CHAPTER 2

DECISION RULE BASED BIOMETRIC IMAGE FUSION

2.1 INTRODUCTION

Biometric system has two distinct applications such as identification and authentication. For example, an Automatic Fingerprint Identification and Verification system have 2 modes of operation such as criminal/searching in database for a match and Civilian/One-to-one matching from captured big metrics/templates creation for a database. The performance measuring metrics for this system are accuracy and speed respectively.

The greatest strength of biometrics is that it does not change over time. But at the same time while using it directly for enhancing the security in network system, if that data has been compromised, it’s compromised forever. Therefore, cancellable biometrics will increase the privacy which means that the true biometrics are never stored or revealed to the authentication server. Biometrics, cryptography and data hiding will provide good perspectives for information security. Most of the researchers confirmed that the finger print is widely used than the iris or face and more over it is the primary choice for most privacy concerned applications. Also many mathematicians proved that Elliptic Curve is the best solution for Cryptography. For finger prints applications, choosing proper sensor is at risk. Many different fingerprint biometric technologies are available on the market nowadays. The critical decision of which one is right for a specific application is difficult by the stress between security and convenience. A
highly secure fingerprint biometrics is also troublesome and time-consuming to use. On the other hand, a convenient fingerprint sensor might enhance the benefits and speed of use at the expense of security Tabassi & Wilson (2005).

The ideal fingerprint sensor would do both. It would identify every person on earth perfectly in any kind of environment including outdoors in the rain, in bright sunlight, in hot and cold weather. This ideal sensor would be small, easy to use, quick and inexpensive. While it is clear that such a perfect fingerprint sensor does not exist, most biometric and security experts would agree that fingerprint technologies, in general, are performing much better today than five or ten years ago.

There are two reasons for this performance improvement:

1) the algorithms that are used to process acquired fingerprint images have improved tremendously; and
2) there is a greater variety of sensors available to obtain reliable fingerprint images in varying applications.

Better fingerprint matching algorithms are used almost universally today to increase performance, but no algorithm can compensate for imperfect or missing images Jain et al (2007). In fact it is extremely difficult or impossible to obtain reliable fingerprint images from a significant percentage of the world population. There are many reasons that fingerprints may be difficult to acquire, including genetic background, damage from manual labor, poor health, and age. Even environmental conditions can cause severe problems. As I alluded to in my description of the ideal sensor, conditions such as low humidity, high humidity, extreme cold, rain, snow, and direct sunlight negatively affect many fingerprint technologies.
The proposed work deals about, how the image quality can be improved by introducing image fusion technique at sensor levels. The results of the images after introducing the decision rule based image fusion technique are evaluated and analyzed with its entropy levels and root mean square error. Then the resultant enhanced image is used for extracting the key for ECC applications.

Finger print recognition is the leading biometric technology and it is the most popular in the market, comprising 32% of the total market in literature (Koblitz 1994). Because it is a proven technology and it is capable of showing very high levels of accuracy. Also, the cost of implementations is very low when compared to other biometric based applications. The major drawback of finger print recognition systems is contact nature of sensors such as inability of the sensing process to accommodate dirt and other environment in Chen et al (2006). The ability of the system to perform well (within the limits of its design) is based almost solely upon the quality of the biometric captured. A well captured biometric is rich in distinguishing information, which in turn gives the feature extraction algorithms the best chance of finding a match with existing records. The desired system performance shall be obtained by using multi modality based biometric system.

An important problem in Image fusion processing is the management of spatial information (in fact, the basic information in images) as in Burt &Lolczynski(1993). Spatial analysis is done to answer questions about the real world including the present situation of specific areas and features Zhang & Blum (1999). Due to their set theoretical and geometrical interpretation, fuzzy sets are well adapted to represent spatial information in images with uncertainty or imprecision. The decision making systems make use of heterogeneous information to identify an object class or a target, which are affected by various kinds of imperfection. The information extracted from
each image or sensor (either numerical or symbolic) is represented as a degree of belief in an event with real values, generally in $[0, 1]$, taking in this way into account the imprecise, uncertain and incomplete nature of information. The fusion of fuzzy sets provides a way to deal with uncertainty and imprecision and takes a decision only when all information has been combined in. Results generated by the proposed method illustrate its capabilities in classifying and preserving internal image details. The design of multi-biometric system could be optimized by effective fusion methods.

2.2 LITERATURE REVIEW

The study report of the need for the proposed system is briefed here as follows:

1) Investigations of Image Fusion

Image Fusion produces a single image from a set of input images. The fused image should have more complete information which is more useful for human or machine perception. The objectives of Image Fusion schemes is to extract all the useful information from the source images, do not introduce artifacts or inconsistencies which will distract human observers or the following processing and reliable and robust to imperfections such as mis-registration.

2) Image Fusion Using a 3-D Wavelet Transform.

The goal of this research work is to present the framework for 2-D image fusion using the wavelet transform and the fusion rules applied. The general idea of all wavelet based image fusion schemes is that the wavelet transforms $w$ of the two registered input images are computed and these
transforms are combined utilizing some fusion rule. Then, the inverse wavelet transform $w$ is computed, and the fused image $l$ is reconstructed.

3) **A Region Based Image Fusion Method Using Expectation – Maximization Algorithm.**

The term fusion means in general an approach to combine the important information simultaneously from several sources (channels). When we approach image fusion, multiscale transforms (MST) are commonly used as the analyzing tool. It transforms the sources into a space-frequency domain which can be understood as a measure of the saliency (activity level). The criterion to fuse consists of taking the decision to preserve the most salient data from the sources. In order to reduce sensitivity against noise the saliency is often averaged over certain neighborhood (window). Traditionally the size of the neighborhood is chosen fixed according to the level of noise present in the sources, which has to be estimated in advance.

4) **Image Fusion Using Fuzzy logic and applications**

The fusion should provide a human/machine perceivable result with more useful complete information. A great deal of interest has recently been shown in literature in Image Fusion because of its application in automotive, medical and other areas. Some techniques are currently available for image fusion. Some new approaches have been suggested in this work in particular, Fuzzy and Neuro-Fuzzy. Algorithms are also proposed for the above said techniques for image fusion process. Fuzzy logic approach has attracted the attention of several investing actors in different disciplines. Zadeh et al (1965) proposed Fuzzy logic. Recently, the approach is being utilized in different disciplines. The system can be trained from the input data obtained from the sensors.
The primitive fusion schemes perform the fusion right on the source images, which often have serious side effects such as reducing the contrast. People found that it would be better to perform the fusion in the transform domain.

2.3 SPATIAL ANALYSIS

An analog image is described by the spatial distribution of detected energy. A photograph on paper may show a black-and-white image with gray levels representing grades of brightness from black to white. For a digital image representation suitable for processing on the computer, the image has to be discretized in both spatial and intensity (gray-level) domains. A discretized spatial location of finite size with a discrete gray-level value is called a pixel. For example, an image of 1024 x 1024 pixels may be displayed in 8-bit gray-level resolution. This means that each pixel in the image may have any value from 0 to 255 (i.e. total of 256 gray-levels). The pixel dimensions would depend on the spatial sampling.

2.4 WAVELET TRANSFORM FOR IMAGE PROCESSING

A brief review based on Shutao Li et al (2001), Shutao Li et al (2004) and Hong et al (1998) of relevant wavelet theory will be useful for a better understanding of the proposed method. The wavelet transform is a method for complete frequency localization of a signal. The Fourier transform provides information about the frequency components present in the signal. However, the Fourier transform does not provide any information about frequency localization, that is, it does not provide information about when a specific frequency occurred in the signal. For applications in image processing and analysis, frequency localization is needed to determine the spatial position of a frequency component in the image. Since image is 2-D signal, let us mainly focus on the 2-D wavelet transforms. After one level of
decomposition, there will be four frequency bands, namely Low-Low (LL),
Low-High (LH), High-Low (HL) and High-High (HH). The next level
decomposition is just applied to the LL band of the current decomposition
stage, which forms a recursive decomposition procedure. Thus, N-level
decomposition will finally have $3N+1$ different frequency bands, which
include $3N$ high frequency bands and just one LL frequency band. The
frequency bands in higher decomposition levels will have smaller size.

2.4.1 Image Smoothing and Sharpening Using Wavelet Transform

The “least asymmetric” wavelets are computed and reported by
Daubechies, Haar and biorthogonal transformation. The wavelet transform
provides a set of coefficients representing the localized information in a
number of frequency bands. A popular method for denoising and smoothing
is to threshold these coefficients in those bands that have a high probability of
noise and then reconstruct the image using the reconstruction filters. The
reconstruction process integrates information from specific bands with
successive upscaling of resolution to provide the final reconstructed image at
the same resolution as of the input image.

The Haar wavelet is the first known wavelet and was proposed in
1909 by Alfred Haar. As a special case of the Daubechies wavelet, it is also
known as D2. The Haar wavelet is also the simplest possible wavelet. The
Daubechies wavelet transform is named after its inventor, the mathematician
Ingrid Daubechies. Each step of the wavelet transform applies the scaling
function to the data input. If the original data set has N values, the scaling
function will be applied in the wavelet transform step to calculate N/2
smoothed values. In the ordered wavelet transform the smoothed values are
stored in the lower half of the N element input vector. Each step of the
wavelet transform applies the wavelet function to the input data. If the
original data set has \( N \) values, the wavelet function will be applied to calculate \( N/2 \) differences (reflecting change in the data). In the ordered wavelet transform the wavelet values are stored in the upper half of the \( N \) element input vector.

There are two types of filter choices, orthogonal and biorthogonal. The biorthogonal wavelet transform has the advantage that it can use linear phase filters, but the disadvantage is that it is not energy preserving. The fact that biorthogonal wavelets are not energy preserving does not turn out to be a big problem, since there are linear phase biorthogonal filter coefficients, which are “close” to being orthogonal.

2.4.2 Inverse Wavelet Transform

The wavelet analysis involves filtering and downsampling, whereas the wavelet reconstruction process consists of upsampling and filtering. Upsampling is the process of lengthening a signal component by inserting zeros between samples. The reconstructed details and approximations are true constituents of the original signal. Since details and approximations are produced by down sampling and are only half the length of the original signal they cannot be directly combined to reproduce the signal. It is necessary to reconstruct the approximations and details before combining them.

2.4.3 Decision Based Fusion

Image fusion usually starts with dividing the channels into sub regions, calculating a measure of information level in the regions and then utilizing some fusion rules to combine the channels. The channel comparison can be done at different levels of abstraction. The lowest possible is the pixel level, which refers to the merging of measured physical parameters (intensity values of pixels). One step higher is feature-level fusion, which operates on
characteristics such as size, shape, edge, contrast and texture. The highest level of abstraction, called decision level fusion, deals with symbolic representations of images.

![Fusion flow diagram](image)

**Figure 2.1 Fusion flow diagram**

Decision Fusion can be implemented on the basis of Probability theory, Bayesian Inference Method and Fuzzy logic. A group decision-making environment was created wherein more than one expert can be involved in the interpretation process. The developed system also combines the decision made by each of them.

### 2.5 PROPOSED METHOD

#### 2.5.1 Generic Multiresolution Fusion Scheme

The basic idea of the generic multiresolution fusion scheme is motivated by the fact that the wavelet transform result in a multiresolution edge representation, it is straightforward to build the fused image as a fused multiscale edge representation. The fusion process is summarized in the following: In the first step the input images are decomposed into their multiscale edge representation, using any wavelet transform. The actual fusion process takes place in the difference respective wavelet domain, where the fused multiscale representation is built by a pixel-by-pixel selection of the
coefficients with maximum magnitude. Finally the fused image is computed by an application of the appropriate reconstruction scheme.

2.5.2 Decision Mapping Wavelet Neural Networks

For the integration scheme we need to design a 3D decision mapping wavelet neural networks, all the virtues above have to be introduced into the procedure of medical diagnostic image fusion. An implementation of a 3D version of the analysis and synthesis filter banks is used. In the 3D case, the 1D analysis filter bank is applied in turn to each of the three dimensions. If the data is of size N1 by N2 by N3, then after applying the 1D analysis filter bank to the first dimension we have two sub band data sets, each of size N1/2 by N2 by N3. After applying the 1D analysis filter bank to the second dimension we have four sub band data sets, each of size N1/2 by N2/2 by N3. Applying the 1D analysis filter bank to the third dimension gives eight sub band data sets, each of size N1/2 by N2/2 by N3/2.

2.5.3 Simulated Fusion Methods

The simulation results demonstrate the effectiveness of the proposed image data fusion method. A number of fusion rules can be used to combine the wavelet coefficients of two 2-D wavelet transforms. Some fusion rules implemented are:

i. Fusion by averaging - For each band of decomposition and for each channel the wavelet coefficients of the two images are averaged.

ii. Fusion by maximum - for each band of decomposition and for each channel, the maximum of the respective wavelet coefficients is taken.
iii. Fusion by maximum - for each band of decomposition and for each channel, the minimum of the respective wavelet coefficients is taken.

iv. Fusion by PCA - The transformation matrix contains the eigenvectors, ordered with respect to their eigenvalues. It is orthogonal and determined either from the covariance matrix or the correlation matrix of the input LRMs (low-resolution multispectral images). Principal Component Analysis performed using the covariance matrix is referred to as unstandardized PCA.

2.5.4 Region Based Image Fusion Technique

The major drawback of fingerprint technology is contact nature of sensors such as inability of the sensing process to accommodate dirt and other environment. The ability of the system to perform well is based almost solely based upon the quality of the biometric captured Stephen et al (2013). Multi-modal biometrics, or biometric fusion, is the process of combining information from multiple biometric readings, either before, during or after a decision has been made regarding identification or authentication from a single biometric. Fused Biometric image has the possibility to make identification more secure and more accurate than single biometric systems Kumud et al (2012).

In this research, it is focused on the objects which carry the information of interest, each pixel or small neighboring pixels are just one part of an object. Thus, a region-based fusion scheme is proposed. While making the decision on each coefficient, it should be considered not only the corresponding coefficients and their closing neighborhood, but also the regions the coefficients are in. So, the regions represent the objects of interest.
Figure 2.2 Block diagram region-based image fusion technique

In the proposed approach, the Neural Network and Fuzzy Logic approach can be used for image fusion. Such an image fusion could belong to a class of image fusion in which case the features could be input and decision could be output. The help of Neuro-fuzzy of fuzzy systems can achieve this. The pixel level image fusion using the above approach by using Fuzzy Logic and the process of defining membership functions and rules for the image fusion process using FIS (Fuzzy Inference System) editor of Fuzzy Logic toolbox in Matlab are provided below as an algorithm.

PROPOSED ALGORITHM

STEP 1

- Read first image in variable M1 and find its size (rows z1, columns: s1).
- Read second image in variable M2 and find its size (rows z2, columns: s2).
- Variables M1 and M2 are images in matrix form where each pixel value is in the range from 0-255. Use Gray color map
- Compare rows and columns of both input images. If the two images are not of the same size, select the portion which are of same size.
STEP 2

- Apply wavelet decomposition and form spatial decomposition Trees
- Convert the images in column form which has C = zl*slentries.

STEP 3

Create fuzzy interference system of type Mamdani with following specifications

STEP 4

- Decide number and type of membership functions for both the input images by tuning the membership functions.
- Input images in antecedent are resolved to a degree of membership ranging 0 to 255.
- Make rules for input images, which resolve the two antecedents to a single number from 0 to 255.

STEP 5

For num=1 to C in steps of one, apply fuzzification using the rules developed above on the corresponding pixel values of the input images which gives a fuzzy set represented by a membership function and results in output image in column format.

STEP 6

Convert the column form to matrix form and display the fused image.
NEURO FUZZY ALGORITHM

STEP 1

- Read first image in variable M1 and find its size (rows z1, columns: s1).
- Read second image in variable M2 and find its size (rows z2, columns: s2).
- Variables M1 and M2 are images in matrix form where each pixel value is in the range from 0-255. Use Gray color map.
- Compare rows and columns of both input images. If the two images are not of the same size, select the portion, which are of same size.

STEP 2

- Apply wavelet decomposition and form spatial decomposition Trees
- Convert the images in column form which has C = z1*s1 entries.

STEP 3

- Form a training data, which is a matrix with three columns and entries in each column are form 0 to 255 in steps of 1.
- Form a check data which is a matrix of pixels of two input images in a column format
- Decide the number and type of Membership Function.
- Create fuzzy interference system of type Mamdani with following specifications
  Name: ’c7’
  Type: ’mamdani’
AndMethod: 'min'
OrMethod: 'max'
DefuzzMethod: 'centroid'
ImpMethod: 'min'
AggMethod: 'max'

STEP 4

- Decide number and type of membership functions for both the input images by tuning the membership functions.
- Input images in antecedent are resolved to a degree of membership ranging 0 to 255.
- Make rules for input images, which resolve the two antecedents to a single number from 0 to 255.

STEP 5

For num=1 to C in steps of one, apply fuzzification using the rules developed above on the corresponding pixel values of the input images which gives a fuzzy set represented by a membership function and results in output image in column format.

STEP 6

- Start training using ANFIS for the generated Fuzzy Interference system using Training data.
- Apply Fuzzification using Trained Data and Check Data.
- Convert the column form to matrix form and display the fused image.
2.6 RESULTS AND DISCUSSION

The performance evaluation is done by quantitative measures such as (1) Information Entropy and (2) Root Mean Square Error.

For an image consists of \( L \) grey levels, the entropy is defined as:

\[
H = -\sum_{i=1}^{L} P(i) \log_2 P(i) \tag{2.1}
\]

where \( P(i) \) is the probability (here frequency) of each grey scale level. The entropy measures the expected uncertainty in \( I \). We also say that \( H(I) \) is approximately equal to how much information we learn on average from one instance of the random variable \( I \). Note that the base of the algorithm is not important since changing the base only changes the value of the entropy by a multiplicative constant. As an example a digital image of type uint8 (unsigned integer 8) has 256 different levels from 0 (black) to 255 (white). It must be noticed that in combined images the number of levels is very large and grey level intensity of each pixel is a decimal, double number. But the equation is still valid to compute the entropy. For images with high information content the entropy is large. The larger alternations and changes in an image give larger entropy and the sharp and focused images have more changes than blurred and miss focused images. Hence, the entropy is a measure to assess the quality of different images from the sensors at different instances.

The results for various methods used are tested with CASIA dataset as shown in Figure 2.4 and 2.5. It is being observed from Table 2.1 (a), the thumb finger and index finger images provide the best performance.
Figure 2.3 Finger print images at two incidents (a & b) and its Entropy (c)

Figure 2.4 Finger prints after various fusion techniques
Figure 2.5 Entropy of fused multi instance biometric images

Table 2.1(a) Entropy of fused image for multimodal biometric images (CASIA dataset)

<table>
<thead>
<tr>
<th>Finger</th>
<th>Image1 (at time 1)</th>
<th>Image2 (at time 12)</th>
<th>Fused Image</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Average</td>
</tr>
<tr>
<td>Right Thumb</td>
<td>7.4712</td>
<td>7.4210</td>
<td>8.2553</td>
</tr>
<tr>
<td>Right Middle</td>
<td>7.3290</td>
<td>7.3034</td>
<td>8.2073</td>
</tr>
</tbody>
</table>

Also Table 2.1 (b) illustrates the test results obtained by using the BioSecure multimodal DS2 samples. These samples are available for free and contain data of two persons (male and female). These samples are represented as f: fingerprint acquired with optical sensor and t: fingerprint acquired with thermal sensor. The images are represented as 1&7: right thumb, 2&8: right index, 3&9: right middle, 4&10: left thumb, 5&11: left index, 6&12: left middle. The Fuzzy and Neuro Fuzzy methods of image fusion technique provide good result with optical sensor.
### Table 2.1 (b) Entropy of fused image for multimodal biometric images (Biosecure DS2)

<table>
<thead>
<tr>
<th>Image</th>
<th>Image1</th>
<th>Image2</th>
<th>Average</th>
<th>Maximum</th>
<th>Minimum</th>
<th>PCA</th>
<th>Fuzzy</th>
<th>Neuro Fuzzy</th>
<th>optical sensor</th>
<th>thermal sensor</th>
</tr>
</thead>
<tbody>
<tr>
<td>1,7</td>
<td>7.411296</td>
<td>7.421077</td>
<td>8.255595947</td>
<td>7.042211071</td>
<td>7.466926598</td>
<td>14.46036</td>
<td>17.28021</td>
<td>17.32121895</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2,8</td>
<td>7.296221</td>
<td>7.22641</td>
<td>8.114098697</td>
<td>6.849086455</td>
<td>7.424170654</td>
<td>13.80593</td>
<td>17.1815</td>
<td>17.30591065</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4,10</td>
<td>7.307055</td>
<td>7.318007</td>
<td>8.186505982</td>
<td>6.94459651</td>
<td>7.445660448</td>
<td>14.07365</td>
<td>17.23159</td>
<td>17.31276186</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6,12</td>
<td>7.411376</td>
<td>7.445545</td>
<td>8.390436532</td>
<td>7.194578691</td>
<td>7.4508466</td>
<td>14.07453</td>
<td>17.20208</td>
<td>17.3059207</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The Root Mean Square Error between the reference image I and the fused image F is defined as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{M} \sum_{j=1}^{N} (I(i,j) - F(i,j))^2}{M \times N}} \quad (2.2)$$

where and i, j denotes the spatial position of pixels, M and N are the dimensions of the images. This measure is appropriate for a pair of images containing two objects.

Firstly, a “ground truth” image needs to be created that can be quantitatively compared to the fusion result images. This is produced using a simple cut-and-paste technique, physically taking the “in focus” areas from each image and combining them. The quantitative measure used to compare the cut-and-paste image to each fused image was taken from Jain et al (2006).

$$\rho = \sqrt{\frac{\sum_{r=1}^{N} \sum_{s=1}^{M} (I_{gt}(i,j) - I_{fd}(i,j))^2}{N^2}} \quad (2.3)$$

where $I_{gt}$ is the cut-and-paste “ground truth” image, $I_{fd}$ is the fused image and N is the size of the image. Lower values indicate greater similarity between the images $I_{gt}$ and $I_{fd}$ and therefore more successful fusion in terms of quantitatively measurable similarity.

The RMSE values represented in Table 2.2 show that neither LPT nor DWT has better performance in all levels, although the best result belongs to the LPT method. However the RMSE results compared to quality and entropy of fused images indicate that RMSE cannot be used as a proper criterion to evaluate and compare the fusion results.
Table 2.2 Results of multi-instance biometric images

<table>
<thead>
<tr>
<th>Different Tech</th>
<th>Entropy</th>
<th>Process Time</th>
<th>Mean Square Error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Image1</td>
</tr>
<tr>
<td>Two Max Averaging</td>
<td>9.3198</td>
<td>0.5150</td>
<td>1.0241e+004</td>
</tr>
<tr>
<td>Maximum</td>
<td>12.2813</td>
<td>0.5150</td>
<td>1.9268e+004</td>
</tr>
<tr>
<td>Minimum</td>
<td>12.9647</td>
<td>0.5460</td>
<td>6.9486e+003</td>
</tr>
<tr>
<td>PCA</td>
<td>10.5563</td>
<td>3.3280</td>
<td>1.8058e+004</td>
</tr>
<tr>
<td>Two Max Fuzzy</td>
<td>14.9813</td>
<td>174.7040</td>
<td>1.5173e+004</td>
</tr>
<tr>
<td>Two Max Fuzzy App</td>
<td>12.4181</td>
<td>44.7030</td>
<td>1.0643e+004</td>
</tr>
<tr>
<td>Two Max Neuro Fuzzy</td>
<td>15.7258</td>
<td>0.8750</td>
<td>1.0241e+004</td>
</tr>
<tr>
<td>Two Max Neuro Fuzzy App</td>
<td>12.4556</td>
<td>0.6250</td>
<td>1.0241e+004</td>
</tr>
</tbody>
</table>

In order to evaluate the results and compare these methods two quantitative assessment criteria Information Entropy is employed. In fact if the result of fusion in each level of decomposition is separately evaluated visually and quantitatively in terms of entropy, no considerable differences are observed. Experimental results demonstrated indicate that LPT algorithm reaches its best quality in terms of entropy in lower levels than DWT.

Finally the experiments showed that the LPT approach is implemented faster than DWT. Actually LPT takes less than half the time in comparison with DWT and with regard to approximately similar performance, LPT is preferred in real-time applications. Fuzzy and Neuro-Fuzzy algorithms have been implemented to fuse a variety of images. The results of fusion process proposed are given in terms of Entropy. The resultant image is being used for further process.
An ROC curve plots, parametrically as a function of the decision threshold, the percentage of impostor attempts accepted (i.e. false acceptance rate (FAR)) on the x-axis, against the percentage of genuine attempts accepted (i.e. 1 - false rejection rate (FRR)) on the y-axis. The Figure 2.6 shows the graphical representation of the test results by using CASIA data set. It is observed that the proposed decision rule based image fusion technique provides good result.

Figure 2.6 ROC (a) Before Image Fusion (b) After Image Fusion
In the recent development of Information Technology, communication with security is becoming as a necessary component in any application development. Also, Security is the foundation to privacy. In this part of our work, the use of DWT, Fuzzy and Neuro Fuzzy, and the fusion of biometric images by multimode and multiple biometrics were studied and identified that the Decision Rule Based Image Fusion Technique could be used in order to obtain a good quality image for cryptographic key generation.