CHAPTER 1

Introduction:

Face recognition technology is a current technology that attracted the world attention especially after September 11, 2001 terrorist attack. The September 11 incident has given this technology a new life through the additional and new application seriously. Face recognition is a visual pattern recognition problem where a three-dimensional object is to be identified based on its two-dimensional image. Face recognition has become an important issue in many applications such as security systems, credit card verification, criminal identification user verification, user access control, crowd surveillance, enhanced human computer interaction. For example, the ability to model a particular face and distinguish it from a large number of stored face models would make it possible to vastly improve criminal identification.

Face recognition is a subsidiary part of Biometrics, Biometrics are methods to automatically verify or identify individuals using their physiological or behavioural characteristics [1]. Biometric technologies include [2]:

- Face Recognition
- Finger Print (dactylogram) Identification
- Hand Geometry Identification
- Iris Identification
- Voice Recognition
- Signature Recognition
- Retina Identification
- DNA Sequence Matching

The necessity for personal identification in the fields of private and secure systems made face recognition one of the main fields among other biometric technologies. The importance of face recognition rises from the fact that a face recognition system does not require the cooperation of the individual while the other systems need such cooperation. Thus, it should not be surprising that a face recognition system is placed in the Statue of Liberty in US. Face recognition algorithms try to solve the problem of both verification and identification [3].

A formal method of classifying faces was first proposed by Francis Galton in 1888 [4, 5]. During 1980’s, work on FR remained largely dormant. However, during 1990’s, the research interest in FR has grown significantly as a result of the following facts:

1. The increase in emphasis on civilian/commercial research projects,
2. The emergence of ANN classifiers with emphasis on real time computation and adaptation,
3. The availability of real time hardware,
4. The increasing need for surveillance related applications due to drug trafficking, terrorist activities, etc.

Face recognition is still an area of active research since a completely successful approach or model has not been proposed to solve the face recognition problem. Face recognition has been an active research area over the last 30 years. The inadequacy of automated face recognition systems is especially apparent when compared to our own innate face recognition ability. We perform face recognition, an extremely complex visual task, almost instantaneously and our own recognition ability is far more robust than any computer's can hope to be. We can recognise a familiar individual under very adverse lighting conditions, from varying angles or view points. Scaling differences (a face being near or far away), different backgrounds do not affect our ability to recognise faces and we can even recognise individuals with just a fraction of their face visible or even after several years have past. Furthermore, we are able to recognize the faces of several thousand individuals whom we have met during our lifetime of their face visible or even after several years have past. Furthermore, we are able to recognize the faces of several thousand individuals whom we have met during our lifetime.

Even the ability to merely detect faces, as opposed to recognizing them, can be important. Detecting faces in photographs for automating color film development can be very useful, since the effect of many enhancement and noise reduction techniques depends on the image content.

People are good in recognition face, it is not at all obvious how faces are encoded or decoded by the human brain. There are millions of neuron in human which help us to recognise a face but developing a computational model of face recognition is quite difficult, because faces are complex, multi-dimensional visual stimuli. Therefore, face recognition is a very high level computer vision task, in which many early vision techniques can be involved.

Since 1960s, automated methods for recognizing individual via their facial characteristic have been developed. Multiples approaches have existed to cater automated face recognition problems to improve face recognition accuracy. In 1990s, automatic face recognition technology moved from laboratory to the commercial world largely because of the rapid development of the technology. Face recognition uses selected features in face image to identify individual identity. The face recognition system required a camera to capture the face image and comparing it with the image stored in the database. A variety of techniques have been developed that uses the human face as a basis of human identification. Amongst them are eigenfaces, neural network, radial basis function, fuzzy logic, etc. Even though much research has focused on development of fully automatic face recognition tracking system, significant advances have been made in the design of classifiers for successful face recognition to overcome the face recognition problems especially for online version.

1.1) Fundamental Issues in Face Recognition

The major concern for developing an automatic face recognition system is, the system which is robust against variance in illumination, expression and pose. Some of possible problems for a machine face recognition system are mainly:

a) Facial expression change: A smiling face, a crying face, a face with closed eyes, even a small nuance in the facial expression can affect facial recognition system significantly.

b) Illumination change: The direction where the individual in the image has been illuminated greatly effects face recognition success. A study on illumination effects on face recognition showed that lighting the face bottom up makes face recognition a hard task [6].

c) Aging: Images taken some time apart varying from 5 minutes to 5 years changes the system accuracy seriously.

d) Rotation: Rotation of the individual's head clockwise or counter clockwise (even if the image stays frontal with respect to the camera) affects the performance of the system.

e) Size of the image: A test image of size 20x20 may be hard to classify if original class of the image was 100x100.

f) Frontal vs. Profile: The angle in which the photo of the individual was taken with respect to the camera changes the system accuracy.

g) At the same time, the system has to take computation and memory cost into consideration for real time applications.

Although there are a number of face recognition algorithms which work well in constrained environments, face recognition is still an open and very challenging problem in real world applications.

1.2) The Face Recognition System Design:

In face recognition system can be divided into two phases; enrolment phase and identification phase. Each phase consists of four main modules; data acquisition, pre-processing, features extraction and classification.

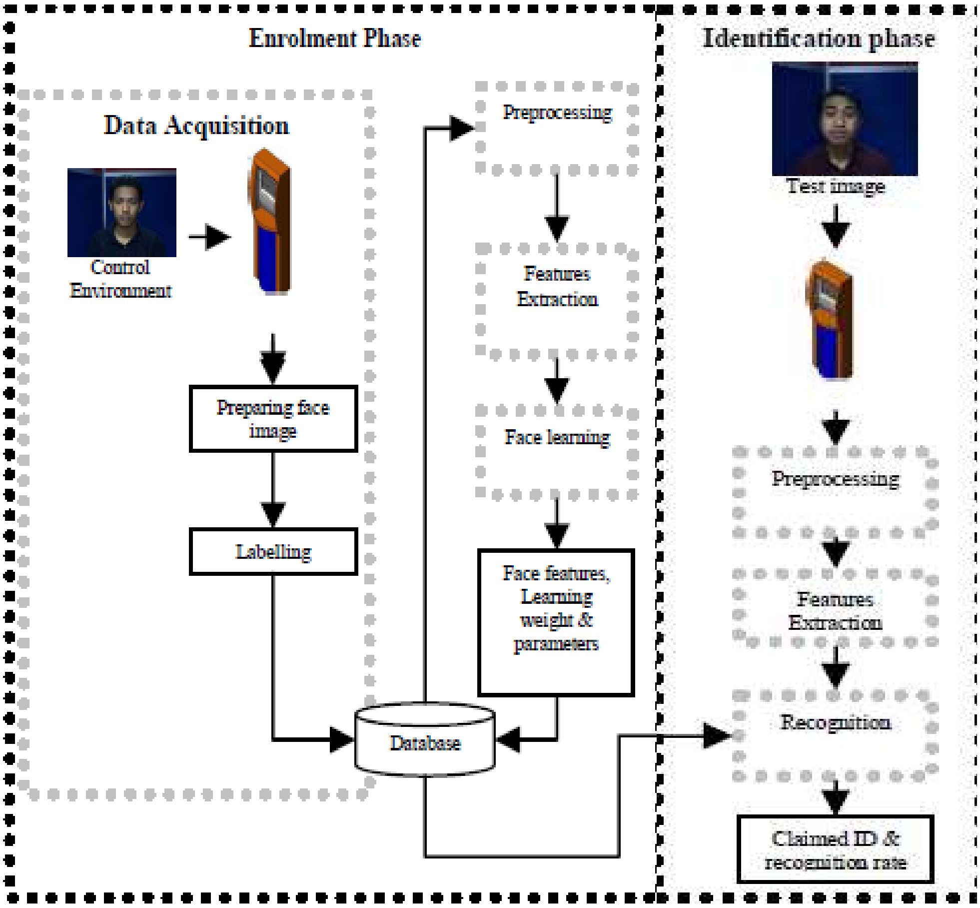

Figure 1.1

1.2.1). Data Acquisition:

This is the entry point of the face recognition process. It is the module where the face image under consideration is presented to the system. In other words, the user is asked to present a face image to the face recognition system in this module. An acquisition module can request a face image from several different environments: The face image can be an image file that is located on a magnetic disk, it can be captured by a frame grabber or it can be scanned from paper with the help of a scanner. The aspects to consider are face orientation and expression, positioning and size, and also background. Under photographic category is position and distance of the camera to subject, and camera attributes. The images are taken under control environment and all the face images are frontal images. Once face image presented in front of the camera, the system will automatically detected the full frontal image. Then, the face detector detected the face image which is called canonical face image. Finally, the face region or localized face image is cropped for further process.

Figure1.2

1.2.2). Preprocessing:

In this module we present the image to the system. We are use various technique to enhance our image use to improve the recognition performance of the system Lighting gives a high impact during face detection. Lighting may cause illumination problems such as shadow, shading, hotspot, etc. This may degrade the face recognition performance. Thus, to enhance the appearance of the image and to eliminate the effect of lighting and geometric distortion, pre-processing is needed. Various pre-processing steps may be implemented in a face recognition system such as Image size normalization, Histogram equalization, Median filtering (For noise detection), High-pass filtering, Background removal , Illumination normalization, etc. To reduce the geometrical distortion, the face image is resizing and rescaling into standard size. For photometric normalization, homomorphic filtering is applying over the face image. The homomorphic filtering helps in illumination correction by normalized the pixel intensity. following pre-processing steps may be implemented in a face recognition system:

- **Image size normalization**. It is usually done to change the acquired image size to a default image size e.g. 128 x 128, on which the face recognition system is operates. This is mostly encountered in systems where face images are treated as a whole.
- **Median filtering.** For noisy images especially obtained from a camera . median filtering can clean the image without loosing any information.
- **High-pass filtering.** Feature extractors that are based on facial outlines, may benefit the results that are obtained from an edge detection scheme. High-pass

filtering emphasizes the details of an image such as contours which can dramatically improve edge detection performance.

- **Histogram equalization.** It is usually done when image is either too dark or too bright in order to enhance image quality and is used to improve face recognition performance. It modifies the dynamic range (contrast range) of the image and as a result, some important facial features become more apparent.
- **Background removal.** In order to deal primarily with facial information itself, face background may be removed in order to process the image. This is especially important for face recognition systems where entire information contained in the image is used. It is obvious that, for background removal, the pre-processing module should be capable of determining the face outline.
- **Illumination normalization.** Face images taken under different illuminations can degrade recognition performance especially for face recognition systems based on the principal component analysis in which entire face information is used for recognition.
- **Translational and rotational normalizations.** In some cases, it is possible to work on a face image in which the head is somehow shifted or rotated. The head plays the key role in the determination of facial features. Especially for face recognition systems that are based on the frontal views of faces, it may be desirable that the pre-processing module determines and if possible, normalizes the shifts and rotations in the head position.

1.2.3). Features Extraction

The feature extraction is used to reduce the dimension of the face space by transforming it into feature representation. It will be responsible for transforming or composing the normalized pixel values of the face image and represents it into an appropriate representation or feature vector by finding the key features that will be used for classification. In other word this module is responsible for composing a feature vector that is well enough to represent the face image. The method used for the proposed face recognition is PCA. PCA transforms face images into a small set of characteristics feature images called “eigenfaces”, which are the principal components of the initial training set of face images [2]. It uses more information by classifying face based on general facial pattern. These patterns include features of the face and other information. PCA is currently the common and most effective feature extraction method for face recognition.

1.2.4). Learning and Classification:

Classification help us in finding pattern in the data, extracted features of the face image is compared with the ones stored in face database. After doing this comparison, face image is classified as either known or unknown. The system determined a label for each person. This label is automatically assigned a unique identification number on their first representation that helps us in classification. With the help of feature extraction and the classification modules we adjust their parameters in order to achieve optimum recognition performance by making use of training sets.

1.3) Motivation :

The applications and the difficulty of face detection make face detection an interesting problem. Would you know how is it the humans are so easily able to distinguish a familiar face from a crowd? Taking just a fraction of a second, the ability to recognise faces so effortlessly is one of the most remarkable attributes of human vision. Face detection plays an important role in today's world. They have many real world applications like human/computer interface, surveillance, authentication and video indexing. However research in this field is still young. Face recognition in a perception system from human beings seems instinctive, but it is really a tough and complex task for a machine-based system. Although the doctor, engineer, scientists are working hard in the field of human face recognition, but their contributions to the mathematical models and engineering solutions for a machine vision system are not satisfying. Therefore, researchers from the computer science are constructing many numbers of mathematical and computational models and dedicated algorithms, which may cover the field of artificial intelligence, statistical learning, image processing and even video signal processing. Mug-shot matching, crowd control, user verification and enhanced human computer interaction would all become possible if an effective face recognition system could be implemented [7]**.** In terms of recognition precision, even the most successful state-of-the-art face recognition technology in general is still far from the level of our human systems.

Most concerned problem with the face recognition lighting changes, indoor outdoor changes, pose variations and elapsed time databases are the critical parameters which greatly influence the performance of a face recognition system. The main problem in video surveillance is to identify any individual in a complex scene, i.e. a system that automatically detects the faces present in a scene and normalizes them with respect to pose, lighting and scale and then tries to associate the face to one or more faces stored in its database and gives the set of faces that are considered as “nearest” to the detected face.

Here, we are proposing an algorithm for the face recognition based on fusion of multiple recognizers namely Fisher’s linear discriminant (FLD) and eigen-face so that we can overcome the limitation of single recognizer and improve the performance of the overall recognition system. The images of a human face lie in a complex subset of the image space that is unlikely to be modelled by a single linear subspace, we use a mixture of linear subspaces to model the distribution of face and non-face patterns. This approach is used to overcome the drawback of the eigen-face approach by integrating Fisher’s linear discriminant (FLD) criteria, while retaining the idea of the eigen-face in projecting faces from a high-dimension image space to a significantly lower-dimensional feature space [8].

Another, maybe more important motivation of facial recognition is that expression itself is an efficient way of communication: it's natural, non-intrusive, has shown that, surprisingly, expression conveys more information than spoken words and voice tone. To build a friendlier Human Computer Interface, face recognition is essential.

1.4). <u>Goal:</u>

This thesis aims is to cover a wide range of face recognition techniques, including the technical background, ideas, concepts and some of the more practical issues involved in the face recognition system. The emphasis will be on research into methods of improving existing systems, while introducing new approaches and investigating unexplored areas of research. Although the focus will tend towards the theoretical, presently we will prototype the algorithms to verify and identify applications applied to real-world problem. We will also touch upon some of the more practical implementation issues that arise when using such systems in the real world, highlighting additional work or technology that must be realised before a final application is implemented. The ultimate aim will be to produce a fully functional face recognition engine which is not impaired by some of the shortcomings of existing face recognition systems.

More specifically, my aim to address the following issues in the thesis:

- Give an overview of existing face recognition systems and the current state of research in this field.
- Identify the problems associated with existing face recognition systems and possible avenues of research that may help to address these issues.
- Improve the effectiveness of existing face recognition algorithms, by introduction of additional processing steps or adaptation of the method.
- Design and implement novel face recognition approaches, taking advantage of the newly emerging technology.
- Analyse and evaluate a range of face recognition systems in order to identify the advantages and disadvantages offered by the various approaches.
- Determine the most effective method of combining methodologies from the range of face recognition techniques, in order to achieve a more effective face recognition system.
- Evaluate this final face recognition system and present results in a standard format that may be compared with other existing face recognition systems.

- Identify limitations of the final face recognition system and propose a line of further research to combat these limitations.

1.5). Organization of the Thesis:

The organization of this thesis as follows

Chapter 1: This chapter gives the brief information about the Face recognition and how it is use and what is the purpose and application of it.

Chapter 2: This chapter presents the historical work carried out in this area and the state of the art in Face Recognition System. All the work described in this chapter is related to the Parallel technology used in this field.

Chapter 3: This chapter contains the information about Research methodology of face recognition algorithm. And in the same chapter I propose my algorithm.

Chapter 4: This chapter presents the Experimental results comes from the software application program and summary are supplemented.

Chapter 5: In this chapter we briefly discussed conclusion of thesis.

Chapter 6: In this chapter we briefly discussed Future work in the field of face recognition system.

Chapter 7: enlists the references used throughout the thesis are mentioned in this section.

CHAPTER 2:

Literature Review

2.1). Objective:

Face recognition is a pattern recognition task performed specifically on the faces of individual. We can classify a face either "known" or "unknown", after comparing it with stored known individuals. It is also desirable that we have a system that has the ability of learning to recognize and classify a unknown faces. Computational models of face recognition must address several difficult problems. This difficulty arises from the fact that faces must be represented in a way that best utilizes the available face information to distinguish a particular face from all other faces. Faces pose a particularly difficult problem in this respect because all faces are similar to one another in that they contain the same set of features such as eyes, nose, mouth arranged in roughly the same manner. In this chapter we are going to study some of parallel technology that is currently using by researcher in the area of face recognition.

2.2). Review on the operation of biometric system:

A biometric system is basically a pattern recognition system that acquires biometric data from an individual person, extracts the salient feature set from the data of individual person, compares this feature set against the feature set that is stored in the database and executes an action based on the result of the comparison [9]. We can be divided generic biometric system into four main modules: a sensor module; a quality assessment and feature extraction module; a database module; and a matching and decision module.

2.2.1). Sensor module: In order to acquire the raw biometric data of an individual, a suitable biometric reader, physical system or scanner is required. Therefore the sensor module can be defined as the human machine interface and is pivotal to the performance of the biometric system. A poorly designed interface can result in a high failure-to-acquire rate and consequently low user acceptability. So that a good quality sensor is required.

2.2.2). Quality assessment and feature extraction module: The quality of the biometric data acquired by the sensor is first assessed in order to determine its suitability for further processing. In most of the cases, the acquired data is subjected to a signal enhancement algorithm in order to improve the quality. However, if the quality of the data is not very good or poor, the user will be asked to present the new data again. After quality assessment, the biometric data is then processed and a set of salient discriminatory features extracted to represent the underlying trait. During enrolment, this individual feature set is stored in the database and is commonly referred to as a template.

2.2.3). Database module: This module acts as the storage of biometric information. During the enrolment process, the individual feature set extracted from the raw biometric sample that is stored in the database along with some biographic information that characterizing the user. The data capture during the enrolment process may or may not be supervised by a human depending on the application. It may be supervised or unsupervised. For instance, a user attempting to create a new computer account in her biometric-enabled workstation may proceed to enroll her biometrics without any supervision; on the other hand, a person desiring to use a biometric-enabled ATM will have to enroll her biometrics in the presence of a bank officer after presenting her non-biometric credentials. Figure 2.1 shows how the enrollment is done in biometric systems.

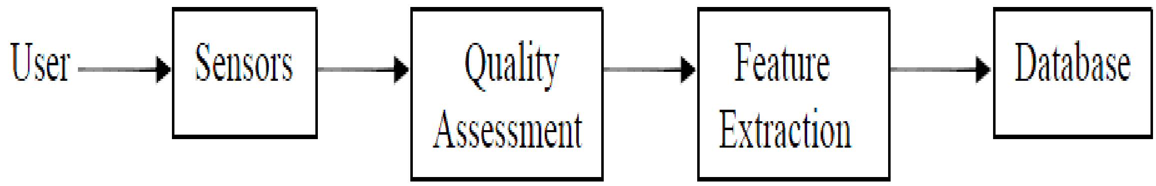

Figure 2.1: Enrolment Processes in Biometric Systems

2.2.4). Matching and decision module: Matching is a process that the extracted features from individual are compared with the stored templates to generate match scores. In a face-recognition based biometric system, the number of matching feature between the input and the template feature sets is determined and a match score calculated. The match score may be moderated by the quality of the presented biometric data set. In a decision process, the match scores are used to either validate a claim to identity or provide a ranking of the enrolled identities in order to identify an individual.

Generally, biometric systems can be operated either in user verification or identification mode. In the verification mode, the system validates the individual's identity by comparing the captured biometric feature with her own biometric template stored in the system database. The system operates a one-to-one comparison to determine whether the claim done by user is true or not. Verification is generally used for positive recognition, where the aim is to prevent multiple people from using the same identity. Figure 2.2 shows how the verification is done in biometric systems.

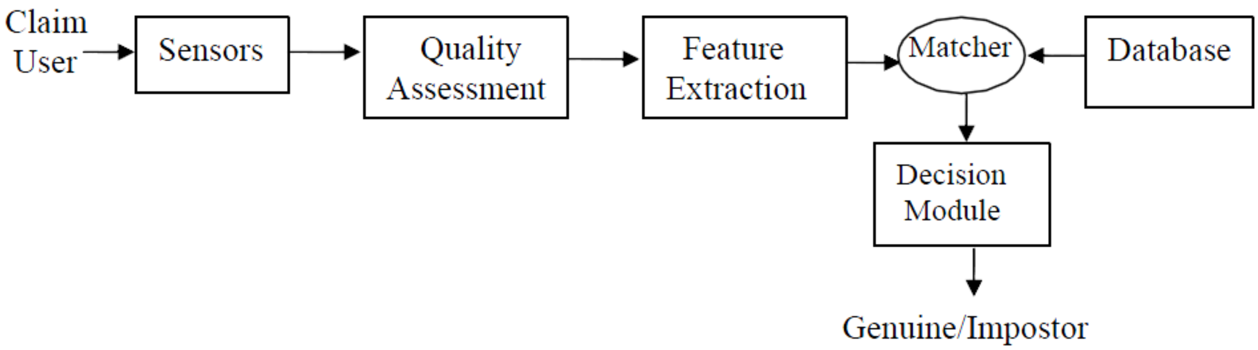

Figure 2.2: Verification processes in biometrics systems

In the identification mode, the system recognizes an individual by searching the templates of all the users in the database for a match. The system performs a one-to-many comparison to establish an individual's identity without the subject having to claim an identity. If the subject is not enrolled in the system database, the system will not be able to identify the subject's identity. While traditional methods of personal recognition such as passwords, PINs, keys and tokens may work for positive recognition, negative recognition can only be established through biometrics.

2.3). Overview of the face recognition system:

Generally, faces are used to recognize individuals in our daily lives. Advancements in technologies such as computing, image processing and pattern recognition enable face recognition automatically. Research in automatic face recognition is motivated not only by the challenges it poses but also by the numerous practical applications where human identification is required such as security systems, credit card verification, criminal identification user verification, user access control, crowd surveillance, enhanced human computer interaction. Face recognition has many advantages over other biometric technologies because it is natural, nonintrusive and easier to use. Automatic face recognition can be used for both identification and verification mode.

Two popular approaches in face recognition system are geometric (featured based) and photometric (appearance base). The geometrical based approach uses spatial configuration of facial features of human. Main geometrical features of the face, such as the nose, eyes and the mouth are firstly located and then faces are classified on the basis of various geometrical position and distances and angles between features of individual. Although it is economical, efficient in achieving data reduction and is insensitive to variations in illumination, automated detection of facial features and measurement of their positions are very challenging task in real life application. Appearance-based subspace representation is computationally more suitable. here crucial assumption made in matching is that prototypes are representative of query face images under various conditions. Therefore, the location and scale of the query face image must be normalized before it is compared to the training samples in the subspace in the database.

Many different face algorithms were developed, as the interest in face recognition research grew. Some of algorithms have been well studied in face recognition literature are:

Principal Component Analysis (PCA)
Linear Discriminant Analysis (LDA)
Tensor Analysis
Fuzzy Clustering Approach
Gabor Filters
Hidden Markov Models (HMM)
Support Vector Machine (SVM)
Bayesian Framework
Kernel Methods
3-D Morphable Model

2.4). <u>Parallel Tech. Available:</u>

Today there are many techniques working in this field. Some of them are:

2.4.1). <u>Face Recognition using Tensor Analysis:</u>

Human recognition processes consider a broad spectrum of stimuli obtained from many, if not all, of the senses. The human brain is a complex system that probably applies contextual knowledge to recognize faces. It is futile to even attempt developing a computer system using existing technologies that can closely resemble the remarkable ability of facial recognition in humans. However, the key advantage that such a computer system would have over a human classifier is due to the limitation of the human brain to accurately remember a large database of individuals.

Over the past couple of decades, face recognition has emerged as one of the primary areas of research in pattern recognition. The fact that it has numerous potential applications in biometrics, surveillance, human-computer interaction, video based communication, and the emergence of technologies that enable the implementation of these algorithms in real-time are the main reasons for this trend. All of the existing FRT systems suffer from a dip in performance whenever the data acquisition systems suffer from a change in pose, illumination and expression. Vasilescu *et al.* [11] tried to solve the problem of facial recognition using Tensor Analysis. They identified the analysis of an ensemble of facial images resulting from the confluence of multiple factors related to scene structure, illumination, and viewpoint as a problem in multilinear algebra in which the image ensemble is represented as a higher-dimensional tensor. FRT systems can be broadly classified into two groups depending on whether they make use of still images or video. The focus was only to develop an FRT system that made use of static images.

Image is represented as a object in image recognition. Based on image object representation, all the algorithms can be roughly classified into two categories, *image-as-vector* and *image-as-matrix*. An example of an *image-as-vector* approach is the Tensor face technique and its extensions. Tensor face represents a 2-D gray-level image as a 1-D vector and organizes the image ensembles of different persons under different illumination, pose and expression into a high-order tensor. tensors define multi-linear mappings over a set of vector spaces. Although *image-as-vector* and *image-as matrix* techniques both apply high-order decomposition to more effectively utilize relationships among the image, their motivations are different. Tensor face aims to utilize relationships among *external* factors such as illumination, pose and expression, whereas *image-as-matrix* methods aim to characterize the variations among *internal* factors of an image object, such as image columns, rows, and Gabor features.

There are so many work has done on this technology. Feiping Nie , Shiming propose the local tensor discriminant analysis for supervised dimensionality reduction [15] . He solve the problem of selecting the suitable dimensions and propose an algorithm to extract the optimal dimensionality for local tensor discriminant analysis. Tao *et al.* [18] extended quadratic programming-based support vector machines and second-order cone programming-based min-max probability machines to their related tensor-based versions. X. He , *D. Cai, and P. Niyogi,* [17] extended their proposed locality preserving projections algorithm to handle second-order data tensors (matrices). This technique was further extended to tensor LPP that handles general tensor input. Dai and Yeung [16] additionally extended neighbourhood preserving embedding, which is the direct linearization of LLE and also local discriminant embedding (LDE) [12], which is a variant of classical nonparametric LDA, to tensor NPE and tensor LDE, respectively. Toan, Park and Lee[21] propose a novel method based on 3D tensor voting is proposed for enhancing text image binarization. The 3D tensor voting is used to detect corrupted regions by analysing surfaces of text stroke and background in a binary image. Our method is effective on binary images having gaps in text stroke or noise regions in background. M. A. O. Vasilescu and D. Terzopoulos [11] introduced tensor algebraic framework for the appearance-based analysis and recognition of images that elegantly and effectively deals with the multifactor variation inherent to image formation . And they use nonlinear approach to exploits multilinear algebra the algebra of higher-order tensors. Xu Yen-Wei and Takanori Igarashi[19] adopt a tensor-based subspace learning method (TSL) for pose synthesis and organize 2D multi-pose images as tensor form and apply tensor decomposition to build a projection subspace. They proposed a tensor-based subspace learning method (TSL) that makes possible the synthesis of human multi-pose facial images from a single 2D image. They organize 2D multi-pose images in a tensor form and apply tensor decomposition to build a projection subspace. An input 2D image is projected into the projection subspace to get a corresponding identity vector. The identity vector is used to generate the novel pose images. Yi Jin, Qiu-Qi Ruan, Yi-Zhi Wang[20] propose its tensorization, the Locality Sensitive Discriminant Analysis with tensor representation. The algorithm is motivated by the Locality Sensitive Discriminant Analysis (LSDA) algorithm, which aims at finding a projection by maximizing the margin between data points from different classes at each local area.

Now days it has become more and more popular to utilize the image data as high order tensor representation for feature extraction and dimensionality reduction[13] propose by Xuelong Li, in which the local geometric properties within each class are preserved according to the locally linear embedding (LLE) criterion, and the separability between different classes is enforced by maximizing margins between point pairs on different classes, as graph-embedding framework [14] which is also based on these dimensionality reduction methods which is very helpful in the field of image recognition. Tensor based discriminant analysis directly treats the data as tensor, and thus effectively avoids the problems derived from treating data as vectors.

They identified the analysis of an ensemble of facial images resulting from the confluence of multiple factors related to scene structure, illumination, and viewpoint as a problem in multilinear algebra in which the image ensemble is represented as a higher-dimensional tensor. This image data tensor is decomposed to separate and parsimoniously represent the constituent factors. In case of facial image data used in our experiments, the various variables are people, views, illumination and pixels. Multilinear analysis enables us to represent each person regardless of pose and illumination with the combination of different base tensors (similar to the case of EigenFaces).

The common problem that is faced when working with high dimensional data such as gene expressions or large image databases is to find lower dimensional structures hidden in a much higher dimensional observation space. Isometric Feature Mapping, popularly known as ISOMAP is often used to solve dimensionality reduction problems. Some of the traditional methods for dimensionality reduction are Principal Component Analysis (PCA) and Multidimensional Scaling (MDS). However, these techniques assume that the data points lie on a linear subspace of the high dimensional input space and cannot be used to capture any inherent non-linearity of the data. The advantage of ISOMAP over these linear techniques and other non-linear techniques is that it is capable of efficiently calculating a globally optimal solution. It is possible for two points to be extremely close in the original data as measured by their Euclidean distances but can be extremely far apart in the lower dimensional manifold when measured by the geodesic or shortest path distances. Isometric Feature Mapping, popularly known as ISOMAP is often used to solve dimensionality reduction problems [10].

In order for Tensor Analysis to be useful, it is required that we have each and every image of all the subjects (*i.e.* with all poses and illuminations). However, it is not reasonable assumption in case of real life applications.

Advantages:

1. It is evident that ISOMAP is an excellent dimensionality reduction technique for facial data.
2. A nearest neighbor classifier when applied to the lower dimensional embedded data results in extremely high face recognition accuracy.

Disadvantage:

1. It is only asymptotically guaranteed to converge to the actual structure.
2. It is likely that the obtained model can change as number of data points increase.
3. The location of face is not same in all images for all the subjects.
4. It could create major problems as the number of individuals in the database increases.

2.4.2). A Fuzzy Clustering Approach for Face Recognition:

The face patterns are divided into several small-scale neural networks based on fuzzy clustering and they are combined to obtain the recognition result. the application of fuzzy sets in a classification function causes the class membership to become a relative one and an object can belong to several clusters at the same time but to different degrees.[22]

A new concept fuzzy curve for determining structure of FNN's was proposed by Y. H. Lin and G. A. Cunningham [23]. This approach is a heuristic one, it is not easy to determine the architecture and the performance. J.-S. R. Jang [24], gives the structure of the adaptive-network-based fuzzy inference system (ANFIS) is mainly determined by expert knowledge. In [25], C. T. Lin proposed the self-organizing learning scheme for structure learning. A hierarchically self-organizing approach was used in [26] that is given by K. B. Cho and B.H. Wang . He tells about adaptive based fuzzy system that is used with Radial basis function and tells their applications in the system identification and prediction C. F. Juang and C. T. Lin [27], describe the structure to determined by clustering the input space. It provide fuzzy interface network. R. P. Li and M. Mukaidono [28] propose a simple and effective method whereby the structure is identified by input–output data pairs rather than by only input data was presented. A new concept fuzzy curve for determining structure of FNN's was proposed in [29]. As this approach is a heuristic one, it is not easy to determine the architecture and the performance. Shiqian Wu and Meng Joo[30] implementing Takagi–Sugeno–Kang fuzzy systems based on the extended RBF neural networks and a novel learning algorithm based on the dynamic fuzzy neural networks using the pruning technology, significant neurons are selected so that a high performance can be achieved. Neurons can be recruited or deleted dynamically according to their significance to system performance. B.-J.Park, W.Pedrycz and S.-K.Oh [31] proposed a comprehensive and efficient framework of information (data) granulation, and involves a hard C-means (HCM) clustering method and genetic algorithms **(CAS).** The main propose is to cast the problem in the setting of clustering techniques and genetic algorithms.

Fuzzy neural networks (FNN), that is intended to capture the advantages of both fuzzy logic and neural networks. The level of granularity of fuzzy sets helps establish a required level of detail that is of interest in the given modelling environment. The form of the information granules themselves becomes an important design feature of the fuzzy model, contributing to its structural as well as parametric optimisation.

Commonly the membership functions of a fuzzy system are designed according to the experience of an expert who knows the behaviour of a process. Fuzzy clustering in the input-output space is a technique widely used to create the membership functions of a fuzzy system. Applying the clustering techniques we can also obtain fuzzy sets that are utilized to model the antecedents of the rules in fuzzy systems. This is realized with the projection of the fuzzy sets. In order to generate the fuzzy rules a clustering algorithm is applied to the input data. Once the clusters are generated, the membership functions of the fuzzy system are created by projecting the clusters to the axes of the input data. These membership functions can be used to define the antecedents of the fuzzy rules.

The fuzzy c-means (FCM) algorithm has successfully been applied to a wide variety of clustering problems. These are the new approaches for the FCM. These approaches were called fuzzy-possibilistic c-means, FPCM, and possibilistic-fuzzy c-means, PFCM. These

are giving one of the major contributions is, these algorithms overcomes the noise sensitivity of FCM. However, these algorithms work better for unlabeled data, and for this project we need an algorithm which can utilize the labels of the data for a better performance. One of the most widely used algorithms for fuzzy clustering is Gath-Geva. The advantages of the GG algorithm is that it can utilize the label of the data to create fuzzy clusters in order to construct the antecedents of a fuzzy inference system.

2.4.3). <u>Face Recognition using Gabor Filters:</u>

Design a robust and accurate classifier in such a nonlinear and non-convex distribution is difficult work. One approach to simplify the complexity is to construct a local appearance-based feature space, using appropriate image filters, so that the distributions of faces are less a by various changes. Gabor wavelet-based features have been used for this purpose.

Face recognition using Gabor features has attracted considerable attention in the field of computer vision, image processing, pattern recognition etc. The principal motivation to use Gabor filters is biological relevance that the receptive field profiles of neurons in the primary visual cortex of mammals are oriented and have characteristic spatial frequencies. Gabor filters can give salient visual properties such as spatial localization, orientation selectivity, and spatial frequency characteristics [32]. Considering these overwhelming capacities and its great success in face recognition.

There are so many algorithm proposed by researcher. *Lades et al.* developed a Gabor wavelet based face recognition system using dynamic link architecture (DLA) framework which recognizes faces by extracting Gabor jets at each node of a rectangular grid over the face image [33]. *Wiskott et al*. subsequently expanded on DLA and developed a Gabor wavelet-based elastic bunch graph matching (EBGM) method to label and recognize facial images [34]. *Liu and Wechsler* have developed a Gabor feature based classification protocol using the Fisher linear discriminate model for dimension reduction [35]. *Shan et al.* have developed an enhanced fisher model using the AdaBoost strategy for face recognition [36]. *Zhang et al* proposed a face recognition method using histogram of Gabor phase pattern [37]. . Gabor transform is used in [38] is robust for the expression, the posture and the illumination. Reference [39] tells how to constructs an eyes feature template and energy function. Those eyes location methods are used on the assumption that the face images have been exactly located, or with clear background. However, the accuracy of eyes location is affected by various factors in the images.

A biometric face recognition system based on local features informative feature locations in the face image are located by Gabor filters, which gives as an automatic system that is not dependent on accurate detection of facial features.

The feature locations are typically located at positions with high information content (such as facial features), at each of these positions we extract a feature vector consisting of gabor coefficients. Gabor filter works as a bandpass filter for the local spatial frequency distribution, achieving an optimal resolution in both spatial and frequency domains. The Gabor representation of a face image is computed by convolving the face image with the Gabor filters.[40].

Fig. 2.3 Gabor Feature

Gabor filter works as a band pass filter for the local spatial frequency distribution, achieving an optimal resolution in both spatial and frequency domains. Design of

Gabor filters is accomplished by tuning the filter with a specific band of spatial frequency and orientation by appropriately selecting the filter parameters. The Gabor representation of a face image is computed by convolving the face image(intensity of pixel) with the Gabor filters.

Gabor filter based on feature selection methods are normally computationally very expensive due to the characteristics of high dimensional Gabor features.

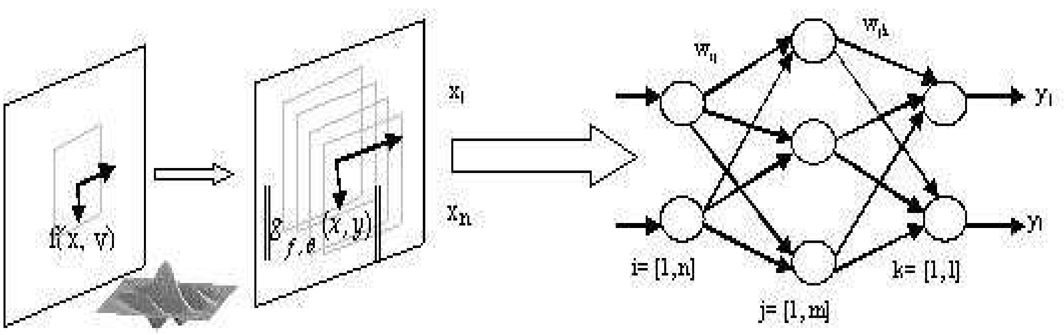

Fig. 2.4 Gabor based MLNN without Patterning.

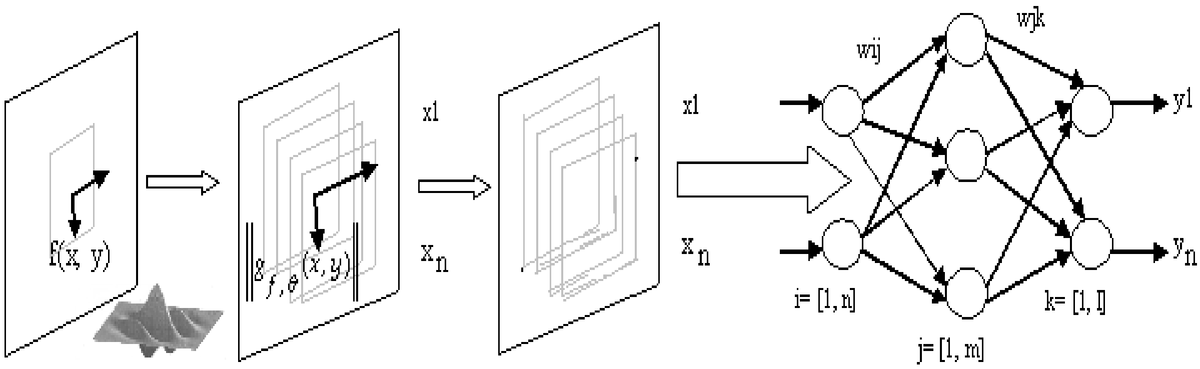

Fig. 2.5Gabor based MLNN with Patterning.

Disadvantage:

(i) Gabor filter based feature selection methods are normally computationally expensive due to high dimensional Gabor features.

(ii) Its huge number of features often brings about the problem of curse of dimensionality.

(iii) Gabor features are usually very high-dimensional data and there are redundancies among them.

CHAPTER 3:

Research Methodology

3.1). Introduction:

Much of the earlier work in human recognition faces has focused on detecting features of individual such as the eyes, nose, mouth, and head outline. Eigen-face approach, is one of the earliest *appearance-based* face recognition method, which was developed by M. Turk and A. Petland[42]. As much as information theory is concerned the main aim is to extract the relevant information from a face image and encode it very efficiently and compared encoded face with a database of models. In mathematical terms we can say that it is finding the principal components of the distribution of faces, or the eigenvectors of the covariance matrix of a set of face images. The main aim behind this procedure is that the face space has a lower dimension than the image space and that the recognition of the faces can be performed in this reduced space. Other promising methods in this literature include Fisher's Discriminant Analysis (FDA) [63] .Face recognition using LDA/FDA is called the Fisher-face method. This method seeks to find a linear transformation to maximize the between-class scatter and minimize the within-class scatter. Most face-recognition algorithms are in some sense minimum distance classifiers and hence make use of the common Euclidean distance.

These methods are pattern recognition techniques widely invoked in various face recognition approaches. Here we are representing two well-known appearance-based recognition schemes utilize principal component analysis (PCA) and Fisher linear Discriminant analysis (FLD).

3.2). EIGENFACE METHOD:

Previous work on automated face recognition has ignored the issue like what aspects of the face stimulus are important for face recognition. This suggests use of information theory approach of coding and decoding of face images and mainly emphasizing on the significant local and global features of the image. These features may or may not be directly related to our intuitive notion of face features such as the eyes, nose, lips, and hair.

In information theory, the important information in a face is extracted and encoded as efficiently as possible, and then compared with stored image. A simple approach to extracting the information contained in an image of a face is to somehow capture the variation in a collection of face images, independent of any judgment of features, and use this information to encode and compare individual face images.

Robust face recognition schemes require both low-dimensional feature representation for data compression purposes and enhanced discrimination abilities for subsequent image retrieval. The representation methods usually start with a dimensionality reduction procedure since the high-dimensionality of the original visual space makes the statistical estimation very difficult, if not impossible, due to the fact that the high-dimensional space is mostly empty. One of the most popular representation methods for face recognition are Principal Component Analysis for dimensional reduction. In mathematical terms, the principal components of the distribution of faces, or the eigenvectors of the covariance matrix of the set of face images, treating an image as point (or vector) in a very high dimensional space is sought. The eigenvectors are ordered, each one accounting for a different amount of the variation among the face images. The basic idea of PCA for dimension reduction is to keep the (top n) largest nonzero eigen values and the corresponding eigenvectors. The idea of this approach is correct from image compression point of view; keeping the largest nonzero principal components means that we keep most of the energy (information) of that image by projecting into lower dimension subspace.

These eigenvectors can be thought of as a set of features that together characterize the variation between face images. Each image location contributes more or less to each eigenvector, so that it is possible to display these eigenvectors as a sort of face image which is called an "eigen-face".

Each eigen-face deviates from uniform gray where some facial feature differs among the set of training faces. Eigen-faces can be viewed as a sort of map of the variations between faces. Each individual face can be represented exactly in terms of a linear combination of the eigen-faces. Each face can also be approximated using only the "best" eigen-faces, those that have the largest eigen values, and which therefore account for the most variance within the set of face images. If the eigen values drops very quickly, that means one can represent the faces with relatively small number of eigen-faces. The best M eigen-faces span an M-dimensional subspace which we call the "face space" of all possible images. This method is also called principal component analysis. PCA has been used in face recognition, handprint recognition, human-made object recognition, industrial robotics, and mobile robotics.

Eigenface technique is a method used for face recognition for many years. Mathematically, Principal component analysis approach will treat every image of the training set as a vector in a high dimensional space. The eigenvectors of the covariance matrix of these vectors would incorporate the variation amongst the face images. Each image in the training set would have its contribution to the eigenvectors (variations). The training data set has to be mean adjusted before calculating the covariance matrix or eigenvectors. The average face is calculated for the each image in the data set and difference is calculated from the average face by the vector. This is actually mean adjusted data. PCA will compute a vector that has the largest variance associated with it. In other word we can say that Principal Component Analysis (PCA) can be used to find a subspace whose basis vectors correspond to the maximum-variance directions in the original space. The high dimensional space with all the eigen-faces is called the image space (feature space). If the eigen-face with small eigen values are neglected, then an image can be a linear combination of reduced number of these eigen-faces. The face image to be recognized and then projected on the face space. The Euclidean distance between the image projection and known projections is calculated. The face image is then classified as one of the faces with minimum Euclidean distance [52].

They calculated a best coordinate system for image compression, where each coordinate is actually an image that they termed an "eigen-picture". Any collection of face images can be approximately reconstructed by storing a small collection of weights for each face, and a small set of standard pictures. This method is used for the dimensionality reduction.

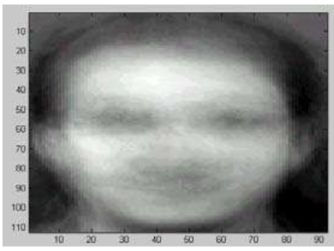

Figure 3.1

The eigenface images calculated from the eigenvectors of L, span a basis set with which to describe face images. S M' can be sufficient for identification, since we does not require an accurate reconstruction of the image. Our main framework was identification of a pattern recognition task. A new face image is transformed into its eigenface components projected onto "face space". This describes a set of point by point image multiplications and summations, operations performed at approximately frame rate on current image processing hardware. that describes the contribution of each eigenface in representing the input face image, treating the eigen-faces as a basis set for face images. The feature vector is then used in a standard pattern recognition algorithm to find which of a number of predefined face classes, if any, best describes the face. But there are some problem with the Principle Component Analysis. A. Pentland, Starner, Etcoff, Masoiu, [51] have empirically shown that superior face recognition results are achieved when the first three eigenvectors are not used (because the first three eigenvectors seem to represent changes in illumination). It has been recently shown that the elimination of more than three eigenvectors will, in general, worsen the result.

To start with the Eigen-face Algorithm, there are different eigenspace-based approaches for the recognition of faces have been proposed by researcher. They differ mostly in the kind of projection method used, e.g. standard, differential, or kernel eigenspace, in the projection algorithm employed, in the use of simple or differential images before/after projection, and in the similarity matching criterion or classification method employed. A lot of work has been already done on this technology from last two decade. PRINCIPAL component analysis (PCA), also known as Karhunen- Loeve expansion, is a classical feature extraction and data representation technique widely used in the areas of pattern recognition and computer vision. Sirovich and Kirby [53], [54] first used PCA to efficiently represent pictures of human faces. They argued that any face image could be reconstructed approximately as a weighted sum of a small collection of images that define a facial basis (eigen images), and a mean image of the face.

In 1991, Principal Component Analysis was used for face recognition by Turk and Pentland [42]. Later, local auto correlations were used for face recognition by Frangois and , Takashi [43]. They focus on the difficult problem of recognizing a large number of known human faces while rejecting other, unknown faces which lie quite close in pattern space. Michael Julien Budynek, and Shigeru proposed an automated method for classification of single facial images was presented in [44]. In which they propose algorithm that automatically classifying facial images based on labelled graph matching and linear Discriminant analysis. Phillips et.al described the FERET evaluation methodology for face recognition algorithms [45].FERET is design to evaluate the performance of laboratory algorithm which provide feasibility of automatic face recognition technolgy. Liu and Wechsler used shape and texture based fisher classifier [46]. Later, Principal Component Analysis was compared with Linear Discriminant Analysis by Aleix M. MartõÂnez, and Avinash C. Kak [47]. They desolve the myths that generally the algorithms based on LDA (Linear Discriminant Analysis) are superior to those based on PCA (Principal Components Analysis). In this communication, they show that this is not always the case. They gives mathematical prove that when training data set is small, PCA can outperform LDA and, also, that PCA is less sensitive to different training data sets. Gabor based Kernel PCA with fractional power polynomial model were used by Liu in [48]. He details how the novel Gabor-based kernel PCA method With fractional power polynomial models for face recognition. Gabor wavelet representation derives desirable features characterized by spatial frequency, spatial locality, and orientation selectivity. These features have variations due to illumination and facial expression. And then kernel PCA works on the Gabor wavelet representation and nonlinearly derives low-dimensional features that incorporate higher order statistics. Finally, the novel Gabor-based kernel PCA method applies fractional power polynomial models for face recognition. Yang et.al proposed two dimensional PCA for face recognition [49]. They propose a straightforward image projection technique, two-dimensional principal component analysis (2DPCA) which is opposed to conventional PCA, 2DPCA is based on 2D matrices rather than 1D vectors. In which the size of the image covariance matrix using 2DPCA is much smaller. The main advantage is that it is easier to evaluate the covariance matrix accurately and less time is required to determine the corresponding eigenvectors. In 2005, Locally Linear Discriminant Analysis (LLDA) was used for face recognition [50]. The idea of the proposed approach is that global nonlinear data structures are locally linear and local structures can be linearly aligned. Single class objects, even if multimodally distributed, are transformed into a cluster that is as small as possible, with a maximum distance to the different class objects, by a set of locally linear functions. If images of a face class in different poses have similar representations in the trained global subspace, it is much easier to recognize a novel view image even when a single model image is provided. Janarthany [55] proposes an approach to face recognition where the facial expression in the training image and in the testing image diverge and only a single sample image per class is available to the system. The input to the system is a frontal face image with neutral expression and identical background where the subjects' hair is tied away from the face. In 1997, Pentland and Moghaddam proposed a differential eigenspace-based approach that allows the application of statistical analysis in the recognition process [56]. The main idea is to work with differences between face images, rather than with single face images. In this way the recognition problem becomes a two-class problem, because the so-called "differential image" contains information of whether the two subtracted images belong to the same class or to different classes. In this case the number of training images per class increases so that statistical information becomes available and a statistical classifier can be used for performing the recognition.

Drawbacks:

1. If this information changes due to face background, recognition performance can significantly decrease.
2. The recognition performance decreases quickly as head size or orientation is misjudged. So input image must be close to that of the eigen-faces for the system to work well which is not always possible.
3. The recognition performance decreases exponentially if correct training set is not selected because it's follow unsupervised learning.
4. It is not scale and light condition invariant.

3.3). FISHERFACE METHOD:

Linear reducing the dimensionality of the features space of image, i.e., feature extraction, is a most common technique in statistical pattern recognition i.e. typically used to lower the size of statistical models and overcome estimation problems, and it is often resulting in an improved classifier accuracy in the lower-dimensional space of image. Fisher Linear Discriminant analysis is probably the most well-known approach to supervised linear dimensionality reduction[63].

Fisher Linear Discriminant (FLD) has recently emerged as a more efficient approach for extracting feature for many pattern classification problems than traditional principal component analysis **(PCA).** One widely used discrimination criterion in the face recognition community is the Fisher linear Discriminant which defines a projection that makes the within-class scatter small and the between- class scatter large. In other words we can say that FLD are based on maximization of between-class variance and minimization of within-class variance. As a result, FLD derives compact and well-separated clusters. It belongs to a more general type of methods, Linear Discriminant Analysis (*LDA*), which aims to find a projection direction to best separate the classes. More specifically, *FLD* uses the *Fisher Criterion* as the objective function which measures the degree of separation between classes.

Fisher's Linear Discriminant (FLD) is an example of a *class specific method*, in the sense that it tries to "shape" the scatter in order to make it more reliable for classification. This method selects *orthogonal matrix of image* in such a way that the ratio of the between-class scatter and the within class scatter is maximized.

Fisher's Linear Discriminant is a "classical" technique in pattern recognition first developed by Robert Fisher in 1936 for taxonomic classification [57]. Ming-Hsuan Yang[58] propose the use of Kernel Principal Component Analysis and Kernel Fisher Linear Discriminant for learning low dimensional representations for face recognition. The aim of Eigen-face and Fisherface methods is to find projection directions based on second order correlation of samples data, and this will gives generalizations which take higher order correlations into account and also maximizes the class separation. Because Since much of the important information may be contained in the high order dependencies among pixels of a face image. Chengjun Liu[59] introduces a novel

Gabor–Fisher Classifier for face recognition. The Gabor–Fisher Classifier method applies the Enhanced Fisher linear Discriminant Model to an augmented Gabor feature vector derived from the Gabor wavelet representation of face images. This method provide the derivation of the augmented Gabor feature vector, whose dimensionality is further reduced using the Enhanced Fisher linear Discriminant Model by considering both data compression and recognition performance; that help in development of multi-class problems and provide an extensive performance evaluation studies. Dattatray and Raghunath propose [60] face recognition that uses Gabor wavelets with five scales and eight orientations that derive desirable facial features characterized by spatial locality, spatial frequency, and orientation selectivity that overcome the variations due to illumination and facial expression changes.

Xiang, Fan, and Lee[61] overcome the problems if the number of classes is small for FLD by a recursive procedure by calculating the Discriminant features. At every step, the calculation of a new feature vector will be based upon all the feature vectors obtained previously. More specifically, at each step when a new feature vector is calculated, the : training samples have to be pre-processed such that all the information represented by those "old" features will be discarded And then the problem of extracting the new feature most efficient for classification based upon the pre-processed database will be formulated in the same fashion as that of FLD. Jian, Frangi, Yang and David[62] examines the theory of kernel Fisher Discriminant analysis in a Hilbert space rather than in the space spanned by training samples is take and develops a two-phase framework, i.e., kernel principal component analysis plus Fisher linear Discriminant analysis . This framework provides the nature of kernel Fisher Discriminant analysis, and proposes a complete kernel Fisher Discriminant analysis algorithm. This algorithm can be used to carry out Discriminant analysis in "double Discriminant subspaces." The fact that, it can make full use of two kinds of Discriminant information, regular and irregular, makes CKFD a more powerful discriminator.

Zheng, Lai, and Pong C. Yuen[63] proposes an automatic and systematic method to select the eigenvectors to be used in LDA using a Genetic Algorithm (GA). A GA-PCA is then developed. It is found that some small eigenvectors should also be used as part of the basis for dimension reduction. Using the GA-PCA to reduce the dimension, a GA-Fisher method is designed and developed. It gives an optimal bases for dimensionality reduction are derived from GA-PCA. And the computational efficiency of LDA is improved by adding a whitening procedure after dimension reduction. . Changjun Zhou1 et.al.[66] introduced a new technique features fusion method for face recognition based on Fisher's Linear Discriminant (FLD). This method extract features by employed Two-Dimensional principal component analysis (2DPCA) and Gabor wavelets, and then fuse their features which are extracted with FLD respectively.

Weihong Deng, Jiani Hu, Jun Guo [64] introduce a Robust Fisher linear Discriminant Model (RFM) for dimensionality reduction. The RFM first estimate the within-class scatter matrix based on the probabilistic learning technique. It can preserve the low variance information while prevent the over-fitting problem due to limited samples. RFM improves the FLD by the robust estimate based on the probabilistic learning technique. To improve the stability of the FLD eigen system, the RFM also decomposes the FLD procedure into diagonalization of two symmetric matrices. Zhi-Guang, Wang *and* Zhu[65] propose an optimal kernel fisher analysis method that extract the nonlinear Discriminant face features. It solve the projection vectors of image which make the fisher criterion function that is larger than zero, and then defines a priority function which is highly co-related with the fisher criterion function. By using this priority function, we will obtain the priority values of all the projection vectors, and then several maximum projection vectors are selected as the final Discriminant vectors. Here it transform the nonlinear disjunctive original sample space to some linear disjunctive high dimension feature space through suitable nonlinear transform function.

3.2.1). **Fisher Linear Discriminant Analysis Method :**

First of all, all the training images are combined into a data matrix of size m * n, where m is number of images and each column is consider as a single image.

$$I = I1, I2, I3, \ldots, Im . \qquad \ldots\ldots \ldots\ldots\ldots\ldots\ldots \quad 1.$$

Calculate the mean of all training images and mean of each class for the image.

$$\Psi = 1/m \sum_{i=1}^{m} I_i \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots 2.$$

Subtract the mean of each class from each image of that class by formula

$$\bar{I} = I - \Psi_i \qquad \text{.....................................3}$$

Subtract the total mean from the mean of each class.

$$\Phi = \Psi i - \Psi$$

The within class scatter matrix measures the amount of scatter between items within the same class. For the ith class a scatter matrix is calculated as the sum of the covariance matrices. The covariance matrix C is calculated by multiplying data matrix with its transpose matrix.

$$S_i = \sum_{i \varepsilon I} \varphi\varphi^t \qquad \text{.............................4.}$$

The within class scatter matrix (Sw) is the sum of all the scatter matrices of image.

$$S_W = \sum_{i=1}^{c} S_i \qquad \text{......................................5}$$

where C is the number of classes.

Now between class scatter matrix is calculated by the sum of all the covariance matrices of all the classes, i.e. weighted by the number of images in each class.

$$S_b = \sum_{i=1}^{c} n_i \varphi\varphi^t \qquad \text{............................6}$$

eigenvectors (V) is the optimal discrimination projection and it can be obtained via solving the generalized eigen value problem. Generalized eigen value and eigenvectors of the within and between class scatter matrices are calculated by equation:

$$S_b V = \lambda S_b V \qquad \text{..............................7.}$$

Sort the eigenvectors by their associated eigen values from higher to lower are kept the first 1- C eigenvectors. These are the Fisher basis vectors alsocalled as fisher faces have face-like images .

Project the entire rotated original (i.e. Not centered) images onto the Fisher basis vectors. First of all project the original images into the ortho-normal basis, and after that project these projected images onto the Fisher basis vectors. The original rotated images are projected onto this line because these are the points where the line has been created to Discriminant , not the centered images.

When we are doing test phase each test image should be mean centralized by subtracting the mean value of face. After this projection the test image in to the same eigen space as defined during the training phase of recognition. This projected test image is now compared with projected training image in the eigen space. Images are compared to each other by using the most common and famous similarity measure, i.e. Euclidean Measure. The training image that is closest to the test image will be matched and used to identify the training image.

Drawback: The main drawback of FLD is that it requires large training sample size for good generalization. For a face recognition problem, however, usually there are a large number of faces (classes), but only a few training examples per face.

In practice, there are some common shortcomings of *FLD*:

The Small Size Size problem(SSS) When the number of training samples are small compared to the dimension, the scatter matrices (particularly **S***w*) would be singular.

- The Overfitting problem. Empirically *FLD* has shown to be very sensitive to the sampling power of the training data, and if the underlying distribution of the whole data space is very different from that of the training data, *FLD* would very probably perform badly.
- FLD is that it simply uses a common covariance matrix for all the classes.
- It is incapable of dealing explicitly with hetero-scedastic data, i.e., data in which classes do not have similar covariance matrices.
- The instability of the within-class scatter matrix due to limited samples.

3.4).**Proposed Algorithm:**

PCA is very effective in reducing the dimensions of the feature space since these eigen values and eigenvectors are arranged in order. So the main advantage is that we can now only select the bigger eigenvectors which contain most significant information of the original data. However, since PCA directly processes the pixel, it can hardly identify the feature of the face accurately with the light and shade part of the image. And because of the information has been processed by reducing the dimensions of the feature matrix, so it is possible that the classified vector is not the best choice. On the other hand, FLD is capable of getting the most ideal classification. But without the process of reducing the dimensions, it might encounter some problem of matrix singularity with large dimensions sub space. Therefore, in order to process FLD effectively, PCA is very necessary as a preceding procedure for reducing the dimensions. Although PCA and FLD both have their own drawbacks, but combining these two methods can reduce the dimensions effectively , achieve the best classification that improve the system's recognition rate, and it avoid complicated calculation. However, FLD can only deal with the problem from varying illumination, if the region of the shade is getting more serious, FLD might also result in lower recognition rate. Furthermore, because human face has plentiful expressions, the positions of facial features might be shifted. If we directly process the image through PCA or FLD might lead to incorrect recognition.

Here two algorithms Principal Component Analysis (PCA) and Fisher Discriminant Analysis (FDA) i.e. the holistic approach of Information theory have been analyzed. Recognition process can be comprises the two steps: training and testing. In the training phase a set of the eigenvectors of the covariance matrix of the images used for training purpose. These eigenvectors are also called as eigen-faces. In testing phase when a new input image is given for recognition of image, this image will be projected into the eigen space by using the already calculated eigenvectors. Test image will be compared with all the images in the eigen space and measures the Euclidean distance. If the calculated Euclidean distance lies below some threshold value then image is treated as the matched image. Both algorithms works in the same manner, the difference lies in the calculation of face space. These two algorithms are evaluated experimentally on two databases each with the moderate subject size. Analysis and experimental results indicates that the PCA works well when the lightening variation is small. FLD works gives better accuracy in facial expression. But if combining these two methods works effectively in the process of face recognition system.

3.4.1). <u>Algorithm:</u>

In applying Fisher's LDA in the context of the face recognition problem we initially encounter a major obstacle in the recognition process. This is because it is our training set that will contain N + g or more images of dataset. N is the dimension of each image and g is the number of individuals in the dataset that we are considering in our training set, consequently N + g has the potential to be an extremely large number of matrix. Further more it is highly possible for Sw that is within class scatter matrix, to be singular and hence we are unable to implement Fisher's LDA directly. However we are able to exploit the fact that the variation within classes lies in a linear subspace of the image space. Thus we know we can perform a dimensionality reduction using a linear projection whilst still preserving this separability. This observation is not only the motivation to used Fisher's LDA but it is also conveniently can utilised this fact for avoiding the problem of singular Sw matrix. That is, we can first use an another linear dimensionality reducing projection that is used to project a feature space of dimension $M - g$, in which we have ensured Sw is unable to be singular whilst still preserving the linear separability of the classes. We can then apply the standard Fisher's LDA in the new feature space without encountering any problems. PCA is first used as dimensionality reducing projection thus formulating the two step procedure to the problem of face recognition in the method of Fisherfaces. The Fisherfaces approach thus can be viewed as a two step method:

1. PCA is first applied to reduce the dimensionality the training set, projecting from the N dimensional image space to a subspace of dimension $M - g$. This gives the feature vector.

This resulting SW in this $M - g$ dimensional feature space is non-singular.

2. Fisher's LDA is then applied in this feature space to provide a second linear projection to the discriminant space of dimension $m \leq g - 1$, such that there is optimal class separability. This gives the discriminant vector So the Fisherface method is given by the linear projection:

Where the optimal projection matrix is given by:

Wopt = WPCAWLDA

So the steps are used in this algorithm is as fallowing:

3.4.2). Create Database:

Align a set of face images (the training set T1, T2, ... , TM)

Description: This function reshapes all 2D images of the training database into 1D column vectors. Then, it puts these 1D column vectors in a row to construct 2D matrix 'T'. Each column of 'T' is a training image, which has been reshaped into a 1D vector. Also, P is the total number of MxN training images and C is the number of classes.

Argument:

TrainDatabasePath	- Path of the training database
T	- A 2D matrix, containing all 1D image vectors

The length of 1D column vectors is MN and 'T' will be a MNxP 2D matrix.

3.4.3). FLD process:

I am using Principle Component Analysis (PCA) and Fisher Linear Discriminant (FLD) to determine the most discriminating features between images of the faces.

Here we gets a 2D matrix, containing all training image vectors and returns four outputs which are extracted from training database. Suppose Ti is a training image, which has been reshaped into a 1D vector.

Also, P is the total number of MxN training images and C is the number of classes. First of all, centered Ti is mapped onto a (P-C) linear subspace by V_PCA transfer matrix:

Zi = V_PCA * (Ti - m_database).

Then, Zi is converted to Yi by projecting onto a (C-1) linear subspace, so that images of the same class (or person) move closer together and images of difference classes move further apart:

Yi = V_Fisher' * Zi = V_Fisher' * V_PCA' * (Ti - m_database)

Argument:

T - (M*NxP) A 2D matrix, containing all 1D image vectors. All of 1D column vectors have the same length of M*N and 'T' will be a MNxP 2D matrix.

m_database - (M*Nx1) Mean of the training database

V_PCA - (M*Nx(P-C)) Eigen vectors of the covariance matrix of the training database

V_Fisher - ((P-C)x(C-1)) Largest (C-1) eigen vectors of matrix J = inv(Sw) * S.

ProjectedImages_Fisher - ((C-1)xP) Training images, which are projected onto Fisher linear space.

3.4.4). <u>Recognition Process:</u>

This function compares two faces by projecting the images into facespace and measuring the Euclidean distance between them.

1.) First of all Extract the FLD features from test image
2.) Calculate Centered test image
3.) Calculate Test image feature vector by
    ProjectedTestImage = V_Fisher' * V_PCA' * Difference;

Calculating Euclidean distances Euclidean distances between the projected test image and the projection of all centered training images are calculated. Test image is supposed to have minimum distance with its corresponding image in the training database.

Argument:

TestImage - Path of the input test image

m_database - (M*Nx1) Mean of the training database, database, which is output of 'EigenfaceCore' function.

V_PCA - (M*Nx(P-1)) Eigen vectors of the covariance matrix of the training database.

V_Fisher - ((P-1)x(C-1)) Largest (C-1) eigen vectors of matrix J = inv(Sw) * Sb

ProjectedImages_Fisher - ((C-1)xP) Training images, which are projected onto Fisher linear space

Returns:
OutputName - Name of the recognized image in the training database.

3.4.5). <u>Classification Process:</u>

Here we use Fisher's LDA to find an optimal projection matrix to linearly project the training set of face images to a new lower dimensional space, defined such that there is maximal class separability. We shall call this space the discriminant space. In this discriminant space we can then seek to define a discriminant rule to classify a new image as one of the g known individuals. This means we can see Fisher's LDA as a two step process:

1. First the Fisher's linear discriminant variables wi are found according to Fisher's criterion, thus describing the discriminant space.
2. Then within this discriminant space we apply a discriminant rule to allocate an unknown observation to one of the known classes.

We have so far completed the first step as have used Fisher's LDA to find the discriminants. We are then able to project our training set into the new discriminant space defined such that there is maximal separability between classes. So we now need to investigate the second step by considering a image not in this training set. We then need to formulate a discriminant rule to classify this image as one of the g known individuals. Fisher proposed the nearest neighbour classification rule for such a discriminant rule.

CHAPTER – 4:

Experimental Results:

In implementing the Fisherface method with PCA method there are several variables that can either be varied or need to be kept constant. In this experiment with these method we will consider effect of variation on only one key variable i.e.:

• Number of Fisher's Linear Discriminants

When we are in process of forming the projection matrix W_{LDA} we will select up to g − 1 eigenvectors, thus W_{LDA} can have a maximum of g – 1 number of columns. Our main aim is in minimise the stored data and computing requirements of the method so that we wish to minimise the number of eigenvectors taken while maximising the face recognition accuracy of the system.

In the same process we shall consider how many number of Fisher's linear discriminants we have to need to accurately discriminate between face images of different individuals. All other variables will be kept constant. We shall consistently use the same training sets, thus calibrate the system using the same images each time.

We shall experiment using faces databases: faces94. This database will have its own associated 900 image training set and there is 3 sets of testing images. So that we shall run the code three times on each testing set that ensure the reliability of the recognition results. There are some snapshot is recorded that show how the algorithm is work:

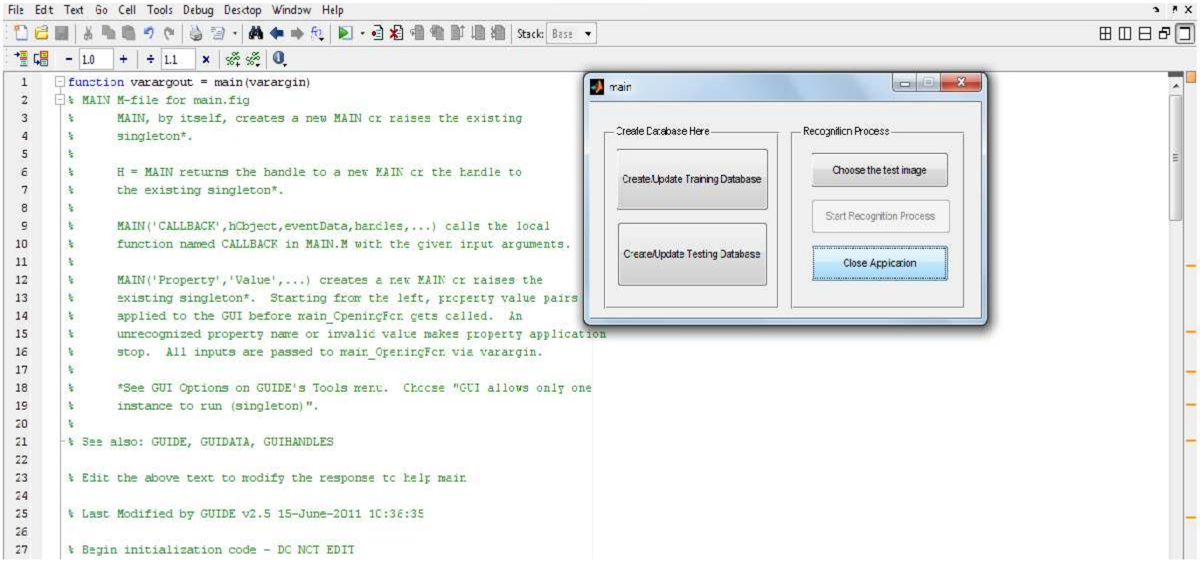

Figure 4.1:

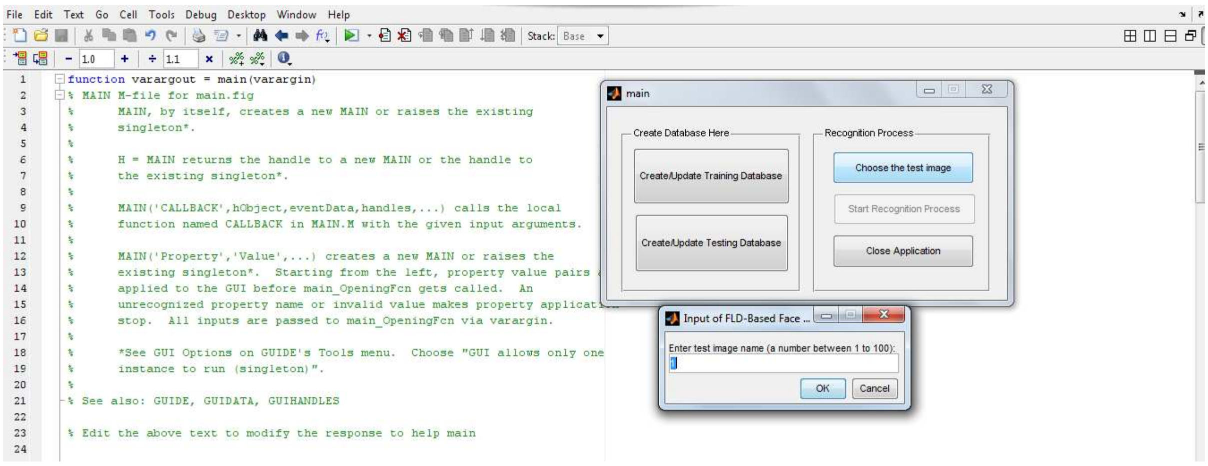

Figure 4.2:

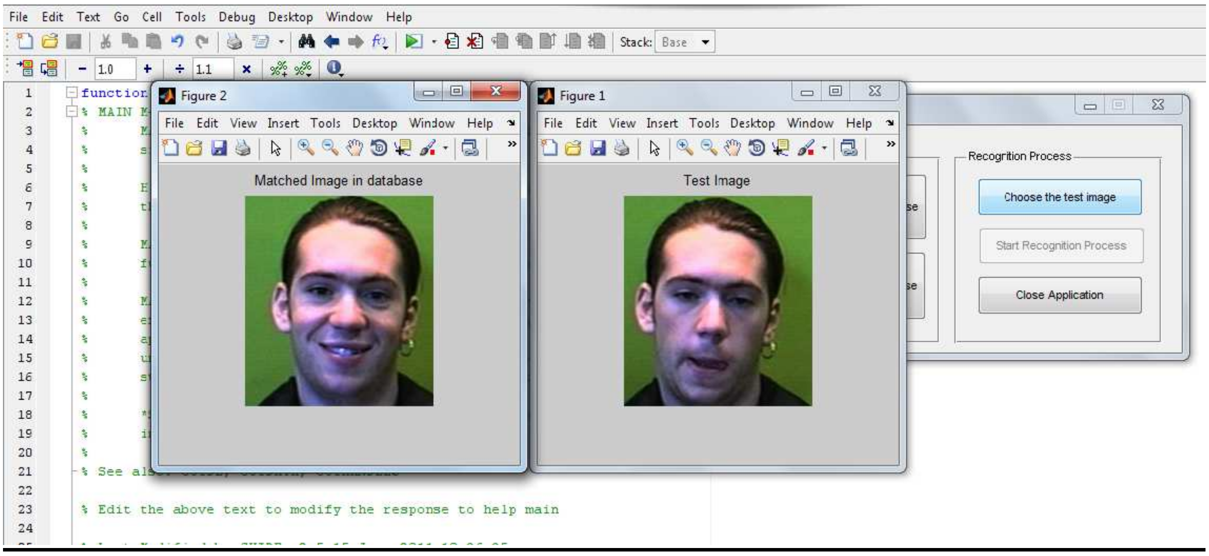

Figure 4.3:

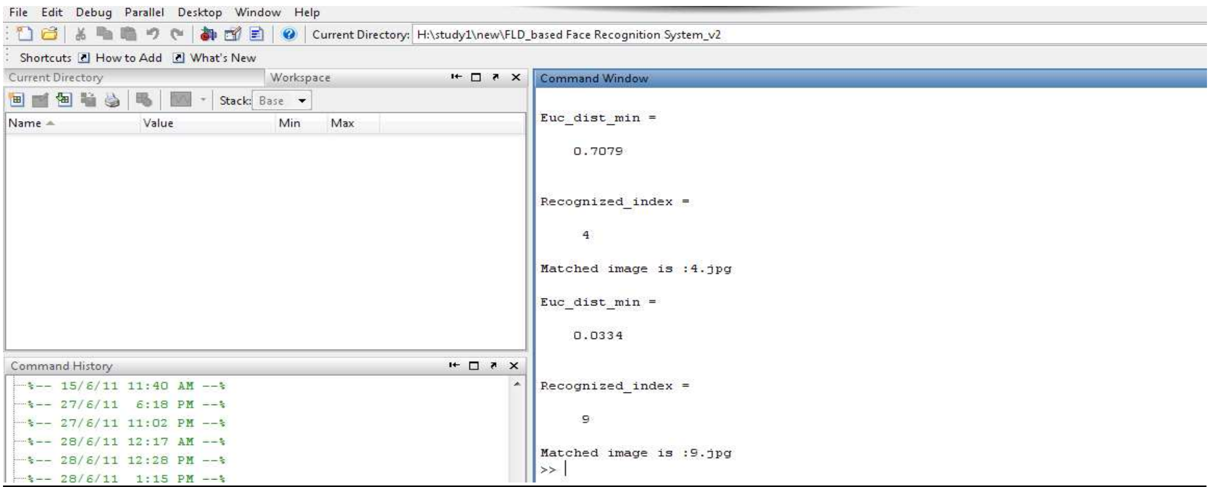

Figure 4.4:

Here in figure 1shows when we execute main program then a window is open that have some boxes. Firstly we have to select a database that has two sets: Training set and Testing set. First of all we train our system with the help of training database and then give some test data to recognise the accuracy of the method.

When training phase was completed the system ask us to select a figure from the test database. We are simply giving the name of image that is in the form of numbers. This process is shown in figure 2.

Now we start recognition process by clicking on start recognition process. When we click on this window system give two images that is test image and matched image from database as shown in figure 3.

Figure 4 shows the corresponding Euclidian distance between the test and matched image and index number of matched image.

We can then define the percentage recognition accuracy of the procedure and calculate the number of correctly classified individuals given a specified distance measure. We will take an average of this recognition accuracy for a given number of eigenvectors over the average values from the 3 repeats for each of the 3 testing sets. This will ensure the reliability of the final results.

Name of the image	Corresponding eigenvalue	status
1.jpg	1.5687	Not Matched
2.jpg	0.7079	Matched
5.jpg	0.0334	Matched
7.jpg	0.1126	Matched
9.jpg	0.7126	Matched
10.jpg	0.6314	Matched
13.jpg	0.6214	Matched
15.jpg	1.3642	Not Matched
24.jpg	0.9240	Matched
25.jpg	0.4530	Matched

Table 4.1:

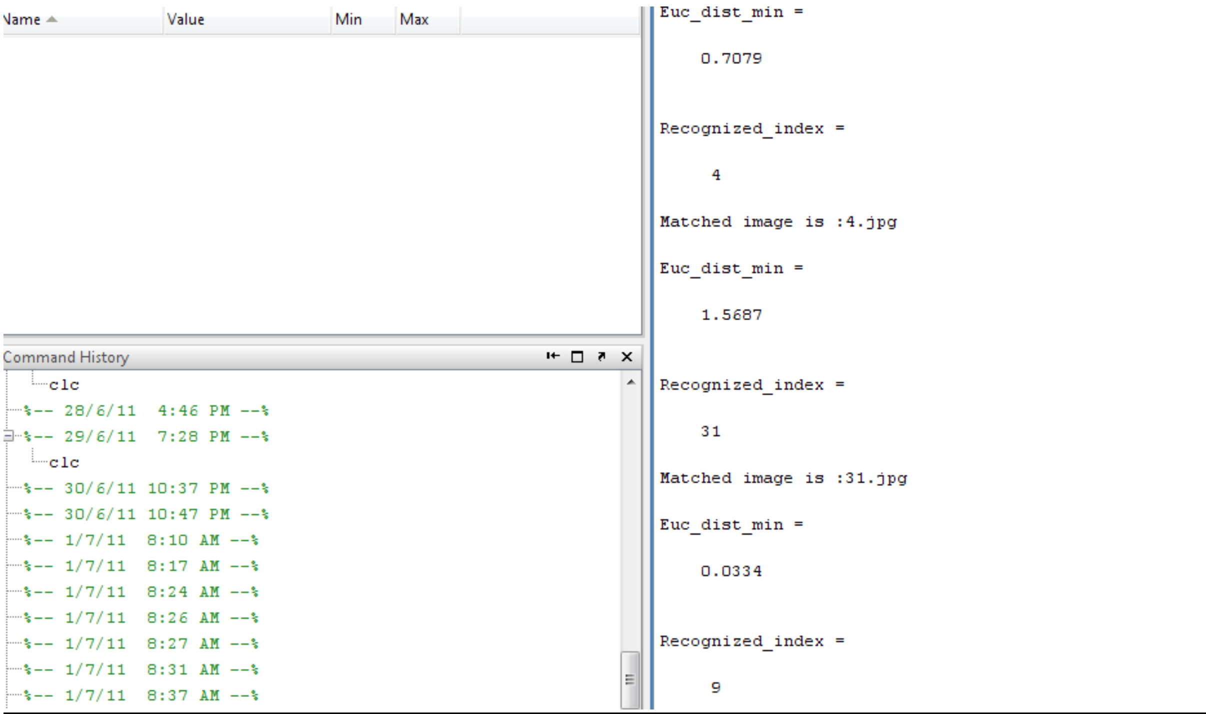

Figure 4.5:

. When we give a set of image then a corresponding eigen value is calculated, the experimental result clearly show when the eigen value is greater than some threshold then face was not matched by the system. See the table 4.1 which show the experimental result.

Number of image in a dataset	Percentage Accuracy
3	66.66 %
5	80 %
9	88.8 %
20	85%
25	88%

Table 4.2:

If we apply this algorithm on different dataset then we can find that how much the algorithm is giving the accuracy. Here I am tested on Face94 database and make the different dataset and apply the algorithm. Table 4.2 gives the experimental result of the implemented system.

In experimenting we know, a priori, that all images in the testing set are of known individuals. We consequently are not so interested in the rejection rate of the Fisherface procedure but the recognition abilities of the method. Experimental result show that the accuracy of the image dataset to correctly recognise a face is nearly eighty seven percent.

4.1). <u>Optimal Number of Fisher's Linear Discriminants:</u>

We can take up to $g - 1$ Fisher's linear discriminants to form the optimal projection matrix W. However, how many are optimal for discrimination using our two datasets? We wish to minimise the number of discriminants used in order to reduce the data storage and computer processing requirements, whilst producing a discriminant space in which recognition accuracy is high. We can make a table that gives percentage recognition accuracy versus the number of face image used in the method. The experiment was run using: $m = 3, 5, 10, 20, 25$ image. In face94 databases, clearly shows there is a large increase in the percentage recognition accuracy.

4.2). <u>faces94 Database:</u>

The major drawback of the Eigenface method is due to the fact that it treats all sources of variation as equal. Hence PCA method fails when there was significant variation due to lighting or pose. In formulation of the Fisherface method we separated the sources of variation, with the aim to improve the accuracy of recognition even when there is significant within class variation is present. We can use the experimental results produced to assess if the method is indeed an improvement. Recall that the faces94 database has limited within class . This indicates that although the recognition abilities of the Fisherface method are still affected by significant within class variation, it is still shown to be an improved, more robust technique in comparison to the Eigenface method. The testing sets have been selected such that the images in testing set one have very limited variation due to lighting and pose in comparison to those of the training set. In contrast the images in testing set two have been selected such that there is significant variation due to the aforementioned sources. Observe the results produced from implementation of the Fisherface method using these two testing sets.

CHAPTER 5:

Conclusion and Future Work:

5.1). Conclusion:

In this report we have focused our efforts on the identification stage of the face recognition problem. We have considered various approaches to determine the optimal way to extract discriminating features from a set of face images and then identify the individual in an image based on these extracted features. As an intuitive first approach to this problem, we begun by considering linear subspace analysis to attempt this feature extraction. The idea was that we would be able to make the high dimensional image space more compact and useful of discriminatory purposes, by linearly projecting face images down into a new lower dimensional subspace, as defined by certain optimal features. We begun by considering the Eigenface method, given in Chapter 3, in which we used PCA to define the low dimensional feature space. The idea of PCA is to select a set of ortho-normal basis eigenvectors, called the principal components, with the aim of retaining as much variability from the original space as possible. We called these principal components Eigenfaces. We showed how any face image can be approximately reconstructed using just a small number of these Eigenfaces. However the success of the Eigenface method is inhibited by the 3 key limitations occurring due to the use of PCA. The first being the assumption that large variances are important, this means the Eigenface method selects the most expressive features, which could include those due to lighting and pose variations. We saw, through our experimental investigations, how such features are not optimal for discriminatory purposes. The second being due to the non-parametric nature of PCA, this is because PCA does not make any assumptions on the structure of the data set. This subsequently leads to data loss, as we do not account for class separability. The third limitation being due to the linear nature of the method, In using a linear projection we are unable to take into account any of the higher order pixel correlations present in face images .The Eigenface method consequently assumes that such non linear relations are not necessary to discriminate between different individuals. We then used these limitations as the motivation behind all further methods we go on to consider. We subsequently aim to construct improved approaches in which we have removed one or more of these restrictions. In Chapter 3 we also consider the use of Fisher linear discriminant analysis, namely Fisher's LDA. We subsequently addressed the first two aforementioned limitations, as we sought to find the optimal discriminant space in which there is maximal group separability. Fisher's LDA thus utilises the class labels of each image as it seeks to find the optimal linear transformation that maximises the between class scatter whilst at the same time minimising the within class scatter. We then constructed the 2 step Fisherface method in which we first applied PCA to the image space and then secondly used Fisher's LDA to extract the optimal discriminant vectors. Implementation of the Fisherface method illustrated its superior performance especially when use with PCA in pose and lighting variation.

In this thesis we have built a Fisher linear discriminate (FLD) based face recognition system. It comprises three modules, the Create Database module, the FLD module, and the recognition module.

In the face Create Database module, we create a database that will use for the face recognition. And create a function that reshapes all 2D images of the training database into 1D column vectors. Then, it puts these 1D column vectors in a row to construct 2D matrix. Each column of constructed 2D matrix is a training image, which has been reshaped into a 1D vector.

For the FLD module, we are implementations, the Eigen-face method, and the other using the Fisher-face method. The outcome is a set of training and testing vectors with fewer dimensions, hence more tractability in the classification phase. And it determine the most discriminating features between images of the faces.

In the Recognition module, the function compares two faces by projecting the images into face space and measuring the Euclidean distance between them. Calculating Euclidean distances Euclidean distances between the projected test image and the projection of all centered training images are calculated. Test image is supposed to have minimum distance with its corresponding image in the training database.

The good results of FLD along with PCA encouraged us to conduct more experiments, using the 'face94' Essex face database data set this time. The 'face94' data set is composed of a corpus of face images taken for 150 persons in far field conditions, as opposed to the face images captured using in varying face module of the system we have built.

5.2). <u>Future Work:</u>

Based on the results of this thesis, there are several promising avenues of research in the field of face recognition that are likely to give useful results. We will develop sophisticated methods that can be enhance face detection by accurately locating the frontier face, pose and minimizing the identification error rates. It will be also interesting to study the biometric information theory in a way to analyze the information content with progressive image segmentation. It will give further insight into how the segmentation is affects the biometric entropy for face recognition.

Throughout this thesis we have only focused on the identification part of the face recognition problem. We subsequently developed methods which enable us to determine if the identity of an individual is known or unknown. However we could alter the face recognition problem and how we address it? For instance, instead of seeking to determine the identity of an individual our main aim to distinguish some other feature. Possible suggestions include: gender; hairstyle; the presence of eye glasses or even facial expression. Hence, instead of classifying the images based on the individual face present, we could group images based on some other defining feature of face. For example we organised our images based on the facial expression the individual is portraying. We would need to access whether there is sufficient variation between say a frown and smile to be easily distinguishable for the system and thus if we apply it in the classification techniques we are easily able to discriminate between the two. If so, we will able to train a machine to recognise emotions of individual.

Also, it is suggested to compare additional face recognition algorithms in order to obtain new valuable information that will help in improving of the recognition accuracy of a face recognition system, and use different recognition strategies.

In the preceding analysis we are implicitly assume a Gaussian distribution for the face space, when considering a nearest neighbour approach to classification. It is difficult if near are not possible to estimate a true distribution of face images. We subsequently have no priori reason to assume particular density function of a face images. It is useful if we could able to develop an unsupervised method that enables us to learn about the distribution of face classes to confirm our Gaussian assumption of propose an alternative model. Nonlinear networks suggest a useful and promising way to learn about the face space distributions.

Overall, the developed techniques in this thesis could be used to improve face recognition system performance under varying pose condition. These type of applications include security surveillance; face tracking in poor lighting conditions, varying pose condition. The results obtained in this thesis help to clarify future research directions in the effort to improve non-cooperative face detection/recognition under varying pose condition performance for low quality face images.

We have also seen the robustness of the Fisherface method with regards to small variations in pose of individual. However, are we able to further improve this robustness and extend the technique to recognise a face image say profile view? One potential suggestion would be to redefine each face class in terms of a set of characteristics views. For example an individual could be represented with the help of a face class that is corresponding to the frontal face image, sides views are at ±45 degrees and then left and right profile images. It is then hoped that we would be able to recognise an image that containing a face anywhere from frontal to profile view by approximating the real views by interpolation among the known fixed views, Various pose views of one individual.

we could also make our approach that develop a method for the computer age estimation and age simulation. Human age can be directly inferred from distinct patterns emerging from facial appearance. Consequently if we are able to organise a method for the images of individual into age groups, would it be possible to develop a classification technique that automatically assign a year to an individual’s face? For example a human can easily figure out the ageing process and assign an age estimate to each of the face images. It would be very interesting and practically very useful approach, to determine if we could train a machine that is able to do the same. The use of the nearest neighbour classifier or Artificial Neural Networks have been suggested as possible approaches. This could leads on to the prospect of face image synthesising, in which we could render an face image aesthetically with natural aging effects. This will used in a wide range of potential applications, from forensic art and security control to cosmetology.

Among the algorithms of face recognition, few of the algorithms show some promises for this biometrics trait. But not a single algorithm is claiming 100% accuracy on the test databases and/or real time system implementation. Now research in this field is gaining more attention on use of Multiple Classifier System (MCS) **or** sometimes called Multiple Recognizer System ***(MRS)*** which is the combination of two or more classifiers /recognizers to get more accuracy. It is important to keep this project more reliable for next study. If this work will keep improving, it is believe the accuracy could be increased up to 99%. Future work need to improve the existing algorithm and technique. There are many more algorithms with more accurate result. It also can be mix with some more other technique and algorithm to acquire more efficient technique in the field of face recognition system. Further work has to be done on how to choose the number of components and how to combine the outputs of the component classifiers.

CHAPTER- 6

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