FEATURE EXTRACTION FROM FINGERPRINTS

2.1 INTRODUCTION

One of the ongoing subjects of research in the field of pattern recognition is proper selection and extraction of features. Given certain measurements of an object, one would like to determine which of these measurements is best suited for identifying the given object. One might naively assume that each of the features can be examined individually to establish a preference ordering for the features. However, the problem is complicated by the fact that it is not only the single best measurement we are searching for, but the best subset of measurements. It may be the case that the single best feature is not an element of this best subset.

The extraction of features from objects/images avoids the "curse of dimensionality", improves the generalization ability of classifiers, and reduce the computational requirements of pattern classification. Feature extraction problem can be formulated as a mapping function \( F \) from an m-dimensional input space to an n-dimensional output space (map space)

\[
F : \mathbb{R}^m \rightarrow \mathbb{R}^n
\]

such that some criterion, \( C \) is optimized.
There are three fundamental features available for recognition / identification of pattern:

(i) *Spectral features*: It describes the average tonal variation in various bands of the visible and/or infra-red portion of an electro-magnetic spectrum,

(ii) *Textural features*: It describes information about the spatial distribution of tonal variations within a band and


Tone refers to the varying shades of gray of resolution cells in a image. Among these three fundamental elements, the textural features have been fruitfully used in the past for identification / recognition of objects or regions of interest in an given image (Weszka *et al* 1976, Tamura *et al.* 1978, Kundu *et al.* 1992 and Sushmita Mitra *et al.* 1994).

This chapter describes the survey of the existing feature extraction methods and extraction of textural and directional features from fingerprints.

### 2.2 EXISTING FEATURE EXTRACTION METHODS

Textural features play an important role in computer vision and pattern recognition problems, and are widely applied to many areas such as industrial automation, bio-medical image processing, and remote sensing. Several models were proposed in the past to extract textural features. They are, auto-correlation functions (Kaizer 1955) and power spectra (Chevalier *et al.* 1968). These models had some degree of success, since they used only some general mathematical transformation which assigns numbers to the
transformed image in a non-specific way. Also some of them have focused on the analysis of first order or second order statistics of textures (Bixby et al. 1967). Later, Gaussian Markov random fields or Gibbs random fields (De Souza 1982, Cross et al. 1983, Perin et al. 1982, Kashya et al. 1986, and Cohen, et al. 1991) have proposed to extract textural features. The advantage of this approach is that a few parameters often describe a texture well. Laws (Laws 1980) has used linear transform, which can detect certain types of pattern commonly found in texture images, to compute features. His work introduced the concept of multi-channel processing. Law's work was extended by a number of researchers (Unser 1986). Recently, multi-resolution and multi-channel methods have been widely studied (Dunn, et al. 1994, Cheng, et al. 1993 & Kundu, et al. 1992). In particular, the wavelet transform and the Gabor filter play important roles. The wavelet transform is a multi-resolution technique which can be implemented as a pyramid or tree structure, and is similar to sub-band decomposition. The Gabor filter can extract the information in an ellipse-shaped frequency band and can be designed to detect some quasi-periodic texture patterns.

Kashya et al. (1986) have first recognised the importance of rotation - invariant texture classification and developed a circular Auto Regressive (AR) model. They have incorporated two AR models. However, their model could only be used for textures with no strong directionality.

Cohen, et al. (1991) modeled textures as Gaussian Markov random fields and used the maximum likelihood to estimate co-efficients and rotation of angles. The problem with this method is that the likelihood function is highly non-linear and local minima may exist. In addition, the algorithm is an iterative method that is computationally expensive for feature extraction.

Chen et al. (1994) used multi-channel sub-band decomposition and a hidden markov model. They have used a two dimensional (2-D) mirror
filter bank to decompose a 2-D image into sub-band images and modeled the features of those sub-band images as an HMM. Texture samples with different orientations are treated as being in the same class.

Recently, ANN models and learning algorithms have been proposed for feature extraction and data projection (Foldaik (1989), Kung (1990), Milky et al. (1990), Rubner et al. (1990), Banour (1995) and Jain et al. (1995)). These research efforts can be loosely classified into two groups. The first group contains design of new neural network models and second group contains analysis of existing models for feature extraction and data projection. Examples of these type of efforts include Kohonen Self Organizing Map (Rubner, et al. 1990) and non-linear discriminant analyses based on the functionality of hidden units in feed forward network classifiers (Milky, et al. 1990).

In this thesis textural and directional features are used for fingerprint identification. Textural features are important characteristics used in identifying objects or regions of interest in an image (Haralick et al. 1973). It is often described as a set of statistical measures of the spatial distribution of gray levels in an image. The gray level co-occurrence matrix method assumes that the textural features in an image is contained in the overall or average spatial relationships among the gray tones. These statistical measures are found to be a powerful input representation of the images (Raghu et al. 1994 & 1995). It has been applied to cloud classification from satellite data and in the identification of human faces, using neural network models (Balakrishnan et al. 1994).

This thesis follows the Haralick (1989) approach with some modifications for extraction of textural features. A set of gray - tone spatial dependence probability distribution matrices for a given image are computed and a set of textural features are extracted from each of these matrices. These features contain image characteristics information such as
homogeneity, linear dependencies, contrast, nature of boundaries and complexity of the image. The data preparation of fingerprint is described in the following section.

2.3 DATA PREPARATION

For the present work, fingerprint images were acquired using a flat bed scanner that outputs binary images. The scanning was done at a resolution of 300 dpi. Physical fingerprint samples were taken on white sheet of paper using special ink called impression ink. A sample of physical prints are as shown in Figure 2.1. Steps in the data preparation are described below.

2.3.1 Steps involved in data preparation

Step-1: Obtain physical patterns for each fingerprint by impression ink in a white sheet.

Step-2: Scan the physical patterns into 256 x 256 pixels size of black and white image.

Step-3: Thin and clean the scanned image.

This entails:

* Reduction of the image ridges to a skeletal structure,
* Smoothing of the resulting fingerprint distortions,
* Selecting a valid fingerprint regions, by deleting regions with no identification significance, such as those generated by over inking.

The deletion criteria is based on visual inspection and

* Store each fingerprint in a separate file.
Figure 2.1 Some of the Scanned Physical Fingerprints
Before going to use scanned image data for recognition purpose, the scanned image has to go through a number of pre-processing steps like noise elimination and ridge direction computation.

2.3.2 Noise Elimination

The images are scanned in picture file format. With the help of Microsoft PaintBrush the image has been taken into visual. Based on visual inspection the areas where noises like dirt, blurred and over inking are deleted.

2.3.3 Computation of directional image

The directional image is a direction computed from the original image. It represents the local orientations of the ridges (lines and curves). The directional image at the point \((i,j)\) is denoted by \(D(i,j)\) and calculated in the following manner.

\[
D(i,j) = \frac{4}{\min_{k=1}^{n}} \left\{ \left| I(i_k,j_k) - I(i,j) \right| \right\}
\]  

(2.2)

where \(I(i,j)\) and \(I(i_k,j_k)\) indicates the gray scale of the points \((i,j)\) and their extrapolation in the direction \(k\) respectively, and \(n\) is the number of pixels chosen for this computation.

The total fluctuation of the gray scale described by the Equation-2.2 is expected to be the smallest (zero) in the tangential to the direction of the ridges and to be the largest in the orthogonal direction.
2.4 EXTRACTION OF FEATURES

2.4.1 Formation of co-occurrence matrices

Let us assume that an image $I$ has $N_x$ number of resolution cells in each row and $N_y$ number of resolution cells in each column. Suppose that the gray tone appearing in each resolution cell is quantized to $N_g$ levels. Let $L_x = \{1, 2, 3, \ldots N_x \}$ be the horizontal spatial domain, and $L_y = \{1, 2, 3, \ldots N_y \}$ be the vertical spatial domain, and $G= \{1, 2, 3, \ldots N_g \}$ be the set of $N_g$ quantized gray tones. The set $L_x \times L_y$ is the set of resolution cells of the image ordered by their row-column designations. The given image $I$ can be represented as a function which assigns some gray tone in $G$ to each resolution cell of pairs of co-ordinates in $L_x \times L_y$; Mathematically,

$$ I : L_x \times L_y \rightarrow G \quad (2.3) $$

The textural features are computed from a set of angular nearest neighbor gray tone spatial dependent matrices (called co-occurrence matrices). The texture information is specified by the co-occurrence matrix of relative frequencies with which two neighboring resolution cells, having gray levels $i'$ and $j'$ and separated by a distance $\mu$ occur in the image, which is denoted by $M(\theta, \mu, i, j)$. The elements of co-occurrence matrix $M(\theta, \mu, i, j)$ are un-normalized frequencies and $\theta$ is quantized to 45 degree intervals as $\theta = \{0, 45, 90, 135, 180, 225, 270, 315\}$. The following equations define co-occurrence matrices for different angles with $\mu=1$.

$$ M(\theta, \mu, i, j) = \# \{ (k,l),(m,n)) \in (L_y \times L_x) \times (L_y \times L_x) \mid k-m =0, \mid l-n \mid = \mu, l(k,l) = i, l(m,n) = j \} \quad (2.4) $$

Where $\#$ denotes the number of elements in the set and $|k-m|$ or $|l-n|$ denotes the positive difference between $k$ and $m$ or $l$ and $n$. Here we have assumed that the matrix $M(\theta, \mu, i, j)$ is non-symmetric; i.e., is $M(\theta, \mu, i, j)$ is not equal to $M(\theta, \mu, j, i)$. 

Illustration

Consider a simple image of 3 x 3 pixels size with gray-tones ranging from 0 to 2 as shown in Table-2.1. The Table-2.2 shows co-occurrence matrices formed using Table-2.1. For example the co-occurrence matrix for $\theta = 45$ for position (2,0) denotes the total number of times gray values 2 and 0 occurred at the right diagonal direction in the whole image and which is adjacent to each other with distance of $\mu$ (here we have taken it as $\mu = 1$). The above co-occurrence matrices elements are un-normalised frequencies. If needed, for making normalized frequencies the normalised constant, say $R$, is calculated in the following manner based on $\theta$ value. That is

$$
R = \begin{cases} 
N_y (N_x - 1) & \text{for } \theta = 0 \text{ and } 180 \\
N_x (N_y - 1) & \text{for } \theta = 90 \text{ and } 270 \\
(N_y - 1)(N_x - 1) & \text{for } \theta = 45, 135, 225, 315
\end{cases}
$$
Table 2.1: Gray values of an image of 3 x 3 size

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

Table 2.2: The co-occurrence matrices for different angles

\[ P_{RH} = \begin{pmatrix} 0 & 1 & 0 \\ 1 & 0 & 2 \\ 0 & 2 & 0 \end{pmatrix} \quad \text{for } \theta = 0 \text{ (Right Horizontal)} \]

\[ P_{URD} = \begin{pmatrix} 0 & 1 & 0 \\ 1 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \quad \text{For } \theta = 45 \text{ (Upper Right Diagonal)} \]

\[ P_{UV} = \begin{pmatrix} 0 & 0 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 0 \end{pmatrix} \quad \text{for } \theta = 90 \text{ (Upper Vertical)} \]

\[ P_{ULD} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 1 & 1 & 0 \end{pmatrix} \quad \text{for } \theta = 135 \text{ (Upper Left Diagonal)} \]

(Continue)
Table 2.2: Continue

| \( P_{	ext{LH}} \) = | 0 & 1 & 0 | for \( \theta = 180 \) (Left Diagonal) \\
| | 1 & 0 & 1 | & \\
| | 0 & 2 & 0 | |

\[
P_{\text{BLD}} = \begin{bmatrix}
0 & 1 & 0 \\
1 & 1 & 0 \\
0 & 0 & 1
\end{bmatrix}
\]

For \( \theta = 225 \) (Below Left Diagonal)

\[
P_{\text{BV}} = \begin{bmatrix}
0 & 1 & 1 \\
0 & 1 & 1 \\
1 & 1 & 0
\end{bmatrix}
\]

For \( \theta = 270 \) (Below Vertical)

\[
P_{\text{BRD}} = \begin{bmatrix}
0 & 0 & 1 \\
0 & 1 & 1 \\
0 & 1 & 0
\end{bmatrix}
\]

For \( \theta = 315 \) (Below Right Vertical)
For example, $\theta = 90$ with $\mu = 1$, there will be $(N_y - 1)$ neighboring resolution cell pairs in each column, and there are $N_x$ resolution cell pairs in each row, hence providing a total of $N_x(N_y - 1)$ neighboring resolution cell pairs in all vertical directions.

A set of 17 features are extracted from each of the co-occurrence matrices. There are eight co-occurrence matrices for each image and hence there are 136 textural features. In addition, three directional features are extracted from the original image. The following sections discuss how the features are computed.

2.4.2 Computation of textural features

Let $m(i,j) = M(\theta, \mu, i, j)/R$ be the $(i,j)^{th}$ position of normalized co-occurrence matrix, where $R$ is based on $\theta$ value. For simplicity, let $m(\theta, \mu, i, j)$ be denoted as $m(i,j)$, i.e.,

$$m(i,j) = m(\theta, \mu, i, j) \quad (2.13)$$

$m_x(i) = \Sigma_j(m(i,j))$ be the $i^{th}$ entry in the marginal-probability matrix obtained by summing up all the rows of $m(i,j)$. (2.14)

Similarly,

$$m_y(j) = \Sigma_i m(i,j) \quad (2.15)$$

$$m_{x+y}(k) = \Sigma_i \Sigma_j(m(i,j)), \text{ if } x+y = k, \quad \text{ where } \quad k=2,3,\ldots2N_g \quad (2.16)$$

$$m_{x-y}(k) = \Sigma_i \Sigma_j(m(i,j)), \text{ if } x-y = k, \quad \text{ where } \quad k=2,3,\ldots(N_g - 1) \quad (2.17)$$
The Angular Second Moment (ASM) gives the measure of the homogeneity of the texture and is defined by

\[
ASM = \sum_{ij} (m(i,j))^2
\]  

The Contrast (C) provides the measure of the local variation in the texture and which is defined by

\[
C = \sum_{n=0}^{N^2-1} n^2 \ast (\sum_j m(i,j)), \text{ for all } |i-j| = n
\]  

The Correlation (CL) and Maximal Correlation (MCL) provide the measure of association between foreground and background regions of given image in the texture and are defined as

\[
CL = \frac{((\sum_j (i^*j^* m(i,j)))-(\mu_x \ast \mu_y))}{(\sigma_x \times \sigma_y)}
\]  

Where \(\mu_x\) & \(\mu_y\) and \(\sigma_x\) & \(\sigma_y\) are the mean of \(m_x\) & \(m_y\) and variance of \(m_x\) & \(m_y\).

Maximal Correlation co-efficient = (Second largest eigen value of \(Q\))^{1/2}

where,

\[
Q(i,j) = \sum_k \frac{(m(i,k) \ast m(j,k))}{(m_x(i) \ast m_y(k))}
\]  

The entropy, Sum entropy and Difference entropy provides the measure of amount of randomness in the texture and are defined as

Entropy

\[
\text{Entropy} = \sum_{ij} m(i,j) \ast (\log(m(i,j)))
\]  

Sum entropy

\[
\text{Sum entropy} = - \sum_{i=1}^{2N^2} (m_{x+y}(i) \ast (\log(m_{x+y}(i))))
\]  

Difference entropy

\[
\text{Difference entropy} = - \sum_{i=0}^{N^2-1} (m_{x-y}(i) \ast \log(m_{x-y}(i))
\]
The variance, Sum of Variance and Difference variance provide the measures of variations in the texture and are defined as

\[
\text{Variance} = \sum_{i,j} \left( 1 - \text{mean}_{xy} \right)^2 m(i,j)
\] (2.25)

Where mean\(_{xy}\) is the mean of \(m_{xy}\).

\[
\text{Sum Variance} = \sum_{i=2}^{2N_{g}} ((i - \text{Sum entropy})^2 m_{xy}(i))
\] (2.26)

\[
\text{Difference Variance} = \text{Variance of } m_{x-y}
\] (2.27)

The information measures of correlation provide the amount of information in the image and are defined as

\[
a_1 = \frac{\text{IM}_{XY} - \text{IM}_{XY1}}{\max\{ \text{IM}_X, \text{IM}_Y \}}
\]

\[
a_2 = (1 - \exp(-2.0 \times (\text{IM}_{XY2} - \text{IM}_{XY1})))^{1/2}
\] (2.28)

\[
\text{IM}_{XY} = -\sum_i \sum_j m(i,j) \times \log(m(i,j))
\]

where \(\text{IM}_X\) and \(\text{IM}_Y\) are the entropies of \(m_x\) and \(m_y\) and

\[
\text{IM}_{XY1} = -\sum_i \sum_j m(i,j) \times \log(m_x(i) \times m_y(i))
\]

\[
\text{IM}_{XY2} = -\sum_i \sum_j m_x(i) \times m_y(i) \times \log(m_x(i) \times m_y(i))
\]

The Inverse Difference Moment (IDM) is defined as

\[
\text{IDM} = \sum_i \sum_j m(i,j)/(1.0 + (i - j)^2)
\] (2.29)

The sum average (SM) is defined as

\[
\text{SM} = \sum_{i=2}^{2N_{g}} (i \times m_{x+y}(i))
\] (2.30)
2.4.3 Computation of directional features

Let us consider an image that has $N_x$ number of pixels in the horizontal direction and $N_y$ number of pixels in the vertical direction. The edges in the image travels through four directions - horizontal, vertical, left diagonal and right diagonal - and each of them traverse 'w' pixels band width (Figure 2.2).

The ridge frequency is defined as the number of times one encounters humps among the gray tone values in the coarse of the traversal. Let the frequencies of the humps in the four directions be $f_h$, $f_v$, $f_{rd}$ and $f_{ld}$. For example, for horizontal direction, it is defined as

$$f_h^{(i)} = (1.0/w \sum_j (\text{Number of humps at the horizontal direction in } D(i,j)))$$  \hspace{1cm} (2.31)

where $D(i,j)$ is the directional image at the point $(i,j)$.

The difference between foreground and background is evaluated as the sequence of the difference in the gray level values between successive pixels, along the direction of traversal. The four corresponding features are designated by $D_h$, $D_v$, $D_{rd}$ and $D_{ld}$. For example, for horizontal direction

$$D_h^{(i)} = (1.0/w \sum_j ((D(i,j) - D(i,j+1))^2)$$  \hspace{1cm} (2.32)

The height of the ridges in the given image is computed as the normalized sum of the gray - tone values along the direction of traversal. Along the four directions, the features are denoted as $H_h$, $H_v$, $H_{rd}$ and $H_{ld}$. For horizontal direction,

$$H_h^{(i)} = (1.0/N_g \sum_j (\text{max}_w (D(i,j)))$$  \hspace{1cm} (2.33)
2.5 CONCLUSION

The method of extraction of textural and directional features have been described in this chapter. There are 136 textural features and 3 directional features which are extracted from each fingerprint and are all used as input for neural network training/identification. One of the advantages of using textural and directional features is that size of input (or memory space) is reduced significantly for training/identification of fingerprints. For example, to store 139 features the required memory space is $139 \times 4 = 556$ bytes compared to full print image storage of 65K. Hence it saves 130 times of memory space compared to existing approaches for identification of a fingerprint.

The features calculated are all functions of distance and angles. The extracted features values are invariant to rotation and translation of given image. For example, an image I has features a, b, c, d, e, f, g and h for angles 0, 45, 90, 135, 180, 225, 270 and 315 respectively. An image J is identical to I except that J is rotated 90 with respect to (w.r.t) I. Then J will have features g, h, a, b, c, d, e, f, g and h respectively. Since the texture context of I is the same as the texture content of J, any decision rule using the angular features a, b, c, d, e, f, g and h must produce the same results for g, h, a, b, c, d, e, f, g and h. Moreover, this work computes the features for eight different angles rather than just for four different angles (Haralick approach). An assumption is made in this work is that the value of co-occurrence matrix for 45 degree is not the same as that of matrix for 225 degree. Similarly, the values of co-occurrence matrix for 90 degree is not same as that for 270 degree. Hence the extracted features for eight different angles have more information about the given image than features from four different angles.
Figure 2.2 The eight directions of traversal (each of width 'w')