4. FEATURE EXTRACTION & PATTERN RECOGNITION

4.1. Feature Extraction of an Image

In image processing the concept of feature is used to denote a piece of information which is relevant for solving the computational task related to a certain application. More specifically, features can refer to

- the result of a general neighborhood operation (feature extractor or feature detector) applied to the image,

- Specific structures in the image itself, ranging from simple structures such as points or edges to more complex structures such as objects.

When features are defined in terms of local neighborhood operations applied to an image, a procedure commonly referred to as feature extraction, one can distinguish between feature detection approaches that produce local decisions whether there is a feature of a given type at a given image point or not, and those who produce non-binary data as result. The distinction becomes relevant when the resulting detected features are relatively sparse. Although local decisions are made, the output from a feature detection step does not need to be a binary image. The result is often represented in terms sets of (connected or unconnected) coordinates of the image points where features have been detected, sometimes with subpixel accuracy.

When feature extraction is done without local decision making, the result is often referred to as a feature image. Consequently, a feature image can be seen as an image in the sense that it is a function of the same spatial (or temporal) variables as the original image, but where the pixel values hold information about image features instead of intensity or
color. This means that a feature image can be processed in a similar way as an ordinary image generated by an image sensor. Feature images are also often computed as integrated step in algorithms for feature detection.

### 4.1.1 Feature Representation

A specific image feature, defined in terms of a specific structure in the image data, can often be represented in different ways. For example, an edge can be represented as a boolean variable in each image point that describes whether an edge is present at that point. Alternatively, we can instead use a representation which provides a certainty measure instead of a boolean statement of the edge's existence and combine this with information about the orientation of the edge. Similarly, the color of a specific region can either be represented in terms of the average color (three scalars) or a color histogram (three functions).

### 4.2. Image Segmentation

The segmentation subdivides an image into its constituent regions or object. The segmentation should stop when the object of interest in an application have isolated. The segmentation accuracy determines the eventual successor failure of computerized analysis procedures.

Image segmentation algorithm generally are based on one of two basic properties of intensity values: discontinuity and similarity. In the first category the approach is to partition an image based on abrupt changes in intensity, such as edges in an image. The principal approaches in the second category are based on portioning an image into region that is similar according to a set of predefined criteria.
4.2.1. Detection of Discontinuities

The several techniques for detecting the three basic type of gray-level discontinuities in digital image: Point, Lines and Edges. The most common way to look for discontinuities is to run a mask through the image. For 3x3 mask procedure involve computing the sum of products of the coefficients with the gray level contained in the region encompassed by the mask.

4.2.1.1. Point Detection

The detection of isolated points in an image is straightforward in principle. Using the mask a point has been detected at the location on which the mask is centered if

\[ |R| \geq T \]

Where \(T\) is negative threshold, basically this formulation measures the weighted difference between the center point and its neighbors. The idea is that an isolated point (a point where gray level is significantly different from its background and which is located in a homogeneous or nearly homogeneous area) will be quite different from its surroundings, and thus be easily detectable by this type of mask.

4.2.1.2. Line Detection

The next level of complexity is line detection. Consider the mask as shown below:

\[
\begin{array}{ccc}
-1 & -1 & -1 \\
2 & 2 & 2 \\
-1 & -1 & -1 \\
\end{array}
\]

\[
\begin{array}{ccc}
-1 & -1 & 2 \\
1 & 2 & -1 \\
2 & -1 & -1 \\
\end{array}
\]

\[
\begin{array}{ccc}
2 & -1 & -1 \\
-1 & 2 & -1 \\
-1 & 2 & -1 \\
\end{array}
\]

Horizontal \(+45°\) \quad Vertical \(-45°\)
The above mask moved around an image, it would respond more strongly to lines (one pixel thick) oriented horizontally. With a constant background, the maximum response would result when the line passed through the middle row of the mask. The mask is rotated in horizontal, vertical, +45° and -45°, these directions can be established also by noting that preferred direction of each mask is weighted with a large coefficient than other possible direction. The coefficient in each mask sum to zero, indicating a zero response from the mask in the area of constant gray level.

4.2.1.3. Edge Detection

The edge detection is the most common approach for directing meaningful discontinuities in gray level. The first and second order derivatives are used for detection of edge of an image. An edge is a set of connected pixels that lie on the boundary between two regions. Fundamentally an edge is a ‘local’ concept where as a region boundary owing to the way it is defined, is a more global idea. A reasonable definition of ‘edge’ requires the ability to measure gray level transitions in a meaningful way.

In edge detection the magnitude of the first derivative can be used to detect the presence of an edge at a point in an image. Similarly, the sign of the second derivative can be used to determine whether an edge pixel lines on the dark or light side of an edge. The two additional properties of the second derivatives around an edge (i) it produces two values for every edge in an image (an undesirable feature) and (ii) an imaginary straight line joining the extreme positive and negative values of the second derivative would cross zero near the midpoint of the edge. This zero crossing property of the second derivative is quite useful for locating the centers of thick edges.

In Edge Detection can be performed in Matlab (See Appendix “G”)
4.2.2. Edge Detection Techniques

The filters are used in the process of identifying the image by locating the sharp edges which are discontinuous. These discontinuous bring changes in pixels intensities which define the boundaries of the object. There are many ways to perform the edge detection. However, it may be grouped into two categories, that are gradient and Laplacian. The gradient method detect the edges by looking for the maximum and minimum in the first derivate of the image. The Laplacian method search for zero crossing in the second derivative of the image to find edges. Some edge detector are as under.

4.2.2.1. Roberts

The Roberts cross operator provide a simple approximation to the gradient magnitude:

\[ G[f(i,j)] = |f(i,j) - f(i+1,j+1)| + |f(i+1,j) - f(i,j+1)| \]

Using convolution masks, this becomes:

\[ G[f(i,j)] = |G_x| + |G_y| \]

Where \( G_x \) and \( G_y \) are calculated using the following mask:

\[
G_x = \begin{bmatrix}
1 & 0 \\
0 & -1
\end{bmatrix}
\quad G_y = \begin{bmatrix}
0 & -1 \\
1 & 0
\end{bmatrix}
\]

The Robert operator is an approximation to the continuous gradient at the interpolated point and not at the point \( [i,j] \) as it might be expected.


### 4.2.2.2 Sobel

A way to avoid having the gradient calculated about an interpolated point between the pixel which is used 3x3 neighbourhood for the gradient calculation. On the arrangement of pixels are about the pixel\([i,j]\). The Sobel operator is the magnitude of the gradient computed by:

\[ M = \sqrt{S_x^2 + S_y^2} \]  

Where the partial derivatives are computed by

\[ S_x = (a_2 + ca_3 + a_4) - (a_0 + ca_1 + a_0) \]
\[ S_y = (a_0 + ca_1 + a_2) - (a_0 + ca_3 + a_4) \]

With the constant \(c=2\)

Like the other gradient operator \(S_x\) and \(S_y\) can be implemented using convolution mask:

\[
\begin{array}{ccc}
-1 & 0 & 1 \\
-2 & 0 & 2 \\
1 & 0 & 1 \\
\end{array}
\quad \quad \quad
\begin{array}{ccc}
1 & 2 & 1 \\
0 & 0 & 0 \\
-1 & -2 & -1 \\
\end{array}
\]

This operator is placed on an emphasizing pixels that are closer to the center of the mask. The Sobel operator is one of the most commonly used edge detector[23][86-87].

### 4.2.2.3. Prewitt

The prewitt operator uses the same operations as the Sabel operator, where constant \(c=1\).

\[
\begin{array}{ccc}
-1 & 0 & 1 \\
-1 & 0 & 1 \\
-1 & 0 & 1 \\
\end{array}
\quad \quad \quad
\begin{array}{ccc}
1 & 1 & 1 \\
0 & 0 & 0 \\
-1 & -1 & -1 \\
\end{array}
\]

Therefore, unlike the Sobel operator, this operator does not place any emphasis that are closer to the center of the mask.
Advantages and disadvantages of different operator.

<table>
<thead>
<tr>
<th>Operator</th>
<th>Advantage</th>
<th>Disadvantage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classical (Sobel, Prewitt)</td>
<td>Simplicity</td>
<td>Sensitivity to noise</td>
</tr>
<tr>
<td></td>
<td>Detection of edges and their orientation</td>
<td></td>
</tr>
<tr>
<td>Zero crossing (Laplacian,</td>
<td>Detection of edges and their Orientation</td>
<td>Responding to some of the existing edges</td>
</tr>
<tr>
<td>Second Directional Derivates</td>
<td>Having fixed characteristics in all direction</td>
<td>Sensitivity to noise</td>
</tr>
<tr>
<td>Laplacian of Gaussian (LoG)</td>
<td>Finding the correct places of edges</td>
<td>Malfunctioning at the corners</td>
</tr>
<tr>
<td>(Marr-Hildreth)</td>
<td>Testing wider area around the pixel.</td>
<td>Curves and where the gray level intensity function varies</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Not finding the orientation of edge because of using the Laplacian filter</td>
</tr>
<tr>
<td>Gaussian(Canny, Shen-Castan)</td>
<td>Using probability for finding error rate</td>
<td>Complex Computation</td>
</tr>
<tr>
<td></td>
<td>Better detection specially in noise conditions</td>
<td>False zero crossing</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Time consuming</td>
</tr>
</tbody>
</table>
4.3 Different Techniques for Feature / Texture Extraction

After the well-aligned ROIs, are obtained from the preprocessing stage, the important features of palm are extracted. Following approaches are available regarding the feature extraction of a image-

4.3.1. Line-based Approach[21]

Xiangqian Wu and David Zhang Kuanquan Wang (2004) have defined the principal lines heart line, life line, head lines based on some conditions. First they detect a set of points before they extract principal lines. They extract smooth the original image and convert it in to binary image and then trace the boundary of the palm. A verification function defined as they devise a horizontal line detector to detect the lines. The horizontal lines can be obtained by looking for the zero cross points of ‘I’ in the vertical direction and their strength are the values of the corresponding points in ‘I’ and extracting potential line initials of principal line. They extract the beginnings of the principal lines from these regions and use these line initials as the basis to extract the principal lines to their entirety.

Advantages-

- This process does not require any statistical or coding algorithm for feature extraction.
- Less Complexities are involved in this method
- Only Simple edge detector or standard filters are used for feature extraction.
- If translation and rotation are eliminated in the image at the time of scanning, this is the simplest method.
- It has tolerance to noise and high accuracy.
Disadvantage-
It is needed to improve the accuracy percentage and reduce misclassification rate.

4.3.2. Subspace-based Approach[12]

Ivan Fratric has proposed appearance-based approaches, observe the entire palm image as a vector (with pixel intensities as its components). This vector is usually subjected to different transformation in order to select a small feature set suitable for recognition.

These transformations include principal component analysis (PCA), Linear Discriminant Analysis (LDA) and Independent Component Analysis (ICA). PCA has widely used in pattern recognition, as well as in the field of biometrics. The PCA applied to a set of images, can be used to find the subspace that is occupied by all of the images from the analysed set. When the image are encoded into this subspace, and then returned to the original images is minimized.

Linear Discriminant Analysis find the optimal subspace for recognition in the sense that it maximizes the distance between classes while minimizing the compactness of class. This is why subspace obtained by LDA can be more appropriate for recognition than those obtained by PCA.

Independent component analysis is a method for finding underlying factor that generate the observed signals. It is assumed that the observed signal save computed as a linear combination of some independent underlying component. The idea of ICA is similar to PCA, but while PCA find component that are just uncorrelated, ICA find component that are also independent (independent components are also uncorrelated, but vice versa).
Disadvantage-

- Generally speaking, subspace-based approach does not make use of any prior knowledge of palm prints.

4.3.3. Statistical Approach[12]

Statistical approach can be further divided into local and global statistical approaches. Local statistical approach transform images into another domain and then divides the transformed images into small regions. Local statistics such as means and variances of each small region are calculated and regarded as features. Gabor filters, wavelets and Fourier transforms have been examined. The small regions are commonly square but some of them are elliptical and circular. According to the collected papers, so far, no one investigates high order statistics for this approach. In addition to local statistics, researchers also employ global statistics, which are computed from whole transformed images. Moments, centers of gravity and densities are considered as the global statistical features.

4.3.3.1. Gabor Filter

In image processing, a Gabor filter, named after Dennis Gabor, is a linear filter used for edge detection. Frequency and orientation representations of Gabor filters are similar to those of the human visual system, and they have been found to be particularly appropriate for texture representation and discrimination. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave. The Gabor filters are self-similar: all filters can be generated from one mother wavelet by dilation and rotation[17][18][27-29][34][43][49][53-55][58][61-65][68-72][76][79].
The circular Gabor filter is an effective tool for texture analysis and has following general form

\[ G(x,y,\Theta,\mu,\sigma) = \frac{1}{2\pi\sigma^2} \exp\{ -x^2 + y^2 / 2\sigma^2 \} \exp(2\pi i (\mu_x \cos \Theta + \mu_y \sin \Theta)) \]  ……… 4.4

Where \( i = \sqrt{-1} \), \( \mu \) is the frequency of the sinusoidal wave, \( \Theta \) controls the orientation of the function and \( \sigma \) is the standard deviation of the Gaussian envelope.

**Disadvantages** :

- Gabor filters have several limitations, mainly due to their high computing costs.
- They generate a complex convolution mask, which requires two convolutions per filter.
- The masks are not separable and should have a medium size to perform an accurate power spectrum partition.
- The amount of data increases with the same ratio as the number of the filters, since each filter output has the same size as the original image.

**4.3.3.2. Wavelet Transform**

This filter can be used for feature extraction of an image. This provides powerful insight into an image’s spatial and frequency characteristics. Multi resolution analysis of the image is performed by using wavelet decomposition. Wavelet transformation is integrated into the features extractor as follows:

- Decompose the palmprint image by using different families of wavelet.
- Retain the low-frequency subband of the approximation coefficients.
- Feed the reduced images into [PCA|FDA|ICA] computation.
According to wavelet theory, it is generally found that most of the energy content is concentrated in the low frequency subband, as compared to higher frequency subband. Low frequency subband is the smoothed version of the original image and it helps to reduce the influence of noise on one hand, and on the other hand preserve the local edges well which helps to capture the feature that is insensitive to small distortion. On the other hand, the higher frequency subband only contain low energy content and their high pass feature tends to enhance the edges detail, including noise and shape distortion.

WT is selected upon other filtering design as it can decompose the palmprint images into different-frequency-multi-resolution subband images for analysis. In decomposing the image into lower resolution images, WT conserve the energy signal and redistribution them into more compact form. Usually the low frequency subband contain most of the energy content and it is able to preserve local edges well which helps to capture the features that are insensitive to small distortion. In addition, as the subband image is only quarter size of the original image, the computational complexity can be reduced by working on the lower resolution image. This makes WT distinguishable from noise/resolution reduction techniques like spatial filters with dyadic down sampling[5][25-26][44][46][66-67][73-75].

4.3.3.3. Fourier Transform

The fourier Transformation that is used in feature extraction on spatial domain and on the frequency domain. In order to represent a palmprint’s crease intensity, the frequency domain image is divided into small parts by a series of circles which have the same center[5][7][9][20].
Palmprint feature exhibited in the frequency domain-

In palmprint identification, Fourier Transform is used in feature extraction. This is because there exist some correspondences between palmprint features on a spatial domain image and those on a frequency domain image. In general, the stronger the creases are on a spatial domain image, the less compact the information is on a frequency domain image. And if a palmprint image in the spatial domain has a stronger line, in the frequency domain there will be more information in the line’s perpendicular direction.

Palmprint feature representation

Palmprint feature representation is to describe the feature in a concise and easy to compare way. If we use polar coordination system \((r, \theta)\) to represent the frequency domain images, the energy change tendency along \(r\) shows the intensity of a palmprint’s creases and that along \(\theta\) shows the direction of a palmprint’s creases.

The image can be converted from a right angle coordination system into a polar coordination system by

\[
I'(r, \theta) = I(64 + r \cos \theta, 64 + r \sin \theta), \quad 0 \leq r \leq 64 \quad 0 \leq \theta \leq \pi \quad \ldots \ldots \ldots \ldots .4.5
\]

Where \(I\) is the image under right angle coordination system and \(I'\) is the image under polar coordination system.

In order to represent a palmprint’s creases intensity, the frequency domain image is divided into small parts by a series of circles which have same center. The energy in each ring like area is defined as
\[ R_i = \sum_{\theta=0}^{\pi} \sum_{r=8(i-1)}^{8i} I'(r, \theta), \quad i=1,2,\ldots, 8 \quad \ldots \ldots \ldots 4.6 \]

Where \( I' \) is the sub image under polar coordination system. \( R_i (i=1,2,3,\ldots, 8) \) is called R feature.

4.3.4 Coding Approach[58]

Coding approach encodes filter response as feature. Gabor filter are commonly applied in this approach. Phase and orientation feature have been encoded. The encoding process is to construct a bitwise representation for high speed matching. The high speed matching is performed by bitwise hamming distance or bitwise angular distance. These two bitwise distance are equivalent. In fact, these coding methods are clustering processes and can be considered as extension of IrisCode.

IrisCode, PalmCode and Fusion Code all are based on phase information for iris or palmprint identification. These two different biometrics traits in fact should have different discrimination information. An effective palmprint features, the orientation field of palmprints constituted by palm lines, is revealed. Using this feature, a coding method called Competitive Code is developed, which utilizes multiple 2-D Gabor filters to extract the orientation fields, a novel coding scheme to generate a bitwise feature representation and bitwise angular distance to compare two feature codes.

4.4 Proposed Method for Feature Extraction

After getting ROI of Palm image following filters can be applied for feature extraction to eliminate the variation caused by rotation and translation.

Some filters are commonly used for texture extraction as under –

65
4.4.1 Standard Spatial Filters

By using this 2 D linear spatial filter, obtained by using function, which generate a filter mask, \( w \), using the syntax

Syntax –

\[
    w = \text{fspecial}('\text{type}', \text{parameter});
\]

where ‘type’ specifies the filter type, and parameter further define the specified filter. The parameter may be following type.

Average, disk, Gaussian, laplacian, log, motion, prewitt, sobel, unsharp.

Prewitt parameter- \text{fspecial}('prewitt'). Output a 3x3 prewitt filter, that approximates a vertical gradient. A filter mask for the horizontal gradient is obtained by transposing result.

Example –

\[
    x7 = \text{fspecial}('\text{prewitt}');
\]

\[
    x77 = \text{filter2}(x7,e);
\]

Images of ROI of palm by applied fspecial filter.

Fig. 4.1. : Images of ROI of Palm after fspecial Filter.
4.4.2 Low Intensity Pixel Selection –

To remove the noise we keep only less than 25 intensity value pixels. The following matlab command applied.

Syntax –

\[
\text{Image variable} = \text{image variable} < 25;
\]

Example -

\[
d=e2<25;
\]

![Images at Less than 25 Pixel Intensity Value](image-url)
4.4.3  Filling the Image & Extraction of Principal Lines

We use imfill command for filling the image or making the connectivity 4x4 by using following matlab command.

Syntax –

\[
\text{Image variable} = \text{imfill(image variable, [no, no])};
\]

Example –

\[
g=\text{imfill}(d, [4,4]);
\]

Images Showing the final extracted palm line from a palm-

---

Fig. 4.3 : Images of Extracted Palm Line from a Palm
4.4.4. Generation of Data Set

Each image is reshaped in column vector of 1 to 2304 column (48x48) by using following matlab command.

Syntax –

Image variable= reshape(image variable, starting no , ending no);

Example -

\[
AA=\text{reshape}(g,1,2304);
\]

After reshaping image in column vector each row represent a sample and saved in input data file by using following matlab command

Syntax-

\[
dlmwrite('pathname\filename.txt', \text{reshaped var} , 'mode' , 'seperator', ' separator symbol');
\]

Example -

\[
dlmwrite('c:\inputfile.txt', AA, '-append', 'delimiter', '');
\]

By using same process we generate a target file for the sample for which we want to test the process. the data set are appeared like the following way.
A pattern is arrangement of descriptor. The feature is used in the pattern recognition to denote the descriptor. A pattern class is family of pattern that show some common properties. Pattern recognition by machine involves techniques for assigning pattern to their respective classes automatically and with human intervention. Three common pattern arrangement used in practice are vector(for quantative description) and string and trees(for structural description). Recognition techniques based on matching represent each class by a prototype pattern vector. An unknown pattern is assigned to the class to which it is closest in terms of predefined matrix.
4.5.1 Different Techniques of Palmprint Recognition

4.5.1.1 Hamming Distance Formula[19]

Given two data sets, a matching algorithm determines the degrees of similarity between them. To describe the matching process clearly, we use a feature vector to represent image data that consists of two feature matrices, real and imaginary. A normalized Hamming Distance is used to determine the similarity measurement for palmprint matching. Let P and Q be two palmprint feature vector. The normalized hamming distance can be described as

$$D_o = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} P_{M}(I,j) \cap Q_{M}(I,j) \cap (P_{R}(i,j) \otimes Q_{R}(i,j)) + P_{M}(I,j) \cap Q_{M}(i,j) \cap (P_{I}(i,j) \otimes Q_{I}(i,j))}{2\sum_{i=1}^{N} \sum_{j=1}^{N} P_{M}(i,j) \cap Q_{M}(i,j)}$$

Where $P_{R}(Q_{R})$, $P_{I}(Q_{I})$ and $P_{M}(Q_{M})$ are the real part, the imaginary part and the mask of $P(Q)$, respectively. The result of the Boolean operator ($\otimes$) is equal to zero, if and only if the two bits, $P_{R}(1)(i,j)$, are equal to $Q_{R}(1)(i,j)$; the symbol $\cap$ represent AND operator, and the size of the feature matrixes in N x N. It is noted that $D_o$ is between 1 and 0. For the best matching, the hamming distance should be zero. Because of imperfect preprocessing, we need to vertically and horizontally translate one of the feature and match again. The ranges of the vertical and horizontal translation are defined from -2 to 2. The minimum value obtained from the translated matching is considered to be the final matching score.

Disadvantages –

- A lot of calculation part involve so it is very difficult to obtain the accurate result.
- This is generally used in biometrics technologies[19]
- The process is very complicated that require more simplicity
4.5.1.2. Euclidean Distance Classifier[35]

Given two data set of feature corresponding to the training and testing samples, a matching algorithm determines the degree of similarity between them. A Euclidean distance is adopted as a measure of dissimilarity for the palmprint matching using both wavelet and fuzzy features.

Chi-square Measure[35]

In the LBP (Local Binary Pattern feature), the matching of an image pair is done by computing the distance between the two LBP feature histogram of training and test samples. The larger the distance between the histograms the more dissimilar are the images. The Chi square distance between the two histograms S and M can be defined as:

\[ X^2(S,M) = \sum_{b=1}^{B} \frac{(S_b - M_b)^2}{S_b + M_b} \] …………………4.8

Where \( S_b \) and \( M_b \) are normalized enhanced histogram; the index \( b \) refer to \( b^{th} \) bin of histogram.

Support Vector Machine[35]

SVM based on the principal of Structural Risk Minimization, construct a set of hyper planes in a high dimensional space for the classification of input features. Considering a two-class problem to be solved by a SVM, it is started with a training sample described by a set of features \( x_i \in \mathbb{R}^n, n=1,2,\ldots,N \), \( N \) being the number of features belong to one of two classes indicated by the label \( y \in \{+1,-1\} \). The data to be classified by the SVM may not be linearly separable in its original domain. In the linear non-separable
case the data is projected onto a higher dimensional feature space using Kernel function defined as:
\[
K(x_i, y_j) = \Phi(x_i)^T \Phi(x_j) \quad I,j=1,2,3\ldots N \quad \cdots \cdots \text{4.9}
\]

Where \( \Phi \) is the function that maps the original data onto the higher dimensional space. The SVM now generates a hyperplane in this space with the decision boundary defined as
\[
f(x) = \sum_{i=1}^{N} y_i \alpha_i K(x, y_i) + b \quad \cdots \cdots \text{4.10}
\]

Where \( \alpha_i \) is the non negative Lagrang multiplier.

**Disadvantages**

- The process is very complicated and involve a lot of calculation
- The main problem for achieving good authentication rate is the choice number of samples for the training and the testing. It is observed that as training samples increase the matching score increase but as the number of testing samples increase the matching scores decrease correspondingly.

**4.5.1.3. Score Formula Calculation**[7]

The palm images under process are divided into elliptical half-rings of some width regardless of the size of the original image, different palm sizes will result in feature vector of different length. Due to the possibility of having variation in the extent the hand is stretched, the resultant maximum palm area may vary within the same subject. Therefore, the distance measure used must be able to fairly compare two feature vectors with unequal dimension.
The score is calculated as the mean of the absolute difference between two feature vectors. If \( \text{feature}_V_i \) represent a feature vector \( N_i \) elements, the score between two images is given as

\[
\text{Score}(i,j) = \frac{\sum_{n=1}^{\text{Min}(N_i, N_j)} \left| \text{feature}_V_i(n) - \text{feature}_V_j(n) \right|}{\text{Min}(N_i, N_j)} \]  ……4.11

4.5.1.4. Fusion Method[24]

The fusion of multiple traits of an individual can improve the matching accuracy of a biometric system. It is based on the type of information available in a certain module, different level of fusion can be defined, (a) Fusion at the data or feature level: Either the data itself of the feature sets originating from multiple sensors/sources are fused.(b)Fusion at match score level: The scores generated by multiple classifier pertaining to different modalities are combined.(c) Fusion at decision level: The final output of multiple classifier is combined.

The feature set contains richer information about the input biometric data than the matching score or the output decision of a matcher, fusion at the feature level is expected to provide better recognition result. Fusion at the decision level is considered to be rigid due to availability of limited information. Thus, fusion at the match score level is usually preferred, as it is relatively easy to access and combine the scores presented by the different modalities.

Disadvantage-

This method is generally applied on biometrics pattern matching only.
4.5.1.5. Artificial Neural Networks as Palm Print Recognition Tool [6]

Typically the network consists of a set of sensory units (source nodes) that constitute the input layer one or more hidden layer of computation nodes and an output layer of Computation nodes. The input signal propagates through the network in forward directions on a layer by layer basis. These neural networks are commonly referred to a multilayer perceptrons, which represent a generalization of the single layer perceptron. Multiplayer perceptrons have been applied successfully to solve some difficult and diverse problem by training them in a supervised manner with highly popular algorithm known as the error back propagation algorithm. This algorithm is based on the error correction learning rule.

Training and Transfer Function
Neural network is trained upon some set of images, and tested upon unseen images. The networks undergoes process of training, continuously in an iterative manner. It calculates the output from each layer, extracting the mean square error and propagating it backwards if it does not approach targets. Due to this backward error propagation, error-signal for each neuron is calculated, which in fact is used for neuron weight updation. If it approaches targets, then it is considered to have been trained. The response of the neural network is dependent upon weight, biases and transfer function. The transfer functions used in feed-forward back propagation neural network. These functions act as summation junction and calculate the output from the input presented.

Testing
Image for testing applied to the trained neural network along with already trained images for calculating the percentage of accuracy and error. In testing, like training incoming images undergone through all the pre-processing and make available to the network for simulation. Simulation is the process in which network object, image data is presented as inputs, and it simulate the network. After checking, each image in the database correct counter along with error counters are incremented[8][10]
**Multilayer Perceptron**

A multilayer perceptron (MLP) is a feedforward artificial neural network model that maps sets of input data onto a set of appropriate outputs. An MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. Except for the input nodes, each node is a neuron (or processing element) with a nonlinear activation function. MLP utilizes a supervised learning technique called backpropagation for training the network. MLP is a modification of the standard linear perceptron and can distinguish data that are not linearly separable.

**Why MultiLayer Perceptron/Neural Network?**

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyse. This expert can then be used to provide projections given new situations of interest and answer "what if" questions. Other advantages include:

1. Adaptive learning: An ability to learn how to do tasks based on the data given for training or initial experience.
2. One of the preferred techniques for gesture recognition.
3. MLP/Neural networks do not make any assumption regarding the underlying probability density functions or other probabilistic information about the pattern classes under consideration in comparison to other probability based models.
4. They yield the required decision function directly via training.
5. A two layer backpropagation network with sufficient hidden nodes has been proven to be a universal approximator.
Advantages of Neural Computing

- Pattern recognition is a powerful technique for harnessing the information in the data and generalizing about it. Neural nets learn to recognize the patterns which exist in the data set.
- The system is developed through learning rather than programming. Programming is much more time consuming for the analyst and requires the analyst to specify the exact behavior of the model. Neural nets teach themselves the patterns in the data freeing the analyst for more interesting work.
- Neural networks are flexible in a changing environment. Rule based systems or programmed systems are limited to the situation for which they are designed--when conditions change, they are no longer valid. Although neural networks may take some time to learn a sudden drastic change, they are excellent at adapting to constantly changing information.
- Neural networks can build informative models where more conventional approaches fail. Because neural networks can handle very complex interactions they can easily model data which is too difficult to model with traditional approaches such as inferential statistics or programming logic.
- Performance of neural networks is at least as good as classical statistical modeling, and better on most problems. The neural networks build models that are more reflective of the structure of the data in significantly less time. Neural networks now operate well with modest computer hardware. Although neural networks are computationally intensive, the routines have been optimized to the point that they can now run in reasonable time on personal computers. They do not require supercomputers as they did in the early days of neural network research.
4.6. **Palmprint Matching Using Artificial Neural Networks**

The proposed work uses the pattern recognition tool in MATLAB in GUI mode. This is a powerful tool for matching a pattern. The following steps are used in MATLAB:

**4.6.1. Pattern Recognition with nprtool of Matlab**

To solve a pattern recognition problem with a two-layer feed forward network. In pattern recognition problem, we want a neural network to classify input into a set of target categories. The neural networks pattern recognition tool helps to select data, create and train a network, and evaluate its performance using mean square error and confusion matrices.

A two-layer feed-forward network, with sigmoid hidden and output neurons, can classify vectors arbitrarily well, given enough neurons in its hidden layer. The network will be trained with scaled conjugate gradient backpropagation. The following steps are performed to get the results:

![Image: Neural Network Pattern Recognition Structure](image)

**Fig. 4.4 : Neural Network Pattern Recognition Structure.**

**Steps for matching of a palm print**

**Step 1.** Open the neural networks start in gui mode with the command `NNSTART`
Step 2. The Select Data window opens. If the dataset (input and target) already loaded in the workspace, then can be selected from the proper combo boxes. Otherwise click on selection button to start import Wizard where can be browsed for proper file. There exist additional datasets accessible from the ‘load example dataset’ button.

Step 3. Select input data set as inputfile.txt file, where sample data set are saved.

Select target data set as outfile.txt file, where a sample data set is saved.

Step 4. Use validation and Test Data window.
Validation and test data sets are each set to 15% of the original data. With these settings, the input vectors and target vectors will be randomly divided into three sets as follows:

- 70% are used for training.
- 15% are used to validate that the network is generalizing and to stop training before overfitting.
- The last 15% are used as a completely independent test of network generalization.

Step 5. The standard network that is used for pattern recognition is a two-layer feed forward network, with sigmoid transfer functions in both the hidden layer and the output layer. The default number of hidden neurons is set to 10. You might want to come back and increase this number if the network does not perform as well as you expect. The number of output neurons is set to 2, which is equal to the number of elements in the target vector (the number of categories).

Step 6. Train the Network here a synopsis of the parameters set so far is displayed.

Step 7. The network start to train and produces results.
4.7. **Experimental Results**

Fifty samples of palm images have been collected in RGB color by 638X878 pixel size by fixing cross point of thumb and index finger with help of a square wooden strip. We have taken 50 Palm samples images, such images have been converted in gray scale and then resized 48X48. This is very small size of image so that processing of big database as well as storage of such images can be done in very short time. The data base of image has been changed in data set where each row has been represented by a sample of palm image which has size 1X2304. The 50 samples of palm images have the size 50X2304 matrixes. Each sample 1X2304 train by neural networks and pattern recognition tool and produce results.

The technique to finding ROI of palm image is very effective because all type of filters like Gabor filter, Wavelet have been ignored for feature extraction. The uses of Gabor filter and wavelet filter is very complex. All efforts are done to align the hand to bring the symmetry in hand scanning that play a very important role.

4.7.1. **ROI Detection Technique**

A technique is proposed to find the ROI of palm image by minimizing the translation and rotation problem. A point is fixed by using a wooden square strip at co-ordinates (445 : 538), a point is selected at root of little finger just opposite diagonal direction having co-ordinate (150 : 365). After setting the co-ordinate, the image is cropped by using matlab command.
4.7.2. Matching of Palmprint

The results produced by using only 10 hidden neuron, input data set 2304 and target data set 50x2304 to train the network and Training, Validation, Testing operation are divided in 70%, 15% and 15% respectively. The mean square error is maximum 0.307543 and minimum 0.001015. The MSE in five different samples is also very low. The percentage ERR maximum 2.357320 and minimum 0 are also reasonable and good. Such results prove the accuracy of the proposed technique.

<table>
<thead>
<tr>
<th>Sample Name</th>
<th>Mean Square Error(MSE)</th>
<th>%E</th>
</tr>
</thead>
<tbody>
<tr>
<td>A (1X2304 dataset)</td>
<td>0.307543</td>
<td>2.357320</td>
</tr>
<tr>
<td>B (1X2304 dataset)</td>
<td>0.123187</td>
<td>0.912849</td>
</tr>
<tr>
<td>C (1X2304 dataset)</td>
<td>0.001044</td>
<td>0</td>
</tr>
<tr>
<td>D (1X2304 dataset)</td>
<td>0.001015</td>
<td>0</td>
</tr>
<tr>
<td>E (1X2304 dataset)</td>
<td>0.001129</td>
<td>0</td>
</tr>
</tbody>
</table>

4.8 Conclusion

It is observed that this technique is very simple. A ROI detection technique is very effective, the rotation and translation part is eliminated at the time of scanning. Only edge detector or standard filter is used for feature extraction. The palm principal lines are extracted effectively. The Multilayer artificial Neural Networks NPRTOOL is used for matching two palm prints. The Mean Square Error is between 0.001015 to 0.307543 and percentage error is between 0 to 2.357320, which is very low and satisfactory. These results show the good performance of the proposed technique.