CHAPTER 2

PREPROCESSING AND FEATURE EVALUATION

2.1 DIGITAL IMAGE PROCESSING

The second chapter deals with image pre processing by using Gabor filter and evaluating normal and overlapped fingerprint images. Digital Image Processing is an emerging research field which is used to progress and advance images for a variety of real time applications. Numerous techniques have been deployed in digital image processing field for the past four to five decades. Digital image processing systems are getting fashionable due to simple accessibility and availability of powerful PC’s, large size memory devices and graphical software’s etc.

Image processing is a rapidly growing technology, with its applications in all domains such as forensic studies, medical imaging, textiles, film industry etc. Image processing is a process that deals with conversion of an unprocessed (i.e.) raw image into an appropriate digital form and it performs number of operations based on its applications of an image. The raw image is obtained from different platforms such as fingerprint image from crime scenes and sensors/scanners that contain some more deficiencies or flaws.

To get the originality of information, the raw fingerprint image has to undergo various phases of image processing. The area of image processing is classified into five most important groups namely: representation, sharpening and restoration, image retrieval, pattern measurement and image recognition. Generally there are eight phases involved in image processing and
they are acquisition, pre processing, feature evaluation, segmentation, feature extraction, representation, description and recognition. The digital image is defined as $f(i, j)$ where $i$ and $j$ are the coordinates in $x$ and $y$ directions. The amplitude of $f(i, j)$ at any point is given as the pixel value of that point of an image.

2.2 PREPROCESSING

Image preprocessing is an important process to prepare the image for operations on images at the most minimal level of abstraction. Preprocessing is a process to enhance the visual appearance i.e. quality of an image and it is more important for an automated fingerprint recognition system. The intention of preprocessing is to improve the image information and enhance the features of an image that is relevant for processing the images for next level. The major steps involved in image preprocessing (Choonwoo et al 2011) are noise removal by using normalization, image enhancement and segmentation is shown in Figure 2.1. The input image is preprocessed by applying Gabor filtering.

![Figure 2.1 Preprocessing and Feature Evaluation](image-url)
2.2.1 Normalization

The input sample is preprocessed by the normalization process which is necessary to standardize all features to the same level. Normalization is to reduce distinction in gray levels. The input fingerprint image is divided into a number of blocks and it calculates the gray-scale variance for each block in the image. It is assumed that all the images are acquired at a resolution of 500 dots per inch (dpi). Gabor filter is used to remove all types of noises and improve image enhancement (Lavanya et al 2009). Normalization is applied to the intensity value of the image for mean and variance.

The normalized image \( N(i, j) \) is defined in Equation (2.1).

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

(2.1)

The mean \( M(I) \) and the variance \( \text{VAR}(I) \) are calculated by using Equation (2.2) and (2.3)

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

(2.2)

\[
\text{VAR}(I) = \frac{1}{N^2} \left( \sum_{i=0}^{N-1} I(i, j) - \sum_{j=0}^{N-1} M(I)^2 \right)  
\]  

(2.3)

where \( I(i, j) \) is an input image. The normalized image is given in Figure 2.2.
2.2.2 Image Enhancement

Image enhancement techniques are used to reduce noise and enhance structures of ridges and valleys for minutiae detection. A fast fingerprint enhancement algorithm is used to improve the clarity of ridges and valley structures of low quality input fingerprint images. There are two basic methods available for fingerprint enhancement as given in Figure 2.3.

\[ \text{Input Image} \rightarrow \text{Preprocessing} \rightarrow \text{Image Enhancement} \rightarrow \text{Segmentation} \rightarrow \text{Feature Evaluation} \]

Figure 2.3 Block diagram for fingerprint enhancement

i. Spatial Domain Method: It operates directly on the pixels of the image and performs some operation on the pixels in the neighbourhood of \( f(x, y) \) in the input image where \( x, y \) are pixel positions and the enhanced image \( \hat{f} \) is the result of \( f \).

ii. Frequency Domain Method: It operates on the Fourier transformation of an image. The Fourier transform of the image is computed.
It multiplies the Fourier transform result by using Gabor filter and enables the inverse transform to generate the improved fingerprint image. The enhanced and binary image is given in Figure 2.4

![Enhanced and Binarized image](image)

**Figure 2.4 Enhanced and Binarized image**

### 2.2.3 Segmentation

A critical step in automatic fingerprint recognition deals with accurate segmentation of fingerprint images. Segmentation in lower quality images faces several challenging technical problems. Especially in lower quality overlapped images, finding the region mask is very important. Segmentation is a technique which is used to decide whether the part of the image either belongs to the foreground or to the background. A number of fingerprint segmentation algorithms are available, which can be divided into block-wise methods and pixel-wise methods. Thresholding is one of a distinguished technique for overlapped fingerprint segmentation which assigns values 0 or 1 to each pixel of an input image based on comparison with threshold value $T$.

$$f_T(i,j) = \begin{cases} 1, & \text{iff } f(i,j) > T \\ 0, & \text{iff } f(i,j) \leq T \end{cases}$$  \hspace{1cm} (2.4)
where $f_T(i,j)$ is the segmented image. Global thresholding is a suitable approach which is capable of estimating the threshold value for each image. It is an iterative algorithm and the detailed steps for this algorithm are as follows

1. Assign initial value for the variable $T$
2. Segment the image by using $f_T(x, y)$.
3. Obtain two groups of pixels $T_1, T_2$.
   - $T_1$ consists of all pixels with intensity values $> T$
   - $T_2$ consists of all pixels with intensity values $\leq T$
4. Compute the average intensity values $i_1, i_2$ for the pixels in $T_1$ and $T_2$.
5. Compute the new threshold value by using the following
   $$ T = \frac{1}{2} (i_1 + i_2) $$
6. Repeat step 2 through 5 until the difference between values of $T$ in successive iterations is smaller than a predefined parameter $\Delta T$.

An overlapped image is segmented from the background images. Overlapped fingerprint image contains only two component fingerprints. The regions of the two component fingerprints are marked in an automatic manner which partitions an image into distinct non-overlapping regions. The label is assigned to each pixel in the image and separate objects within the curtained threshold value. The region of connected pixels is computed with similar label values and it removes unwanted regions.

2.3 **FINGERPRINT FEATURES**

Fingerprint image can be viewed as ridges in black colour and valleys in white colour. It is an iterative algorithm and the detailed steps for this algorithm are as follows
**Terminology 1**: Level 1 features are a macro detail of ridge flow and pattern types. The level 1 feature is orientation, singular points, loop, whorl and arch is given in Figure 2.5 and 2.6.

**Terminology 1.1**: Orientation field is defined as the direction of the ridges in fingerprint.

**Terminology 1.2**: The singular points are the discontinuities in the orientation field. Every fingerprint contains two types of singular points.

**Terminology 1.2.1**: Core is the uppermost or topmost interior point of the innermost curving ridge.

**Terminology 1.2.2**: Delta is the centre of triangular regions where three ridge flows meet. Each fingerprint contains maximal of 2 core points and 2 delta points.

**Figure 2.5 a. Orientation field b. Singular points core and delta.**

**Terminology 1.3**: Loop is defined as the ridges starting on one side of the finger, reaching the center of the finger and then coming back to the same side.

**Terminology 1.4**: Right loop is defined as the ridges starting and ending in right side of the finger.
Terminology 1.5: Left loop is defined as the ridges starting and ending in left side of the finger.

Terminology 1.6: Twinned loop, the recurring ridges present two loop formations which are separate and apart.

Terminology 1.7: Whorl is defined as the concentric circles formed by the ridges.

Terminology 1.8: Arch is defined as the ridges starting on one side of the finger and the center of the finger to the other side.

Terminology 1.9: Tented arch consists of at least one rising ridge.

Figure 2.6 a. Loop b. Left loop c. Right loop d. Twined loop e. Whorl f. Arch and g. Tented Arch

Terminology 2: Level 2 features are minutiae points like bifurcations and endings.

Terminology 2.1: Bifurcation is defined as single ridge that is split into two ridges.
**Terminology 2.2:** Ridge ending is defined as the termination of ridges.

Level 2 features are shown in Figure 2.7 where the colour image in red represents ridge ending and colour image in blue represents the ridge bifurcation.

**Terminology 3:** Level 3 features incorporate the intra ridge details. The details are ridge width, shape, pores and scars.

![Figure 2.7 Minutiae Feature](image)

**Terminology 3.1:** Pores are located on ridges as shown in Figure 2.8 where yellow circle represents pore. A pore can be visualized as open or closed depending on pressure.

**Terminology 3.2:** Closed pore is an isolated dot appeared in the ridge.

**Terminology 3.3:** Open pore is associated with one or more of the valleys that are surrounding it.
Terminology 4: Divergence is defined as it is the point where parallel ridges either spread apart or join collectively.

Terminology 5: Lake or Enclosure is defined as a ridge that splits into two branches and then comes together again shortly afterwards.

2.4 ORIENTATION FIELD ESTIMATION

The orientation field of an image represents the direction of the ridges and it is estimated by using Fourier analysis. The input image is typically split into a number of non-overlapping blocks and it computes its gradient $\nabla I$ of an image. The gradient $I_x$ and $I_y$ is computed by using sobel filters (Gonzaga et al 2008). The sobel filter window is given below

$$S_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}, \quad S_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

The orientation of the gradient can be estimated by using the following Equations (2.5) and (2.6)

$$\|\nabla I\| = \sqrt{I_x^2 + I_y^2} \quad (2.5)$$
\[ \text{arg}(I) = \tan^{-1} \left( \frac{l_x}{l_y} \right) \] (2.6)

The block orientation can be calculated from the pixel gradients by using averaging method. The pixel wise orientation is obtained from 16x16 size block starting at central pixel. The pixel wise gradient magnitude is calculated as \( \partial_x (u,v) \) and \( \partial_y (u,v) \) along x and y directions as given in Equation (2.7), (2.8) and (2.9)

\[ V_x(i,j) = \sum_{u=i-w}^{i+w} \sum_{v=j-w}^{j+w} 2 \partial_x (u,v) \partial_y (u,v) \] (2.7)

\[ V_y(i,j) = \sum_{u=i-w}^{i+w} \sum_{v=j-w}^{j+w} (\partial_x^2 (u,v) - \partial_y^2 (u,v)) \] (2.8)

\[ \theta(i,j) = 0.5 \tan^{-1} \left( \frac{V_x(i,j)}{V_y(i,j)} \right) \] (2.9)

where \( w \) is block size, \( \partial_x \) and \( \partial_y \) are the gradients in horizontal and vertical directions respectively. Sobel operators have been used for computations of \( \partial_x \) and \( \partial_y \), where \( \theta (i,j) \) is the least mean square estimation at each block of center pixel \( \theta \). Gabor filter is defined by a sinusoidal plane wave in the spatial domain (Lavanya et al 2009). The Gabor filter is defined in two dimensional functions that has the form given in Equation (2.10).

\[ G(x, y, \theta, f) = \exp \left\{ \frac{-1}{2} \left[ \frac{x_\theta^2}{\sigma_x^2} + \frac{y_\theta^2}{\sigma_y^2} \right] \right\} \cos(2\pi fx_\theta) \] (2.10)

where \( x_\theta = x\cos\theta + y\sin\theta \), \( y_\theta = -x\sin\theta + y\cos\theta \), \( f \) is the frequency, \( \theta \) is the orientation \( \sigma_x \) and \( \sigma_y \) are the standard deviations of the Gaussian envelope along the x and y axes. The \( x_\theta \) and \( y_\theta \) is calculated by using the Equation (2.11)


\[
\begin{bmatrix}
  x_\theta \\
y_\theta
\end{bmatrix} =
\begin{bmatrix}
  \cos (90^0 - \theta) & \sin (90^0 - \theta) \\
  -\sin (90^0 - \theta) & \cos (90^0 - \theta)
\end{bmatrix}
\begin{bmatrix}
x \\
y
\end{bmatrix} =
\begin{bmatrix}
  \sin \theta & \cos \theta \\
  -\cos \theta & \sin \theta
\end{bmatrix}
\begin{bmatrix}
x \\
y
\end{bmatrix}
\]

(2.11)

Image enhancement is done by using Gabor filters (Gonzaga et al 2008). For these necessary four parameters are f, \( \theta \), \( \sigma_x \) and \( \sigma_y \). The lateral and top view of Gabor filter is shown in Figure 2.9. The graphical representation of Gabor filter is shown in Figure 2.10 which is defined by the parameters \( f=1/5, \theta=135^\circ \) and \( \sigma_x=\sigma_y=3 \).

![Gabor filter diagram](image)

**Figure 2.9 Lateral and top view of Gabor filter**

Gabor filters are used to construct four component images with values of \( \theta=0^\circ, 45^\circ, 90^\circ, \) and \( 135^\circ \)) as shown in Figure 2.10.
Each pixel \([x, y]\) in the image is convolved in the spatial domain with filter \(G_{ij}(x, y)\) such that \(\theta_i\) is the discretized orientations, \(\{\theta_i | i=1,2,\ldots d_o\}\) closest to \(\theta_{xy}\) where \(d_o\) is the number of discrete orientations and \(f_j\) is the discretized frequency \(\{f_j | i=1,2,\ldots d_f\}\) closest to \(f_{xy}\) and where \(d_f\) is the number of discrete frequencies. The sample Gabor filter is set for fingerprint image with discretize orientation and frequency values, \(d_o = 8, f_j = 3\) are shown in Figure 2.11.

Figure 2.10  Gabor filters a. 0° Orientation b. 45° Orientation c. 90° Orientation and d. 135° orientation
Figure 2.11  Graphical representation for discretize orientation $d_o = 8$ and frequency values $f_j = 3$.

Thinning, region mask and orientation fields for non overlapped and overlapped images are calculated by using the Gabor filter as given in Figure 2.11 and 2.12.

Figure 2.12  a. Thinning  b. Region mask and c,d. Orientation fields for non overlapped image

Figure 2.13  a. Thinning  b. Region mask and c,d. Orientation fields for overlapped image
2.5 FINGERPRINT FEATURE EVALUATION

In this research work, the first, second order and third order features are investigated for normal and overlapped images. To classify overlapped and normal images, some important features such as median, variance, skewness, kurtosis, covariance, contrast, correlation, homogeneity, energy, ridge distance and ridge frequency, etc are evaluated to identify overlapped images. During feature evaluation, the features are analyzed and values from the overlapped and normal images are extracted.

2.5.1 Normal image

Fingerprint image contains either a single fingerprint or non overlapped fingerprints. Normal image \( (N_i) \) consists of a set of non overlapped ridges and valleys. It is defines as

\[
N_i = \{ r, v \}
\]

where \( r, v \) denote the non overlapped ridges and the valleys.

2.5.2 Overlapped Image

During criminal investigation, the forensic experts may collect the fingerprints from the crime scenes that are overlapped or damaged. There is a chance to acquire several fingerprints that are overlapped i.e. each fingerprint can sit on the top of each other fingerprints. Overlapped fingerprint is shown in Figure. 2.14 pose a serious challenge to existing fingerprint recognition algorithms. Overlapped image \( (O_i) \) consists of a set of overlapped ridges and valleys. It is defines as

\[
O_i = \{ r_o, v_o, n \}
\]
where \( r_0 \) and \( v_0 \) denotes the overlapped ridges, valleys and \( n \) denotes the number of overlapped ridges and valleys.

![Overlapped Fingerprint](image)

**Figure 2.14 Overlapped Fingerprint**

Overlapped fingerprints are classified into three categories namely small, medium and large based on the amount of overlapped ridges and valleys.

### 2.5.3 First order features

The first order features are the primitive features of any image. The features are median, variance, covariance, skewness and kurtosis. Let \( I(i, j) \) be an input image, \( n \) is the number of pixels, \( \mu \) is the mean, \( \sigma \) is the standard deviation and \( H(n) \) is the histogram of the image. The primary features are defined below.

#### Median

Median is defined as the measure of intensity level of all pixels presented in the image. It separates both high intensity value pixels and lower intensity value pixels. The median \( \hat{f}(x, y) \) is given in Equation (2.11).

\[
\hat{f}(x, y) = \text{median}\left\{ \frac{I(i,j)}{(i,j)} \right\}
\]  
(2.11)
Variance

The variance is defined as deviation in the gray levels from the mean and it calculates the set of remaining values that are spread out in the image by using a histogram. The variance $\sigma^2$ is given in Equation (2.12).

\[ \sigma^2 = \sum_{n=0}^{N} (n - \mu)^2 H(n) \]

It is the second order of the moment of pixel value distribution.

Skewness

Skewness is defined as the amount of histogram irregularity around the mean in the images i.e probability distribution of pixel value throughout the images. The skewness value can be positive or negative, or even undefined. Mathematically skewness $sk$ can be calculated by using Equation (2.13)

\[ sk = \frac{1}{\sigma^3} \sum_{n=0}^{N} (n - \mu)^3 H(n) \]

It is the third order of the moment of pixel value distribution.

Kurtosis

Kurtosis is defined as the probability distribution pixel values i.e sharpness of the histogram. Kurtosis $k$ is given in Equation (2.14)

\[ k = \frac{1}{\sigma^4} \sum_{n=0}^{N} (n - \mu)^4 H(n) \]

It is the fourth order of the moment of pixel value distribution.
**Covariance**

Covariance is a measure of change that the random variable undergoes between two values. The value of one variable corresponds with the values of the other. Covariance $cv$ is calculated by using Equation (2.15)

$$cv = \frac{\sigma}{\mu} \tag{2.15}$$

### 2.5.4 Second order statistical features

The second order statistical features are horolick features of an image (Ala Balti et al 2012). It gives about the textural information of the images. The features are energy, homogeneity, correlation and contrast. Let $P_{ij}$ be the probability distribution of grey level values i.e the number of times the particular pixel has occurred. The second order features are defined as follows

**Energy**

It is defined as the information present on the image. It gives information about the distribution of a gray image. It is used to calculate the regularity of ridges within the range of [0, 1]. The energy $e$ is calculated by using Equation (2.16).

$$e = \sum_{i=1}^{k} \sum_{j=1}^{k} P_{ij}^2 \tag{2.16}$$

**Homogeneity**

Homogeneity is defined as a measure that takes high values for low contrast images. Homogeneity $s$ is calculated by using Equation (2.17).

$$s = \sum_{i=1}^{k} \sum_{j=1}^{k} \frac{P_{ij}}{1+|i-j|} \tag{2.17}$$
Correlation

Correlation is used to calculate the similarities between pixels in two distinct directions. Correlation is calculated by using Equation (2.18)

\[
\text{cor} = \sum_{i=1}^{k} \sum_{j=1}^{k} (i - m_r)(j - m_c) P_{ij}
\]

(2.18)

where \( m_r \), \( m_c \) represent the mean along the rows and columns, respectively.

Contrast

Contrast is a measure of neighbourhood level variation which takes excessive values for images of high contrast. Contrast is calculated by using Equation (2.19)

\[
\text{con} = \sum_{i=1}^{k} \sum_{j=1}^{k} (i - j)^2 P_{ij}
\]

(2.19)

2.5.5 Gray level Co-occurrence Matrix

The Gray level Co-occurrence Matrix (GLCM) is the most well known extraction method for second order statistical (textural) characteristics. The features of texture extracted from images are organized into feature vectors. To perform the feature extraction, a co-occurrence matrix of the analyzed image is generated. The co-occurrence matrix consists of relative distance (\( d \)) and orientation (\( \theta \)) parameters. Co-occurrence matrices are calculated for directions 0°, 45°, 90° and 135° that represent the four directions horizontal, diagonal, vertical and anti diagonal pointed out by the relative frequencies \( Q(x, y, z, \theta) \) which happens in a direction indicated by plot angle \( \theta \), with gray levels \( x, y \) where the pixels are separated by distance \( z \).
An occurrence of gray-level values can be defined by a matrix of relative frequencies \( F_{\theta, d}(x, y) \). It shows that the gray level pixels \( x, y \) appear in the particular mask separated by a distance \( d \) in the direction \( \theta \). In practice, for each \( d \), the resulting values for the four directions are averaged out. This will generate features that will be rotations invariant. Co-occurrence matrices are calculated by using the following Equations (2.20), (2.21), (2.22) and (2.23).

\[
P_{0^\circ, d}(x, y) = \left\{ \begin{array}{c} (k, l), (m, n) \in O : \\ k - m = 0, |l - n| = d, \\ f(k, l) = x, f(m, n) = y \end{array} \right\} \tag{2.20}
\]

\[
P_{45^\circ, d}(x, y) = \left\{ \begin{array}{c} (k, l), (m, n) \in O : \\ (k - m = d, l - n = -d) \vee (k - m = -d, l - n = d), \\ f(k, l) = x, f(m, n) = y \end{array} \right\} \tag{2.21}
\]

\[
P_{90^\circ, d}(x, y) = \left\{ \begin{array}{c} (k, l), (m, n) \in O : \\ k - m = d, |l - n| = 0, \\ f(k, l) = x, f(m, n) = y \end{array} \right\} \tag{2.22}
\]

\[
P_{135^\circ, d}(x, y) = \left\{ \begin{array}{c} (k, l), (m, n) \in O : \\ (k - m = d, l - n = -d) \vee (k - m = -d, l - n = d), \\ f(k, l) = x, f(m, n) = y \end{array} \right\} \tag{2.23}
\]

where |{………}| refers to the cardinality of set, \( f(k, l) \) intensity at pixel position \( (k, l) \) in the image \( m \times n \), \( O \) is the order of matrix.

A simple 4 x 4 image with four grey levels is considered for range in between 0 and 3. The \( P_{H}, P_{RD} \), \( P_{V} \) and \( P_{V} \) denotes the co-occurrence matrices obtained from image pixel values in horizontal, right diagonal, vertical and left diagonal along with four angular specifications 0°, 45°, 90° and 135° is given in Table 2.1
Table 2.1 Co occurrence matrix with four different angles

<table>
<thead>
<tr>
<th></th>
<th>0</th>
<th>0</th>
<th>1</th>
<th>1</th>
</tr>
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<td>2</td>
<td>3</td>
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<td>3</td>
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</tbody>
</table>

Feature vector is generated based on the second order features for normal and overlapped images by using gray level concurrence matrix is given in Table 2.2. The values in Table 2.2 strongly recommend that the second order features are different for normal, simulated overlapped and latent images.

2.5.6 Third order features

Ridge distance and ridge frequency are considered as third order features of the overlapped and non overlapped fingerprint images.

Ridge distance

Ridge distance is defined as the distance between its neighbouring ridges. It can be measured as the distance from the center of different ridges. Generally, three methods are used to calculate the ridge distance (Yilong & Jie 2004). They are spectral analysis, statistical and hybrid methods. Hybrid method is one of the traditional methods (Feng et al 2012) for ridge distance estimation in fingerprint images.

The steps for hybrid method are as follows:

Step 1: Divide the input image into non overlap block images of size $m \times n$. 

```
<table>
<thead>
<tr>
<th>θ−0°</th>
<th>θ−45°</th>
<th>θ−90°</th>
<th>θ−135°</th>
</tr>
</thead>
<tbody>
<tr>
<td>4 2 1 0</td>
<td>4 1 0 0</td>
<td>6 0 2 0</td>
<td>2 1 3 0</td>
</tr>
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<td>2 4 0 0</td>
<td>1 2 2 0</td>
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</tr>
<tr>
<td>1 0 6 1</td>
<td>0 2 4 1</td>
<td>2 2 2 2</td>
<td>3 1 0 2</td>
</tr>
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<td>0 0 1 0</td>
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<td>0 0 2 0</td>
</tr>
</tbody>
</table>
```
Step 2: Calculate Discrete Fourier Transform $F(u, v)$ and radial distribution $R(r)$ at different block levels in an input image.

**Table 2.2 Feature Vector for normal and overlapped images by using GLCM**

<table>
<thead>
<tr>
<th>Images</th>
<th>Second order Features</th>
<th>Directions</th>
<th>$\theta=0^\circ$</th>
<th>$\theta=45^\circ$</th>
<th>$\theta=90^\circ$</th>
<th>$\theta=135^\circ$</th>
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<tr>
<td>Normal</td>
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<td>0.0622</td>
<td>0.0681</td>
<td>0.0621</td>
<td>0.0598</td>
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<td>Fingerprint Image#1</td>
<td>Ridge Correlation</td>
<td>0.8555</td>
<td>0.8658</td>
<td>0.8254</td>
<td>0.7526</td>
<td></td>
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<tr>
<td></td>
<td>Ridge Homogeneity</td>
<td>0.8232</td>
<td>0.8152</td>
<td>0.7980</td>
<td>0.8100</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Ridge Contrast</td>
<td>0.9342</td>
<td>0.9817</td>
<td>0.9457</td>
<td>0.9142</td>
<td></td>
</tr>
<tr>
<td>Normal</td>
<td>Ridge Energy</td>
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<td>0.0654</td>
<td>0.0633</td>
<td>0.0561</td>
<td></td>
</tr>
<tr>
<td>Fingerprint Image#2</td>
<td>Ridge Correlation</td>
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<td>0.8852</td>
<td>0.8234</td>
<td>0.8526</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Ridge Homogeneity</td>
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<td>0.8752</td>
<td>0.7680</td>
<td>0.8140</td>
<td></td>
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<td>0.9815</td>
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<td>0.0227</td>
<td>0.0231</td>
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<td>0.6870</td>
<td>0.7452</td>
<td>0.7125</td>
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Step 3: The ridge distance $d(m_i, m_j)$ is calculated by using Equation (2.24)

$$d(m_i, m_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$  (2.24)

where $x_i$, $x_j$, $y_i$ and $y_j$ denote the adjoining ridges in vertical and horizontal directions.

Step 4: It is assumed that, the given fingerprint image has $n$ number of ridges with different widths $w_1$, $w_2$,...,$w_n$ and it is separated by $n-1$ valleys with different widths $v_1$, $v_2$,....$v_{n-1}$ as shown in Figure 2.15. The average ridge distance (ARD) is defined in Equation (2.25)

$$ARD = \frac{1}{n-1} \sum_{i=1}^{n-1} \left( \frac{w_i}{2} + v_i + \frac{w_{i+1}}{2} \right)$$  (2.25)

Figure 2.15 Ridge Distance

Ridge frequency

It defines a reciprocal of ridge distance. It significantly varies in different segments of the fingerprint image (Yilong & Jie 2004). Let the image $I(i, j)$ with $m \times n$ dimensions be considered

Step 1: To calculate pixels in horizontal line $L_h \in \{1, 2, ..., m\}$ and pixels in vertical line $L_v \in \{1, 2, ..., n\}$. 
Step 2: To estimate local minimum points for ridges \( L_{Mi}P_r \) and local maximum points for valleys between ridges \( L_{Mi}P_v \), where \( r = 1, 2, \ldots, n \), \( v = 1, 2, \ldots, k \), \( n \) determines the number of fingerprint ridges and \( k \) the number of valleys.

Step 3: The average ridge frequency (ARF) can directly be estimated by using the formula given in Equation (2.26)

\[
ARF = \frac{\sum_{r=1}^{n} R_r + \sum_{v=1}^{k} V_v}{n + k - 2}
\]  

(2.26)

where \( R_r, V_v \) are the ridges and valleys. The waveform of a given fingerprint ridges is shown in Figure 2.16. The square grey points represent \( L_{Mi}P_r \) and square white points represent maximal points \( L_{Mi}P_v \).

![Waveform representation for \( L_{Mi}P_r, L_{Mi}P_v \)](image)

Figure 2.16 Waveform representation for \( L_{Mi}P_r, L_{Mi}P_v \)

Together all these first, second and third order features are used to distinguish overlapped and non overlapped images.
2.6 SUMMARY

This chapter presents the need for digital image processing and its applications, level1, level2 and level3 features of fingerprint image, preprocessing for fingerprint images and the steps involved in fingerprint preprocessing such as normalization, image enhancement, segmentation, evaluation of the fingerprint features for normal and overlapped fingerprint images by using first, second and third order features. The grey level cooccurrence matrix is generated for second order features. Ridge distance and ridge frequency are estimated for the images.