CHAPTER 6

MULTIMODAL RECOGNITION SYSTEM USING HYBRID FUZZY RCE (HFRCE) MODEL

6.1 INTRODUCTION

Personal identification based on biometric traits needs to correctly identify a person who is a registered user and at the same time rejects an impostor not registered into the system. Unimodal biometric systems have to struggle with a variety of problems such as noisy data, intra-class variations, restricted degrees of freedom, non-universality, spoof attacks, and unacceptable error rates. Some of these limitations can be addressed by deploying multimodal biometric systems that integrate the evidence presented by multiple sources of information. Multimodal biometrics serves to improve the recognition efficiency and also accepts more number of users because of the multiple features extracted. Multimodal biometrics utilizes more than one modality for verification. Use of Multimodal biometrics can increase the accuracy and reduce vulnerability. Arun Ross et al. (2004). Face, fingerprint, nail and iris modalities have been successfully fused in matching module with Hybrid Fuzzy Reconstructed Columb Energy (HFRCE) method.

Proposed HFRCE method combines both the fuzzy and Reconstructed Columb Energy (RCE) in the matching level. The proposed
HFRCE method provides a common solution to authentication for human recognition. Multimodal biometrics fusion system is shown in the Figure 6.1.

![Multimodal Biometric System](image)

**Figure 6.1 Multimodal Biometric System**

### 6.2 LITERATURE SURVEY

Sudhamani et al. (2014) proposed a feature extraction technique for finger vein and iris traits. This approach combines the decisions of the individual modalities using the conventional AND rules. The authors claims that the effectiveness of the multimodal authentication system for accurate person authentication.

Lee et al. (2016) proposed a method with high performance rate while reducing the data dimensionality by face and palm print fusion with bit-plane decomposition approach. Pixel level fusion is applied by using simple averaging method before bit-plane feature extraction. Principal Component Analysis is also used on the hybrid face-palm bit planes for further dimension reduction before being classified by Feed forward Back propagation Neural Network.
Haghighat et al. (2016) proposed a discriminant correlation analysis (DCA) based feature level fusion technique that incorporates the class associations into the correlation analysis of the feature sets. DCA performs an effective feature fusion by maximizing the pair wise correlations across the two feature sets and, at the same time, eliminating between-class correlations and restricting the correlations to be within the classes. This method uses the pattern recognition applications for fusing the features extracted from multiple modalities or combining different feature vectors extracted from a single modality.

Roy et al. (2015) proposed a method which deploys the Fuzzy C-Means clustering with Level Set (FCMLS) method in an effort to localize the non-ideal iris images accurately. The FCMLS method incorporates the spatial information into the level set (LS)-based curve evolution approach and regularizes the LS propagation locally. Along with that genetic and evolutionary feature extraction (GEFE) is applied towards multimodal biometric recognition. GEFE uses genetic and evolutionary computation to evolve local binary pattern feature extractors to elicit distinctive features from the iris and facial images. Different weights for each modality are investigated to determine the significance of each modality.

Bahrampour et al. (2015) proposed a multimodal task-driven dictionary learning algorithm under the joint scarcity constraint (prior) to enforce collaborations among multiple homogeneous/heterogeneous sources of information. This task-driven formulation, the multimodal dictionaries have learned simultaneously with their corresponding classifiers. The resulting multimodal dictionaries can generate discriminative latent features (sparse codes) from the data that are optimized for a given task such as binary or multiclass classification. The author’s claims that compare to counterpart
reconstructive-based dictionary learning algorithms, the task-driven formulations are more computationally efficient.

Rank level fusion or in other words biometric rank aggregation is a process of combining the individual ranking preferences of several biometric matchers, into a single ranking list of the alternatives, which represents the consensus and which would aid in establishing the final authentication decision (Ross et al 2006). In most commercial biometric systems, match score or feature level fusion is not possible due to the unavailability of such information (Kumar et al. 2010). A few of such systems output ranked identities instead of the final (yes/no) decision, thus rank level fusion is a feasible option for those systems.

Zadeh et al. (1965) Fuzzy logic based fusion, often called fuzzy fusion, uses fuzzy logic. Fuzzy fusion method has been widely used in many applications, including automatic target recognition, biomedical image fusion and segmentation, gas turbine power plants fusion, weather forecasting, aerial image retrieval and classification, vehicle detection and classification, and path planning.

Solaiman et al. (1999) proposed a fuzzy-based multisensor data fusion classifier which was applied to land cover classification. The authors used a Fuzzy Membership Map (FMM) to combine information gathered from multiple sensors. Due to the use of fuzzy concepts, their proposed classifier was ideally suited for integrating multisensor and a priori information and also results in confidence maps. In another study, authors developed a new vehicle classification algorithm using fuzzy logic( Kim et al. 2001). In the algorithm, authors used vehicles’ weight and speed to classify different vehicles using fuzzy rules. With their experimental results, they showed that the proposed
classification algorithm using the fuzzy logic significantly reduces the errors in vehicle classification.

Another key contribution to the fuzzy fusion domain of literature is the work of (Wang et al. 2007) where authors used fuzzy fusion for multimodal medical image application. To overcome the problem of blurriness of the most medical images, the authors proposed a new method of medical image fusion using fuzzy radial basis function neural networks (Fuzzy-RBFNN), which is functionally equivalent to T-S fuzzy model. Genetic algorithm was used to train the networks. The research outcome demonstrated good performance when compared to other methods for blurry images.

The authors represented both the individual attribute of target in the model database and the sensor observation as fuzzy membership function and constructed a likelihood function to deal with fuzzy data collected with each sensor. At the end, sensor data from different sources was fused based on the Dempster combination rule. In another research on applying fuzzy fusion in the medical imaging research domain, Chaabane and Abdelouahab in 2011 (Chaambanne et al. 2011) proposed a system of fuzzy information fusion framework for the automatic segmentation of human brain tissues.

From the above discussion, it can be concluded that many multimodal biometric systems with various methods and strategies have been proposed over the last decade to achieve higher accuracy rate and to increase robustness against spoof attacks and external conditions. A general rule in theory assumes that the integration at an early stage of processing leads to systems which might be more accurate than those where the integration is introduced at later stages. Unfortunately, in practice fusion at sensor level is hard to achieve, due to the different natures of the biometric traits, which might be hardly compatible (e.g., fingerprint and face). Moreover, most
commercial biometric systems do not provide access to the feature sets which
minimizes the feasibility of a fusion at feature level. A well research on
information fusion methods for combining multimodal information with the
main concentration is given to rank information fusion. Among all of the
fusion approaches they investigated, the usage of nonlineairities in conjunction
with the weights resulted in the highest performance improvement.

6.3 ARCHITECTURE OF HYBRID FUZZY RCE (HFRCE) MODEL

The architecture of Hybrid Fuzzy Reconstructed Columb Energy
Model is shown in the figure 6.2. The proposed architecture consists of four
phases pre-processing, segmentation, feature extraction and matching. Initially
the biometric face, fingerprint, nail and iris images are pre-processed by using
a Gaussian filter which removes the noise from the image without affecting
the quality. From the pre-processed images ROI region is segmented and the
biometric significant key features are extracted by applying the Hermittan
based Haar Wavelet technique. Finally the matching process is performed by
applying the Fuzzy based RCE neural networks for recognition.

Proposed HFRCE algorithm consists of two phases in matching
process such as training and testing. In first phase various inputs are collected
and final nets are selected. The second is a weighted decision maker which
fuses the different nets derived from the first step to predict the outputs. In the
RCE network, there is no need for setting the number of required neurons
before learning because the RCE network makes new neurons automatically to
classify input data into correct categories. The proposed HFRCE model and its
network with RBF output function in order to reduce the number of neurons
created in the network, and evaluate the performance measures such as False
Acceptance Rate (FAR), False Rejection Rate (FRR) and Equal Error Rate (EER). Ali Shamsoddini et al. (2012).

In the first phase, machines are provided by different subsets derived randomly with replacement in the same way as in bagging and boosting. Bagging and boosting are well-known approaches for aggregating different neural networks in the training datasets through different procedures, and more popular examples for addressing regression problems. These subsets are used along with some datasets to train learners in a number of iterations. After generating different versions of the nets, the more reliable nets are selected in a filtering method. Then, the selected learners are used to form the inputs for the decision learner. In step two, the decision learner is trained for a number of iterations using these inputs which have been predicted using the best learners derived from the previous step. Finally, the weighting function will determine the final output of the ensemble method.

Figure 6.2   Architecture of Hybrid Fuzzy RCE System
6.3.1 Compendium of Computer Vision (CV) online database

The database used for this proposed system is CV (Compendium of Computer Vision) online database. The database consists of several biometric features in which BIO face database has 1521 gray level images, the resolution of the image is of 384x286 pixel and 23 test person images which are captured in the front view and the database consists of 1000s of fingerprint image in terms of four different datasets that were captured by applying four different sensor types, namely Low-cost Optical Sensor, Low-cost Capacitive Sensor, Optical Sensor and Synthetic Generator. Each finger dataset consists of 110 wide fingers, 8 impressions, 880 fingerprints which are producing good performance results during the authentication. The dataset has 100 users of nail images which is captured from participants right index finger nail. The nail images were captured with indoor scenario, using diffuse lighting to acquire a better quality image Meraoumia et al. (2012). Sample image datasets are shown in the Figure 6.3

![Figure 6.3 CV Online Database Images](image-url)
6.4 PRE-PROCESSING

The biometric images such as face, fingerprint and nail have some of the noises which lead to reduce the performance of the matching process. The noise must be removed from the grayscale image by applying the Gaussian filter Savithiri et al. (2010) which removes the impulse noise from the image with effective manner.

The Gaussian filter eliminates the impulse noise by applying the Gaussian weighted function that reduces the noise present in the grayscale image and smooth the image. If the images are having the zero mean value then the Gaussian filters works well while removing the noise in the image. Then the filtering process is formulated as in the Equation (6.1),

\[
h(m, n) = \left[ \frac{1}{\sqrt{2\pi \sigma}} e^{\frac{m^2}{2\sigma^2}} \right] \ast \left[ \frac{1}{2\pi \sigma e^{2\sigma^2}} \right]
\]  

(6.1)

Where \( \frac{1}{\sqrt{2\pi \sigma}} e^{\frac{m^2}{2\sigma^2}} \) the standard deviation of corrupted pixel is present in the input image pixel. \( \frac{1}{2\pi \sigma e^{2\sigma^2}} \) is the Gaussian distribution of the input pixel.

Thus the Gaussian filter removes the noise in all the directions using the distribution function and the degree of smoothing is measured by the variance value. From the pre-processed image, the ROI region is extracted which is used to improve the further matching performance. Ashish Mishra et al. (2010).

6.5 ROI REGION EXTRACTION

Region of Interest (ROI) is the process of identifying and extracting the exact region from the whole region, which lead to reducing the
unwanted activities and processing. The main aim of the ROI is to form a region with rectangular or square region with maximum number of pixels. Initially the pre-processed images are divided into the vertical and horizontal strips and the statistical property need to be calculated for each region Selvi et al. (2015).

Statistical properties such as variance, probability for grouping pixels into regions and then images are formed for each statistical property. Based on the statistical property the optimized region has been either selected or rejected. The statistical property is used to determine the activities of the particular strips which is identified by counting the number of connected lines. The connected line is calculated based on the Sobel operator. It can be used to identify the edges in input images. Then the statistical properties standard deviation, variance and the related threshold value are computed in the Equation (6.2)

\[ T = \text{Mean} - n \times \text{Stddeviation} \]  

(6.2)

Where T is the threshold value, n is the number of strips by default. The threshold value is used to estimate the activities of the particular strips based on that value the strips may be accepted or rejected.

6.6 FEATURE EXTRACTION USING HERMITTAN BASED HAAR WAVELET

The next stage is feature extraction which is used to extract the useful information from the pre-processed face, fingerprint and nail image. In this chapter the Harmittan based Haar Wavelet descriptor (Kataria et al. 2013) is used to extract the information that is used during the matching process. The pre-processed images are represented as the Hermittan Matrix, which is
complex of the image pixels, then the image is divided into the detailed and approximated coefficient and detailed coefficient which is calculated using the Equation (6.3) and (6.4).

\[
\text{Approximation coefficient} = a_n = \frac{f_{2n-1} + f_{2n}}{\sqrt{2}}
\]  
(6.3)

\[
\text{where } n = 1, 2, 3, \ldots \frac{N}{2}.
\]

\[
\text{Detailed coefficient} = d_n = \frac{f_{2n-1} - f_{2n}}{\sqrt{n}}
\]  
(6.4)

\[
\text{where } n = 1, 2, 3, \ldots \frac{N}{2}
\]

After dividing the images into the detailed and approximate coefficients, the signature should be calculated for each pixel which is done by calculating the average of the two pixels. The average calculation operation is performed for all image pixels. Then the difference between the average pixel value is recorded for whole image by using the filter bank approach Dighe et al. (2012)

After dividing the images into the detailed and approximate coefficients, the signature should be calculated for each pixel which is done by calculating the average of the two pixels. The average calculation operation is performed for all image pixels. Taouche et al. (2014). Then the difference between the average pixel values is recorded for whole image by using the filter bank approach. After that image is decomposed into 4 and 8 which is continued up to 10 signature extraction. The signature is calculated using Equation (6.5)

\[
f_r = \frac{\sqrt{C_{ij}}}{\sqrt{i+j}}
\]  
(6.5)

Where \(f_r\) is the computed texture feature from the image and \(C_{ij}\) is the intensity value of the image and \(i+j\) is the size of sub image. This process is repeated for
all the biometric image to get the important signature or feature and it is
considered as the template that is stored in the database for further matching
process. Sui et al. (2011).

6.7 MATCHING PROCESS

The final step is template matching where, user query related
features are compared with the database features to manage the people’s
identities. The similarity matching (Jiawei Li et al. 2010) process is done with
the help of the Hybrid Fuzzy RCE (HFRCE) classifier which is performed in
two stages namely training and testing. In the training stage the stored
templates are trained to classify the new test user’s features.

6.7.1 Fuzzy System

Fuzzy system is a set of fuzzy ”IF-THEN” rules that maps the
input variables x to the response variable y. Additive fuzzy systems
reconstruct the underlying functional dependence by covering the joint input-
output distribution with fuzzy patches. Fuzzy patches form coordinate-wise
fuzzy sets in the premise part of the fuzzy rules, and local regression models in
the consequent part. Given G fuzzy rules, the i\textsuperscript{th} fuzzy rule is given and the
values of i are represented in the following rule i.

\begin{equation}
   i = 1..G.
\end{equation}

Rule \textsubscript{i} : IF x Is A\textsubscript{i} THEN y is f\textsubscript{i} (x)\textsubscript{i}

A\textsubscript{i} is a fuzzy set defined on x, i = 1..G;

f\textsubscript{b\textsubscript{i}} (x) is a consequent model of the rule \textsubscript{i}. 

Figure 6.4  Neural Network representation of Fuzzy Model

Output of the network is calculated as the weighted average of consequents, with weights equal to normalized aggregated memberships. The overlapping fuzzy rules are fused with respect to their relative certainty. The resulting fuzzy model is given in Equation (6.6)

$$\hat{y} = \frac{\sum_{i=1}^{G} \mu A_i \hat{f}_i}{\sum_{i=1}^{G} \mu A_i}, \quad i = 1..G.$$  \hspace{1cm} (6.6)

6.7.2  Fuzzy Neural Networks

The fuzzy function estimator can be represented in the form of a feed forward neural network with two parametric layers, containing the evaluation of the premise and consequent parts of fuzzy rules. The resulting neural network architecture is shown in the Figure 6.4. The only difference is that the membership functions are conveniently reorganized in the form of multidimensional clusters $\mu A_i$, each of which corresponds to the Cartesian product of marginal membership functions $\mu A_{ij}(x_j)$, $i = 1..G$, $j = 1..d$. To
efficiently initialize the fuzzy rule-base, unsupervised clustering procedures can be used.

The joint input output $x \times y$ space is covered with cluster patches in an unsupervised way. Then, the obtained clusters are marginalized over $y$, in order to get cluster projections on $x$ and extract the fuzzy rule’s membership functions parameters. Having the initial estimate of the membership function parameters, one can proceed to learning the resulting neural network model. For the demonstration purposes, synthetic noisy $\sin(x)$ function was used as the data input. The final smoothed estimate of the local linear consequents is plotted on the first picture together with the fuzzy patches. At first the two-dimensional Gaussian patches are fitted to the data and marginalized over $y$ in order to extract functions of $x$ only. To fit the local linear consequents, the membership functions are normalized and these normalized

6.7.3 Fuzzy Model Fusion

To proceed with the fuzzy fusion model, operating on the external consequent models $\hat{f}$, there is one important transformation. In order to maintain the model stability, the fuzzy rules should be learned on the joint distribution of the noise terms $\epsilon = \hat{f} - E(\hat{f})$ and $E(\hat{f})$, where $E(\hat{f})$ is the mean prediction over the whole set of predictors. This transformation is essential because the high correlation of both the consequents $\hat{f}$ among each other, and their joint correlation with $y$ may lead to both unstable and unreliable clustering results in this joint space. It is important to note that the consequent layer in this type of model will still be using the true values of $\hat{f}$, concentrating the fuzzy rule learning on the differences between models. To initialize the appropriate fuzzy rules, the complete joint space of $\epsilon \times E(\hat{f}) \times y$. The option of considering the complete $x \times \epsilon \times X \times E(\hat{f}) \times y$ space in order to extract more
discriminative information from the complete distribution is also feasible, however it becomes more prone to the curse of dimensionality. Afterwards, given the number of rules G, then apply the Gaussian Mixture Model, fitted to the data with the Expectation-Maximization algorithm. The choice of the number of Gaussians G, which corresponds to the number of fuzzy rules in the model, can be done by trial-and error by means of Bayesian Information Criterion, which is well suited for this type of model. To proceed with learning of the whole model, one can apply the hybrid learning algorithm. At each iteration, at first, the membership function parameters $M_{ij}, S_{ij}$ are modified by means of gradient descent. Afterwards, given the new parameter estimates, the normalized membership values are calculated $W = \{W_i, \ldots, W_G\}$ in the Equation (6.7)

$$W_i(x) = \frac{\mu A_i(x)}{\sum_{j=1}^{G} \mu A_j(x)} \quad (6.7)$$

Similarly the weighted values for face, fingerprint, nail and iris values can be calculated by using the following Equation (6.8)

$$W_x = \frac{\mu A_i(x)}{\sum_{j=1}^{G} \mu A_j(x)} \quad (6.8)$$

$W_x$ Weighted Factor values, $X$ Modalities
$\mu A_{ij}$ Clusters.

These individual scores are finally combined into a total score, which is passed to the decision module. The same steps for fusion at classifiers level are followed for multiple modalities level i.e., matching scores are computed for each trait (face, fingerprint, iris and nail) followed by normalization to the common scale and distance to similarity score conversion for all the four traits. The matching scores are further rescaled so that the threshold value becomes common for all the subsystems. Finally, the sum of
score technique is applied for combining the matching scores of four traits i.e., face, fingerprint, iris and nail. Thus the final score $MS_{\text{Final}}$ is given by the Equation (6.9)

$$MS_{\text{FINAL}} = \frac{1}{4} (MS_{\text{FACE}} + MS_{\text{FINGERPRINT}} + MS_{\text{IRIS}} + MS_{\text{NAIL}}) \quad (6.9)$$

### 6.7.3.1 Feature Training

For the regression problem it is more difficult to determine a reliable boundary between easy and difficult examples due to an inevitable discrepancy between predicted and actual values. In a constant value is preliminarily selected according to the prediction error statistics of a single machine. For executing a calibration process before starting the ensemble method to find the optimum value of the threshold to separate easy and difficult examples. This calibration will add more time to the training. For calculating the loss of the predicted training the proposed relative error function which does not work when there are some examples with zero values in the training dataset. Finally, the threshold that is utilized in the proposed methods is not set automatically and consequently requires calibration. The losses of the predicted examples are calculated using the following equation that is the same as the loss Equation in (6.10)

Adaboost.R2:

$$L_t(i) = |f_t(x_i) - y_i| \quad (6.10)$$

where, $f_t(x_i)$ is the predicted value of the example $i$ in iteration $t$ and $y_i$ is the actual value of the example. Then the Normalized Losses (NL) of each training are calculated using the Equation (6.11)
where, $l_t(i)$ is loss for the example $i$ in the iteration $t$. $\mu$ represents the mean value of the losses while $\sigma$ is the standard deviation of these values. In this normal distribution, the values which are less than threshold, $\Phi$, are considered as easy samples in the current training iteration. The relationship between $\Phi$ and $\sigma_N$ which is the standard deviation of normalized loss values (almost equal to 1) is determined in Equation (6.12)

$$\Phi = -C \times \sigma_N$$

where, $C$ is in $[0, 2]$. If $C$ is 0, it means the examples whose normalized loss values are less than the mean are considered as easy examples and consequently the number of easy examples will increase, whereas setting $C$ to 2 can decrease the number of easy examples. In order to avoid these extreme situations, it is better to select a value for $C$ between these extremes, such as 1; however as the analyses of the effect of different $C$ values on the results, the value of $C$ does not significantly influence the final outcome.

### 6.7.3.2 Feature Matching

Using replacement in the sampling process generates some overlapped subsets. Although, the probability of using samples 1 decreases during the iterations, they may still be used in the next training subset. This consequently leads to less emphasis on the more samples 2. In order to overcome this deficiency and increase attention on the samples, which is the aim of this new ensemble method, hard partitioning is used instead of the probability updating. In this manner, the examples which are predicted to an acceptable level of accuracy ($NL$ less than $\Phi$) are removed from the training
subset. Hence, there is no need to update the probability of examples during the training process.

Feature matching is compared to the trained templates that were stored in the database. The test feature similarity is computed between the training and testing features with the threshold value Bharadi et al. (2014). So, in the proposed system the user features or templates are compared with the training feature set by using the Equation (6.13)

\[ D_B(p, q) = \frac{1}{4} \ln \left( \frac{1}{\sigma_p^2} \left( \frac{\sigma_q^2 + \sigma_p^2}{\sigma_p^2} \right) \right) + \frac{1}{4} \left( \frac{\mu_p - \mu_q}{\sigma_p^2 - \sigma_q^2} \right)^2 \]  

(6.13)

Where, \( D_B(p, q) \) Similarity between the training and testing features.

The computed similarity value is compared with the threshold value 0.2. If the value is greater than the threshold value, the user template considers as the valid template otherwise leaves the template as invalid. Thus the proposed system recognizes the identities with different biometric features such as fingerprint, face and nail by extracting the Hermittan based Haar feature and those features are valid by Fuzzy RCE neural network classifier. Thus the proposed methodology verify the users details with effective manner and the performance of the system FAR, FRR and EER is evaluated and presented in the result and discussion section.

6.8 PERFORMANCE MEASURES

To improve the recognition rate performance measures are calculated in the following sections.
6.8.1 False Acceptance Rate (FAR)

False Acceptance Rate (FAR) (Vala et al. 2014) is the process of calculating the rate of unauthorized user acceptance during the identity identification process.

The FAR is estimated by using the following Equation (6.14)

\[
\text{FAR} = \frac{\text{Number of features accepted}}{\text{Number of features tested}} \times 100
\]  \hspace{1cm} (6.14)

From the Equation (6.14) False Acceptance Rate of different classifiers such as Hausdorff distance, SVM, ANN, MLP and Fuzzy RCE neural networks were obtained for different biometric features which is shown in figure 6.10 and 6.11, it is clearly shown that the proposed Fuzzy RCE classifier matches the testing templates with the training templates with highest accuracy which is justified with the help of the false acceptance rate because, the proposed system accepts the authorized biometric features with less probability when compared to other classifiers.

6.8.2 False Rejection Rate

False Rejection Rate (FRR) (Ravi Subban et al. 2013) is the process of incorrectly rejecting the authorized user during the matching process which was measured in terms of percentage.

The FRR is measured by using the following Equation (6.15)

\[
\text{FRR} = \frac{\text{Number of original features rejected}}{\text{Number of original features tested}} \times 100
\]  \hspace{1cm} (6.15)
From the Equation (6.20) False Acceptance Rate of different classifiers such as Hausdorff distance, SVM, ANN, MLP and Fuzzy RCE neural networks were obtained for different biometric features. It is clearly shown that the proposed Fuzzy RCE classifier matches the testing templates with the training templates with highest accuracy which is justified with the help of the false acceptance rate because, the proposed system accepts the unauthorized biometric features with less probability when compared to other classifiers.

6.8.3 Equal Error Rate

Equal Error Rate (TarunaPanchal et al.2013) is the rate in which acceptance and rejections is equal which is easily calculated from the above described false acceptance and false rejection rate.

6.8.4 Recognition Rate

The recognition rate is calculated by the share of positive decisions in the total number of asylum (First decision and Final Decision) decisions for each stage of the first instance and final on appeal. The total number of decisions consists of the sum of positive and negative decisions. The recognition rate can be calculated by using the Equation (6.16)

\[
\text{Recognition Rate} = \frac{TP + TN}{TP + TN + FP + FN}
\]  

(6.16)

TP True Positive, TN True Negative, FP False Positive and FN False Negative
6.9 SIMULATION RESULTS

This session discusses the equipment and experimental procedures used to authenticate a person based on the fusion modalities such as face, fingerprint, iris and nail. The system is implemented using MATLAB 2009 in Windows 8 Operating System with 4 GB RAM.

The multimodal biometric system identifies the user’s identities and authorizes those users with the help of face, fingerprint, iris and nail features because these features never changes their structural and behavioral characteristics. The images are preprocessed by applying the Gaussian Filter. From the preprocessed image the ROI region and the features are extracted and those extracted features are matched by using the Fuzzy RCE classifier. Then the performance of the system is evaluated by False Acceptance Rate (FAR), False Rejection Rate (FRR) and Equal Error Rate (ERR) to analyzing the accuracy of the proposed matching classifier.

6.9.1 Pre-processing using Gaussian Filter

Face, fingerprint, iris and nail images are preprocessed by using the Gaussian filters.

Figure 6.5 Pre-processing of Face
Respective histogram equivalence values are calculated in each modality. Once pre-processing is done modalities are segmented to ROI.
6.9.2 Key Features are Extracted using Hermittan Based Haar Wavelet Technique

Region of Interest is the process of identifying and extracting the exact region from the whole region, which lead to reducing the unwanted activities and processing. Sample ROI feature is extracted in the Figure 6.9.

![Figure 6.9](image)

Figure 6.9  Face, Fingerprint, Nail and Iris Segmentation by ROI method

6.9.3 Fuzzy Fusion

Multimodal authentication system is combined with face, fingerprint, iris and nail in a mono model system and a fusion system. Fusion strategy takes combining all the modalities features together in order to obtain the authentication result: imposter or genuine user.

The proposed and implemented fuzzy based fusion methods uses the fuzzy logic principles for combining the feature scores of modalities. The processes of Fuzzy logic imprecise information like human thinking and it allows to acquire intermediate values between true and false, accepted and refused, by partial membership set. The four biometric modalities given as input and can be used to obtain the output variables by using a fuzzy system. The decision of the whole system depends on the output variables. The fuzzy
system uses the knowledge base built with above fuzzy rules. Each rule has the following common guidelines

1 IF “S (Security) is very low” THEN “T (Threshold) is very low”
2 IF “S (Security) level is low” THEN “T (Threshold) is low”
3 IF “S (Security) is medium” THEN “T (Threshold) is medium”
4 IF “S (Security) level is high” THEN “T (Threshold) is high”
5 IF “S (Security) is very high” THEN “T (Threshold) is very high”.

Face, Fingerprint, nail and Iris False acceptance Rates calculated and the values are tabulated using the Equation 6.14 and 6.15

<table>
<thead>
<tr>
<th>False Acceptance Rate (Training)</th>
</tr>
</thead>
<tbody>
<tr>
<td>False Acceptance Rate</td>
</tr>
<tr>
<td>FACE</td>
</tr>
<tr>
<td>No. of Features Accepted</td>
</tr>
<tr>
<td>No. of Images Tested</td>
</tr>
<tr>
<td>FAR (%)</td>
</tr>
</tbody>
</table>

Figure 6.10  FAR with different Matching Classifiers for Training
### Table 6.2 False Acceptance Rate (Testing)

<table>
<thead>
<tr>
<th>Calculation of False Acceptance Rate</th>
<th>FACE</th>
<th>FINGERPRINT</th>
<th>IRIS</th>
<th>NAIL</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of Features Accepted</td>
<td>0.01</td>
<td>0.09</td>
<td>1.8</td>
<td>1.8</td>
</tr>
<tr>
<td>No. of Images Tested</td>
<td>100</td>
<td>100</td>
<td>200</td>
<td>200</td>
</tr>
<tr>
<td>False Acceptance Rate</td>
<td>1%</td>
<td>0.9%</td>
<td>0.9%</td>
<td>0.9%</td>
</tr>
</tbody>
</table>

Figure 6.11 FAR with different Matching Classifiers for Testing

It is clearly shown that the proposed Fuzzy RCE classifier matches the testing templates with the training templates with highest accuracy with the help of the false acceptance rate, the proposed system accepts the unauthorized biometric features with less probability when compared to other classifiers.
Table 6.3  False Rejection Rate (Testing)

<table>
<thead>
<tr>
<th>Calculation of False Rejection Rate</th>
<th>FACE</th>
<th>FINGERPRINT</th>
<th>IRIS</th>
<th>NAIL</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of Features Rejected</td>
<td>0.4</td>
<td>0.3</td>
<td>0.6</td>
<td>0.6</td>
</tr>
<tr>
<td>No. of Images Tested</td>
<td>100</td>
<td>100</td>
<td>200</td>
<td>200</td>
</tr>
<tr>
<td>False Rejected Rate</td>
<td>4.3 %</td>
<td>2%</td>
<td>3%</td>
<td>3%</td>
</tr>
</tbody>
</table>

Figure 6.12  FRR with different Matching Classifiers for Training
Figure 6.13  FRR values with different Matching Classifiers for Testing

Figure 6.14  ERR values with different Matching Classifiers for Training
Figure 6.15 ERR with different Matching Classifiers for Testing

Table 6.4 Comparisons of FAR, FRR and Recognition Rates

<table>
<thead>
<tr>
<th>Methods</th>
<th>FAR</th>
<th>FRR</th>
<th>Recognition Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM</td>
<td>3.642</td>
<td>6.732</td>
<td>89.65%</td>
</tr>
<tr>
<td>Haudroff Distance</td>
<td>2.312</td>
<td>4.986</td>
<td>93.75%</td>
</tr>
<tr>
<td>KNN</td>
<td>1.345</td>
<td>4.786</td>
<td>96.25%</td>
</tr>
<tr>
<td>MLP</td>
<td>0.986</td>
<td>3.873</td>
<td>97.32%</td>
</tr>
<tr>
<td>HFRCE (Proposed)</td>
<td>0.925</td>
<td>3.075</td>
<td>98.34%</td>
</tr>
</tbody>
</table>
From the above figure 6.14 and 6.15 it is clearly shown that the proposed Fuzzy RCE classifier matches the testing templates with the training templates with highest accuracy and Figure 6.16 shows that the recognition rate for the multimodal gives 98.34%. The proposed system accept and rejects the authorized biometric features with efficiently when compared to other classifiers. These performance metrics are used to justify the Fuzzy RCE classifier as best to identify and classify the person from the unauthorized activities.

6.10 SUMMARY

In this chapter multimodal biometrics such as face, fingerprint, iris and nail are fused. A detailed literature survey on multimodal is done. This hybrid fuzzy fusion algorithm was implemented. Various factors contributing to the recognition rate is discussed. Various performance measures of multimodal recognition is analyzed and calculated. The ultimate aim of this research is to improve the authentication recognition rate and reduced the FAR, FRR and EER.
A detailed study of the multimodal HFRCE algorithm and various selection mechanisms have been made. It is observed that HFRCE method gives a best authentication. The parameters of FAR, FRR, EER are utilized for calculating the recognition rate. The desired FAR is 0.6%, FRR is 4.3%, and the recognition rate is 98.34%. When compared to existing methods such as SVM, Haudroff Distance, ANN and MLP.

It is concluded that the fuzzy RCE networks based fusion process models can be extensively used for security in the application of security areas. It is suggested to adopt the HFRCE model for effective human authentication in security areas.