OPTIMAL FACIAL FEATURE SUBSETS SELECTION USING META-HEURISTIC ANT COLONY OPTIMIZATION ALGORITHM

BY

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ABSTRACT

One of the main challenges in face recognition is how to describe and extract accurately the features for face representation. Several approaches have been proposed for representation of facial features (extraction) such as Local Binary Pattern, Elastic Bunch Graph Matching, Principal Component Analysis (PCA) Linear Discriminant Analysis (LDA), Independent Component Analysis (ICA) and so on. Gabor-filter method among other algorithms has gained much attention in image processing and pattern recognition. This technique remains a powerful and useful tool in image coding and processing. Its optimal functionality in face recognition is traceable to its biological importance (similarity to the receptive fields of simple cells in primary visual cortex) and computational properties (optimal for calculating local spatial frequencies). Gabor filters have the ability of obtaining multi-orientation features from a facial image at several scales, with the derived information being of local nature. In spite of the outstanding characteristics of Gabor-filters in facial recognition system, this technique suffers high feature dimensions. Thus makes any Gabor-based facial recognition system to possess prolong computational time and complexity.

This study aimed at reducing the huge feature dimensionality by applying a population-based meta-heuristic Ant Colony Optimization Algorithm. This was achieved through the following objectives: (i) apply a bank of Gabor-filters with 5 scales and 8 orientations to extract frontal facial features; (ii) employ Ant Colony Optimization Algorithm for feature subsets selection; (iii) use four distance measure metrics; Chebysev, City-block, Malahanobis and Euclidean for face matching; (iv) Evaluate the performance of the system based on the training time, testing time, classification and recognition accuracies. The performance evaluation of the proposed system was done using two face image databases; Locally Acquired Student Face Image Database (LASFI) and Olivetti Research Laboratory Database of Images (ORL). Experimental results showed that the proposed facial recognition system performed effectively in term of recognition time and accuracy.

1. Background to the Study

Biometrics is an automated method that involves the recognition of an individual based on a feature vector derived from individual biological traits (Jain, Ross & Prabhakar, 2004; Singhal, Gupta & Garg, 2012). Biometric has become the most recent promising technique of recognition (Parmar & Mehta, 2013). Face recognition is a biometric technique for verifying and identifying a person from digital image or video using dataset of face images (Joshi & Deshpande, 2015). The recognition of a face image is achieved by comparing selected facial features from database of stored face images in order to identify the input image (Barbu, 2010). This biometric technology is one of the most successful representative applications in computer vision that has received a great interest in commercial and law enforcement domains such as human-computer interaction, access control, digital libraries, telecommunication and security systems (Shen & Bai, 2006; Jin & Ruan, 2009; Haider, Bashir, Sharif, Sharif & Wahab, 2014).

Facial recognition is user friendly and confidentiality respectful biometric recognition technique with high accuracy and low intrusiveness (Kashem, Akhter, Ahmed, & Alam, 2011). This recognition system compared with other biometric methods does not require the complete cooperation of the test subject to work (Singhal et al., 2012). A properly designed facial recognition systems installed in public environments such as seaports and airports can identify individuals among the crowd without passers-by being fully notified of the system. Other biometrics like fingerprint, iris, retina, vein, Deoxyribonucleic acid (DNA), odour and voice recognition cannot perform this kind of mass identification. Biometric techniques that engage different people using the same particular equipment with direct contact such as finger print, hand vein and palm print to capture their biometric data indirectly expose the user to transmission of germs from other users. Face recognition approach is completely less intrusive and does not bear any health hazards (Bakshi & Singhal, 2014).

One of the main challenges in facial recognition algorithm is how to describe and extract accurately the features for facial image representation (Tan & Triggs, 2007). In pattern recognition method like face recognition, the extraction of features is considered to be difficult problem because best features is required to be obtained with minimum classification and low running time (Shah, Sharif, Raza & Azeem, 2013). The most essential and unique features are extracted from localized image in feature extraction phase (Kaur & Rajput, 2013). The feature extraction method involves the formation of new set of features from original facial image simply to reduce the feature measurement cost, increase classifier efficiency, and allow higher recognition accuracy (Chitra & Balakrishnan, 2012). The feature extraction represents the most important phase of face recognition due to the direct dependency of accuracy of any face recognition model on the level of extracted features from face region (Shebani, 2015).

A number of algorithms have been employed for face representation such as Linear Discriminant Analysis (LDA), Principal Component Analysis (PCA), Independent Component Analysis (ICA) and so on (Jin & Ruan, 2009). Gabor-filter among other algorithms has gained so much interest in image processing and pattern recognition (Bhuiyan & Liu, 2007). This technique remains a useful tool in computer and image process due to its best localization properties for frequency domain and spatial analysis (Hafez, Selim & Zayed, 2015). Its optimal functionality in face recognition is linked to its biological importance (similarity to the receptive fields of simple cells in primary visual cortex) and computational properties (optimal for calculating local spatial frequencies) (Shen & Ji, 2009).

Gabor filters have the ability of obtaining multi-orientation features from a facial image at several scales, with the derived information being of local nature. Although, it has been used widely in pattern recognition but its application domain is majorly for feature extraction. The Gabor-based method has achieved great success and considered as one of the best technique for face representation (Bouzalmat, Belghini, Zarghili, Kharroubi & Majda, 2011; Bhele & Mankar, 2012).

The Gabor-filters have been used in several applications like texture segmentation, edge detection, image representation and face recognition (Grigorescu, Petkov & Kruizinga, 2002;

Bellakhdhar, Loukil, & Abid, 2013). Among the techniques used for feature extraction process, it has been established that Gabor filters have the ability to extract maximum information from local image regions (Deng, Jin, Zhen & Huang, 2005; Mounika & Reddy, 2012). Gabor wavelets ability to capture the local structure relating to spatial localization, spatial frequency and orientation selectivity makes this method to be invariant to rotation, translation, scale and illumination changes (Dai & Qian, 2004). Gabor-based technique ranks high and functions optimally in removing useless and redundant feature in pattern recognition (Ismaila, Adetunji & Falohun, 2012).

Despite the several overwhelming achievements of Gabor-based method in recognizing face images with different pose, illumination and expression (Shen & Bai, 2006). This technique suffers high feature dimension (Peng Yang, Shiguang Shan, Wen Gao, Li & Dong Zhang, 2004). The dimension of the feature vectors extracted by applying Gabor filters to the whole face image through convolution is very high (Jin & Ruan, 2009). The dimensionality of the input face images is usually so large that when performing classification on the original images become a more difficult task. The general approach when employing Gabor filters for recognition of face involves the construction filter bank with filters of different scales and orientations to filter a given face image with all filters from the bank. Thus, this approach makes the dimensionality of Gabor features very high and resulting to computational complexity (Vinay, Shekhar, Murthy & Natarajan, 2015). In pattern recognition, orthogonality remains the most important component however Gabor filters of different filters from the filter bank are not orthogonal one to another (Štruc, Gajšek & Pavešić, 2009). Hence, this makes the final information contained in Gabor-filter technique to be redundant and this might further affect the classification accuracy.

In this study, a meta-heuristic optimization feature selection algorithm was introduced for Gabor feature dimensions reduction (Deng et al., 2005; Kumar, Shaikh & Jamdar, 2014). Ant Colony Optimization an iterative probabilistic meta-heuristic algorithm (Kanan, Faez & Taheri, 2007) and also nature inspired computational methods (Dorigo & Blum, 2005) which possesses a distinguishing feature of constructive random search space procedure using an indirect memory referred to pheromone was applied to obtain the optimal feature subsets from Gabor feature dimensions before classification (Al-ani, 2007). Several distance measure classifiers; Euclidean, City-block, Mahanolobis and Chebysev were applied on the computed Gabor feature subspace for recognition.

2. PROBLEM STATEMENT

Finding robust or effective features that represent face image is identified to be a difficult task (Pal, Chourasia & Ahirwar, 2013). In computer vision, raw image data cannot be used directly due to high dimensionality of image. The high feature dimension problems include consumption of large storage space, long computational time and misclassification. The face representation usually begins with a feature reduction process since the huge visual information space makes the statistical estimation very difficult and time consuming (Gandhe, Talele & Keskar, 2007). Although, Gabor-filter is a widely used technique for facial feature extraction (representation) (Shen & Bai, 2006). The Gabor face representation from a given face image I(x, y) is derived by using a bank of Gabor filters of different orientations and scales. This procedure leads into an explosion of the original image pixel space of face image dimensions.

However, the computation time of this technique is both time and memory intensive due to high feature dimensions (Zhang, Shan, Gao, Chen & Zhang, 2005). It is therefore necessary to project Gabor features from high feature dimension into feature subspace without losing computational speed and classification accuracy. In Gabor-based facial recognition, it is generally not certain to distinguish in advance which features will give the best discrimination between feature classes and also not feasible to represent all possible features of the original images to be classified. Some dimensionality reduction methods only perform the function of feature extraction, they produce the linear combination of original image features without considering the irrelevancy and redundancy of features.

The inclusion of irrelevant and redundant features increases the size of search space which as a result gives a prolong recognition time and makes generalization more difficult (Liu & Yu, 2005). If features are not suitably represented, the best classifiers will not produce accurate recognition result (Shan, Gong & McOwan, 2009). In face recognition, the reduction in the number of features considered by a classifier during classification enhances the recognition speed by reducing training time and improving the accuracy (Al-ani, 2007). Dimensionality reduction through the selection of appropriate feature subset selection results in several advantages such as performance upgrading, the reduction in curse of dimensionality, promotion of generalization abilities, speedup by depreciating computational power and reducing costs by avoiding expensive features (Vignolo, 2014).

Several approaches have been applied on huge Gabor features such as down sampling, feature selection techniques, reduction of filter bank parameters and subspace projection methods to reduce computational complexity of Gabor feature into low dimension before being passed into a classifier (Štruc et al., 2009). The down sampling technique involves the use of only selected feature points, but the final output consists of high number of image feature matrix which could cause the loss of feature distinct information and may eventually affect classification accuracy (Vinay et al., 2015). Subspace projection technique involves the mapping of high dimensional features into lower dimensions: - Principal Component Analysis (PCA) had been used by many researchers to construct subspace for representing feature class but the principal component which are the largest eigen vector of the co-variance matrix generated are not always the optimal features in lower dimension for classification purposes (Han & Kim, 2005; Babatunde, Olabiyisi, Omidiora & Ganiyu, 2015).

The Independent Component Analysis (ICA) which is a generalization of PCA requires high computational time during training (Déniz, Castrillón & Hernández, 2003). The Linear Discriminant Analysis (LDA) for feature selection requires much computation time and its performance can be degraded when sample (feature) size is large (Bhuiyan & Liu, 2007). It is therefore very important to select relevant features in facial recognition in order to have better accuracy in classification phase (Aghdam, Ghasem-Aghaee & Basiri, 2009). The selection of quality features representing a pattern could affect the success of the computational time and classification accuracy (Imani, Pourhabibi, Keyvanpour, & Azmi, 2012). With the feature selection, the complexity and computational cost of classifier can be reduced by minimizing the number of features to be used into measurable forms while still maintaining acceptable recognition accuracy (Miche, Bas, Lendasse, Jutten & Simula, 2007; Hira & Gillies, 2015).

Obtaining an optimal feature subset in feature selection turns out to be usually intractable (Liu & Yu, 2009), and many other problems related to feature selection shown to be non-deterministic polynomial hard problem (NP)(Imani et al., 2012). There is need to apply meta-heuristic optimization technique in order to avoid prohibitive complexity for optimal feature subset selection. Among feature selection methods, the population-based meta-heuristic optimization approaches such as Genetic Algorithm (GA) and Ant Colony Optimization (ACO) have received great attention (Aghdam et al., 2009). The meta-heuristic feature-based selection algorithms produce effective solution by using knowledge from previous iteration (Kanan, Faez & Taheri, 2007). The application of ACO meta-heuristic technique to Gabor feature dimensions will result into optimized features and thus also contribute to the reduction of irrelevant or redundancy in features. The selection of features used for classification has an effect on the accuracy of the classification function, the time taken for classification, training dataset requirements and implementation costs associated with the classification (Derakhshii & Ghaemi, 2014).

3. AIM AND OBJECTIVES

The aim of this study is to develop an optimal feature-based facial recognition system. The objectives of the study are to:

(i) Extract frontal facial features using filter bank of Gabor filters with 8 orientations and 5 scales.

(ii) Use ACO Meta-heuristic Algorithm for optimal feature subset selection of Gabor features.

(iii) Apply four distance measures classifier; Chebyshev, City block, Malahanobis and

(iv) Evaluate the performance of the proposed facial recognition system using training time, testing time and classification accuracy in MATLAB environment.

Euclidean for face image recognition / matching

4. LITERATURE REVIEW

4.1 Two-Dimensional Gabor-filters Technique

Gabor technique is a method that involves the use of Gabor filters (wavelets) for facial feature representation. The application of Gabor wavelets originally applied to facial recognition using Dynamic Link Architecture (DLA) framework (Lades et al., 1993). The DLA creates a flexible template comparison between Gabor wavelet representations of different face images. Wiskott, Fellous, Krüger, and von der Malsburg (1997) developed face recognition by expanding DLA using a Gabor wavelet-based elastic bunch graph matching (EBGM) algorithm to label and recognize human faces. The experimental test conducted on the FERET database revealed a high recognition rate for frontal face images. Gabor filters and Gabor wavelets are directly related since both can be designed for a number of dilations and rotations. The Gabor wavelet representation captures salient visual properties such as orientation selectivity, spatial localization and spatial frequency. It represents data at different scales and orientations. Gabor filters have been employed successfully and broadly in many applications such as handwritten numeral recognition and fingerprint recognition (Thangairulappan & Jeyasingh, 2012). The Gabor wavelets generally used in Facial recognition can be defined as follows (Liu & Wechsler, 2002; Bellakhdhar et al., 2013)

$$Gabor(x, y, u, v) = \theta(x, y, u, v)(\alpha - \beta) \tag{4.1}$$

Where

$$\theta(x, y, u, v) = \frac{\|k_{u,v}\|^2}{\sigma^2}\, e^{-\frac{\|k_{u,v}\|^2 (x^2 + y^2)}{2\sigma^2}} \tag{4.2}$$

$$\alpha = e^{ik_{u,v}\, z} \tag{4.3}$$

$$\beta = e^{-\frac{\sigma^2}{2}} \tag{4.4}$$

$$\varphi_{u,v}(z) = \frac{\|k_{u,v}\|^2}{\sigma^2}\, e^{-\frac{\|k_{u,v}\|^2 \|z\|^2}{2\sigma^2}} \left[e^{ik_{u,v}\, z} - e^{-\frac{\sigma^2}{2}} \right] \tag{4.5}$$

Where z = (x, y) is the point with the horizontal coordinate x and the vertical coordinate y in the image plane. θ Is the anticlockwise rotation of Gaussian and the plane wave. α is the sharpness of the Gaussian along the major axis parallel to the wave. β is the sharpness of the Gaussian along the minor axis perpendicular to the wave. The parameters u and v define the orientation and scale of the Gabor kernel. $\|.\|$ denotes the norm operator, and σ refers to standard deviations of the Gaussian window in the kernel. The wave vector K_{uv} is defined as:

$$k_{uv} = k_v\, e^{i\varphi u} \tag{4.6}$$

Where $k_v = \frac{k_{max}}{f_v}$, (4.7)

$$\varphi_u = \frac{\pi\mu}{8} \tag{4.8}$$

K_{max} is the maximum frequency and f_v is the spatial frequency between kernels in the frequency domain. Gabor filters are selected relative to following parameters:

$$K_{max} = \frac{\pi}{2} \tag{4.9}$$

$$f = \sqrt{2}\,, \tag{4.10}$$

$$\sigma = \pi \tag{4.11}$$

The parameters ensure that frequencies are spaced in octave steps from 0 to π, typically each Gabor wavelet possess a frequency bandwidth of an octave that is sufficient to have less overlap and cover the entire spectrum. Two-dimensional Gabor filters correspond to a family of bi-dimensional Gaussian functions modulated by cosine function (real part) and sine function (imaginary part) representing orthogonal directions. These two components may be formed into a complex number or used separately as illustrated in equation (4.12), (4.13) and (4.14) respectively.

Complex Part:

$$g(x, y;\ \lambda, \theta, \sigma, \gamma) = \exp\left(-\ \frac{x'^2 + \gamma^2 y^2}{2\sigma^2}\right) \exp\left(i\left(2\pi \frac{x'}{\lambda}\ +\ \varphi\right)\right) \qquad (4.12)$$

Real Part (cosine function):

$$g(x, y;\ \lambda, \theta, \sigma, \gamma) = \exp\left(-\ \frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) \cos\left(i\left(2\pi \frac{x'}{\lambda}\ +\ \varphi\right)\right) \qquad (4.13)$$

Imaginary part (sine function):

$$g(x, y;\ \lambda, \theta, \sigma, \gamma) = \exp\left(-\ \frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) \sin\left(i\left(2\pi \frac{x'}{\lambda}\ +\ \varphi\right)\right) \qquad (4.14)$$

Where

$x' = x \cos\theta + y \sin\theta$

$y' = x \sin\theta + y \cos\theta$

λ = wavelength of the cosine wave

θ = orientation of the filter (wavelet)

φ = phase of the sine wave

σ = Standard deviations of Gaussian envelope along x and y dimensions (σ =λ)

γ = spatial aspect ratio of the Gaussian envelope

4.2 Two-Dimensional Gabor Filter for Facial Representation

A two-dimensional Gabor filter in spatial domain is a Gaussian kernel modulated by sinusoidal plane wave (Kyrki, Kamarainen & Kälviäinen, 2004). The general procedure when using Gabor filters for face recognition is achieved by construction of a filter bank with filters of different scales and orientations in order to filter the given facial image with all the filters from bank (extraction of information is based on the use of bank of Gabor filters) (Kaur & Rajput, 2013). The bi-dimensional Gabor wavelet representation of a facial image is derived by the convolution of face with Gabor filters (Bellakhdhar et al., 2013). The convolution of image I and Gabor kernel $\varphi_{u,v}(z)$ is defined as follows:

$$G_{u,v}(z) = I(z) * \varphi_{u,v}(z) \tag{4.15}$$

Where z = (x, y) denotes the image position on coordinate x and y, the symbol $*$ denotes the convolution operator, $G_{u,v}(z)$ is the convolution result corresponding to the Gabor kernel at orientation u and scale v. The filtering process with Gabor filter with a face image can be rewritten as follows (Shen & Bai, 2006):

$$G_{u,v}(x,y) = I(x,y) * \varphi_{u,v}(x,y) \tag{4.16}$$

The Gabor wavelet coefficient is a complex function with a real and imaginary part, which can be rewritten as:

The convolution of an image with Gabor wavelet can be illustrated using the following mathematical procedures; if f (x, y) represents the intensity at the coordinate (x, y) in gray scale face image, its convolution with Gabor filter $\varphi_{f,\theta}$(x, y) is defined as:

$$g_{f,\theta}(x, y) = f(x, y) * \varphi_{f,\theta}(x, y) \tag{4.17}$$

Where $*$ is the convolution operator and $g_{f,\theta}(x,y)$ denotes the complex convolution result of a face image with a Gabor filter which can be decomposed into a real and an imaginary part; $\mathcal{R}\{g_{f,\theta}(x, y)\}$ and $\mathfrak{Z}\{g_{f,\theta}(x, y)\}$. The magnitude response $\|g_{f,\theta}(x,y)\|$ is expressed as:

$$\|g_{f,\theta}(x,y)\| = \sqrt{\mathcal{R}^2\{g_{f,\theta}(x,y)\} + \mathfrak{Z}^2\{g_{f,\theta}(x,y)\}} \tag{4.18}$$

This magnitude response $\|g_{f,\theta}(x,y)\|$ produces Gabor face features. A Gabor wavelet feature j is described by three key parameters. J(z, u, v) = $\|g_{f,\theta}(x,y)\|$. Where z represents position, u denotes orientation and v represents scale. Hence for a given image I(z) with N ×M pixels the number of Gabor wavelet feature representation is N × M × 40.

4.3 META-HEURISTIC OF ANT COLONY OPTIMIZATION (ACO)

The ACO meta-heuristic is described as a distributed stochastic search technique based on the indirect communication of a colony of artificial ants which is mediated by pheromone trails (Dorigo, Birattari & Stutzle, 2006). The ACO algorithm implementation on an image undergoes some modifications. The solution construction space for ants now is the 2-dimensional Gabor face image, artificial ants are made to move over the image (Dorigo & Stützle, 2004). Thus, the artificial ants simulating the natural ants leave a pheromone on each node or image pixels. The edges of an image become the food for ants. Therefore, in this manner the ants develop pheromone matrix.

(a) Transition Rule

The decision of path taken is influenced by the local intensity value. Parameters considered here are total ants K and $\tau_{i,j}$. $\tau_{i,j}$ is the starting initial value of pheromone matrix, construction of ant solution is made possible through the local search on the solution space (image data matrix). Ants decide to move from node i to another j through probability rules (transition rule) as shown in equation (4.1).

$$P_{i,j}^{\boldsymbol{k}}(t) = \frac{[\tau_{i,j}]^{\propto}[\eta_{i,j}]^{\beta}}{\sum_{j\in J_i^k}[\tau_{i,j}(t)]^{\alpha}[\eta_{i,j}]^{\beta}} \text{ , if } j \in j_i^k \qquad (4.19)$$

Where $P_{i,j}^{k}(t)$ is the probability of k ant to move from node i to node j at i iteration time. j_i^k is the set of nodes in the neighborhood of the k ant in the i node. $\tau(t)$ represents the pheromone information or trail intensity value that encodes a long-term memory about the whole ant search procedure. η heuristic information that denotes the priori information about the problem instance definition. $[\tau_{i,j}]^{\propto}$ is the pheromone amount on the arc connecting node i and node j weighed by α. α and β are two constant parameters that determine the importance of pheromone value and heuristic function. $[\eta_{i,j}]^{\beta}$ is the heuristic value of the arc connecting node i and node j weighted by β. α shows the extent to which pheromone information is used as the ants develop their solution. β shows the extent to which heuristic information is used.

(b) Pheromone Trail Update

When reaching the destination node, the ant switches from the forward mode to the backward mode and then retraces step by step the same path backward to the source node. An additional feature is that, before starting the return trip, an ant eliminates the loops it has built while searching for its destination node. In ACO, loop elimination is implemented so that loops are eliminated in the same order as they are created. During its return travel to the source the *k-th* ant deposits an amount $\Delta\tau^{k}$ of pheromone on arcs it has visited. The Update of pheromone after movement of each ant within each construction step is shown in equation (4.20).

$$\tau_{i,j}^{k} \leftarrow (1-\rho).\tau_{ij} + \rho.\Delta(i,j)^{k} \qquad (4.20)$$

where $\rho \in (0,1)$ is the pheromone update parameter and

$$\Delta(i,j) = \sum_{k=1}^{m} \Delta\tau_{i,j}^{k} \qquad (4.21)$$

$$\tau_{i,j}^{k} \leftarrow (1-\rho).\tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{i,j}^{k} \qquad (4.22)$$

$$\Delta\tau_{i,j}^{k}(t) = \{ {}^{Q}/_{C^{k}} \ if\ arc\,(i,j) \epsilon\ \tau_{i,j}^{k} \qquad (4.23)$$

Where ρ is the evaporation rate, m is the number of ants, and $\Delta\tau_{i,j}^{k}$ is the quantity of pheromone laid on edge (i, j) by ant k

(c) Pheromone trail evaporation

Pheromone trail evaporation makes ants to search for some new paths and in this manner opportunity to find a new shorter path in the unexplored area during the complete search process is opened. This mechanism is referred to as path exploration, which avoids the system quick convergence towards a suboptimal route. ACO exploits the advantage of exploitation and exploration to obtain solution through iteration of the optimal search part. The pheromone trail evaporation seems to be important in artificial ants probably due to the fact that the optimization problems tackled by artificial ants are much more complex than those real ants can solve. Evaporation of pheromone trails is accomplished after movement of all k ants within each construction step as indicated in equation (4.24)

$$\tau^{(n)} = (1 - \varphi).\tau^k + \varphi.\tau^{(0)} \quad (4.24)$$

where φ is the decay coefficient.

4.3.1 Distance Measure Metrics

This is a simplest techniques for identifying object based on closest training samples in the feature space (test set) (Imandoust & Bolandraftar, 2013). The object of interest is compared to every sample in training set by applying a distance measure, similarity measure or the combination of two measures (Sergyán, 2009). The unknown object is recognized as fit in to the equivalent class as the closest sample in training set, this is identified by the smallest number if it is a distance measure or largest number it applies similarity measure. Many facial recognition systems perform their classification based on a distance measure (Rady, 2011). The distance measure methods have been applied in many applications such as text categorization, pattern recognition, data mining and object recognition (Alkasassbeh, Altarawneh & Hassanat, 2015). There are various examples of Nearest Neighbor methods of classification such as Euclidean, Manhattan, Chebyshev and Malanobis distance (Sodhi & Lal, 2013).

(a) Euclidean Disatnce

The Euclidean distance is the commonly used distance classifier in most applications. Euclidean distance classifier is used in testing for the calculation of minimum distance between test image and image to be classified from database. It is referred to l_2 distance (Sharma & Batra, 2014).

The Euclidean distance can be illustrated as follows: If $u = (x_{1,}\, y_1)$ and $v = (x_{2,}\, y_2)$ are two points, then the Euclidean Distance between u and v is given by

$$EU(u,v) = \sqrt{(x_1 - x_2)^2 + (y_1 - x_2)^2} \qquad (4.25)$$

If the dimensions is of n terms, such as $a = (x_{1,}\, x_2,\, \ldots\ldots x_n)$ and $b = (y_{1,}\, y_2,\, \ldots\ldots y_n)$ then equation 2.29 can be generalized by defining the Euclidean distance between a and b (Thakur & Sahayam, 2013) as

$$EU = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + \cdots + (x_n - y_n)^2} \qquad (4.26)$$

(b) Chebyshev Distance

This is a metric defined on a vector space where the distance between vectors is the greatest of their differences along any coordinate dimension. The chebyshev distance between two vectors on point p and q, with standard co-ordinates p_i and q_i as shown by the following formula.

$$\text{Dchebyshev(p,q)} = max_i\ (\ |p_{i\,-}\ q_i|\ ) \qquad (4.27)$$

This equals the limit of the l_p metrics:

$$\lim_{k\to\infty}(\textstyle\sum_{i=1}^{n}|p_{i-}\ q_i|^k)^{\frac{1}{k}}$$

In the two dimensions, if the points p and q have Cartesians coordinate $(x_{1,}y_{1,})$ and $(x_{2,}y_{2,})$ then the chebyshev distance is

$$\text{Dchebyshev} = \max\ (|x_{1\,-}\ x_2|),\ |y_{2\,-}\ y_1| \qquad (4.28)$$

(**c) Manhattan Distance (City Block Distance)**

It examines the sum of absolute differences between the two feature vectors (Sodhi & Lal, 2013). It is real distance function because it follows the triangle inequality. As Manhattan or Taxicab distance is that passing from a point A to point B is achieved by walking around the block compared to straight line in Euclidean distance (Gomathi & Karthkeyan, 2014). The Manhattan distance (MH) between a point u and v can be illustrated as follows:

If u = (x_1, y_1) and v = (x_2, y_2) are two points, then MH (u, v) is

$$MH\ (u, v) = |x_1 - x_2| + |y_1 - y_2| \tag{4.29}$$

with points of u and v dimensions, as in a = (x_1, x_2 ……, x_n) and b = (y_1, y_2……., y_n) the equation (4.29) is generalized as:

$$MH\ (u, v) = |x_1 - y_1| + |x_1 - y_2| + \ldots\ldots\ldots.. |x_n - y_n| = \sum |x_{i-}\ y_i| \tag{4.30}$$

for i = 1,2, …………., n

Where i is the number of variables x_i and y_i are the values of the ith variables at point x and y respectively.

(d) Mahalanobis Distance

It is a descriptive statistic that gives a relative measure of data points distance from common point (Patil & Kiran, 2014). The Malanobis distance shows dissimilarity measure between two random vectors $\vec{x}, \vec{y}$ of same distribution with covariance matrix S (Sharma & Batra, 2014) as shown in equation (2.36). Malahanobis distance of observation x = $(x_{1,}\ x_2\ ,x_{3,}\ \ldots\ldots\ldots\ x_N\ )^T$ from set of observation with mean μ = $(\mu_{1,}\ \mu_2\ ,\ \mu_{3,\ldots\ldots\ldots\ldots}\ \mu_N)\ ^T$ and covariance matrix S is defined as:

$$D(x) = \sqrt{(x - \mu)^T S^{-1}\ (x - \mu)} \tag{4.31}$$

$$D(\vec{x}, \vec{y}) = \sqrt{(\vec{x} - \vec{y})^T S^{-1}\ (\vec{x} - \vec{y})} \tag{4.32}$$

4.4 Related work

Mohammed, Deeba, Bui & Wahid (2016) proposed ant colony optimization algorithm to find a feature subset most relevant to the classification task. The study incorporated a new heuristic information component based on classification accuracy. The system was applied to multi-class classification problem of capsule endoscopic image, where image regions are classified as bleeding, non-bleeding and uninformative regions. 75 dimensional features were extracted from five colour spaces. The system efficiently found the optimum feature subset over five colour spaces including RGB, HSV, Lab, YCbcr and CMYK. The comparative analysis with state of the art methods of feature selection showed that proposed system provided most relevant features and improvement in terms of accuracy , sensitivity and computational

Ali Jan Ghasab, Khamis, Mohammad and Jahani Fariman (2015) presented an expert system for automatic recognition of different plant species through leaf images by employing the ant colony optimization as a feature decision making algorithm. The ACO algorithm was applied to get the best discriminant features for the recognition of individual species. The study established a feature search space, a set of feasible characteristics such as shape, morphology, texture and colour were extracted from the leaf images. The selected features were used by Support Vector Machine (SVM) to classify the species. The efficiency of the system was tested on 2050 leaf images collected from plant databases (FCA and Flava). The experimental result achieved an average accuracy of 95.53% from ACO-based approach showing the potential of using proposed system for classification.

Rashno, Sadri and SadeghianNejad (2015) developed a novel content-based image retrieval (CBIR) schema with wavelet and colour features using ACO. The ACO was used to select the most relevant features from a complete feature set. A new feature extraction schema including texture features from wavelet transformation, HSV domain and colour features in RGB as representation feature vector for images in database. The performance of CBIR schema was compared with existing systems, results showed that the precision and recall of proposed outperformed the older systems.

A face recognition was developed by applying Gabor-filter based feature extraction method with Anisotropic Diffusion as a pre-processing technique to improve the performance of face recognition algorithm (Abhishree, Latha, Manikantan, & Ramachandran, 2015). Gabor filter was employed to capture the features of face image aligned at specific angles. A binary particle swarm optimization based feature selection algorithm was applied to find the feature space for optimal feature subset. The model was evaluated on four benchmark facial image datasets; ORL, Color FERET, Cropped Yale B and FEI datasets. The result showed outstanding performance compared with existing methods in the presence of pose, illumination and expression variation.

A new approach to improve 3D face recognition system performance was developed (Hafez et al., 2015). The model pre-processed and normalized all images in the database using 2D normalized cross correlation 2DNCC. The 3D face features were extracted by applying a set of selected orthogonal Gabor filters, which minimized the feature vectors extracted when compared to those ones that use complete Gabor filters bank. The study further employed linear discriminant analysis to compress dimensionality of the extracted features before classification. The model tested on CASIA and Gavab 3D face image database achieved 98.35% and 85% respectively. Experimental results showed the effectiveness of the system in term of dimensionality and recognition accuracy when compared with existing systems.

A comparative study on Face recognition Gabor wavelet features with PCA and KPCA (Vinay et al., 2015). The study used Gabor wavelet for feature extraction system. The face recognition algorithm applied Principal Component Analysis (PCA) and Kernel Principal Component Analysis (KPCA) for a post processing method after feature extraction to reduce dimensionality of filtered face images. Comparison analysis was carried out between the two methods. The model was evaluated using the publicly available ORL database. Results reviewed that GABOR-PCA outperformed the GABOR-KPCA method for facial recognition.

Mohammed (2014) developed a face recognition system using principal Gabor-filter. The system extracted facial features through the use of Gabor-filter. The feature vectors from Gabor filter were used as the input of the classifier, which was a feed forward neural network on reduced feature subspace learned by Principal Component Analysis for recognition of face images. The effectiveness of the system was justified over a face database with faces captured under different illuminations and orientations.

Elgarrai et al., (2014) conducted a face recognition system using Gabor features and HIK Toolkit. Facial image features are extracted using Gabor filters. The dimensionality of those features was reduced using the linear discriminant analysis (LDA) method to keep only the most relevant information. The system injected the resulting feature vectors to the Hidden Markov Model Toolkit (HIKT). Experimental results on YALE and ORL database showed the efficiency of the proposed system.

Bellakhdhar et al (2013) came up with a face recognition system using Gabor wavelets, Principal Component Analysis (PCA) and Support Vector Machine (SVM). The model combined magnitude and phase of Gabor filter. PCA was applied to extract the eigenvectors of the face images. SVM used for classification. The performance of the model tested on the public and largely used datasets of FRGCV2 and ORL. Experimental results showed that the combination of the magnitude with the phase of Gabor features can achieve better results.

Imani et al., (2012) developed a new hybrid of Ant Colony Optimization (ACO) and Genetic Algorithms (GAs) as a feature selector, and Support Vector Machine as a classifier as a classifier are integrated effectively. Based on the combination of the fast global search ability of GA and the positive feedback mechanism of ACO, a novel algorithm was proposed in the domain of feature selection. The system tested on the extracted features of ten common Persian fonts. Experimental result showed that proposed feature selection achieved better performance than normal GA and ACO.

Mounika et al (2012) proposed a neural network based face detection system using Gabor filter response. They convolved a face image with series of Gabor filter coefficients at different scales and orientations. Gabor features were fed to feed forward neural network which was based on

Bi-directional Memory (BAM) for dimensional reduction and multilayer perception with back propagation algorithm for training the Gabor features. The recognition performance was improved by contrast equalization using the root mean square value of image pixel. The application of hybrid network (Bi-directional Association Memory (BAM) and Back Propagation Neural Network (BPNN)) takes less iteration to train and less time to recognize. The effectiveness of their recognition model was evaluated using Yale database with different illumination conditions.

An efficient face recognition using Gabor filters to extract facial features presented (Thangairulappan, Beulah, & Jeyasingh, 2012). In the study, the large dimensional Gabor features were reduced by wavelet transformation. Discriminative common vectors were obtained using within-class matrix method to get a feature representation of face images with enhanced discrimination and also classification was done using radial. Radial basis function network. The proposed system was validated with three face datasets: ORL, JAFFE and Essex face database. Experimental results showed that the recognition model reduces the number of features, minimizes the computational complexity and also yielded better recognition accuracy.

An intelligent neural network system for facial recognition proposed by (Bouzalmat et al., 2011). Gabor filters used for the feature extraction as these filters present desirable characteristics of spatial locality and orientation selectivity. The study applied Sparse Random projection (RP) technique to reduce large feature dimensions into feature subspace. Back Propagation Neural Network (BPNN) was used on the feature vectors for classification. The face recognition model was evaluated using AR database with a collection of twenty people from database. Each person represented by twenty samples, ten used for training and ten for testing. The recognition system achieved higher recognition rate and better classification efficiency when feature vectors have low dimensions.

Kisku, Gupta, Sing, and Hwang (2010) came up with multispectral palm image fusion for person authentication using Ant Colony Optimization. The study captured the palm features, fused image was convolved with Gabor wavelet transformation. The Gabor wavelet feature representation contained high dimensional space. ACO was applied to select relevant, distinctive and also reduced feature set from Gabor responses. The reduced set of features was trained with support vector machines. The system was evaluated using CASIA multispectral palm-print database. Experimental results revealed the robustness of the proposed system.

Karnan, Akila and Kalamani (2009) developed a feature subset selection in keystroke dynamics for identity verification. The results of experimenting Ant Colony Optimization technique on keystroke duration, latency and digraph for feature selection. ACO was used to reduce the redundant feature values and also minimised the search space. Optimal feature subset was obtained using keystroke duration values when compared with other two feature values.

Principal Gabor-filters for face recognition by (Štruc et al., 2009). A novel orthogonal Gabor filters constructed from the linear combination of the original Gabor filters to reduce the problem of high dimensionality of Gabor features. The novel filters were derived from correlation matrices of the original filters by means of principal component analysis. XM2VTS and YaleB datasets used to evaluate their model. Experimental results obtained in a series of verification and identification analyses reviewed that the new filters result to better performance with a significantly reduced computational complexity.

Daoud (2009) proposed enhancement of face recognition using modified Fourier Gabor filter. They performed experiments to verify the effectiveness of the proposed model using five popularly used techniques in face recognition applied to four datasets (AT&T, IFD, Faces 95 and Yale datasets); the methods are implemented without and with suggested filters. The experimental results showed that using suggested Fourier-Gabor filter enhances the classification rates for all methods, datasets, training and testing percentage. The highest classification rates obtained when Fourier Gabor filter with batch linear discriminant analysis (FG-Batch-ILDA).

A Gabor filter coefficient based neural network method for face recognition (Bhuiyan & Liu, 2007). Convolved a face image with a series of Gabor filter coefficients at different scales and orientations. The study introduced contrast equalization and fuzzily skewed filter technique at image pre-processing phase which contributed to the performance of the face recognition model. Fifteen Gabor filters (three for scaling and five for orientations) were used to reduce the huge dimension of Gabor features. A neural network based on multi-layer perceptron (MLP) architecture with back propagation algorithm was applied for classification.

5. RESEARCH METHODOLOGY

5.1 Optimized Feature-Based Facial Recognition System

The development of the proposed system commenced with the creation of face image databases. This study employed two face image datasets for training and testing phase; Olivetti Research Laboratory (ORL) database and locally acquired image database (Locally Acquired Images of Students from University of Ilorin). All face images were taken against a dark homogenous background with the subjects (images) in uprights and frontal positions. Preprocessing / normalization technique was performed on each facial image of the two datasets by cropping, resizing of facial image and the contrast adjustment. Gabor filters were used to obtain frontal facial features representation which represents Gabor features. The meta-heuristic Ant Colony Optimization algorithm was applied to select optimal feature subsets from huge Gabor features. The generated feature subsets were used as template for matching with four different distance measure classifiers. Figure 5.1 shows the system block diagram.

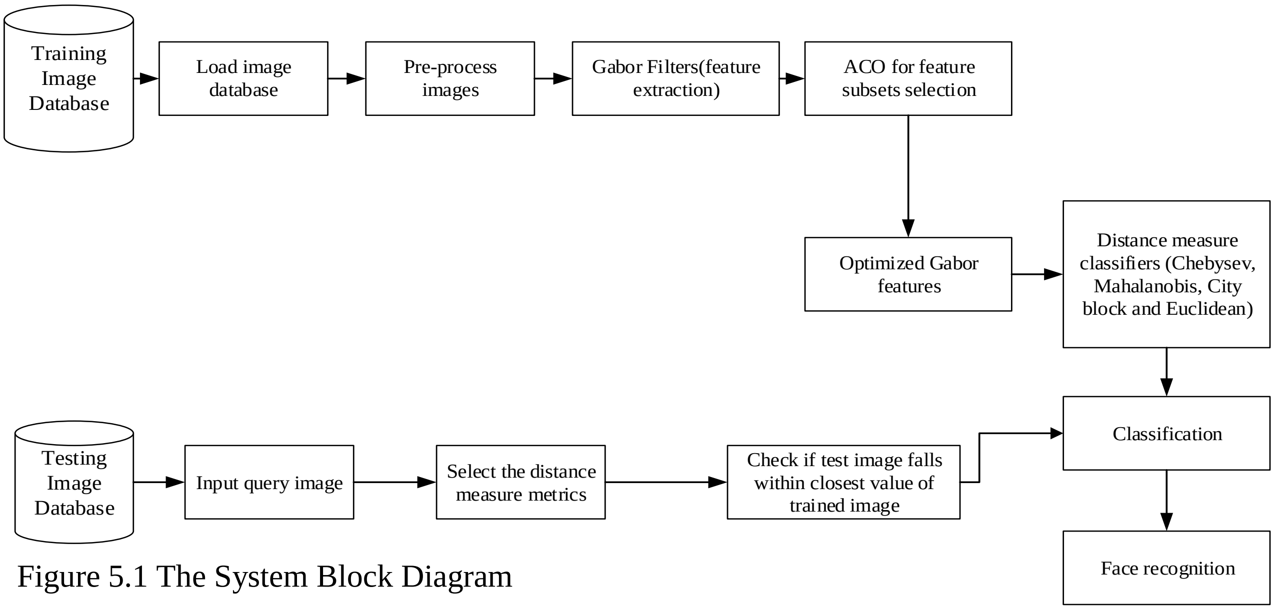


Figure 5.1 The System Block Diagram

5.2 Acquisition of Facial Images

The evaluation of face recognition system is necessary and should be carried out with image database. There is a need to create an image database of different people. Although, certain provision has been made available for several standard online face datasets, general features of these commonly available datasets include face image taking in a well-controlled environment and image tailoring towards a specific requirement of an algorithm. On the other hand, the performance of face recognition systems is affected when datasets used to benchmark the algorithms changes due to differences in facial features from race to race. These conditions result to the need for a new database. Facial Images used in this work was acquired from Olivetti Research laboratory (ORL) Database and locally acquired student faces of the University of Ilorin.

5.2.1 Locally Acquired Student Facial Image (LASFI) Database

The original frontal face images of various students of the University of Ilorin were captured using static HP Digital Camera. The images were taken under different lighting conditions and backgrounds to form a facial database. The LASFI face database was developed by the collection of 60 face images of 4 subjects per person, which gave the total number of 240 images all together captured from the students of University of Ilorin from the month of April, 2016 to

September, 2016. Total number of 180 images were used for training while the remaining 60 images were used for testing. It has been duly considered that there can be a change in the expressions of the people. So this database was designed with different expressions for all

subjects for better results.

Figure 5.2 Sample of faces from LASFI

5.2.2 Olivetti Research Laboratory (ORL) Database of Faces

The ORL face database was developed at the Olivetti Research Laboratory in Cambridge, United Kingdom between April 1992 and April 1994. The face image database is composed of

1

erent face images from 40 people. Images were taken at different times, varying the lighting (illumination conditions not consistent from image to image), expressions (open, closed eyes and smiling) and occlusions (glasses, no glasses) as illustrated in figure 1.5. Out of the images in the database only 111 images were employed for training and 21 images for testing

Figure 5.3: Sample faces from ORL 2D Database

5.3 Extraction of Frontal Facial Features

The frontal features of the face was extracted using Gabor filters. The process involves Geometrical Normalization, Image Grayscale conversion, Photometric normalization and feature extraction.

5.3.1 Geometrical Normalization

The images in two face image datasets were preprocessed for consistency or normalization. The preprocessing phase involves the improvement with deference to the quality of the image, but not to head position (tilt) or emotion. Locally acquired face images were properly preprocessed since they were not captured under a controlled condition compared to what is obtainable in ORL database. The face images from LASFI databases were cropped from the original size of the image picture using Adobe Photoshop Software to a reduced size which varies across the images. The cropping process was conducted just to retain only the face region with the removal of parts like ear and fore-head with no distortions. Each image from the two image datasets were then resized into following sizes 75 x 75, 100 x 100, 125 x 125, 150 x 150 pixels, resulting into 5625, 10,000, 15625, 22500 dimensions.

5.3.2 Image Grayscale Conversion

In order to retain much information contained in face images (Suganya & Menaka, 2014), the colour images from the LASFI database were converted into grayscale images. Pixels in grayscale images then later stored as 8 bit integer to representation into black and white. The grayscale of image was achieved using the function in Matlab environment.

5.3.3 Photometric Normalization

The variability on the 2D face images brought by illumination changes. This is one of the greatest problems for reliable and robust face recognition system. Images obtained using cameras over longer distances or under poor visibility conditions are often not suitable for investigation and observation. Only marginal improvement in the images captured from the camera can be captured using standard camera settings such as contrast, diaphragm, brightness and shutter time. To handle the contrast problem in this work, images were sorted out to obtain better set of images. The images gathered are subject to some illumination variations. So therefore, it is necessary to conduct normalization process on face images of the datasets to elimination illumination variations, improve contrast and standard visual quality in order to have uniform histogram equalization for all images. Adaptive Histogram Equalization with high information retaining capability compared to conventional histogram equalization was used to normalize illumination effects.

5.3.4 Gabor-filters for Features Extraction

Gabor filters was applied for extraction of features in this level. The first stage involved the design of Gabor filters parameters. The parameters were set as follows: F_u and θ_v are defined as $F_u = \frac{F_{max}}{2}$ (u = 1,2,….., 5) and $\theta_v = \frac{v\pi}{8}$. (v = 1, 2, ……, 8). F_u is the center frequency and

θ_v orientation. F_{max} represents the maximum frequency of the filters set to F_{max} = 0.25. Then face image of size 75 x 75, 100 x100, 125 x 125 and 150 x 150 image pixel from the two datasets (ORL and LASFI Database) were convoluted separately by applying the a bank of Gabor-filters on each face image as shown in figure 5.4. The convolution result was decomposed into real and magnitude part. For this two parts, magnitude of filter responses calculated and then concatenate to produce Gabor features.

Algorithm for 2-Dimensional Gabor-filters for Feature Extraction

1. Design of a filter banks (set up parameters for filters).

2. Input face image from the image database

3**.** Check if the face image is in gray scale format, if the image is not, thus gray scale

4**.** Pre-process the gray face image

5**.** Apply the created filter on pre-processed face image, convolution of face image I (x, y)

with a filter bank containing filters of different 5 scales (u) and 8 orientations (v).

6. Decompose convolution result $G_{u,v}(x, y)$ into complex values of real and imaginary part

$$G_{u,v}(x, y) = I(x, y) * g_{u,v}(x, y)$$

$$E_{u,v}(x, y) = Re[G_{u,v}(x, y)]$$

$$O_{u,v}(x,y) = Im[G_{u,v}(x,y)]$$

7. Compute the magnitude $A_{u,v}(x,y)$ of filter responses and $\emptyset_{u,v}\,(x,y)$of phase

$$A_{u,v}(x,y) = \sqrt{E^2 u,v(x,y) + O^2 u,v(x,y)}$$

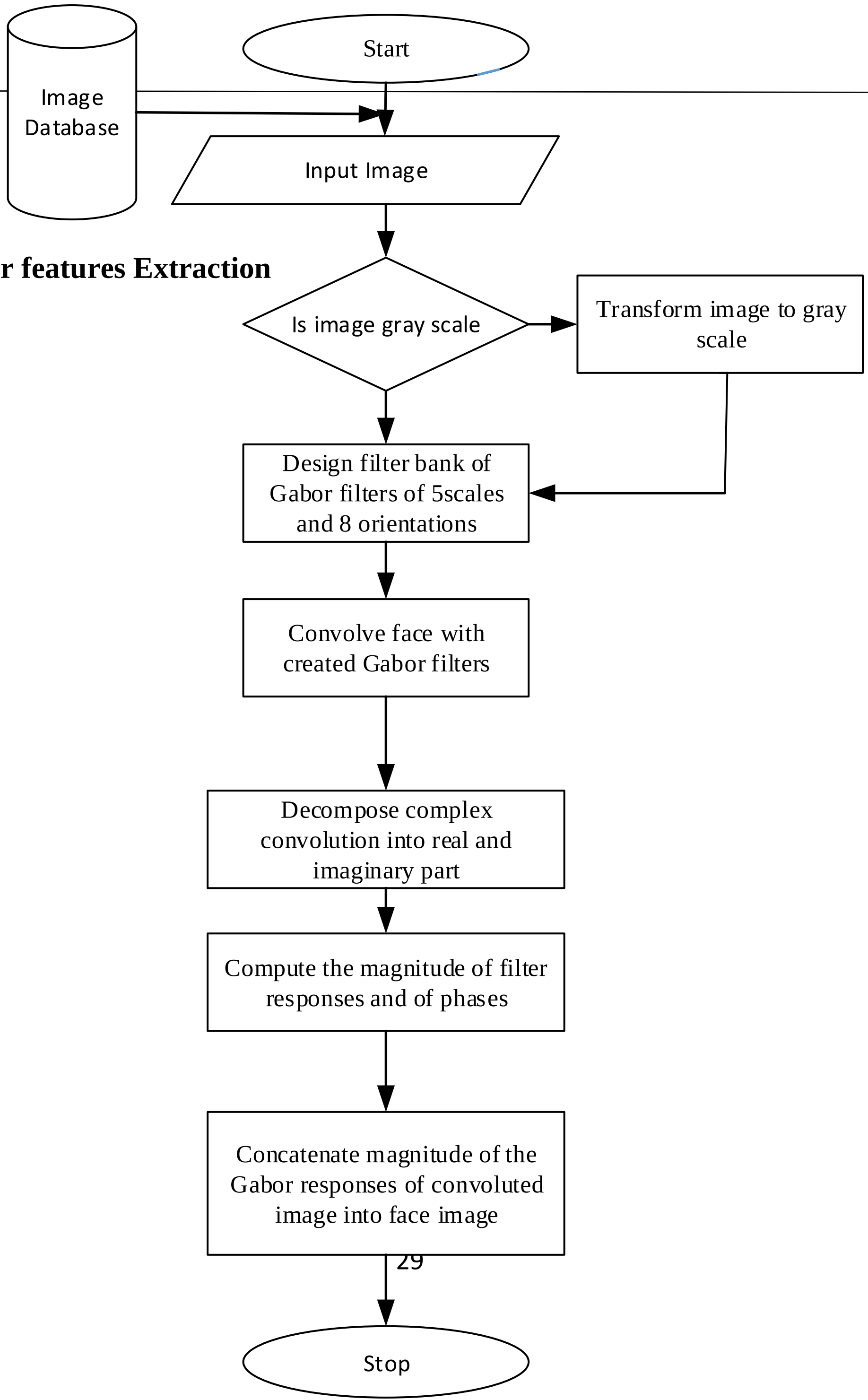
$$\emptyset_{u,v}(x,y) = \arctan\left(\frac{O_{u,v}(x,y)}{E_{u,v}(x,y)}\right)$$

8. Discard the Gabor phase features

9. Concatenate magnitude of the Gabor responses of convoluted image into face image

10. End

5.3.5 Gabor-filter features Extraction flowchart



5.4 Optimal Feature Selection using ACO

The meta-heuristic Ant Colony Optimization algorithm was applied to select optimal feature subsets from huge Gabor features. The Gabor features obtained from extraction stage contains high feature dimensions. The high dimensional features was then passed to ACO Meta-heuristics Algorithm for the feature subsets selection which is the optimal feature dimensions. The generated feature subsets were used as template for matching with four different distance measure classifiers.

5.4.1 Algorithm for Ant Colony Optimization for Optimal Feature Selection

1. Create ACO parameters α, β, ρ, τo, η, K, N,
2. Initialize pheromone matrix on Gabor image data matrix
3. Construct solution

$$p_{ij}^{k}(\mathrm{t}) = \frac{[\tau_{ij}\,(t)]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{j\epsilon j^{k}}[\tau_{ij}\,(t)]^{\alpha}[\eta_{ij}]^{\beta}}$$

4. Find the first update of the pheromone matrix (Global update of pheromone matrix)

$$\tau^{(n)} = (1-\varphi).\tau^{k} + \varphi.\tau^{(0)}$$

5. All K ants move over Gabor feature dimensions **Goto STEP 6** or If All K ants do not move else **Goto STEP 2.**

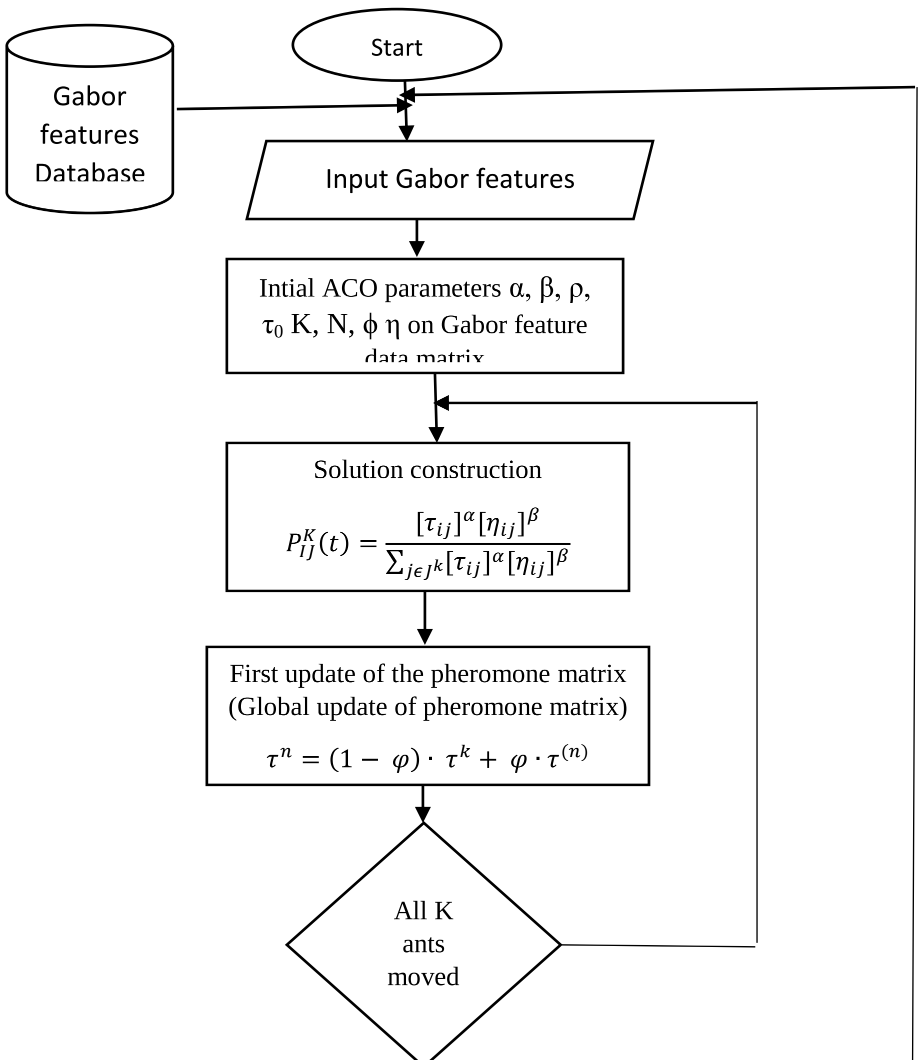
6. Find the second update of pheromone matrix (Local update of pheromone matrix).

7. If all iterations performed **Goto STEP 8** or if not else **Goto STEP 2.**

8. Return optimal feature subsets.

9. End

5.4.2 ACO feature subset selection of Gabor features flowchart



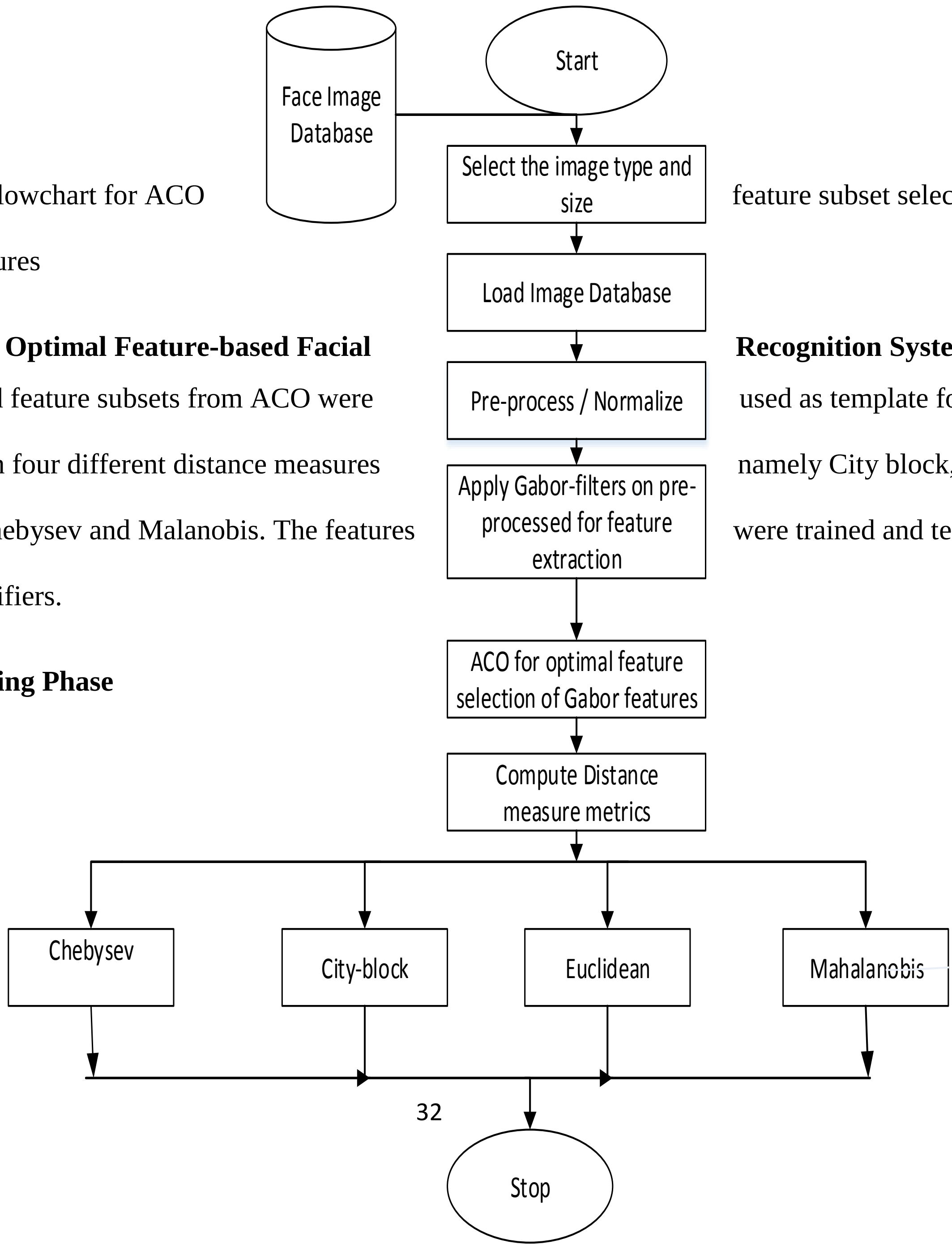


Figure 5.4: Flowchart for ACO feature subset selection of Gabor features

5.5 Proposed Optimal Feature-based Facial Recognition System

The generated feature subsets from ACO were used as template for matching with four different distance measures namely City block, Euclidean, Chebysev and Malanobis. The features were trained and tested with the classifiers.

5.5.1 Training Phase

Figure 5.5 Flowchart of Training Phase for Proposed System

5.5.2 Testing / Recognition Phase

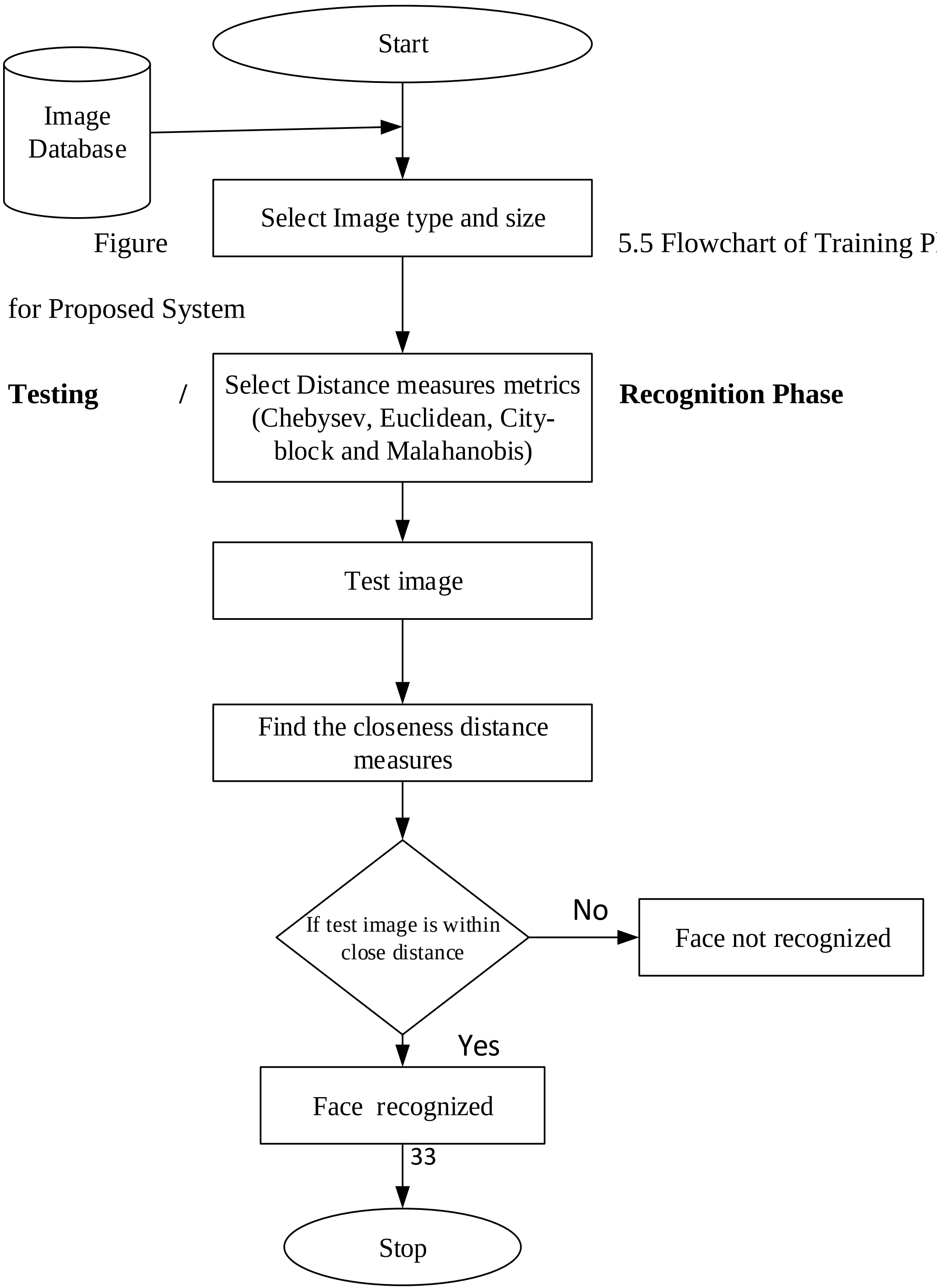


Figure 5.6 Flowchart for testing phase of proposed system

5.5.3 Algorithm for Optimal Feature-Based Facial Recognition System

1. Select face image type and size

2**.** Load face image database

3**.** Preprocessing / Normalization of face image

4. Apply Gabor filter on pre-processed face image, convolution of face image I (x, y) with a filter bank containing filters of different 5 scales (u) and 8 orientations (v).

5. Apply Ant Colony Optimization Algorithm on the extracted Gabor feature vectors

6. Compute optimized Gabor features (Gabor feature subsets)

7**.** Select distance measure metrics, City block, Malanobis, Euclidean and Chebysev to be applied on optimized Gabor features for classification.

8. Test image within training template of distance measure classifiers for matching,

9. If test image falls within the closest distance measures recognize image, if not image not recognize.

10. End.

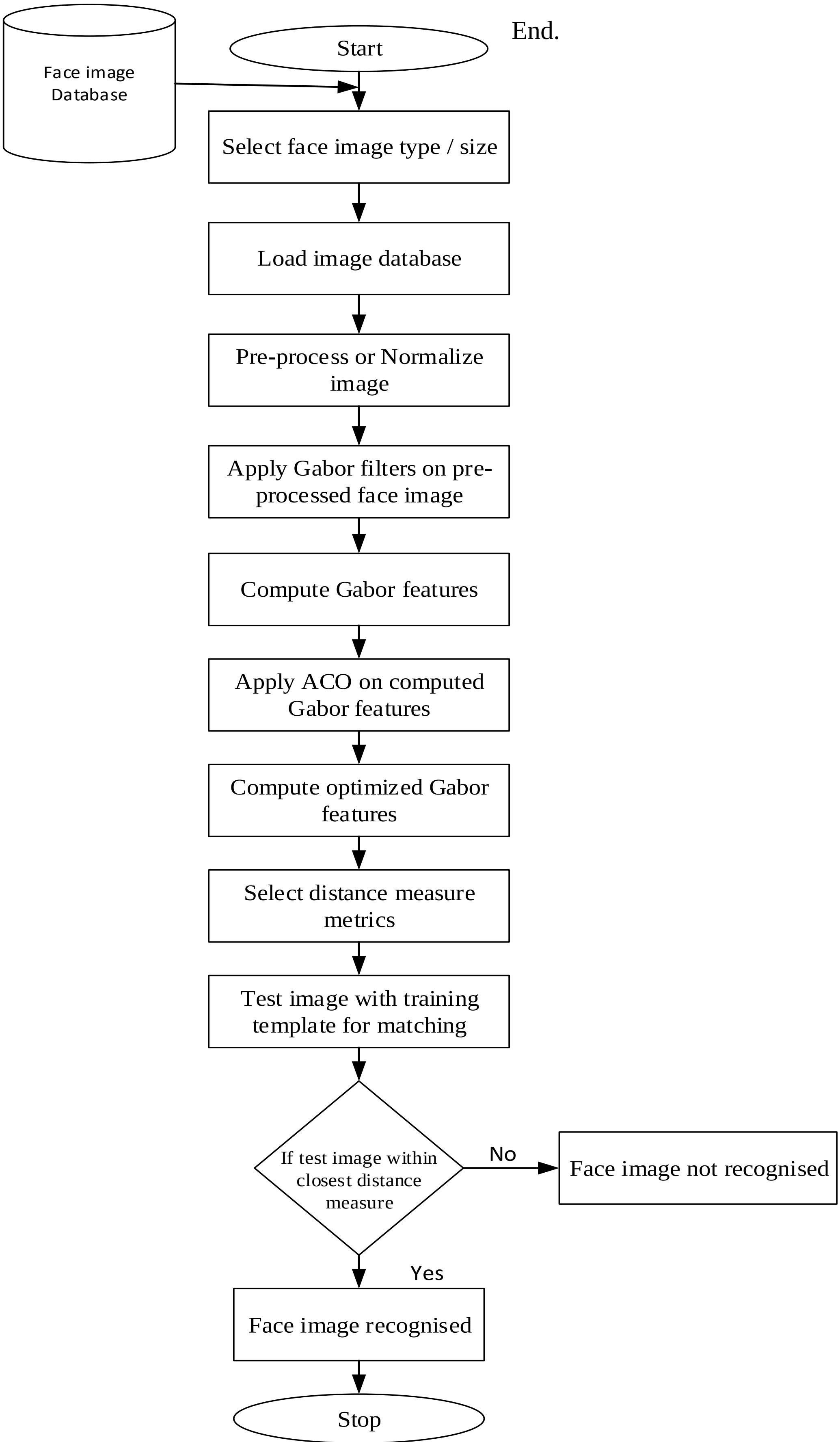


Figure 5.7: Flowchart for Optimal feature-Based Facial Recognition System

6 RESULTS AND DISCUSSION

6.1 Sample of Face Images

The locally acquired frontal face images obtained from University of Ilorin students (LASFI database) were converted to a gray scaling leveling as with what is obtainable in the ORL database as illustrated in figure 6.1(a). The face images from the two databases then passed through size (geometric) normalization. The result obtained from geometric normalization of LASFI database together with ORL were further preprocessed by applying Adaptive Histogram Equalization method for illumination compensation and contrast improvement. It was discovered during the experiment that all of the face images performed well to the preprocessing method used as shown in sections 6.2 and 6.3

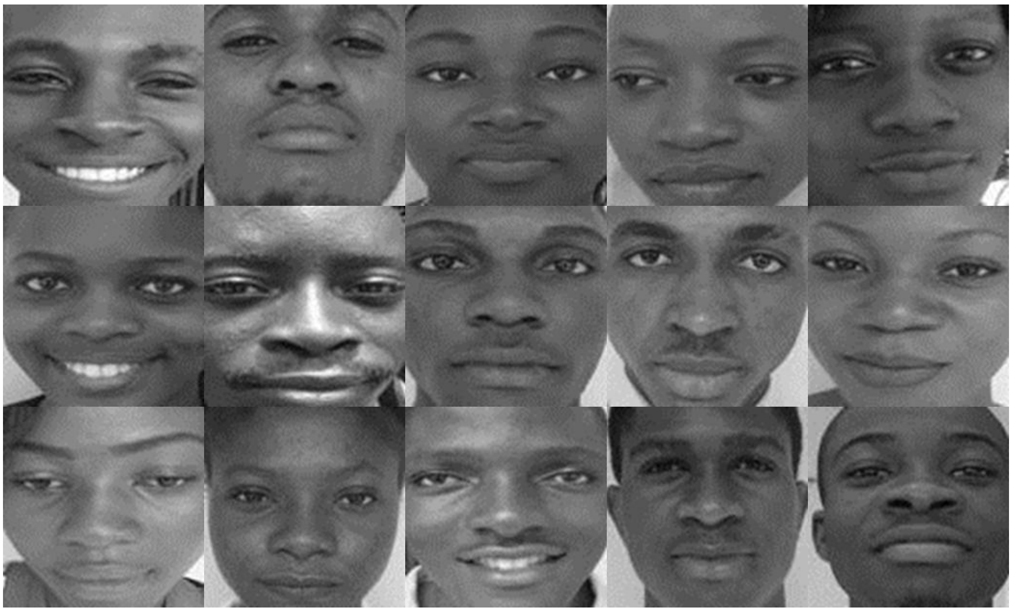
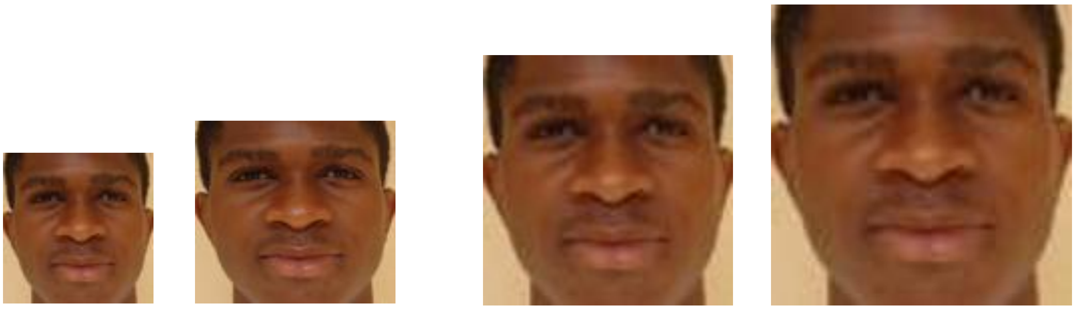


Figure 6.1(a). Samples of LASFI Database gray scale images

(b) Samples of ORL

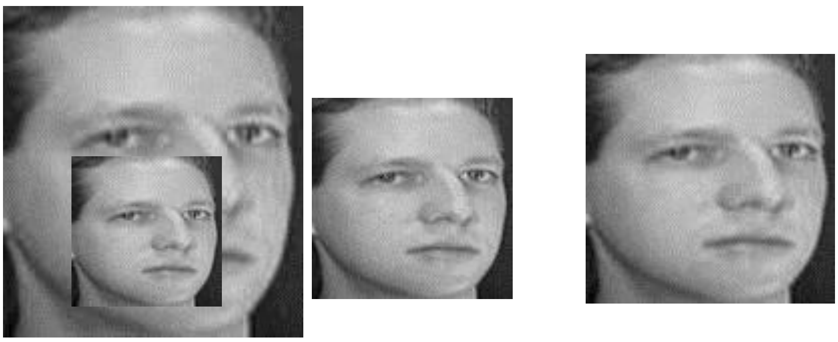
6.2 Result for Geometric Normalization

The face images from LASFI and ORL database were normalized geometrically by cropping and resizing. The sample results of the geometric normalization are shown in Figures 6.2 and 6.3 for LASFI and ORL respectively. These various sizes show varying number of fundamental facial features and the sizes were chosen arbitrarily to test for the effect of the variation in image size on training time, testing time, and recognition accuracy of the developed face recognition system. In each category of the pixel resolution, there are total number of 240 images for LASFI and 132 images for ORL. The total number of images used in the experiment for each category of 75x75, 100x100, 125x125 and 150x150 of LASFI database.



75x75 100x100 125x125 150x150

Figure (6.2): Sample result of geometric normalization of LASFI



75x75 100x100 125x125 150x150

Figure 6.3: Sample result of geometric normalization of ORL face images

6.3 Result for Photometric Normalization

The original face images from LASFI database as indicated in figure 6.4 (a) after geometric normalization were further passed through Adaptive Histogram Equalization Technique (AHE) as shown in figure 6.4 (b). This is to stretch the contrast on all parts of the face image and adjust the intensity of image pixels. It was observed based on visual quality of the original image from database, original grayscale image and the enhanced image that the face images responded well to the enhancement technique adopted for photometric normalization. Furthermore, the normalization, histogram of the grayscale image and that of the enhanced image by AHE is shown in Figure 6.4(b). From Figure 6.4(b) it was observed that the histogram (frequency distribution of pixels on the face image) of the original image is not equalized. This implies that the frequencies of occurrence of the pixel values are not evenly distributed. The histogram of the enhanced image as shown in Figure 6.4 (c) is well balanced as the histogram value for the entire bin which represents the frequency of occurrence of the pixels is evenly distributed.

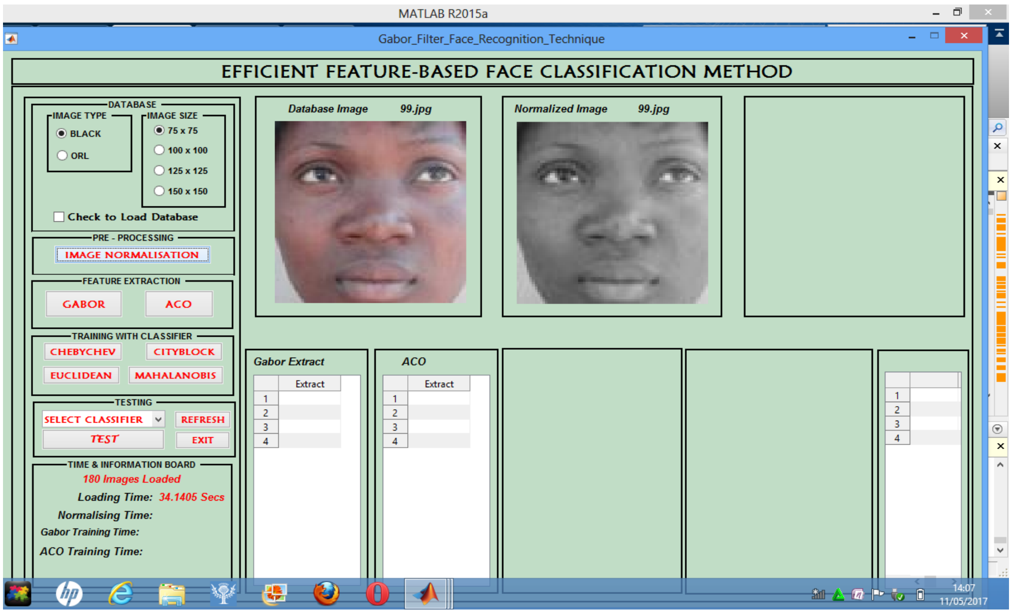


Figure 6.4 (a) Normalization of Original faces (LASFI Database)

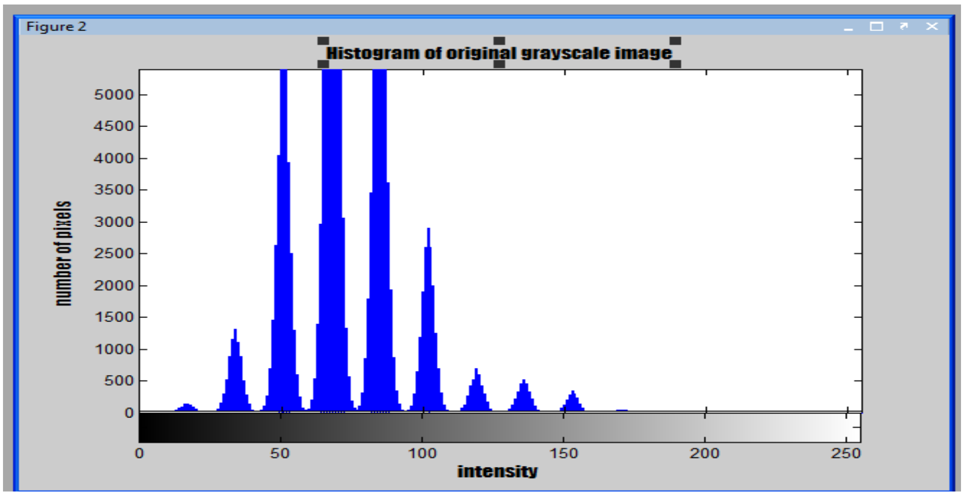


Figure 6.4 (b) Histogram of the original grayscale image (LASFI Database)

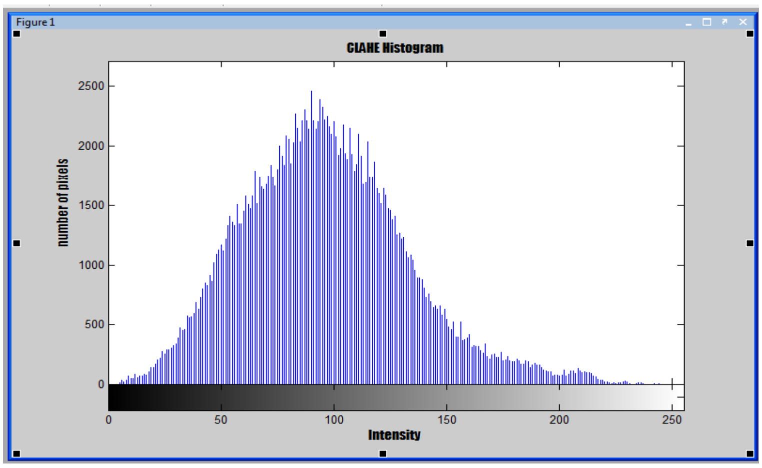


Figure 6.4 (c) Histogram of the AHE (LASFI Database)

In this study, several experiments were carried to show the efficiency of the proposed face recognition algorithm. All experiments were conducted on hp ProBook 4330s laptop with the following configuration: 2.40 GHZ CPU, with window 7 operating system, 64-bit Operating System and 4 GB RAM. The proposed face recognition varied with feature vectors based on 75x75, 100x100, 125x125 and 150x150 pixels of cropped face images were tested. The loading time and normalizing time for the two datasets used is indicated in table 6.1 and 6.2.

Table 6.1: Database Loading Time for Images in the Database

Image Size	**Loading Time for Database (secs)**	
(pixel)	**LASFI(secs)**	**ORL(secs)**

75X75	23.8136	16.2905
100X100	24.8083	16.2922
125X125	24.7050	16.6637
150X150	25.8455	17.0716

Number of Training Images in (LASFI = 180), (ORL = 111)

Table 6.2: Normalization Time for Images in the Database

Image Size (pixel)	Normalizing Time for Database (secs)	
	LASFI(secs)	ORL(secs)
75X75	7.1382	4.6632
100X100	7.1853	4.4848
125X125	7.3437	4.5865
150X150	7.4691	5.1716

Number of Training Images in (LASFI = 180), (ORL = 111)

6.4 Result of Feature Extraction process

Feature extraction process linearly transforms the original facial features into a lower dimensional feature space. Figure 6.1(a) illustrates the original image before the gray scale conversion process. The extraction of features in this study was carried out using a bank of Gabor filters for information extraction as illustrated by the GUI in figure 6.5(b) for LASFI Database and the GUI of Extracted Gabor features is showed in figure 6.5(b) for ORL Database. Table 6.3 shows the total time taken to extract Gabor features from 180 face images of the LASFI used for training; 75x75 is 118.2510secs, 121.1642secs for 100x100, 156.4176secs for 125x125 and 197.1528secs for 150x150 pixel size. Also for the ORL, the total time taken to extract Gabor features from 111 faces used for training the 75x75 pixel size is 68.2107secs, while that of 100x100 is 76.0976secs, for 125x125 is 94.6172secs and for 150x150 is 154.0028secs. It was observed and also deduced that the time taken to perform feature extraction for two databases increase with increase in image sizes. The Gabor features obtained from the face images in the feature extraction phase serves as a platform which provides ACO a suitable representation for encoding the procedure for optimal feature subsets selection.

Figure 6.5(a) Original Image for LASFI Database

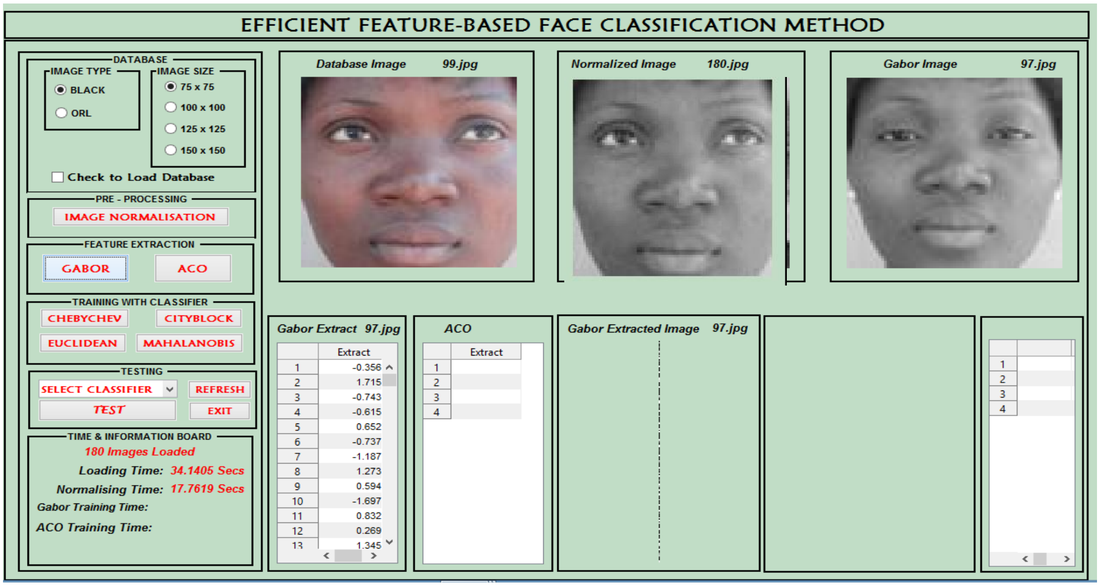


Figure 6.5(b) GUI for Extracted Gabor facial features (LASFI Database)

Figure 6.6 (a) Original Image from ORL Database

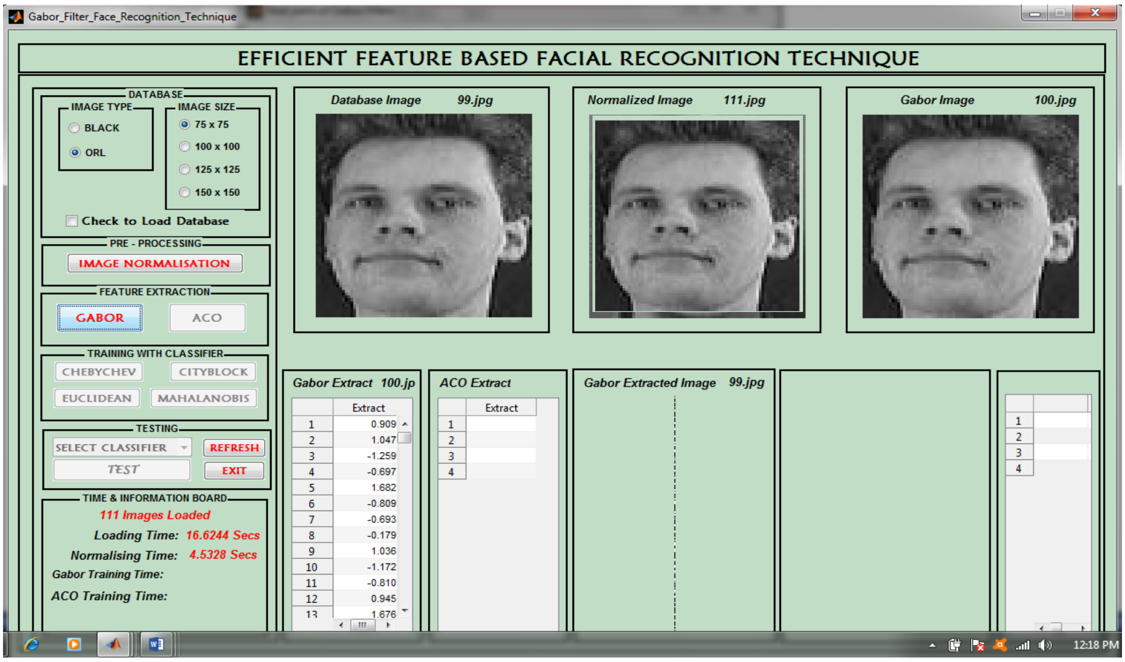


Figure 6.6 (b) GUI for Extracted Gabor features (ORL Database)

Table 6.3: Training Time for Feature Extraction using Gabor-filters

Image Size	Gabor-filter Training Time(secs)

	LASFI(secs)	ORL(secs)
75X75	118.2510	68.2107
100X100	121.1642	76.0976
125X125	156.4176	94.3117
150X150	197.1528	154.0028

Number of Training Images in (LASFI = 180), (ORL = 111)

6.5 Result of Optimized Feature Subsets

The input to the ACO feature subset selection process was the product of Gabor feature dimensions obtained from the feature extraction phase. Only subset from feature vectors of Gabor features was retained by the feature selection algorithm as indicated in figure 6.7(a) which shows GUI for the optimal feature subsets of Gabor features, figure 6.7(b) shows the optimized Gabor features for LASFI Database and figure 6.8(a) indicates the GUI optimal feature subsets of Gabor features and figure 6.8(b) depicts optimized Gabor features for ORL Database. The size of feature input is the dimension of the faces used in this experiment, which are 5625, 10000, 15625 and 22500 pixels for 75x75, 100x100, 125x125 and 150x150 sizes respectively. The time taken during feature subset selection of ACO training for LASFI database are; 56.6105secs for 75x75, 82.5845 for 100x100, 123.1755secs for 125x125 and 124.2482secs for 150x150. Also for ORL database; 23.1815secs for 75x75, 51.7021secs for 100x100, 76.3117secs for 125x125 and 77.6617secs for 150x150 as illustrated in table 6.4.

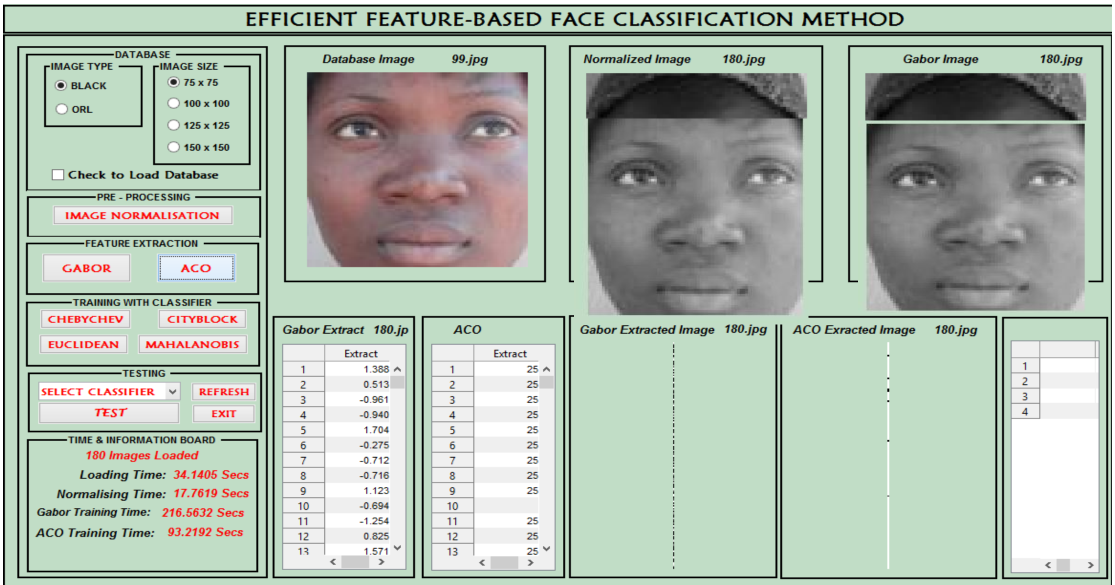


Figure 6.7 (a) ACO Feature Subset Selection (LASFI Database).

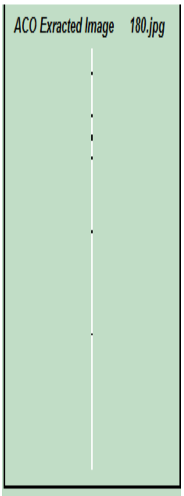


Figure 6.7(b) shows the optimized Gabor features for LASFI Database

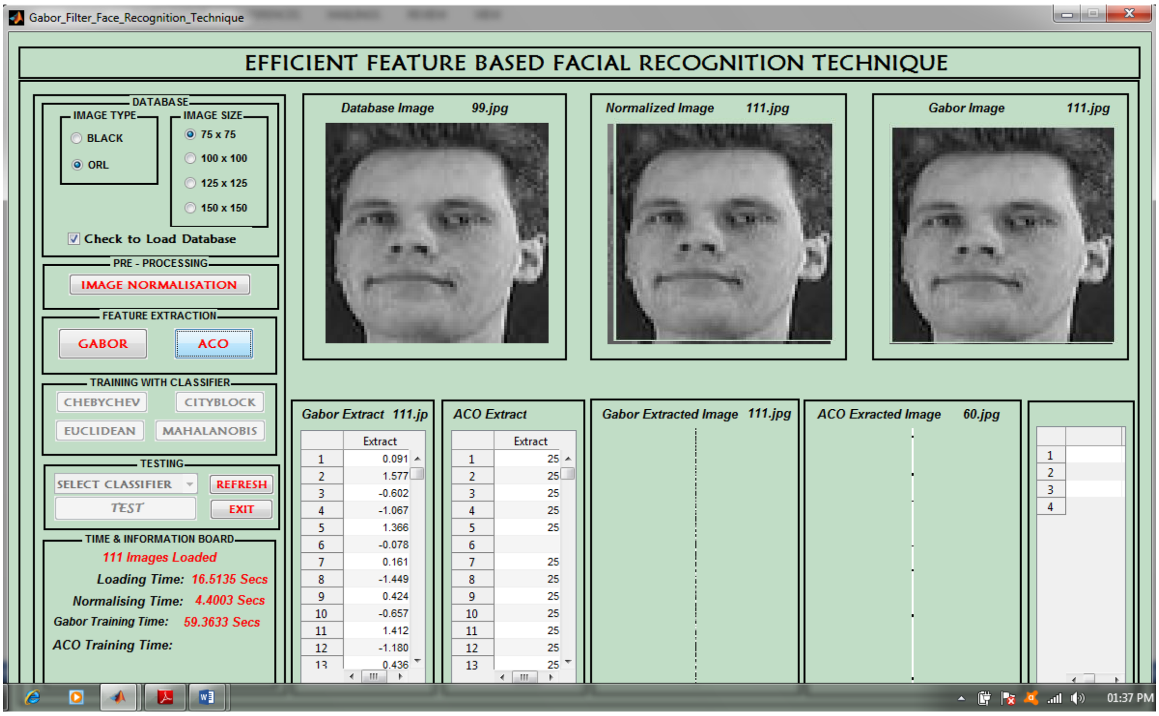


Figure 6.8 (a) GUI for ACO Feature Subset Selection (ORL Database)

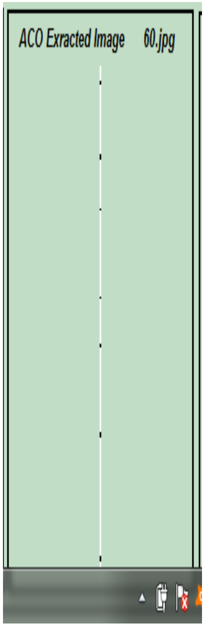


Figure 6.8 (b) Optimized Gabor Features (ORL Database)

Table 6.4: Training Time for Feature Subset Selection using ACO

Image Size (pixel)	Total Time (secs) for Training ACO feature Subset selection	
	LASFI Database(secs)	ORL Database(secs)
75x75	56.6105	23.1815
100x100	82.5845	51.7021
125x125	123.1755	76.3117
150x150	124.2482	77.6617

Number of Training Images in (LASFI = 180), (ORL = 111)

6.6 Results for Training and testing

6.6.1 Result for Training Time of Distance Measure Metrics

The training of face image for the proposed system was conducted using several distance measures metrics; Chebysev, Mahanolobis, City block and Euclidean. The training time taken by each distance measure classifier varies. Considering LASFI Database For Chebysev of image size of 75x75 is 14.7883, 100x100 is 14.7921, 125x125 is 15.1184, 150x150 is 15.3934, for City-block of image 75x75 is 8.4460, 100x100 is 8.7711, 125x125 is 9.0309, 150x150 is 9.4321. The distance measures for train time of image size 125x125 and 150x150 is indicated in table 6.5 Also for the ORL Database of images, the training for each distance measure metrics is shown in table 6.6. The comparison of the two databases used in the study indicated that the training time by each distance measure metrics required by LASFI database is higher than the ORL database. This is subject to the number of images involved during training phase.

Table 6.5: Distance Classifiers Training Time (secs) (LASFI Database)

Image Size (pixel)	Chebysev (secs)	City-Block (secs)	Euclidean (secs)	Mahalanobis (secs)
75x75	14.7883	8.4460	8.4068	8.8091
100x100	14.7921	8.7711	8.6734	8.9823
125x125	15.1184	9.0309	9.1230	9.5742
150x150	15.3934	9.4321	9.7215	9.8243

Number of Training Images in LASFI (180)

Table 6.6: Distance Classifiers Training Time (ORL Database of images)

Image Size (pixel)	Chebysev (secs)	City-Block (secs)	Euclidean (secs)	Mahalanobis (secs)
75x75	4.2309	2.8654	2.8122	2.7808
100x100	4.1622	2.9726	3.4840	2.8146
125x125	4.2743	2.9218	2.9272	2.9957
150x150	4.6363	2.9830	3.1722	3.1689

Number of Training Images in ORL (111 images)

6.6.2 Result for Testing / Recognition Time of Distance Measure Metrics

The recognition of face image was carried out in this study using four different distance measure classifiers; Chebysev, City-block, Euclidean and Mahalanobis. The GUI for image testing is shown in figure 6.9 for LASFI Database and figure 6.10 for ORL Database. The classifiers recognized face image at different time intervals with respect to image size for the two image databases. The total time required by a classifier was drastically reduced, this reflects the ability of ACO to reduce and select feature subsets before classification phase. Also the image size and distance measure classifiers have effect or influence on the image testing time This is shown in table 6.7 and table 6.8.

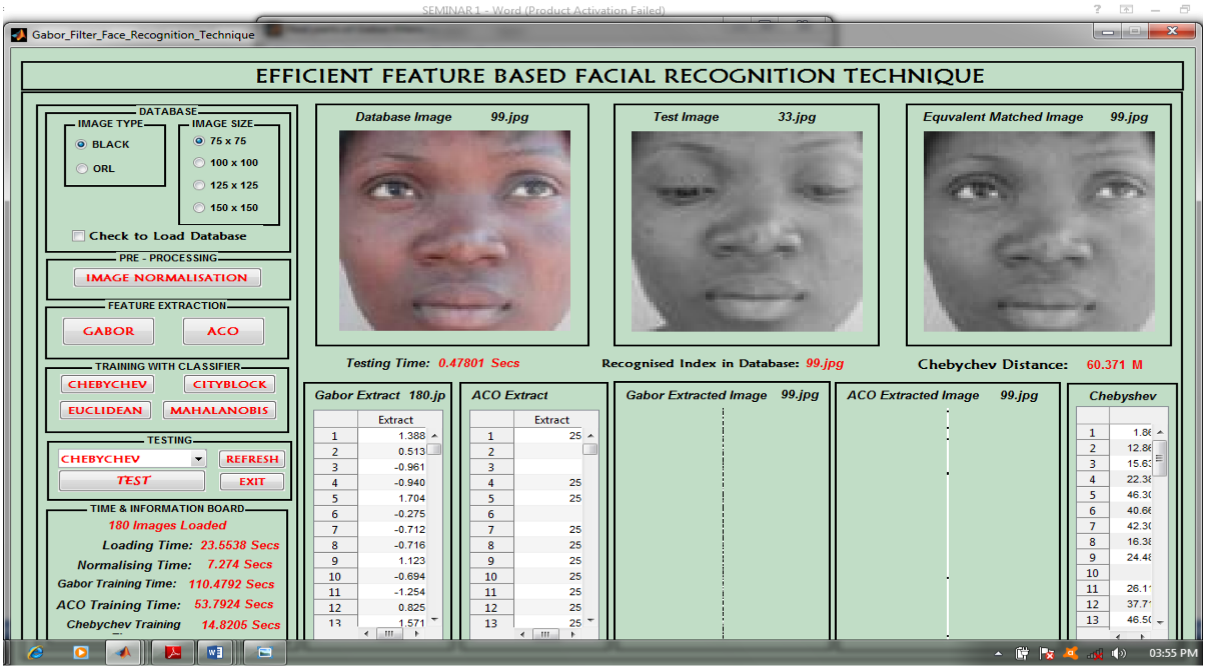


Figure 6.9(a): GUI for testing of image with one of the distance measure classifiers (LASFI Database)

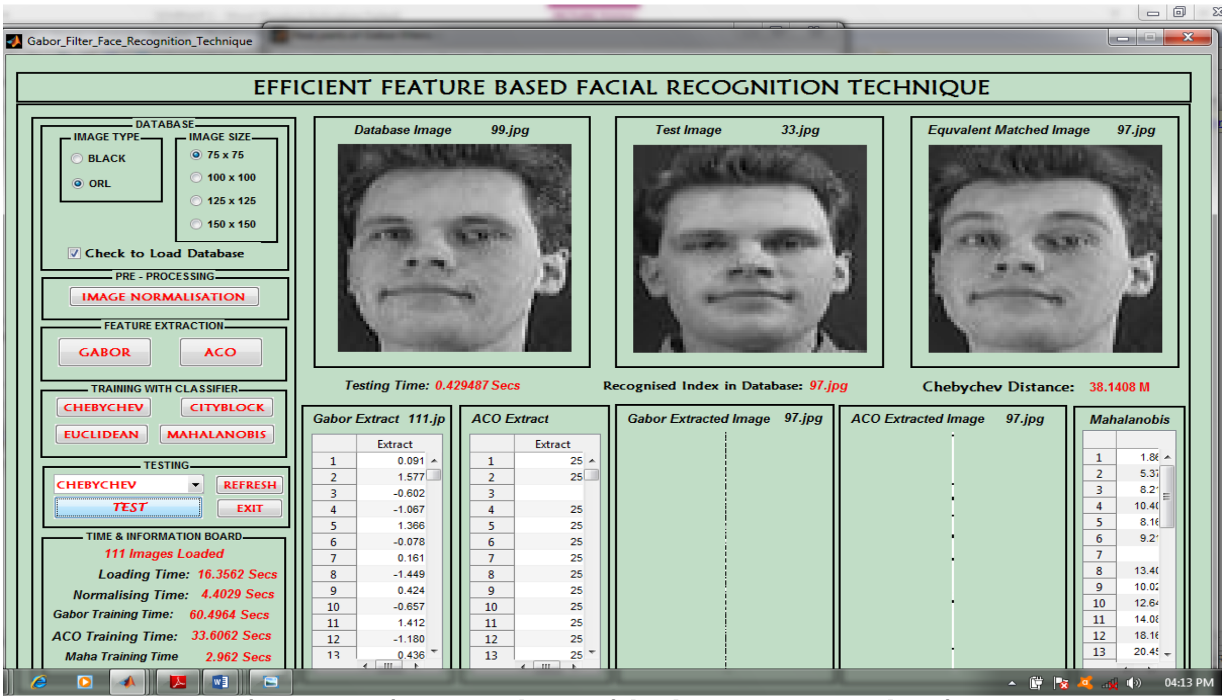


Figure 6.10(a): GUI for testing of image with one of the distance measure classifiers

(ORL Database)

Table 6.7: Distance Classifiers Testing / Recognition Time (secs) for LASFI Database

Image Size (pixel)	Chebysev (secs)	City-Block (secs)	Euclidean (secs)	Mahalanobis (secs)
75x75	0.52173	0.45392	0.45587	0.44391
100x100	0.53045	0.43615	0.47108	0.43864
125x125	0.46210	0.44232	0.43426	0.42507
150x150	0.47792	0.42599	0.43206	0.43414

Number of Testing Images in LASFI (60 Images)

Table 6.8: Distance Classifiers Testing / Recognition Time (secs) (ORL Database of Images)

Image Size (pixel)	Chebysev (secs)	City-Block (secs)	Euclidean (secs)	Mahalanobis (secs)
75x75	0.53147	0.49849	0.42027	0.49157
100x100	0.49332	0.42079	0.41824	0.42006
125x125	0.93616	0.43647	0.42954	0.60422
150x150	0.56846	0.83880	0.42266	0.43292

Number of Testing Images in LASFI (21 images)

7. Conclusion

Gabor-features representation for a face image has attracted much interest and achieved great success in facial recognition due to its biological, computational and empirical properties. Despite the outstanding success recorded by this technique, still suffers high feature dimensionality. This study has addressed the problem of high features dimensionality by introduction of a population-based feature selection algorithm. ACO a meta-heuristic inspired by behaviour of real ants in their search for shortest paths to food sources was applied. The ACO optimization algorithm randomly selected most relevant, discriminant and optimal features from Gabor features before being passed to mult-disatnce measure classifiers. The experimental results showed that developed optimal feature subset selection performed effectively in term of recognition time and accuracy.

8. Contributions to Knowledge

The major contributions of this study to knowledge are as follows:

1. The application of the population-based meta-heuristic ACO optimization algorithm has really effectively aided the reduction of curse of dimensionality which has been identified as a predominant challenge to Gabor features-based approach for facial recognition. The reduction effect will encourage face biometric security system developers to come up with a real life time facial biometric security applications.
2. The relevancy of features to be used as a face descriptor or representation is very important. The developed optimal feature subset selection approach allowed most relevant and discriminant features to be selected, which further reduces the level of features redundancy and also increase the accuracy in face recognition.
3. Introduction of locally acquired student facial images (real time facial black images) aside the publicly available white images as a database provides analysis on how the proposed system performed using the created black face images compared to ORL database of images. Secondly, the designed locally acquired student image database can be made available online for researchers.
4. Application of multi distance measure classifiers to the matching of face images gives clue or significant information of which classifier performs better out of several classifiers used for recognition.

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