<tr>
<td>DB7</td>
<td>AES3400</td>
<td>Capacitive Press</td>
<td>144x144</td>
<td>500dpi</td>
<td></td>
</tr>
<tr>
<td>DB8</td>
<td>FPC1011C</td>
<td>Capacitive Press</td>
<td>152x200</td>
<td>363dpi</td>
<td></td>
</tr>
<tr>
<td>DB9</td>
<td>TCRU26</td>
<td>Capacitive Press</td>
<td>208x288</td>
<td>500dpi</td>
<td></td>
</tr>
</tbody>
</table>
3.3.2 MCYT-100 fingerprint database

MCYT bimodal database [1] consists of fingerprints and signatures. Fingerprint acquisition is done by two sensors, optical and capacitive. 12 samples of each finger are acquired from 100 subjects using two different sensors (optical and capacitive). Therefore, $100 \times 12 \times 10 \times 2 = 24000$ fingerprint samples are included in MCYT-100 database. Table 3.2 gives detailed information about the database.

<table>
<thead>
<tr>
<th>Sub Database</th>
<th>Sensor Name</th>
<th>Sensing Technology</th>
<th>Interaction Type</th>
<th>Image Size</th>
<th>Image Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>DB1</td>
<td>Digital Persona [122]</td>
<td>Optical</td>
<td>Press</td>
<td>256 x 400</td>
<td>500dpi</td>
</tr>
<tr>
<td>DB2</td>
<td>Precise Biometrics [123]</td>
<td>Capacitive</td>
<td>Press</td>
<td>300 x 300</td>
<td>500dpi</td>
</tr>
</tbody>
</table>

*Table 3.2: Details of MCYT-100 fingerprint database [1]*

3.3.3 University of Pune In-house Database

Pune University multi-sensor bimodal database is an in-house private database consists of fingerprints and iris. Fingerprint acquisition is done by two optical sensors with same resolution, but sensor-1 is a single finger scanner and sensor-2 two is multi-finger (slap) scanner. Table 3.3 gives detail information about the database.

<table>
<thead>
<tr>
<th>Sub Database</th>
<th>Sensor Name</th>
<th>Sensing Technology</th>
<th>Interaction Type</th>
<th>Image Size</th>
<th>Image Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>DB1</td>
<td>Sensor-1</td>
<td>Optical</td>
<td>Single-Finger Press</td>
<td>300 x 300</td>
<td>500dpi</td>
</tr>
<tr>
<td>DB2</td>
<td>Sensor-2</td>
<td>Optical</td>
<td>Multi-Finger Press</td>
<td>Unfix</td>
<td>500dpi</td>
</tr>
</tbody>
</table>

*Table 3.3: Pune university Multi-Sensor fingerprint database*

3.3.4 Quality Analysis

In MCYT-100 database, we found that, there are 61% of images captured from optical sensor are of best quality (NFIQ=1) whereas only 13% of images captured from
capacitive sensor are of best quality (NFIQ=1). We also found that, out of 1000 classes (100 subjects with 10 fingers) there are only 16 classes for which all 12 impressions form both the sensors are of best quality (NFIQ=1). Fig. 3.19 shows some of the samples of very poor quality fingerprint images form MCYT-100 database. Thus for interoperability study we had to prune out bad quality images.

![Figure 3.19: Samples of very poor quality fingerprint images form MCYT-100 database](image)

### 3.4 Data Pruning

After analysing the data we perform the data pruning based on following parameters:

- Quality of all fingerprint images should be *excellent* i.e. 1 as per the proposed quality estimation method
- Fingerprint images from only touch (press) type sensors are considered
- Fingerprint images from optical and capacitive technology are considered
- Fingerprint images having minimum resolution of 500 dpi are used
- Fingerprint images having minimum size of 200 x 200 pixels are considered

### 3.5 Summary

To study interoperability issue we used three databases, Chinese Academy of science database, MCYT-100 database and University of Pune private database. NIST’s Bozorth3 fingerprint matching algorithm is used as benchmark for this research. Equal
Error Rate is used as a performance measure. Effect of poor quality fingerprint images on interoperability issue is eliminated by proposed quality estimator.