CHAPTER 2

MULTI-SWARM OPTIMIZATION BASED FACE RECOGNITION

2.1 INTRODUCTION

Face recognition is a type of biometric software application that can identify a specific individual in a digital image by analysing and comparing the patterns. Facial recognition systems are commonly used for security purposes but are increasingly being used in a variety of other applications such as ATM, human recognition and identification. Face recognition or classification is a very complex form of pattern recognition due to the gross similarity of all human faces compared to large differences between face images of the same person because of the variations in lighting conditions, view point, pose and facial expressions. Even with these variations, there exists a gross similarity among the human faces. Face recognition consists of classifying highly ambiguous input signals with multiple dimensions and matching them with the known signals.

Though recent researches like Independent Component Analysis (ICA) (Bartlett et al. 2002), hybrid classifiers, symbolic modules involving Radial Basis Function (RBF), Decision Tree (DT) (Bemard et al.1996) and Neural Networks (NN) (Steve Lawrence et al. 2001) have focused on diminishing the impact of nuisance factors like sensitivity to higher order
image statistics on face recognition, these approaches still face the difficulty 
to separate each class owing to large variation in illumination and facial 
expressions. The automated face recognition becomes important in 
determining personal identity which has shown increased interest in the fields 
of biometrics, various commercial applications such as access of credit card, 
Automatic Transaction Machines, video surveillance, law enforcement and 

In Face recognition Multi Swarm Optimization (MSO) based 
DCT and DWT technique is proposed for developing a face recognition 
system in order to verify both the uniqueness of the human face and also 
improving its performance. In this proposed system, a 2D face image is given 
as input image. By using canny operator and coherent point drift, facial feature 
points are detected. Principle Component Analysis is applied to extract the 
facial feature points. K-Nearest Neighbor classifier is used to classify the 
extracted feature points. This proposed method is able to identify the given 
image with the database image. Experiments are performed on the Color 
FERET database. This method can handle pose variations up to ±90°.

2.2 LITERATURE SURVEY

Multi-task Pose-Invariant face recognition (Changxing Ding et al. 
2015) method uses the Patch Based Partial Representation (PBPR) for face 
recognition. In this method partial face recognition is taken as partial frontal 
face recognition problem. A patch based face representation scheme is 
developed and the face recognition is performed at patch level rather than 
holistic level. In this method experiments are performed on multiple databases 
like FERET, CMU-PIE and Multi-PIE. It can handle pose variations up to 
±90° of yaw.
Unrestricted Pose Invariant Face Recognition by Sparse Dictionary Matrix (Ali Moeini et al. 2015) method uses Sparse Dictionary Matrix for face recognition. In this method a 3D facial expression Generic Elastic Model is used to renovate a 3D model of the human face. A Sparse Dictionary Matrix (SDM) is created by rotating the 3D reconstructed models and extracting features from it. Each SDM is extracted based on triplet angles of face poses. Experiments are performed on FERET, CMU PIE and LFW databases. It can handle pose variations up to ±90°.

Sparse Feature Extraction for Pose-Tolerant face recognition (Ramzi et al. 2014) method uses the sparse features for face recognition. Here 3D face modelling is performed using 3D generic elastic model and sparse features are extracted using subspace modelling. Experiments are performed on Multi-PIE and FERET databases.

This algorithm matches 45° to frontal images at an average of around 75% verification rate at 0.1% false accept rate. It can handle up to 60° of pose variation.

Pose-Invariant Face Recognition uses Markov Random Fields (HuyThoHo et al. 2013) method for pose invariant face recognition. Input face image is divided into a web of overlying patches and a set of local warps are estimated to combine the patches at frontal view. These alignments are performed in Fourier domain using Lucas-Kanade algorithm and the reconstructed images can be used for matching. Experiments are performed on FERET, CMU-PIE, Multi-PIE and USF 3D databases. It can handle up to 45° of pose variations.

Towards Pose Robust Face Recognition (Dong Yi et al. 2013) method uses Gabor filters for face recognition. In this method a 3D
deformable model is built and a 3D classic fitting algorithm is proposed for estimating the pose of face image. Then Gabor filters are used for feature extraction. Finally PCA is applied for removing redundancies to evaluate the similarity. Experiments are performed on FERET, PIE and Labelled Faces in the Wild (LFW) database.

Coupled Bias-Variance Trade-off for Cross-Pose Face Recognition (Annan Li et al. 2012) method performs the Cross-Pose face recognition using a regress or with a joined bias variance trade off. In this method the rigid regression and lasso regression are explored. Experiments are performed on CMU-PIE, the FERET and the Multi-PIE face databases. It can handle up to 90° of pose variations.

Pose Invariant Approach for Face Recognition at Distance (Eslam Mostafa et al. 2012) uses the extended Active Shape Model (ASM) to accurately align the face and Principle Component Analysis to model the intrinsic variations in shape and texture. Local Binary Pattern is used to match the probe image with the sample image. Experiments are performed on FERET, CMU-PIE and stereo based human face database. It can handle pose variations up to ±45°in yaw angles.

Fully automatic Pose-Invariant Face recognition via 3D Pose Normalization (Akshay Asthana et al. 2011) method uses 3D Pose Normalization for face recognition. In this method viola-jones-typeface and feature detectors are used to accurately initialize a view-based active appearance model. It uses 68 facial landmark points to estimate the yaw and pitch angles. After pose normalization local Gabor binary pattern recognizer is used to get the gallery and probe image. Experiments are performed on FERET, CMU-PIE, USF 3D, Multi-PIE and Face Pix databases.
To handle pose variations in real-world, 3D Face recognition (Georgios Passalis et al. 2011) method uses the facial symmetry for handling pose variation. This method uses an automatic landmark detector for estimating the pose and occluded areas for each facial image. The missing information are filled using facial symmetry. Wavelet based biometric signature is used to perform the comparison among interpose scans. Experiments are performed on FRGCv2, UND-F and G database. The research gives the candid picture of 3D face recognition at its best which paves way to study the architecture of the proposed recognition system.

2.3 ARCHITECTURE OF THE PROPOSED FACE RECOGNITION SYSTEM

Face feature extraction, classification and recognition system for verifying personal identity is unique, passive and non-intrusive. Face classification and recognition system consist of automated methods for classifying and recognizing a person based on the facial characteristics. Classification and recognition technologies have become the foundation for an extensive array of highly secure identification and personal verification solutions (Ramji et al. 2011). The proposed architecture is shown in Figure 2.1 that provides a comprehensive view of the face classification and recognition system. Figure 2.2 gives the detailed overview of the proposed system.

Figure 2.1  Human Face Recognition System
2.3.1 Color FERET Database

The DOD Counterdrug technology program sponsored the Facial Recognition Technology (FERET) program and development of the FERET database. The National Institute of Standards and Technology (NIST) is serving as Technical Agent for distribution of the FERET database. The database is used to develop, test, and evaluate face recognition algorithms. The sample data of faces are shown in the Figure 2.3.
2.4 PRE-PROCESSING

The input color image is converted into a gray image. Using suitable cropping (face detection) schemes, the image is cropped and then resized to meet the requirement. The image is then normalized to have uniform intensity gray level. Image is then filtered using a low pass filter represented in Figure 2.4.

![Figure 2.4 Pre-processing](image)

2.4.1 Image Cropping

Image cropping is also an important task to achieve high recognition rate. Cropping can be done using viola jones, opencv and Local Binary Patterns (LBP) face detection techniques. Face detection involves detecting a face from an image using complete image (image based approach) or by detecting one or more features from the image (Feature based approach) such as nose, eyes and lips etc. T. M. Blackwell et al. (2006). In this stage image based approach includes a window scanning technique with fixed and dynamic mask size and feature based approach includes color segmentation. Mask size is determined empirically for better results.

In feature based approach, image is transferred from RGB color space to YCbCr color space provided Cb and Cr values satisfies following conditions: $77 \leq C_b \leq 127$ and $133 \leq C_r \leq 173$. Using dilation, erosion and morphological operations face is detected.
2.4.2 Normalization

Illumination variation is one of the important challenges in face recognition. Image with uncontrolled lighting conditions contains non-uniform contrast. That is the distribution of intensity or gray levels is not alike. Matthew Turk et al. (1991). To make these levels equal or almost equal histogram equalization technique is used. Given an M x N image, Cumulative Distribution Function (CDF) at each pixel value (V) is used to find pixels equalization value over gray levels (L), Histogram values (h). Mathematically it is given in Equation (2.1)

\[ h = \left( \frac{CDF(V) - CDF_{\text{min}}}{MXN - CDF_{\text{min}}} \right) (L - 1) \]  

(2.1)

2.4.3 Filtering

Images having Gaussian noise due to illumination variations. Pixel Based Filtering (PBF) technique is used to de-noise the image. Low Pass Filter (LPF) is used to eliminate high frequency information and retain only with low frequency information Taher Khadhraoui et al. (2016).

2.5 FEATURES POINT DETECTION

Pre-processed images are given as an input of feature extraction scheme to extract features Eigen Face approach and Discrete Cosine Transform (DCT) approach were used to extract features. Recognition rate of these methods were computed with and without image pre-processing prior to feature extraction. Sompong Valuvanathorn et al. (2012)
2.5.1 **Principal Component Analysis**

Principal Component Analysis (PCA) is used to extract Eigen faces. Initially Eigen vectors are computed using covariance matrix derived from the set of training images. Probe image is then projected into the face space and the distance between mean Eigen face and probe image is computed using spatial differential operators such as Euclidean distance and Cosine distance. Ermioni et al. (2010).

2.6 **EDGE DETECTION**

Edge detection is a crucial task in image processing. It is a mathematical tool in pattern recognition, image segmentation, scene analysis in face recognition. When an edge detection algorithm is applied to a digital image, it reduces the amount of data to be processed further to the greater extent and therefore filters out information that is less relevant, without the important structural properties being lost. An edge detector is a filter which is used to extract the edge points in an image. Yanjiang et al. (2008).

The Canny Edge Detector is an edge detection operator that uses a multi-stage algorithm to detect a wide range of edges in images. Edge detection, especially step edge detection, has been widely applied in various computer vision systems, which is an important technique to extract useful structural information from different vision objects and dramatically reduce the amount of data to be processed. Canny has found that, the requirements for the application of edge detection on diverse vision systems are relatively the same. Thus, a development of an edge detection solution to address these requirements can be implemented in a wide range of situations.
The general criteria for edge detection includes

1. Detection of edge with low error rate, which means that the detection should accurately catch as many edges.

2. The edge point detected from the operator should accurately localize on the center of the edge.

3. A given edge in the image should only be marked once, and where possible, image noise should not create false edge.

4. The Canny operator was designed to be an optimal edge detector. It takes as input a gray scale image, and produces as output an image showing the positions of tracked intensity discontinuities.

The Canny method finds edges by looking for local maxima of the gradient of image. The gradient is calculated using the derivative of a Gaussian filter. The method uses two thresholds, to detect strong and weak edges, and includes the weak edges in the output only if they are connected to strong edges. This method is therefore less likely than the others to be “fooled” by noise, and more likely to detect true weak edges. EDGE specifies sensitivity thresholds for the Canny method. THRESH is a two-element vector in which the first element is the low threshold, and the second element is the high threshold.

2.6.1 Orthographic Projection

Point set registration is the process of aligning two point sets. It is also known as point matching. It is the process of finding a spatial transformation that aligns two point sets. The purpose of this transformation is
merging multiple datasets into globally consistent model and mapping a new measurement to known data set to identify features or to estimate its pose. In the feature based image registration, a point set may be a set of features obtained by feature extraction from an image, for example corner detection. The facial contour is obtained by a point set registration algorithm called Coherent Point Drift (CPD). CPD iteratively aligns the facial contour to the edge point set with affine transformations. The imposter contour points can gradually be detected and ignored using this method.

2.7 FEATURE EXTRACTION

Feature extraction is an external stage in Face recognition system. A typical feature extraction algorithm tends to build a computational model through some linear or nonlinear transform of the data so that the extracted feature is as representative as possible. In this chapter DCT and DWT were used for feature extraction and also explained in the following Sections.

2.7.1 Discrete Cosine Transformation (DCT)

DCT has emerged as a popular transformation technique widely used in signal and image processing. This is due to its strong “energy compaction” property. Most of the signal information tends to be concentrated in a few low-frequency components of the DCT. The use of DCT for feature extraction in Face recognition has been described by several research groups. DCT was found to be an effective method that yields high recognition rates with low computational complexity. DCT exploits inter-pixel redundancies to render excellent de-correlation for most natural images. After de-correlation each transform coefficient can be encoded independently without losing compression efficiency Blackwell et al. (2003). DCT helps to separate the image into parts (or spectral sub-bands) of differing importance (with respect
to the image's visual quality). DCT transforms the input into a linear combination of weighted basis functions. These basis functions are the frequency components of the input data. DCT is similar to the discrete Fourier Transform (DFT) in the sense that they transform a signal or image from the spatial domain to the frequency domain, use sinusoidal base functions, and exhibit good de-correlation and energy compaction characteristics (Blackwell et al. 2004). The major difference is that the DCT transform uses simple cosine-based basis functions whereas the DFT is a complex transform and therefore stipulates that both image magnitude and phase information be encoded. In addition, studies have shown that DCT provides better energy compaction than DFT for most natural images.

The DCT of an N x M image f(x,y) is defined by the following Equation (2.2)

\[
F(u,v) = \alpha(u)\alpha(v)\sum_{x=0}^{N-1}\sum_{y=0}^{M-1} \cos\left(\frac{\pi u}{2N}(2x+1)\right)\cos\left(\frac{\pi v}{2M}(2y+1)\right)f(x,y)
\]

(2.2)

Where f(x,y) is the intensity of the pixel in row x and column y; u = 0,1, ..., N-1 and v=0,1, ..., M-1 and the functions \( \alpha(u), \alpha(v) \) are defined in Equation (2.3)

\[
\alpha(u), \alpha(v) = \begin{cases} 
\sqrt{\frac{1}{N}} & \text{for } u,v = 0 \\
\sqrt{\frac{2}{N}} & \text{for } u,v \neq 0 
\end{cases}
\]

(2.3)

For most images, much of the signal energy lies at low frequencies (corresponding to large DCT coefficient magnitudes) these are relocated to the upper-left corner of the DCT array. Conversely the lower-right values of the DCT array represent higher frequencies, and turn out to be small enough to be truncated or removed with little visible distortion, especially as u
and v approach the sub-image width and height, respectively. This means that the DCT is an effective tool that can pack the most effective features of the input image into the fewest coefficients.

The first face picture can be generally reproduced just by few DCT coefficients. This settles on the decision of the quantity of DCT coefficient at first utilized as a part of the face acknowledgment framework. The impact of the quantity of DCT coefficients utilized as components for face acknowledgment is inspected in the investigation Brunelli et al. (1993). This incorporates the impact of the quantity of coefficients on the nature of the reproduced picture and the acknowledgment rate. The study is stretched out by analysing the execution of the powerfully created highlight subset produced by the MSO highlight determination calculation.

### 2.7.2 Discrete Wavelet Transformation

Wavelets have many advantages over other mathematical transforms such as the DFT or DCT. Functions with discontinuities and functions with sharp spikes usually take substantially fewer wavelet basis functions than sine-cosine functions to achieve a comparable approximation. Wavelets have been successfully used in image processing since 1985. Its ability to provide spatial and frequency representations of the image simultaneously motivates its use for feature extraction. The deterioration of the information into a few layers of division in space and recurrence and permits us to seclude the recurrence segments acquainted by characteristic distortions due with expression or outward variables (like brightening) into certain sub-groups. Wavelet-based techniques prune away these variable sub bands, and spotlight on the space or recurrence sub-groups that contain the most important data to better speak to the information and help in the arrangement between various pictures. Evison et al. (2010).
There exists a large selection of wavelet families depending on the choice of the mother wavelet. In this proposed face recognition the DWT is based on the facial features extracted from a Haar Wavelet Transform. The Haar wavelet transform is a widely used technique that has an established name as a simple and powerful technique for the multi-resolution decomposition of time series. Earlier studies concluded that information in low spatial frequency bands play a dominant role in face recognition. In 1986, Sergent shows that the low frequency band and high frequency band play different roles. The low frequency components contribute to the global description, while the high frequency components contribute to the finer details required in the identification task. Branke et al. (1999). Sergent has also demonstrated that as human face is a non-rigid object, it has abundant facial expressions and expressions influence local spatial components of face.

The Haar Wavelet has been demonstrated for picture investigation and highlight the extraction. It speaks to a sign by limiting it in both time and recurrence spaces. Wavelets can be utilized to enhance the picture enrolment precision by considering both spatial and unearthly data and by giving multi-determination representation to obtain from losing any worldwide or nearby data. Extra focal points of utilizing the wavelet-disintegrated pictures incorporate conveying information with various spatial determination to a typical determination utilizing the low recurrence sub-groups while giving access to edge highlights utilizing the high recurrence sub-groups.

Each level of the wavelet decomposition, four new images are created from the original N x N-pixel image. The size of these new images is reduced to ¼ of the original size, i.e., the new size is N/2 x N/2. The new images are named according to the filter (low-pass or high-pass), which is applied to the original image in horizontal and vertical directions. For example
the LH image is a result of applying the low-pass filter in horizontal direction and high-pass filter in vertical direction. Thus the four images produced from each decomposition level are LL, LH, HL, and HH. The LL image is considered as a reduced version of the original as it retains most details Hsu et al. (2010).

The LH image contains horizontal edge features, while the HL contains vertical edge features. The HH contains high frequency information only and is typically noisy and is, therefore, not useful for the registration. In wavelet decomposition, only the LL image is used to produce the next level of decomposition.

In Figure 2.5 the sub band LL corresponds to the low frequency components in both vertical and horizontal directions of the original image. Therefore, it is the low frequency sub band of the original image. The sub band LH corresponds to the low frequency component in the horizontal direction and high frequency components in vertical direction. Therefore it holds the vertical edge details.

Figure 2.5  A 3-level wavelet decomposition of an N x N-pixel image

Comparable elucidation is made on the sub groups HL and HH. As the change of outward appearances primarily fluctuates in eyes, mouth and
other face muscles, from the specialized perspective, it includes predominantly changes of edges. Figure 2.5 as a case, the flat elements of eyes and mouth are clearer than its vertical elements. The sub band HL along these lines delineate real outward appearance highlights. The sub band LH, the vertical components of blueprint and nose are clearer than its even elements, delineates face posture highlights. The sub band HH is consequently the most critical for unbending item acknowledgment since it delineates the structure highlight of the article. Be that as it may, human confronts in fact are non-unbending items, the sub band HH is the precarious band in all sub groups since it is effortlessly aggravated by clamors, expressions and stances. Shi et al. (1998). Along these lines, if wavelet change is connected to break down face pictures, the sub band LL will be the most stable sub band.

2.8 CLASSIFICATION

Classification contains two different stages. These stages are explained below.

2.8.1 Geometrical Features

A set of geometrical features such as nose width and length, mouth position and chin shape. This set of features is then matched with the features of known individuals. A suitable metric such as Euclidean Distance (finding the closest vector) is used to find the closest match. Most pioneering work in face recognition was done using geometric features. Hsu et al. (2010).

The benefit of utilizing geometrical components as a premise for face acknowledgment is that acknowledgment is conceivable even at low resolutions and with boisterous (pictures with numerous scattered pixel intensities). In spite of the fact that the face cannot be seen in subtle element its
general geometrical setup can be separated for face acknowledgment. The strategy's fundamental disadvantage is that automated extraction of the facial geometrical features is very hard. Automated geometrical feature extraction based recognition is also very sensitive to the scaling and rotation of a face in the image plane. Wei et al. (2011).

This is apparent in Kanade's results where he reported a recognition rate of between 45-75 % with a database of only 20 people. However if these features are extracted manually as in Goldstein et al., and Kaya and Kobayashi satisfactory results may be obtained. Figure 2.6 and 2.7 shows Spatio-Temporally filtered image with scattered pixel intensities transformed to geometrical features.

![Figure 2.6 Spatio-Temporally filtered image](image1)

![Figure 2.7 Geometrical features (white)](image2)
2.8.2 Template Matching

This is comparable to the format coordinating procedure utilized as a part of face identification, with the exception of not attempting to characterize a picture as a "face" or 'non-face' attempting to perceive a face. The premise of the layout coordinating system is to concentrate entire facial locales (network of pixels) and contrast these and pictures of known people. Wei et al. (2011). Euclidean separation can be utilized to locate the nearest coordinate. The basic strategy of contrasting dark scale power values for face acknowledgment was utilized by Baron.

However there are far more sophisticated methods of template matching for face recognition. These involve extensive pre-processing and transformation of the extracted grey level intensity values. For example, Turk and Pentland used Principal Component Analysis (Turk et al.1991), sometimes known as the Eigen faces approach, to pre-process the gray levels and Wiskott et al. used Elastic Graphs encoded using Gabor filters to pre-process the extracted regions. An investigation of geometrical features versus template matching for face recognition by Brunelli and Poggio came to the conclusion that although a feature based strategy may offer higher recognition speed and smaller memory requirements, template based techniques offer superior recognition accuracy. Sompong et al. (2012). Sample template matching strategy is shown in the Figure 2.8.
Multi-PSO swarms do not immediately generalize, since the swarms do not interact (i.e. the dynamics governing the position and velocity updates of a particle in a particular swarm are specified by parameters belonging to that swarm only). Multi PSO’s may interact if swarms have access to attractors from other swarms. However, this reduces to a single swarm with different information sharing topologies.

A multi-swarm is, however, easily constructed as combination of Charged Particle swarm optimization (CPSO) swarms. Multiple CPSO swarms will interact since charged particles repel charged particles from any swarm, including their own. However a few difficulties are apparent. Many researchers have considered multi-populations as means of enhancing the diversity of EAs to address Dynamic Optimization Problems [DOPs].

A self-Organizing Scouts (SOS) algorithm that has been shown to give excellent results on the many peaks benchmark. Zeng et al. proposed an Orthogonal Design based Evolutionary Algorithm, called ODEA, where its
population consists of “niches” and an orthogonal design method is employed. ODEA borrows some ideas from the SOS algorithm, however, the experimental results show that the performance of ODEA is better than the SOS algorithm.

Parrott and Li developed a specification based PSO (SPSO), which dynamically adjusts the number and size of swarms by constructing an ordered list of particles, ranked according to their fitness, with spatially close particles joining a particular species. The atomic swarm approach has been adapted to track multiple optima simultaneously with multiple swarms in dynamic environment by Blackwell and Branke. In their approach, a charged swarm is used for maintaining the diversity of the swarm, and the exclusion principle ensures that no more than one swarm surrounds a single peak. This strategy is very efficient for moving peaks benchmark (MPB) function.

The undertaking for the MSO calculation is to hunt down the most illustrative component subset through the removed DCT or DWT highlight space. Every molecule in the calculation speaks to a conceivable applicant arrangement (highlight subset). Advancement is driven by a wellness capacity characterized as far as class partition (dissipate list) which gives a sign of the normal wellness on future trials. Bhatt et al. (2010).

2.9.1 Chromosome Representation

The initial coding for each particle is randomly produced where each particle is coded to imitate a chromosome in a genetic algorithm each particle was coded to a binary alphabetic string $P = F_1 F_2 \ldots F_n$, $n = 1, 2, \ldots$, $m$ ; where $m$ is the length of the feature vector extracted by the DCT or the DWT. Each gene in the $m$-length chromosome represents the feature selection, “1” denotes that the corresponding feature is selected, otherwise denotes
rejection. The binary PSO algorithm is used to search the 2m geno space for the optimal feature subset where optimality is defined with respect to class separation. For example, when a 10 dimensional data set (n=10) \( P = F_1 \ F_2 \ F_3 \ F_4 \ F_5 \ F_6 \ F_7 \ F_8 \ F_9 \ F_{10} \) is analysed using MSO to select features, select any subset of features smaller than n. i.e. MSO can chose a random 6 features, \( F_1 \ F_2 \ F_4 \ F_6 \ F_8 \ F_9 \) by setting bits 1, 2, 4, 6, 8, and 9 in the particle chromosome. Branke et al. (1999). For each particle, the effectiveness of the selected feature subset in retaining the maximum accuracy in representing the original feature set is evaluated based on its fitness value.

2.9.2 Fitness Function

The m-qualities in the molecule speak to the parameters to be iteratively developed by MSO. In every era, every molecule (or individual) is assessed, and an estimation of goodness or wellness is returned by a wellness capacity. This development is driven by the wellness capacity \( F \) that assesses the nature of advanced particles regarding their capacity to amplify the class detachment term showed by the dissipate list among the distinctive classes. Let \( w_1, w_2, \ldots, w_L \) and \( N_1, N_2, \ldots, N_L \) mean the classes and number of pictures inside every class, individually. Give \( M_1, M_2, \ldots, M_O \) a chance to be the method for comparing classes and the fabulous mean in the element space, \( M_i \) can be ascertained in Equation (2.4)

\[
M_i = \frac{1}{N_i} \sum_{j=1}^{N_i} W_{j(i)}, \quad i = 1, 2, \ldots, L
\]

(2.4)

Where \( W_{j(i)} \), \( j=1,2,\ldots,N_i \), represents the sample images from class \( w_i \) and the grand mean \( M_0 \) is:
Where \( n \) is the total number of images for all the classes. Thus, the fitness function \( F \) is computed. Computed \( F \) values are used to match the facial features in fitness function and the simulation results are shown in the next sessions.

2.10 SIMULATION RESULTS

A manual face discovery framework was acknowledged by measuring the facial extents of the normal face, computed from 30 test subjects. To recognize a face, a human administrator would distinguish the areas of the subject's eyes in a picture and utilizing the extents of the normal face, the framework would section a region from the picture. A template matching based technique was implemented for face recognition. Recognition accuracy is compared with geometrical features based techniques and automated geometrical features based technique would have required complex feature detection pre-processing. There are \( T \) numerous conceivable layout coordinating systems. The output of the pre-processing and edge detection and feature extractions are shown in the Figure 2.9, Figure 2.10 and Figure 2.11.

2.10.1 Experimental Setup

This session discusses the equipment and experimental procedures used to authenticate a person based on the modality face. The system is implemented using MATLAB 2009 in Windows 8 Operating System with 4 GB RAM.

\[
M_0 = \frac{1}{N} \sum_{i=1}^{L} N_i M_i
\]

(2.5)
2.10.2 Pre-processing

Figure 2.9  a. Input image, b. Cropping, c. Resizing d.Normalization, e.Filtering

Figure 2.9 depicts the pre-processing of face recognition. The input image passes through cropping, resizing, normalization and filtering process.

2.10.3 Edge Detection

Figure 2.10 Edge Detection

Figure 2.10 shows the transition from input image to edge detection.
2.10.4 Face Points Detection

Figure 2.11 reveals the Face point Detection and Figure 2.12 shows the coherent point drift detection.

2.10.5 Feature Extraction

Figure 2.12 Coherent Point Drift Detection
Figure 2.13  Feature Extraction

From the Figure 2.13 it is observed that the face image is divided into blocks and the histogram from each block is shown clearly. The concatenated feature histogram depicts the concatenated values.

Figure 2.14. (a) Recognition results for different DCT-feature based vectors and Feature selection Algorithms. (a) No. of Selected Features
Figure 2.14. (b) Recognition results for different DCT-feature based vectors and Feature selection Algorithms. (b) Training Time

Figure 2.14. (c) Recognition results for different DCT-feature based vectors and Feature selection Algorithms. (c) Recognition Rate

Figure 2.14 (a) Recognition results for different DCT-feature based vectors and Feature selection Algorithms. (a) No. of Selected Features  (b) Recognition results for different DCT-feature based vectors and Feature selection Algorithms. (b) Training Time (c) Recognition results for different DCT-feature based vectors and Feature selection Algorithms. (c) Recognition Rate
Table 2.1  Comparisons of FRR and FAR for various face recognition algorithms

<table>
<thead>
<tr>
<th>Method</th>
<th>False Rejection Rate</th>
<th>False Accept rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hybrid NN: SOM+a convolution NN</td>
<td>0.0495</td>
<td>0.2453</td>
</tr>
<tr>
<td>Hidden Markov Model(HMMs)</td>
<td>0.0596</td>
<td>0.3443</td>
</tr>
<tr>
<td>SVM with a binary tree</td>
<td>0.5756</td>
<td>0.4461</td>
</tr>
<tr>
<td>Eigen face</td>
<td>0.0531</td>
<td>0.6033</td>
</tr>
<tr>
<td>2D-HMM</td>
<td>0.7037</td>
<td>0.0958</td>
</tr>
<tr>
<td>DCT+MSO FS</td>
<td>0.0214</td>
<td>0.0278</td>
</tr>
<tr>
<td>DWT +MSO FS</td>
<td>0.0243</td>
<td>0.0245</td>
</tr>
</tbody>
</table>

In this investigation the DWT coefficient highlights have been separated from every face picture. The Two-dimensional Haar Wavelet change is connected to the info picture decreasing its size to 1/4 of its unique size. 4-level wavelet decay is performed and the estimate of the info picture at every deterioration level is utilized as a component vector. The measurements of the component vectors are 46x56, 23x28, 12x14 and 6x8 relating to level-0, level-1, level-2 and level-3 wavelet deteriorations separately.
Figure 2.15 (a) Recognition results for different DWT-feature based vectors and Feature selection Algorithms. (a) No. of Selected Features

Figure 2.15 (b) Recognition results for different DWT-feature based vectors and Feature selection Algorithms (b) Training Time
Figure 2.15 (c) Recognition results for different DWT-feature based vectors and Feature selection Algorithms (c) Recognition Rate.

Figure 2.15 (a) Recognition results for different DWT-feature based vectors and Feature selection Algorithms. (a) No. of Selected Features (b) Recognition results for different DWT-feature based vectors and Feature selection Algorithms (b) Training Time (c) Recognition results for different DWT-feature based vectors and Feature selection Algorithms (c) Recognition Rate.

Preparing time, and acknowledgment rates for various component vector measurements utilizing the MSO and GA based element choice calculations. The best normal acknowledgment rate of 95.2% is accomplished utilizing the DWT component vector and the MSO-based element determination calculation utilizing just 88 chosen highlights and with around 35% less chose highlights than GA. The MSO and GA choice calculations have similar execution in most tried occasions however with less chose highlights utilizing MSO.
The DCT and the DWT calculation is used to aspect the component space for the ideal element subset. Development is driven by a wellness capacity characterized as far as class division. The classifier execution and the length of chose highlight vector were considered for execution assessment utilizing the ORL face database.
Table 2.2  Comparison of recognition rates for various face recognition algorithms

<table>
<thead>
<tr>
<th>METHOD</th>
<th>RECOGNITION RATE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hybrid NN: SOM+ A convolution NN</td>
<td>96.2%</td>
</tr>
<tr>
<td>Hidden Markov Model (HMMs)</td>
<td>87%</td>
</tr>
<tr>
<td>SVM with a binary tree</td>
<td>91.21%</td>
</tr>
<tr>
<td>Eigen face</td>
<td>90%</td>
</tr>
<tr>
<td>2D-HMM</td>
<td>95%</td>
</tr>
<tr>
<td>DCT+MSO FS</td>
<td>94.7</td>
</tr>
<tr>
<td>DWT +MSO FS</td>
<td>96.8</td>
</tr>
</tbody>
</table>

Test results demonstrate the predominance of the MSO-based element choice calculation in creating fabulous acknowledgment precision with the negligible arrangement of chose elements. The execution of the proposed calculation is contrasted with the execution of a GA-based component determination calculation and was found to yield amount acknowledgment results with less number of chose elements.

2.11 SUMMARY

This chapter focus the face recognition, the architecture and a detailed survey on feature selection in face recognition. Various factors contributing to the performance of the feature extraction algorithms is discussed. Various recognition improvement methods have been analysed. The ultimate aim of this research is to improve the recognition rate and reduce the FAR, FRR and EER.
A detailed study of the MSO-based DCT and DWT feature selection methods have been made. MSO based DCT and DWT feature selection recognition rate is 94.7% and 96.8%. The extraction procedures DCT and DWT highlights the key feature for the ideal element subset.

The result shows that the MSO based methods projects the best optimal results compared to the existing methods. The test results demonstrate that the DWT +MSO FS give the better recognition rate 2% with the difference of other methods. Another segmentation based on fingerprint recognition also gains more importance like face recognition.