Design and Implementation of a Real Time Face Recognition System

A thesis report submitted to the department of Computer Science and Engineering of the World University of Bangladesh in partial fulfillment of the requirement for award of the degree of Bachelor of Science in Computer Science & Engineering

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February, 2019

LETTER OF TRANSMITTAL

February 6th, 2019

To
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House # 3/A, Road # 4, Dhanmondi
Dhaka 1205, Bangladesh.

Subject: Submission of Thesis Report.

Dear Sir,

We are pleased to submit the report entitled **Design and Implementation of a Real Time Face Recognition System**. It was a great pleasure to work on such an important topic. The report is prepared according to the requirements and guidelines of the Department of Computer Science and Engineering, World University of Bangladesh (WUB).

We believe that the report will help you in evaluating our project work. It would be a great pleasure for us to interpret any part or whole of the report whenever necessary.

Sincerely yours:	Sincerely yours:
_______________________	_______________________
Abid Samdany	Md. Fazlul Karim
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World University of Bangladesh

DECLARATION

We hereby solemnly declare that the project work entitled **Design and Implementation of a Real Time Face Recognition System**, has been supervised by Mithun Kumar PK, Senior Lecturer of the department of Computer Science & Engineering, World University of Bangladesh. We ensure that the project report has not been submitted either in whole or part for any degree or Diploma in any university previously.

We hereby warrant that the work we have presented does not breach any existing copyright rule.

We further undertake to indemnify the university against any loss or damage arising from breach of the forgoing obligation.

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CERTIFICATE

I hereby certify that the Project Report on **Design and Implementation of a Real Time Face Recognition System**, is a confide record of project work done by Abid Samdany and Md. Fazlul Karim for partial fulfillment of the requirements for award of the degree of the Bachelor of Science in Computer Science and Engineering from World University of Bangladesh.

The project report has been carried out under my guidance and is a record of the bona-fide work carried out successfully by the students.

Supervisor:

…………………………

Mithun Kumar PK

Senior Lecturer of the department of Computer Science and Engineering

World University of Bangladesh (WUB)

ACKNOWLEDGEMENTS

We are extremely grateful and remain indebted to Al-mighty ALLAH who has guided in all ventures to complete successfully our project. We are thankful to the grace and the help received from him. It is our pleasure to thanks our Vice Chancellor of WUB, Professor **Dr. Abdul Mannan Chowdhury**, to whom we owe a lot for having given us an opportunity to complete our project.

The thesis would not be successful, without the proper and valuable guidance of **Mithun Kumar PK,** Senior Lecturer, our supervisor for the project, who is rendering all sorts of help as and when required. We are thankful for his constant constructive criticism and valuable suggestions, which benefited us a lot while implementing the thesis on **"Design and Implementation of a Real Time Face Recognition System".** He had been a constant source of inspiration and motivation for hard work. Through this column, it would be our most pleasure to express our warm thanks to him for his encouragement, cooperative and consent.

We are also thankful to **Kazi Hassan Robin**, Assistant Professor, Head of the Department of Computer Science and Engineering for his valuable guidance.

We are greatly indebted to all teachers and staffs of the Department of Computer Science and Engineering and other Departments of the **World University of Bangladesh** for their kind assistance in accomplishment of the project paper.

We are grateful to all our classmates, who are indeed, very close to our heart. One can never find the right words to thank one's parents. We will always be indebted for the love and care that our parents have showed on us, and have done every possible effort to reach us at this stage. We are very lucky to get such loving and caring parents.

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Abstract

Face recognition is one of the most important image processing research topics which is widely used in personal identification, verification and security applications. Face recognition has been achieved using many methods for ages. Such as feature based recognition, appearance based recognition, soft computing based recognition. Among these methods feature based recognition produces most efficient and error free results. In this paper, a face recognition system, using eigenfaces based on the principal component analysis (PCA) is developed. The objectives of this paper is to design and develop a face recognition system that is based on eigenface method to recognize still frontal face image and to implement this recognition system on real time video stream.

The first human face recognition experiments began to select from a large database of images a small set of records that matched with the input photograph. Later fully automated face recognition system was built with a computer program which performs a complex picture processing task. The task is to choose, from a collection of pictures of people taken by a TV camera, those pictures that depict the same person. Later feature based facial recognition advanced, where some selected feature is extracted from face image to match with face database. To extract feature properly eigenface method has been invented using principle component analysis (PCA).

The eigenface method reads face images as image vectors, extracts face features or eigenfaces from covariance matrix using PCA and calculate weight and then match the euclidean distance of input image weight and trained image weight. In this paper, a technique of selecting eigenfaces with maximum variance has been proposed.

The method has been applied to several static face image databases and checked for accuracy. Accuracy of databases has increased by minimum of 0.2% to 2.1%. The method has been applied to real time video stream through web-cam. The real time face recognition approach has achieved 90% accuracy.

The system is built to work in three phases. Loading phase, training phase and classification phase. In loading phase, a static image database is loaded or the web-cam is initialized by the algorithm and face images are detected and cropped for training. In training phase, eigenfaces are generated using eigenface method which holds the key features of training images. In classification phase, an untrained image of test set is selected to classify the input image.

In this paper, face recognition has been approached with eigenface method based on principle component analysis (PCA). An approach to select minimum number of eigenvectors, which can represent and maintain highest percentage of variance to create eigenfaces, has been proposed. This approach has been applied to multiple face image data sets and maximum of 98.75% recognition accuracy has been achieved.

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Chapter :1 Introduction

1.1 Introduction

It is impossible for a human to identify a specific cow or sheep in a herd. In a forest not everyone can distinguish a tree from another. Yet people can identify a familiar faces from any number of crowd. How can he do that? It is a practice human has been doing since the day they are born. Identifying a person, discerning a person from a group of people is a repetitive process we have been doing regularly on a daily basis. We, subconsciously, use is simple yet tricky method. Human brain is well equipped to find, extract and learn facial expression, as to read the facial expressions of others is an essential skill for our social performance. Although not all of us can identify each tree in a forest but if we observe closer we will see that not all tree are same. They each has their own unique class specific feature. Human does the same with people. We start discerning unique feature of individuals and learn to identify one from others. Recognizing a face is easy for human vision but not so for computer vision. Research on face recognition for computer started in late 1960s, yet it is the most challenging problem in computer vision to date.

Research in face recognition is not only motivated by the challenges it poses, but the multitude of practical fields where human face recognition is a compulsory. Handheld mobile phone has become popular to general people since 1990. Security for these devices became the main issue for the consumers. Users were requesting more security for their devices, with this motivation first biometric security for mobile devices was introduced in 2011 as fingerprint recognition by Motorola. Biometric is a unique, measurable characteristic of a human being that can be used to automatically recognize an individual or verify an individual's identity. Biometric attributes can be physiological and behavioral both. Fingerprint-scan, Facial Recognition, Iris-scan, Retina-scan are categorized as physiological biometric and Voice-scan, Signature-scan, Keystroke-scan are behavioral biometric.

In 2005 Japans OMRON corporation made first face recognition for mobile devices, though it was available for general people as the secure biometric verification in 2017 as Face ID by Apple corporation. Biometric verification is the most efficient and goto technique for the security purpose in our regularly increasing population. Security companies invest their major focus and resource in improving the efficiency of this technology. In our mass populated world identifying a person is now a necessary for social and national security.

Face recognition has been achieved using many methods for ages. Such as feature based recognition, appearance based recognition, soft computing based recognition. Among these methods feature based recognition produces most efficient and error free results. There are multitude ways for feature based recognition; such as Multidimensional scaling (MDS), Two dimensional maximum local variations (2DMLV), Fast Fourier Transform (FFT), Local Binary Pattern (LBP), Neural Network, Eigenfaces. This research paper shall focus on detecting face on live video stream and recognizing the face using eigenfaces method.

1.2 Objectives

1. To design and develop a face recognition system that is based on eigenface method to recognize still frontal face image.

2. To implement this recognition system on real time video stream (e.g. security camera, webcam, etc.).

1.3 Justification of Study

In our current social standard, face recognition is the most sought out technology for the purpose of security. Every high security system, now days, has face recognition feature. Face recognition is one of the primary biometric technologies, alongside finger printing, iris scanning and voice recognition.

Human face detection has drawn considerable attention in the past decades because from the last two decades, face recognition is playing an important and vital role especially in the field of commercial, banking, social media and law enforcement area, as it is one of the fundamental problems in computer vision.

Face recognition is basically used for two primary authenticity modes: verification and identification. There are numerous application areas in which face recognition can be exploited as solution. The rapid advances in technologies such as mobile devices, digital cameras, the Internet and the ever increasing demands on security, the use of biometrics is becoming increasingly important within every aspect of modern society. 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. All the latest mobile phone system has face recognition and verification as its security measure. Surveillance and security systems, access control system, Image database investigations, identification and attendance systems can be derived from the face recognition method.

1.4 Scope of Study

Further research can be done to increase performance and efficiency of the system. Such as improving image preprocessing techniques so that the recognition system can provide better result. In preprocessing removing background, light and the face orientation complexity and also getting rid of noise, enhancing contrasts increase the accuracy. Developing the face detection algorithm makes the recognition system more accurate. The face recognition system can also be equipped with emotion classification, age prediction, gender detection. A recognition system showing match with embedded meta data inside the pixels of face image which indicates the corresponding subject would be a more fine tuned face recognition model.

In today's world, the scope and applications of face recognition systems either as standalone or as an integrated module into a larger system cannot be ignored.

Chapter :2 Literature Review

Face recognition, as a mean of biometric verification, is most popular and a major aspects in computer vision. In ages, Different face recognition techniques and approaches are practiced to get the desired solution. In late 1960s automated human face recognition experiments began. It can be said that Woodrow Wilson Bledsoe is the father of face recognition. W.W. Bledsoe started working, with funding from an unnamed intelligence agency, on face recognition (Bledsoe, 1966). His goal was to select from a large database of images a small set of records that matched with the input photograph. The success of the program was measured by the ratio of the answer list to the number of records in the database. Later H. Chan and Bledsoe started research on programming computers to recognize human faces (Chan and Bledsoe, 1965). Their system was labeled as man-machine because facial features had to be pointed out manually. They used GRAFACON or RAND TABLET to extract the coordinates of features such as the center of pupils, the inside corner of eyes, the outside corner of eyes, point of widows peak, and so on. From these coordinates, a list of 20 distances, such as width of mouth and width of eyes, pupil to pupil, were computed. Their system could process about 40 pictures an hour. For recognition phase, the set of distances was compared with the corresponding distance for each photograph, resulting a distance between the photograph and the database record. The closest records were returned. The difficulties they faced was the great variation created by head rotation and tilt, lighting intensity and angle, facial expression, aging, etc. The system could not find any correlation between two pictures of the same person with two different head rotations. Unfortunately, their system was limited severely by the technology of the era and computer processing power.

Fully automatic face recognition system was built in early 1970s. In 1970 Kelly and Micheal David describes a computer program which performs a complex picture processing task. The task is to choose, from a collection of pictures of people taken by a TV camera, those pictures that depict the same person. The primary purpose of their research work was directed toward the development of new techniques for picture processing (Kelly, 1970).

Later some American scientists were able to add increased accuracy to man-machine manual facial recognition system (Goldstein et al., 1971). They were able to generate a set of 22 features from an initially larger set to provide relevant, distinctive, relatively independent measures which can be judged reliably. Their model predicts that under certain conditions at least 6 of an individual's features are required to isolate him. Their model also predicts that for a population of 4×10^6, only 14 feature-descriptions are required. Their studies form a foundation for continuing research on real-time man-machine interaction for computer classification and identification of multidimensional vectors specified by noisy components.

In 1974 Kanade and Takeo of Kyoto University sucessfully analyzed pictures of human faces in their thesis work. Their program which extracts face feature point, such as nose, mouth, eyes and so on. They tested the program with more than 800 photos and Emphasis is put on the flexible picture analysis. Their program extract feature measurements from digital image and classify the feature vector, which was first employed in the picture analysis and that was a remarkable success (Kanade, 1974).

In face recognition Appearance based approaches Eigenfaces, Support Vector Machine (SMV) are used and also other efficient techniques like Neural Networks, Hidden Markov Models (HMM), Geometrical Feature Matching, Line Edge Map (LEM), 3D Morphable Model and Genetic Algorithms are used to recognize face. In early 1990s a verity of work had been done on neural networks to get better solution. Face recognition system based on supervised and unsupervised feature extraction on neural networks both was developed in early 1990s. In the unsupervised case, the leaning is formulated as a restoration error minimization problem while the supervised learning is formulated by function approximation error minimization problems. For both cases the origin and spanning bases are calculated by gradient methods with annealing processes which serve for obtaining solutions with small errors. Professor Garrison W. Cottrell In 1990, used unsupervised feature extraction for face recognition (Cottrell, 1990). In 1990, another researcher M. Flemming also derived face recognition using unsupervised feature extraction (Flemming, 1990). In year of 1990 theses two researcher Garrison W. Cottrell and M. Flemming done a combined work together titled 'Categorization of Faces Using Unsupervised Feature Extraction', (Fleming and Cottrell, 1990). Their developed network achieved nearly perfect recognition rates for familiar test images and extremely high classifications rates for completely novel stimuli. The examination of the network solution revealed an internal representation that is holistic in nature. These findings constitute a strong support for the utility of the proposed model, and warrant its further investigation as an account of the facial recognition process as it occurs in humans.

In the early 90's researchers developed graph matching algorithm technique to implement face recognition model i.e. range data to build face recognition models. In 1990, Lee & Milions worked on the problem of matching range images of human faces for the purpose of establishing a correspondence between similar features of two faces is addressed (Lee and Milios, 1990). Distinct facial features correspond to convex regions of the range image of the face, which is obtained by a segmentation of the range image based on the sign of the mean and Gaussian curvature at each point. Each convex region is represented by its extended Gaussian image, a 1-1 mapping between points of the region and points on the unit sphere that have the same normal. Several issues were examined in their research that are associated with the difficult problem of interpolation of the values of the extended Gaussian image and its representation and a similarity measure between two regions is obtained by correlating their extended Gaussian images. Lee & Milions established the optimal correspondence, a graph matching algorithm is applied. The algorithm used the correlation matrix between convex regions of the two faces and incorporated additional relational constraints that accounted for the relative spatial locations of the convex regions in the domain of the range image.

In 1992 Gaile G. Gordon explored the face recognition system from a representation based on features extracted from range images (Gordon, 1992). Gaile G. Gordon pointed out that the depth and curvature features have several advantages over more traditional intensity based features. Specifically, curvature descriptors 1) have the potential for higher accuracy in describing surface based events, 2) are better suited to describe properties of the face in areas such as the cheeks, forehead, and chin, and 3) are viewpoint invariant. Faces were represented in terms of a vector of feature descriptors and comparison between two faces is made based on their relationship in the feature space. His work provided detailed analysis of the accuracy and discrimination of the particular features extracted, and of the effectiveness of the recognition system for our test database of 24 faces. The experiment results were very promising. In many cases it was shown that feature accuracy is limited more by surface resolution than by the extraction process. Recognition rates in Gaile G. Gordon's experiments were in the range of 80% to 100%.

Kirby and Sirovich in 1990, introduced linear algebra to the problem of facial recognition (Kirby and Sirovich, 1990). They showed that principal component analysis can be used to the problem of facial recognition. Their idea was to use principal component analysis on a set of face images to form a set of basis features. These basis features are known as eigenpictures or eigenfaces. Basically, eigenfaces are the principal components of a distribution of face images. Their exploitation of natural symmetries (mirror images) in a well-defined family of patterns (human faces) was discussed. This results in an extension of the data and imposes even and odd symmetry on the eigenfunctions of the covariance matrix, without increasing the complexity of the calculation. According to their resulting approximation of faces projected from outside of the data set onto this optimal basis improved on average.

In 1991, the seminal work of Matthew Turk and Alex Pentland popularised the Eigenfaces method, a well studied method of face recognition (Turk and Pentland, 1991). Turk and Pentland used eigenfaces method to face detection and recognition both. They introduced ways to extract the eigenvectors based on matrices sized by the number of images rather than the number of pixels because conventional principal component analysis was intractable on large face image sets.

After Turk and Pentland (Turk and Pentland, 1991) established the eigenface approch, Bruce A. Draper and his research group, improved the eigenface method by proper selection eigenvectors and distance measurement (Yambor et al., 2002). Their study examined the role of Eigenvector selection and Eigenspace distance measurement procedure on PCA-based face recognition systems. In particular, their system built on earlier results from the FERET face recognition evaluation studies, which created a large face database (1,196 subjects) and a baseline face recognition system for comparative evaluations. This study looked at using a combinations of traditional distance measures (City-block, Euclidean, Angle, Mahalanobis) in Eigenspace for improved performance in the matching stage of face recognition. A statistically significant improvement was observed for the Mahalanobis distance alone when compared to the other three alone. However, no combinations of these measures appear to perform better than Mahalanobis alone. This study also examined questions of how many Eigenvectors to select and according to what ordering criterion. It compares variations in performance due-to different distance measures and numbers of Eigenvectors. Ordering Eigenvectors according to a like-image difference value rather than their Eigenvalues also had to be considered.

In 2001 Wan-Chi Siu and his team designed an algorithm where a pair of eye candidates are selected by means of the genetic algorithm to form a possible face candidate (Wong et al., 2001). The fitness value of each candidate is measured based on its projection on the eigenfaces. In order for them to improve the level of detection reliability, each possible face region is normalized for illumination. After a number of iterations, all the face candidates with a high fitness value are selected for further verification.

In case of face recognition a wide variety of research work has been done, as one of the main challenges faced by the face recognition techniques lies in the difficulties of collecting samples also a consideration in many circumstances. In 2006, F. Zhang and his research group surveyed on the training set sample optimization (Tan et al., 2006). The main discretion of their paper was fewer samples per person mean less laborious effort for collecting them, lower cost for storing and processing them. Many reported face recognition techniques rely heavily on the size and representative of training set, and most of them will suffer serious performance drop or even fail to work if only one training sample per person is available to the systems. This situation is called 'one sample per person' problem: given a stored database of faces, the goal is to identify a person from the database later in time in any different and unpredictable poses, lighting, etc. from just one image. Such a task is very challenging for most the algorithms due to the extremely limited representative of training sample. Numerous techniques have been developed to attack this problem, and the purpose of their work was to categorize and evaluate these algorithms. The prominent algorithms were described and critically analyzed. Relevant issues such as data collection, the influence of the small sample size, and system evaluation were discussed, and several promising directions for future research were also proposed in their survey paper.

Principle Component Analysis (PCA) technique is an important and well-developed area of image recognition and to date many linear discrimination methods have been put forward. Despite these efforts, there persist in the traditional PCA some weaknesses. In 2005, Nhat and his fellow researchers worked on the improvement on PCA algorithm based face recognition (Nhat and Lee, 2005b). In their paper, they proposed a new PCA-based method that can overcome one drawback existed in the traditional PCA method. In face recognition where the training data were labeled, a projection often required to emphasize the discrimination between the clusters. PCA could fail to accomplish this easy task, as they were unsupervised techniques. The directions that maximized the scatter of the data might not be as adequate to discriminate between clusters. So they proposed a new PCA-based scheme which can straightforwardly take into consideration data labeling, and makes the performance of recognition system better. Experiment results of their method achieved better performance in comparison with the traditional PCA method. In the same year 2005, Nhat an his research team also worked on the improvement of another polpular technique of face recognition Linear discrimination analysis (LDA) technique, (Nhat and Lee, 2005a).

As the solution of the face recognition problem many techniques and methods are practiced but the Principle Component Analysis (PCA) based eigenface method is very effective and one the most practiced and polpular method, which is improved and practiced by many researcher over and over to achieve the best result. In 2011, Müge Çarıkçı and Figen Özen applied Eigenfaces method for face recognition and achieved a high success rate (üge Çarıkçı and Özen, 2012). The objective of Principle Component Analysis (PCA) is the replacement of correlated vectors of large dimensions with the uncorrelated vectors of smaller dimensions and calculate a basis for the data set. Main advantages of the Principle Component Analysis (PCA) are its low sensitivity to noise, the reduction of the requirements of the memory and the capacity, and the increase in the efficiency due to the operation in a space of smaller dimensions, these advantages and the objectives are mentioned by Müge Çarıkçı and Figen Özen in their work of eigenface method based face recognition system. The success rate for the large database used is found to be 94.74% by their proposed method.

In most recent works the techniques that have been practicing along with the Principle Component Analysis (PCA) and producing remarable results is 3D face modeling and convolutional neural networks (CNN), both techniques are based on deep learning. In 2019, Rajeev Ranjan and his fellow research mates developed deep convolutional neural networks (CNN) based face recognition and classification model (Ranjan et al., 2019). They presented an algorithm for simultaneous face detection, landmarks localization, pose estimation and gender recognition using deep convolutional neural networks (CNN). Their proposed method was called, HyperFace, fuses the intermediate layers of a deep CNN using a separate CNN followed by a multi-task learning algorithm that operates on the fused features. It exploited the synergy among the tasks which boosts up their individual performances. Additionally, they proposed two variants of HyperFace: (1) HyperFace-ResNet that builds on the ResNet-101 model and achieves state-of-the-art performance, and (2) Fast-HyperFace that uses a high recall fast face detector to improve the speed of the algorithm. Their extensive experiments showed that the proposed models were able to capture both global and local information in faces and performed significantly better than many competitive algorithms for each of these four tasks but their work was not focused on face recognition, though the classifier algorithm they proposed is dynamic an multi purposed classifier.

In 2014, Yaniv taigman and his team worked on 3D face modeling system to recognize face and their system performance was close to human-level performance (Taigman et al., 2014). In their working procedure the face representation step was done by employment of explicit 3D face modeling in order to apply a piece wise affine transformation, and a face representation was derived from a nine-layer deep neural network. This deep network was involved with more than 120 million parameters using several locally connected layers without weight sharing, rather than the standard convolutional layers. They trained it on a very larges facial dataset, an identity labeled dataset of four million facial images belonging to more than 4,000 identities. Their method achieved an accuracy of 97.35% on the Labeled Faces in the Wild (LFW) dataset.

Chapter :3 Methodology

3.1 Methodology

The task of identify an already detected face as a known or unknown face, and in more advanced cases exactly classify the identified face is the primary motive of the face recognition system. Face recognition system uses a persons face as its corresponding input and acts as a biometric identification and verification system. Similar to other biometric system such as fingerprint or voice recognition system, face has many unique structures and features and face recognition is the most natural means of biometric identification of human beings.

Real time face recognition process requires a image dataset by image acquisition and preprocessing on the images. The recognition system works on only face image, so the face has to be detected from the image set. Then feature extraction method will be applied on the input faces and based on the features the system classify the faces.

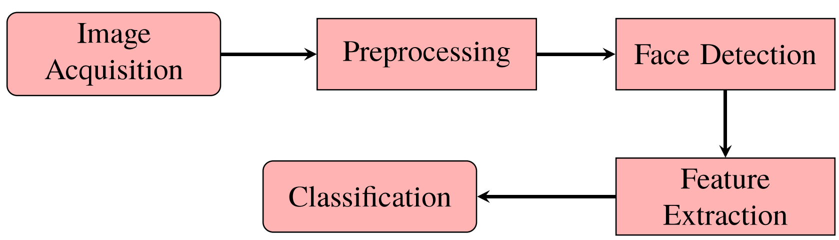

Figure 3.1: Stages in Face Recognition

Face recognition systems are built on the idea that each person has a particular face structure and facial symmetry, computerized face-recognition is possible using those signatures. Because the face itself is considered a global feature, and that's why feature extraction is the most crucial step in face recognition and in pattern matching in general. In figure 3.1 The stages of face recognition are mentioned.

3.1.1 Image Acquisition

The primary stage in fact the first step is to gather some face image data set and split them into training set to train the recognition system classifier and testing set to test classifier. The image acquisition is done in two different ways to implement the real-time face recognition system. The first way is import a static face image database and the other way is to build a database by capturing images from real-time video stream.

Image Acquisition from image dataset

Image Acquisition from image dataset is the easiest way to acquire images. A database comprised with face set is needed to import which can be either collected from a source or can be created with real life subjects face images. Both of the procedure is practised to acquire images. The image data sets are collected from the Cambridge University Computer Laboratory and University of Stirling, and also a dataset is created with face images of some pupils of World University of Bangladesh.

- **The AT&T face database** The popular AT&T image set a database of faces created by AT&T Laboratories Cambridge is used to demonstrate the method. The AT&T data set which contains 10 different images of each of 40 distinct subjects. For some subjects, the images were taken at different times, varying the lighting, facial expressions (open / closed eyes, smiling / not smiling) and facial details (glasses / no glasses). All the images were taken against a dark homogeneous background with the subjects in an upright, frontal position.The files are in portable gray map (.pgm) format. The size of each image is 92×112 pixels, with 256 grey levels per pixel. The images are organised in 40 directories one for each subject, which have names of the form sX, where X indicates the subject number in between 1 to 40. In each of these directories, there are ten different images of that subject, which have names of the form Y.pgm, where Y is the image number for that subject in between 1 to 10.

- **The Color image database** The Color image database is a image data set that is being created with face images of some pupils of World University of Bangladesh. The data set comprised with 22 different people as subject and this data set contains ten to thirteen (10-13) different images of each distinct subject. For some subjects, the images were taken at different times, varying the lighting, facial expressions (open / closed eyes, smiling / not smiling) and facial details (glasses / no glasses). All the images were not taken against a fixed or homogeneous background but the background of this image set is more inconsistent and complex. In these image set the face detection is necessary because the images were taken with the subjects in an upright, frontal position in a vast background, not only containing the face portion which is demand of the eigenface method. The images are high color image and the files are in .JPG format. The size of each image is 1280×720 pixels, with three differnt channel Red, Green and Blue (RGB) and each channel has 256 grey levels per pixel. The images are organised in 22 directories one for each subject, which is named after the subject name 22 subjects with unique name. In each of these directories, there are ten to thirteen (10-13) different images of that subject.

- **Utrecht ECVP 2D Face set** Utrecht ECVP 2D Face set is collected from the School of Natural Sciences, University of stirling. The images taken and collected at the European Conference on Visual Perception in Utrecht, 2008. The image set contains total 131 images of 52 persons with three to four (3-4) different images of each subject. The face expression is usually a neutral and a smiling pose of each subjects. The image is comprised with frontal face so face detection is not needed. The images are high color image and the files are in .JPG format. The image resolution is 900×1200 pixels, with three differnt channel Red, Green and Blue (RGB) and each channel has 256 grey levels per pixel. The images of all subjects are organised in a single directory.

- **Pain expressions 2D Face set** Pain expressions 2D Face set is collected from the School of Natural Sciences, University of stirling. The image set contains total 220 images of 23 subjects, nine to ten (9-10) images of each subject. This data set contains posed expressions, usually 2 of each of the six basic emotions plus a 45 degree and profile neutral. For this image data set face detection is necessary. The images are high color image and the files are in .JPG format. The image resolution is 720×576 pixels, with three differnt channel Red, Green and Blue (RGB) and each channel has 256 grey levels per pixel. The images of all subjects are organised in a single directory.

- **Abrdeen 2D Face set** Abrdeen 2D Face set is collected from the School of Natural Sciences, University of stirling. The image set contains total 440 images of 42 subjects, ten to twelve (10-12) images of each subject. This data set contains posed expressions, got some variations in lighting, 8 have varied viewpoint. For this image data set face detection is necessary. The images are high color image and the files are in .JPG format. The image resolution is variable from 336×480 to 624×544 pixels, with three differnt channel Red, Green and Blue (RGB) and each channel has 256 grey levels per pixel. The images of all subjects are organised in a single directory.

- **Stirling Faces Database** Stirling Faces Database is collected from the School of Natural Sciences, University of stirling. The image set contains total 309 images of 35 identities, eight to nine (8-9) images of each subject. This data set contains images with different posed expressions. No need for face detection for this image data set. The images are monochrome and the files are in .GIF format. The image resolution is 269×369 pixels. The images of all subjects are organised in a single directory.

Image Acquisition from real-time video

In real time face recognition there is no need of static data set, image acquisition is done from the real time video stream and real-time training data set is being created. From the real time video stream (i.e. webcam) a snap shot has been taken with a constant time interval and the cropped face image to be saved in training data set during training the classifier, to train the classifier 10 images were taken. The training images are color images (RGB), saved in Bitmap format (.bmp) and the size of each image is 1280×720 pixels. The images are organised in n training directories created one for each subject, which have names of the form sX, where X indicates the subject number in between 1 to n. In each of these directories, there are ten different images of that subject, which have names of the form Y.bmp, where Y is the image number for that subject in between 1 to 10.

To recognize a new face as for testing, the test image will be taken during the initialization of the video player in testing period. If, a face appeared in the real time video frame that face image is cropped and that was used as test image to classify the subject.

3.1.2 Preprocessing

Preprocessing the images of data set provides more robustness and accuracy to face recognition system. The proprocessing images increases the efficiency and make the recognition system more correct. Resizing the images into a uniform dimension and grayscale format is mandatory according to the eigenface method.

As image acquisition was done in previous step, the images was then converted to gray scale image for farther processing. For preprocessing Median filter and Histogram Equalization filter has been used.

The Median filter considers each pixel in the image in turn and looks at its nearby neighbors to decide whether or not it is representative of its surroundings. Instead of simply replacing the pixel value with the mean of neighboring pixel values, it replaces it with the median of those values. The median is calculated by first sorting all the pixel values from the surrounding neighborhood into numerical order and then replacing the pixel being considered with the middle pixel value. If the neighborhood under consideration contains an even number of pixels, the average of the two middle pixel values is used. The median is a robust average so a single very unrepresentative pixel in a neighborhood will not affect the median value significantly. The median value must actually be the value of one of the pixels in the neighborhood, the median filter does not create new unrealistic pixel values when the filter straddles an edge. Using Median filter, any salt and paper noise is removed.

Histogram Equalization has been used to enhance the images. Image enhancement is the process of adjusting digital images so that the results are more suitable for display or image analysis. Histogram equalization is a technique for adjusting image intensities to enhance contrast. This method usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values. Using Histogram Equalization, the contrast of images has been increased.

After the images has been converted to gray scale, noise removed and contrast increased the images are segmented to only select and crop face images.

The AT&T data set and Stirling faces database are already preprocessed and simple image sets to work with. Images of these data sets are denoised, histogram equalized and resized suitably in 112×92 pixels and the images are containing only face portion ignoring the background.

Image dataset containing color images needs proprocessing. The image set that is being created needs proprocessing as the imageset contains true color images. In figure 3.2 the steps of necessary image proprocessing steps of images of color image database and real-time video was highlighted.

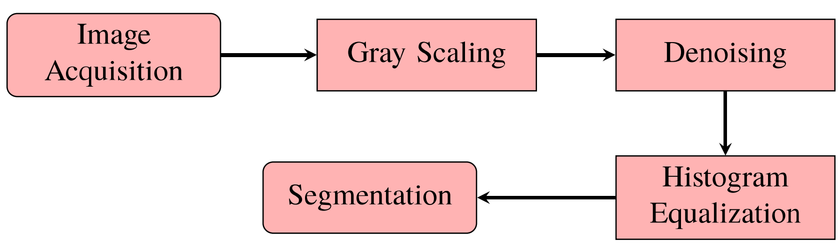

Figure 3.2: Preprocessing Steps

First the images are converted into grayscale because the original images were true color image. Then median filter is used to denoise the images and histogram equalization filter is used to increase the contrast of images. Then the images are resized to smaller dimension as the captured images are too large in dimension as the images of color image database and real-time video is size 1280×720 pixels, which is way too large and complex to process by the feature extraction method. So, images of those both database are resized suitably in 112×92 pixels. Then the eigenface method works on the face portion of image, so images are cropped to ignore the background show only the face, this is done in the stage of face detection.

The proprocessing steps of the real time video stream is almost same as the preprocess the color image set. On real time video stream, when detection module detects a face, it locks on face feature and starts tracking. Then detection module selects a single image frame and applies gray scaling, median filter, histogram normalization filter and cropping respectively.

The Utrecht ECVP 2D Face set, Pain expressions 2D Face set and Aberdeen 2D Face set are consist of colored, front facing peoples images. In these image sets gray scale conversion, median filter and histogram equalization filter is applied to gain gray scale, noise free and high contrast images. As the eigenface method works on the face portion of image, so images are cropped to ignore the background and show only the face.

3.1.3 Face Detection

The problem to be solved is detection of faces in an image. A human can do this easily, but a computer needs precise instructions and constraints. Viola and jones's algorithm presented by Paul Viola and Michael Jones is used as the basis of the design of the face detection module (Viola and Jones, 2004). To make the task more manageable, Viola-Jones requires full view frontal upright faces. Thus in order to be detected, the entire face must point towards the camera and should not be tilted to either side. While it seems these constraints could diminish the algorithm's utility somewhat, because the detection step is most often followed by a recognition step, in practice these limits on pose are quite acceptable. Viloa-Jones algorithm works as an examining box for a sliding window in an image to try to match different dark/light regions so it can identify a face. The size of the window varies on different scales for different faces, however, the ratio of the window remains unchanged. The reasons of using Viola-Jones algorithm are as follow,

- Robust - very high detection rate (true-positive rate) & very low false-positive rate always.
- Real time - For practical applications at least 2 frames per second must be processed.
- Face detection only - The goal is to distinguish faces from non-faces.

Viola and jones's algorithm is 15 times quicker than any technique at the time of release with 95% accuracy at around 17 fps, a fast and robust technique for face detection(Viola and Jones, 2004).

Face Tracking

For face tracking KLT (Kanade-Luas-Tomasi) algorithm has beed used. After detection module detects a face, it selects some face features or interest points and tries to find their shift continuously. This algorithm is based on feature point tracking on the first face and keeps on tracking it until there is no feature point available. For the first feature points set on tracking, eigenvalue algorithm is used to find the corner points(Tomasi and Kanade, 1991). It directly computes the value of eigenvalues to determine whether it is a point of interest or not. For each consecutive frame it tries to match the points from the previous step. As long as there are at least 2 points exist in the video-frame, it continues to track the face by finding out the affine transformation of those points.

3.1.4 Feature Extraction

Feature extraction is the most vital stage of real time face recognition system. There are some popular feature extraction method for face recognition based on various classification techniques of machine learning.

- Principal Component Analysis(PCA) based Eigenfaces Algorithm
- Linear Discriminate Analysis(LDA)
- Support Vector Machine

- Elastic Bunch Graph Matching using Fisherface Algorithm
- Hidden Markov model
- Neural Motivated Dynamic Link Matching
- Convolutional Neural Network (CNN)

The feature extraction process is designed based on Principal Component Analysis (PCA) and the procedure is called eigenface method. The merit of this particular feature extraction method is to judged on the basis of how much it is effective and appropriate in discrimination between objects of interest, herein called human faces, and the eigenface method based on principal component analysis is an efficient approach to extract features.

3.1.5 Principle Component Analysis

Principal Component Analysis (PCA) is the main prerequisite of the eigenface method. Digital image classification is a high dimensional problem and as the dimensionality of data grows density of observation decreases, so the classification problem complexity arises. Principal Component Analysis (PCA) mainly works on the dimension reduction. In case of images, working on the original dimension is wasting the machine learning algorithm. Principal Component Analysis (PCA) combines all the attributes of original dimensions and construct a new set of dimension which is lower than the original to represent the data.

Principal Component Analysis (PCA) is a mathematical tool to find the direction of the greatest amount of variance, which actually extracts features by finding the principle components. To get the principal components of a dataset, the first task is to centering the data by subtracting the mean from every attributes. Then the covariance matrix has to be computed, the covariance matrix indicates the nature of change or the correlation among the attributes. Then deriving the eigenvectors and eigenvalues from the covariance matrix to get the principal components. The principle components are the eigenvectors with largest eigenvalues which indicates towards the direction of greatest variance.

3.1.6 The "Eigenface" Method

The eigenvectors (principal components) of the set of faces are called "eigenfaces" which are the characteristic features of faces. We can extract them from the original face image using mathematical tool called Principal Component Analysis (PCA). Face recognition systems are based on the assumption that each person has a specific face structure, meaning any faces possess characteristic features. The eigenfaces method is developed by deriving Principal Component Analysis (PCA) and used in computer vision for human face recognition. The seminal work of Turk & Pentland popularised the Eigenfaces method, a well studied method of face recognition (Turk and Pentland, 1991). Although the approach has now largely been superseded, it is still often used as a benchmark to compare the performance of other algorithms against, and serves as a well introduction to subspace-based approaches to face recognition.

The strategy of the Eigenfaces method consists of extracting the characteristic features on the face and representing the face as a linear combination of the so called eigenfaces obtained from the eigenvector retrieved by feature extraction.

The Eigenfaces method is a simplest approach is to think of it as a template matching problem but problems arise when performing recognition in a high dimensional space because working with digital image comes along with high dimensionality. Applying Principal Component

Analysis (PCA), significant improvements can be achieved by first mapping the data into a lower dimensionality space. PCA is a method of transforming a number of correlated variables into a smaller number of uncorrelated variables and using PCA technique we can transform any original face image from the training set into a corresponding eigenface from high dimension to low. Recognition occurs by projecting a new unknown face image into the subspace which is called face space spanned by the eigenfaces and then we can classify the face by comparing its position in face space with the faces position of the training set.

3.1.7 Classification

Once the face images have been projected into the eigenspace, the distance between any pair of face images can be calculated by ïňĄnding the Euclidean distance between their corresponding weight vectors. The smaller the distance between the feature vectors, the more similar the faces. This distance can be defined as similarity score based on the inverse Euclidean distance to classify an input face image. Using inverse Euclidean distance shows that the match with smallest distance got the highest similarity score.

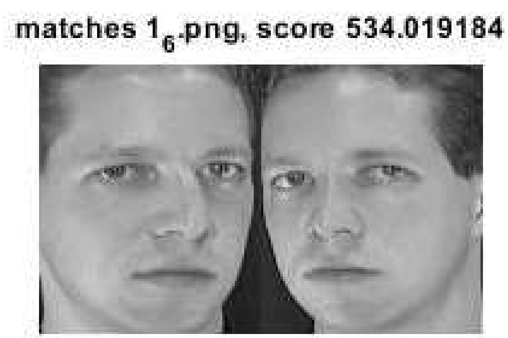

Figure 3.3: True positive match with similarity score

To perform face recognition, the similarity score is calculated between a test face image and each of the training images. The matched face is the one with the highest similarity, and the magnitude of the similarity score indicates the conïňĄdence of the match (with a unit value indicating an exact match). In figure is an example of a true positive match that was found on the training set with a score of 534.0191.

To detect cases where no matching face exists in the training set, a minimum threshold value is set for the similarity score and ignore any false positive matches below this score. Thus system can reject the wrong results, which makes the system more reliable.

The threshold resolves the false positive result acceptance problem. The mechanism of the threshold value factor rejecting the false positive match and accepting the true positive match is illustrated In figure 3.4.

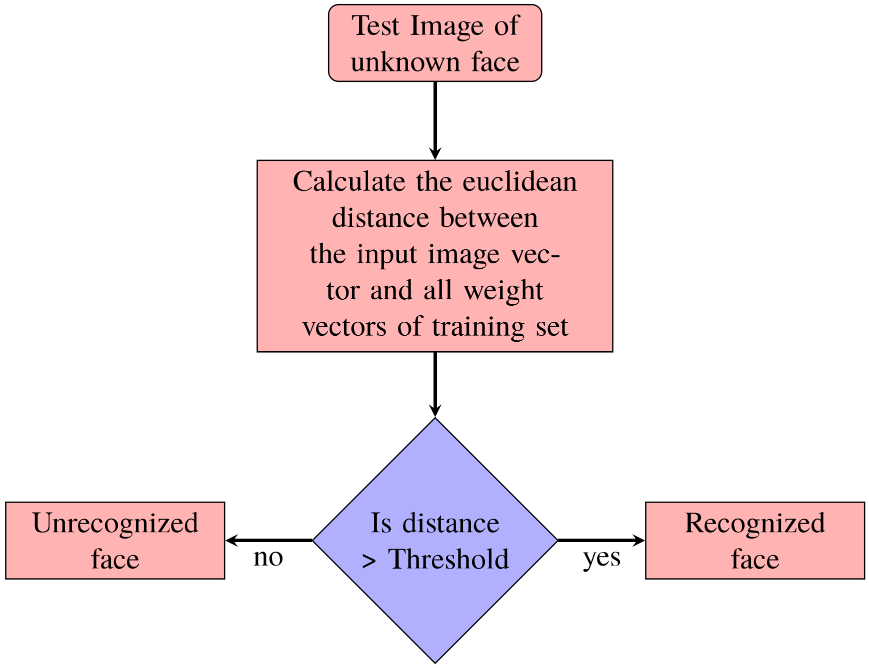

Figure 3.4: Threshold value rejects false positive result

3.2 Justification of Methodology

3.2.1 Viola-Jones Algorithm

At the time of its development, Viola-Jones algorithm was one of the first object detection algorithms to run in real-time and was widely used for face detection. It was and still is quite popular. The Viola-Jones approach offers real-time performance and scale/location invariance, but it still has a few disadvantages - intolerance to object rotations, sensitivity to illumination variations, etc.

3.2.2 KLT Tracker Algorithm

The Kanade–Lucas–Tomasi (KLT) feature tracker is an approach to feature extraction. It is proposed mainly for the purpose of dealing with the problem that traditional image registration techniques are generally costly. The KLT feature tracker is based on two papers: In the first paper, Lucas and Kanade (Lucas et al., 1981) developed the idea of a local search using gradients weighted by an approximation to the second derivative of the image. In the second paper Tomasi and Kanade (Tomasi and Kanade, 1991) used the same basic method for finding the registration due to the translation but improved the technique by tracking features that are suitable for the tracking algorithm. The proposed features would be selected if both the eigenvalues of the gradient matrix were larger than some threshold.

KLT algorithm makes use of spatial intensity information to direct the search for the position that yields the best match. It is faster than traditional techniques for examining far fewer potential matches between the images. After Viola-Jones algorithm detects a face, KLT algorithm selects some face features or interest points and tries to find their shift continuously. This algorithm is based on feature point tracking on the first face and keeps on tracking it until there is no feature point available. For the first feature points set on tracking, eigenvalue algorithm is used to find the corner points(Tomasi and Kanade, 1991). It directly computes the value of eigenvalues to determine whether it is a point of interest or not. For each consecutive frame it tries to match the points from the previous step. As long as there are at least 2 points exist in the video-frame, it continues to track the face by finding out the affine transformation of those points.

3.2.3 Eigenface Method based on Principle Component Analysis

Eigenfaces is the name given to a set of eigenvectors when they are used in the computer vision problem of human face recognition. The approach of using eigenfaces for recognition was developed by Sirovich and Kirby (Kirby and Sirovich, 1990) and used by Matthew Turk and Alex Pentland (Turk and Pentland, 1991) in face classification. The eigenvectors are derived from the covariance matrix of the probability distribution over the high-dimensional vector space of face images. The eigenfaces themselves form a basis set of all images used to construct the covariance matrix. This produces dimension reduction by allowing the smaller set of basis images to represent the original training images. Classification can be achieved by comparing how faces are represented by the basis set.

The reason of using eigenface method for face recognition are its features. The features of eigenface method are as follow,

- Its independence from the facial geometry
- The simplicity of realization
- Possibility of real-time realization even without special hardware
- The ease and speed of recognition with respect to the other methods
- The higher success rate in comparison to other methods

3.3 Description of Methodology

3.3.1 Eigenface Method for Face Recognition

The basis of the eigenfaces method is the Principal Component Analysis (PCA). Eigenfaces and PCA have been used by Sirovich and Kirby to represent the face images efficiently (Kirby and Sirovich, 1990) . They have started with a group of original face images, and calculated the best vector system for image compression. Then Turk and Pentland applied the Eigenfaces to face recognition problem (Turk and Pentland, 1991). The Principal Component Analysis is a method of projection to a subspace and is widely used in pattern recognition.

The objective of PCA is the replacement of correlated vectors of large dimensions with the uncorrelated vectors of smaller dimensions and calculate a basis for the data set. Main advantages of the PCA are its low sensitivity to noise, the reduction of the requirements of the memory and the capacity, and the increase in the efficiency due to the operation in a space of smaller dimensions, these advantages and the objectives are metioned by Müge Çarıkçı and Figen Özen in their work of eigenface method based face recognition system (üge Çarıkçı and Özen, 2012). The strategy of the Eigenfaces method consists of extracting the characteristic features on the face and representing the face in question as a linear combination of the so called 'eigenfaces' obtained from the feature extraction process.

After done with image acquisition and preprocessing, next step is loading the images to prepare the data and the eigenface method is ready to work on. As the method follows the procedure given below:-

Calculating the eigenfaces:

The first task is calculate principle components the eigenfaces of the training set. Evaluation of the calculation procedure flowchart of eigenfaces is illustrated in figure 3.5.

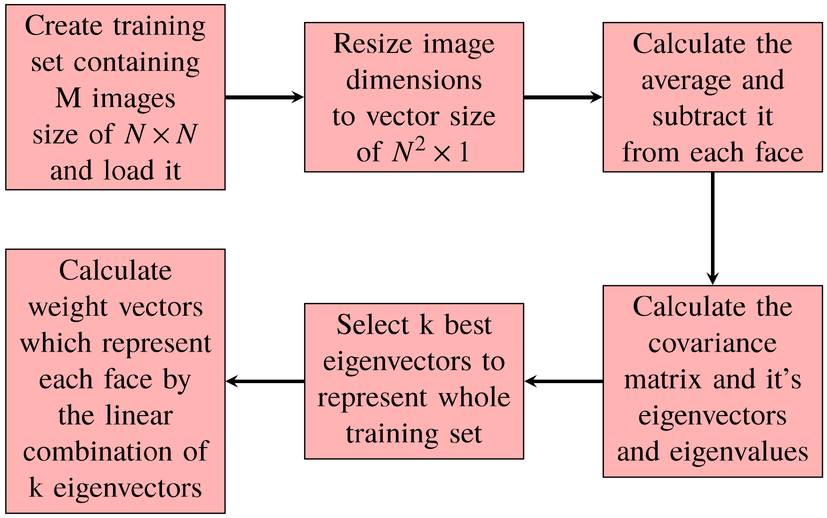

Figure 3.5: Steps to calculate the eigenfaces

1. Read the images $I_1, I_2, ...I_M$ of training set containing M images.

2. Convert each face image I size of $N * N$ to vectors Γ_i size of $N^2 * 1$.

3. Calculate the average/mean vector of training face vectors:

$$\Psi = \frac{1}{M}\Sigma_{i=1}^{M}\Gamma_i$$

   Normalize the face vectors, subtract the mean from the face vectors to obtain the mean-shifted vector:

$$\Phi_i = \Gamma_i - \Psi, i = 1, 2, ..., M$$

4. Calculate the eigenvectors and eigenvalues of the covariance matrix $C = A \cdot A^T$, where $A = [\Phi_1, \Phi_2, ...\Phi_M]$. But the matrix AA^T is very large. So, compute the eigenvectors v_i of $C = A^T \cdot A$ to calculate the the eigenvectors u_i of AA^T.

   Note: AA^T and $A^T A$ have the same eigenvalues and their eigenvectors are related as follows: $u_i = Av_i$.

5. Order the eigenvectors by their corresponding eigenvalues, in decreasing order. Retain only k best eigenvectors with the largest eigenvalues (the principal components) such that $k <= M$ and can represent the whole training set.

6. Represent each face image a linear combination of all k eigenvectors. Calculate the weight vector for each face which is the eigenface representation of that corresponding face. The formula to calculate weight vector is:

$$w_j = u_j^T \cdot \Phi_i, i = 1, 2, ...M; j = 1, 2, ...k$$

   The whole set of weight vector, $\Omega = [w_1, w_2, ...w_k]$

Using eigenfaces recognize a new face:

The test image is going to be represented by the eigenvectors projected on the eigenspace to recognize a new face. The process to recognize a new face is described in figure 3.6 step by step.

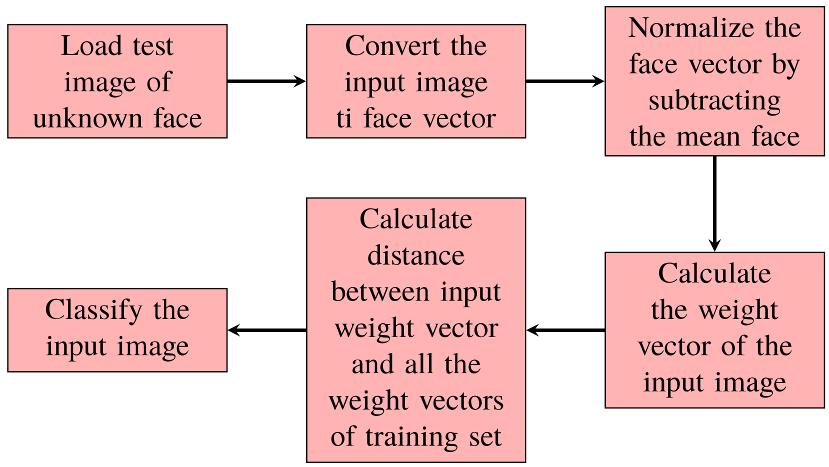

Figure 3.6: Steps to recognize a new face

1. Read the test image I_{new}.
2. convert the test image into face vector Γ_{new}.
3. Normalize the face vector by subtracting the mean face.
$$\Phi_{new} = \Gamma_{new} - \Psi$$
4. Project the normalized face onto eigenspace and calculate the weight vector of the input image.
$$w_i = u_i^T \cdot \Phi, i = 1, 2, \ldots k$$
The input image weight set, $\Omega_{new} = [w_1, w_2, \ldots . w_k]$
5. Calculate the distance between the input image weight vector and all the weight vectors of training set.
$$\varepsilon = ||\Omega_{new} - \Omega||^2$$
6. The distance against a threshold value is going to recognize the new face either known or unknown.

3.3.2 Proposed Eigenface method selecting Discriminant eigenvectors

Implementing the eigenface method, the most important part is the selection of the feature vectors i.e. the eigenvectors. The proposed method is focusing on the selection of the k best eigenvectors by selecting the discriminant eigenvectors. The flow diagram of the proposed eigenface method selecting the discriminant eigenvectors is illustrated in figure 3.7.

The eigenspace or the face space was created of the combination of the selected eigenvectors derived from the training set. The result of the eigenface method depends on selection accuracy

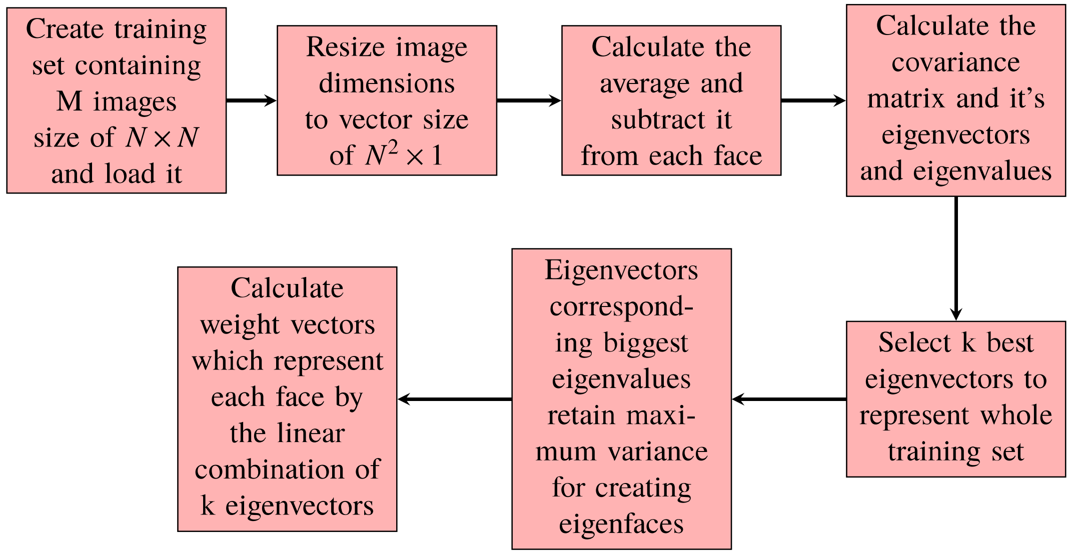

Figure 3.7: The Proposed Method

of eigenvectors as the test image will be projected on the eigenspace. The eigenspace should contain the most of variance of the training set to judge test image features and restore the equivalent image from training set. So, selecting the of eigenvector the selection process used is the discriminant eigenvectors for which variance accounted for.

The way to select the discriminant eigenvectors is select the eigenvectors with corresponding large eigenvalues. So, set of the eigenvector with corresponding large eigenvalues retains most of the variance. The observation of the behavior of eigenvectors and eigenvalues is the key to select discriminant eigenvectors.

It can be useful to take a look at the eigenvectors or eigenfaces that are generated during training. In figure 3.8 the 10 eigenfaces that was generated by images of training set, number of the eigenfaces was chosen arbitrary.

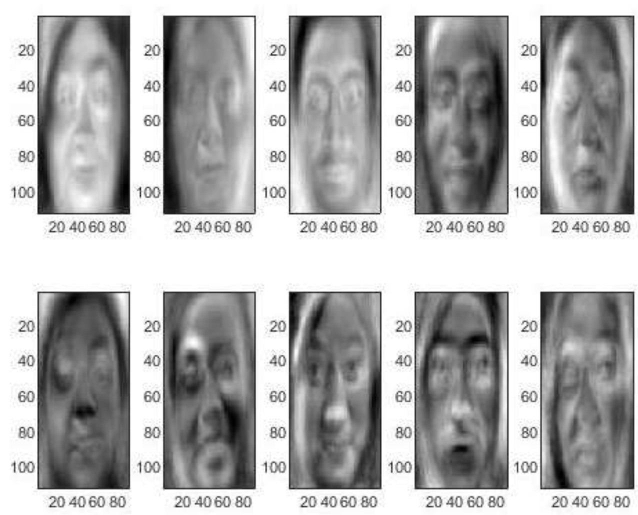

Figure 3.8: Selected 10 eigenfaces

The facespace projection that performed in the final step of training generated a feature vector of 10 coefficients for each image. The feature vectors represent each image as a linear combination of the eigenfaces defined by the coefficients in the feature vector; the multiplication of each eigenface by its corresponding coefficients and then sum these weighted eigenfaces together, roughly the reconstruction of input image can possible. The feature vectors can be thought of as a type of compressed representation of the input images. Notice that the different eigenfaces shown above seem to accentuate different features of the face. Some focus more on the eyes, others on the nose or mouth, and some a combination of them. If we generated more eigenfaces, they would slowly begin to accentuate noise and high frequency features. It is mentioned earlier that the choice of 10 principal components was somewhat arbitrary. Increasing this number would mean that we would retain a larger set of eigenvectors that capture more of the variance within the data set. We can make a more informed choice for this number by examining how much variability each eigenvector accounts for. This variability is given by the eigenvalues.

To find out the discriminant eigenvector first have calculate the normalized eigenvalue:

$$eval_{norm} = \frac{evals}{sum(evals)}$$

This normalized eigenvalues plotted against the a number of eigenvectors shows the graph of the variance accounting eigenvector. The graph in figure 3.9 shows discriminant eigenvector accounted for most variance.

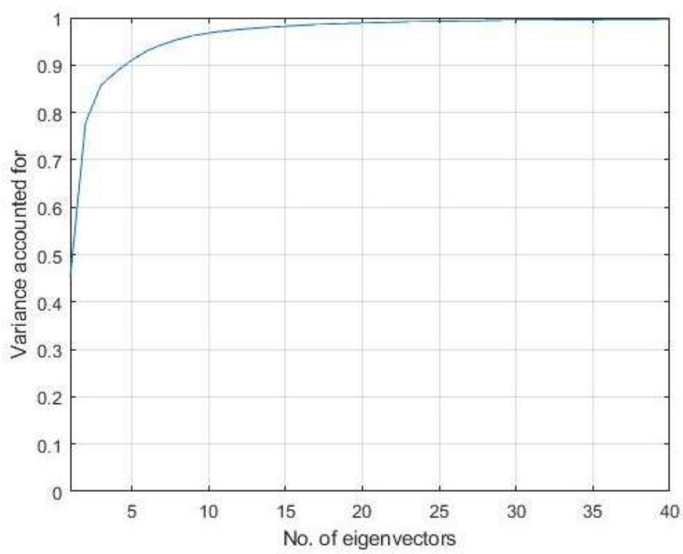

Figure 3.9: Discriminant eigenvector

In graph of figure 3.9 it is shown that the first eigenvector accounts for 50% of the variance in the data set, while the first 5 eigenvectors together account for just over 90%, and the first 10 eigenvectors together account for over 95%. So, the selected 10 eigenfaces was previously said arbitrary but now the selection is justified. By selecting the first 8 eigenvectors, which together account for just around 95% of variance and which is quite capable represent the training set.

Increasing the number of eigenvectors generally increases recognition accuracy but also increases computational cost. Note, however, that using too many principal components does not necessarily always lead to higher accuracy, since we eventually reach a point of diminishing returns where the low-eigenvalue components begin to capture unwanted within-class scaer. The ideal number of eigenvectors to retain will depend on the application and the data set, but in general a size that captures over 90% of the variance is usually a reasonable trade-off.

3.4 Analysis of Requirement

To design and implementation a real time face recognition system specific hardware and standard software platforms are required. To develop a robust real-time face recognition system the required hardware and software should compatible to each other and this should be maintained.

3.4.1 Hardware Requirement

Required hardware to design and implementation a real time face recognition system are mentioned with minimum standard quantity:

- Processor: Intel Core i3
- RAM 4GB
- Hard drive space 80GB
- Real-time video capturing device: Webcam

3.4.2 Software Requirement

Required software to design and implementation a real time face recognition system are mentioned with standard possible options:

- Operating System: Mac OS, Microsoft Windows or Linux.
- Programming platform: MATLAB, GNU Octave, Java or Python.

3.4.3 Programming Platform

The design and implementation of the real time face recognition system is done by using programming language and simulation tool MATLAB. The current version MATLAB 2018a is used for implementation. The MATLAB Add-On Toolboxes: Image Processing Toolbox and Computer Vision System Toolbox are installed, which used to Image processing, analysis and algorithm development. Image Acquisition Toolbox a support package for OS generic video interface also installed to capture real time video stream from a webcam.

3.4.4 Justification of Platform

The reason behind picking up MATLAB is it makes things a lot easier. In MATLAB reading in the image is just reading in a matrix where one can easily modify this matrix using the built-in/custom functions; As MATLAB stands for matrix laboratory.

In other programming languages (e.g. java, python) the learning curve for image processing is steeper as the code for reading in different images are different, not to mention that the code for processing different images are different. Comparing to MATLAB, java or python may be more suitable for multiple platforms on cellphones or tablets, but for prototyping and learning new concepts, MATLAB is definitely the way to go for image vision, because it provides easy accesses to all elements in the image.

Another reason for choosing MATLAB is because of its real-time debugging system. That can test almost every line of code by running it in command line. This reduces the large amount of time for debugging. MATLAB offers many built-in functions, Add-on Toolboxes that make image processing simple and smooth.

Chapter :4 Analysis of Results

The eigenface method was applied to twenty image sets. Among them, the result of six databases (i.e. AT&T Database, Created Color Image Database, Utricht ECVP 2D Face Set, Pain Expression 2D Face Set, Abrdeen 2D Face Set and Stirling Faces Database) has been given in this report to show variation. For each image set, same number of eigenvectors were chosen. For the same number of eigenvectors each image set shows different level of occurrence of variance. The table 4.1 shows the characteristics of each image set on different number of eigenvectors.

Database Name	Selected no. of Eigenvectors	Occurrence of Variance (%)	Time Complexity (seconds)	Proposed no. of Eigenvectors
AT&T face Database	5	93	.558	6
	10	96	.435	
	15	97	.678	
	20	98	.887	
Created Color image Database	5	90	.486	10
	10	95	.564	
	15	98	.980	
	20	99	.781	
Utrecht ECVP 2D Face set	5	79	.480	12
	10	90	.398	
	15	94	.673	
	20	96	.599	
Pain expressions 2D Face set	5	95	.560	15
	10	97	.490	
	15	98	.897	
	20	99	.733	
Abrdeen 2D Face set	5	92	.632	13
	10	96	.870	
	15	97	.598	
	20	98	.976	
Stirling Faces Database	5	89	.655	8
	10	95	.675	
	15	96	.592	
	20	97	.995	

Table 4.1: Selecting the best eigenvector by observing the occurrence of variance & time complexity

AT&T face database shows, 93% variance occurrence with only 5 eigenvectors. The number of eigenvectors was increased to 10, 15, 20 and the occurrence of variance has increased respectively to 96%, 97%, 98%. The execution time of the method also changes depending on the number of eigenvectors. For 5, 10, 15, 20 eigenvectors the time complexity changes to 0.558, 0.435, 0.678, 0.887 seconds respectively.

Created color image database shows, 90% variance occurrence with only 5 eigenvectors. The number of eigenvectors was increased to 10, 15, 20 and the occurrence of variance has increased respectively to 95%, 98%, 99%. The execution time of the method also changes depending on the number of eigenvectors. For 5, 10, 15, 20 eigenvectors the time complexity changes to 0.486, 0.564, 0.980, 0.781 seconds respectively.

Utretch ECVP 2D face set shows, 79% variance occurrence with only 5 eigenvectors. The number of eigenvectors was increased to 10, 15, 20 and the occurrence of variance has increased respectively to 90%, 94%, 96%. The execution time of the method also changes depending on the number of eigenvectors. For 5, 10, 15, 20 eigenvectors the time complexity changes to 0.480, 0.398, 0.673, 0.599 seconds respectively.

Pain epression 2D face set shows, 90% variance occurrence with only 5 eigenvectors. The number of eigenvectors was increased to 10, 15, 20 and the occurrence of variance has increased respectively to 95%, 98%, 99%. The execution time of the method also changes depending on the number of eigenvectors. For 5, 10, 15, 20 eigenvectors the time complexity changes to 0.560, 0.490, 0.897, 0.733 seconds respectively.

Abrdeen 2D face set shows, 93% variance occurrence with only 5 eigenvectors. The number of eigenvectors was increased to 10, 15, 20 and the occurrence of variance has increased respectively to 96%, 97%, 98%. The execution time of the method also changes depending on the number of eigenvectors. For 5, 10, 15, 20 eigenvectors the time complexity changes to 0.632, 0.870, 0.598, 0.976 seconds respectively.

Stirling faces database shows, 93% variance occurrence with only 5 eigenvectors. The number of eigenvectors was increased to 10, 15, 20 and the occurrence of variance has increased respectively to 96%, 97%, 98%. The execution time of the method also changes depending on the number of eigenvectors. For 5, 10, 15, 20 eigenvectors the time complexity changes to 0.655, 0.675, 0.592, 0.995 seconds respectively.

Accuracy test on each image set has been done. Different image set results in different percentage of accuracy.

AT&T face Database				
Total images	Training images	Testing images		Accuracy (%)
		True positive result	False positive result	
400	320	79	1	98.75

Table 4.2: Accuracy of Eigenface Method on AT&T face Database

The AT&T face database consists of total 400 images of 40 different people. For training and testing respectively 320 and 80 images has been selected. Over the course of testing AT&T face database 98.75% accuracy is achieved.

Created Color image Database				
Total images	Training images	Testing images		Accuracy (%)
		True positive result	False positive result	
222	197	20	5	80

Table 4.3: Accuracy of Eigenface Method on Created Color image Database

The Created color image database consists of total 222 images of 22 different people. For training and testing respectively 197 and 25 images has been selected. Over the course of testing the Created Color image Database 80% accuracy is achieved.

Utrecht ECVP 2D Face set				
Total images	Training images	Testing images		Accuracy (%)
		True positive result	False positive result	
131	117	10	4	71.42

Table 4.4: Accuracy of Eigenface Method on Utrecht ECVP 2D Face set

The Utrecht ECVP 2D databse consists of total 131 images of 52 different people. For training and testing respectively 117 and 14 images has been selected. Over the course of testing Utrecht ECVP 2D Face set 71.42% accuracy is achieved.

Pain expressions 2D Face set				
Total images	Training images	Testing images		Accuracy (%)
		True positive result	False positive result	
220	170	39	11	78

Table 4.5: Accuracy of Eigenface Method on Pain expressions 2D Face set

The Pain expressions 2D face set consists of total 220 images of 23 different people. For training and testing respectively 170 and 50 images has been selected. Over the course of testing Pain expressions 2D face set 78% accuracy is achieved.

Abrdeen 2D Face set				
Total images	Training images	Testing images		Accuracy (%)
		True positive result	False positive result	
440	378	48	14	77.41

Table 4.6: Accuracy of Eigenface Method on Abrdeen 2D Face set

The Abrdeen 2D face set consists of total 440 images of 42 different people. For training and testing respectively 378 and 62 images has been selected. Over the course of testing Abrdeen 2D Face set 77.41% accuracy is achieved.

Stirling Faces Database				
Total images	Training images	Testing images		Accuracy (%)
		True positive result	False positive result	
309	277	24	8	75

Table 4.7: Accuracy of Eigenface Method on Stirling Faces Database

The Stirling faces database consists of total 309 images of 35 different people. For training and testing respectively 277 and 32 images has been selected. Over the course of testing Stirling Faces Database 75% accuracy is achieved.

Real-time video recognition				
Total subjects	Training subjects	Testing subjects		Accuracy (%)
		True positive match	False positive match	
20	20	18	2	90

Table 4.8: Accuracy of Eigenface Method on real time face recognition

For the real-time face recognition system has been trained with twenty (20) subjects and the system has been tested against the same subjects. The system has recognized 18 of the tested subjects as true positive match and provided two false positive match. Therefore, over the course of the real-time face recognition system 90% accuracy is achieved.

Chapter :5 Project Description

5.1 The Face Recognition Process

The design and implementation of real-time recognition system is developed in two phase. In the preliminary phase first attempt is to recognize static frontal face image from a image database. The core method is same in the both phase but the prepocessing, face detection techniques are not same for all image set, differs as need of the image set. Along with any image data set the demonstration of the method can done in three prior steps as mentioned below:

1. **Loading the images:** The initial step is to read image data set and load it applying all the necessary preprocessings and also the face detection if necessary for the image set.

2. **Training phase:** The next is to split the data set into training set and testing set, the classifying method trains the images of training set.

3. **Classifying an unknown face image:** An untrained image of test set is selected to classify the image.

This approach is implemented with the AT&T data set and Stirling faces database containing gray-scaled images and also with Utrecht ECVP 2D Face set, the created color image database, Pain expressions 2D Face set, Aberdeen 2D Face set which comprised with true color (RGB) images. The created color image database, Pain expressions 2D Face set and Aberdeen 2D Face set Image set containing true color (RGB) images needs a additional step of face detection which also a additional step for recognizing face from real-time video.

Achieving advancement in recognizing static face image, this technique is implemented in real-time video stream along with some other techniques that support handling real-time video.

5.1.1 Face Recognition in static image dataset

Static face image dataset can be a lot different from one another in many aspects. Different datasets can have uneven number of subject with unequal number of images but occurrence of variation that make datasets dissimilar are the dissimilarities in image file format, image size, color channels/ levels and image organization. Also the difference of facial orientation, face expressions, face details, angles, lighting and illumination makes different datasets more distinguishable.

So, the recognizing technique varies for different datasets of static face images but the core technique or more specifically the algorithm is same the eigenface method, as the supporting preprocessing techniques and requirement of face detection is not always same for all the datasets is tried demonstrate and analyze the method. Demonstration of the face recognition system with these different static face image datasets not only different in procedure but also produced different results.

The demonstration of the face recognition system of static image dataset is tried with six (06) different datasets. They are following:

- AT& T Face Database
- The Color Image Database
- Utrecht ECVP 2D Face set
- Pain expressions 2D Face set
- Aberdeen 2D Face set
- Stirling faces database

Demonstration with AT& T Face Database

The AT& T Face Database is obtained from the Cambridge Computer laboratory.

1. **Loading the images:** The first step is to load the training images from the database. The AT&T data set is quite a preprocessed and simple image set to work with. Images of AT& T data set are grayscaled, sized suitably in 112×92 pixels and the images are containing only face portion with a fixed background. The database contains 10 different images each of 40 different subjects.

   In figure 5.1 a illustration of the database is shown after loading the training images.

Figure 5.1: AT& T Face Database

Different images of an individual subject from training set is shown in figure 5.2.

Figure 5.2: Images of first subject

2. **Training phase:** In the training phase the database is split into 80:20 partition, 8 images is used to train the classifier and 2 images is used to test the classifier. The feature vectors i.e. the eigenfaces are generated in the training phase. The selection of the discriminant best eigenfaces are also done in the training phase.

3. **Classifying an unknown face image:** Selected a face image with unknown face from the dataset that is not trained, as the input of the classifier for testing purpose.

   In figure 5.3 it is shown that an untrained and unidentified face image of a subject is selected classify.

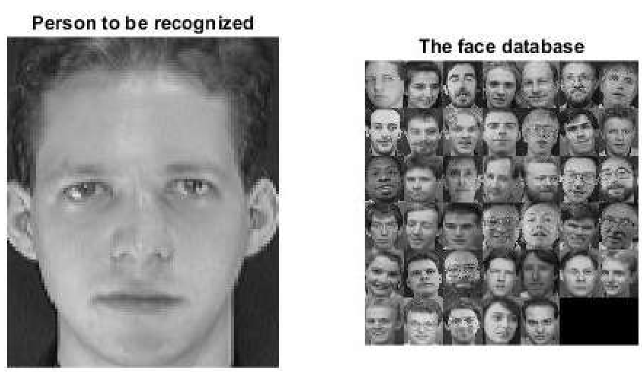

Figure 5.3: Test image to be recognized

The classifier find a true positive match in the training set with similarity score of 534.019, the output is shown in figure 5.4.

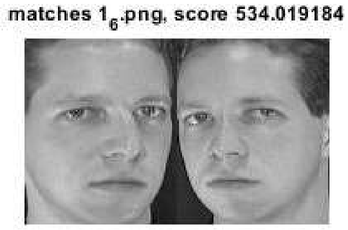

Figure 5.4: True positive match

Demonstration with The Color Image Database

The color image database is created for the purpose of the face recognition system.

1. **Loading the images:** The color image dataset contains color images of 22 different subjects, the first step is to load the training images from the database. The images are resized and grayscaled in proprocessing stage. Face part of each person has to be detected to create the training set of the classifier.

   The database contains 10-13 different images each of 22 different subjects. In figure 5.5 a illustration of the database is shown after loading the training images.

   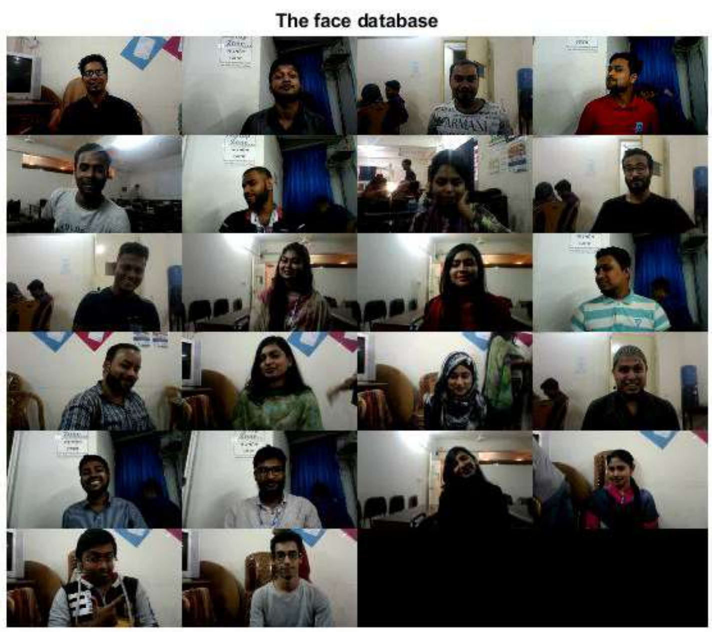

   Figure 5.5: The color image Database

   Different images of an individual subject from training set is shown in figure 5.6.

2. **Training phase:** In the training phase the database is split into 80:20 partition, 9-11 images is used to train the classifier and 2-3 images is used to test the classifier. The

Figure 5.6: Images of first subject

feature vectors i.e. the eigenfaces are generated in the training phase. The selection of the discriminant best eigenfaces are also done in the training phase.

3. **Classifying an unknown face image:** Selected a face image with unknown face from the dataset that is not trained, as the input of the classifier for testing purpose. In figure 5.7 it is shown that an untrained and unidentified face image of a subject is selected classify.

Figure 5.7: Test image to be recognized

The classifier find a true positive match in the training set with similarity score of 885.494, the output is shown in figure 5.8.

Figure 5.8: True positive match

Demonstration with Utrecht ECVP 2D Face set

Utrecht ECVP 2D Face set is a collection of 2d face images that is collected from the university of Stirling.

1. **Loading the images:** The Utrecht ECVP 2D Face set contains color images of 68 different subjects, the first step is to load the training images from the database. The images are resized and grayscaled in proprocessing stage. Face part of each person has to be detected to create the training set of the classifier.

   The database contains 3 different images each of 68 different subjects. In figure 5.9 a illustration of the database is shown after loading the training images.

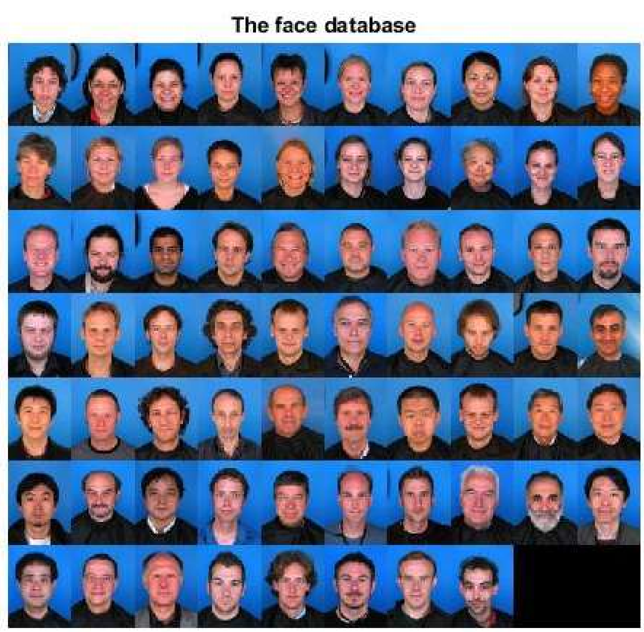

Figure 5.9: Utrecht ECVP 2D Face set

Different images of an individual subject from training set is shown in figure 5.10.

Figure 5.10: Images of first subject

2. **Training phase:** In the training phase the database is split into around 70:30 partition, 2-3 images is used to train the classifier and 1 image is used to test the classifier. The feature vectors i.e. the eigenfaces are generated in the training phase. The selection of the discriminant best eigenfaces are also done in the training phase.

3. **Classifying an unknown face image:** Selected a face image with unknown face from the dataset that is not trained, as the input of the classifier for testing purpose. In figure 5.11 it is shown that an untrained face image of a subject is selected classify.

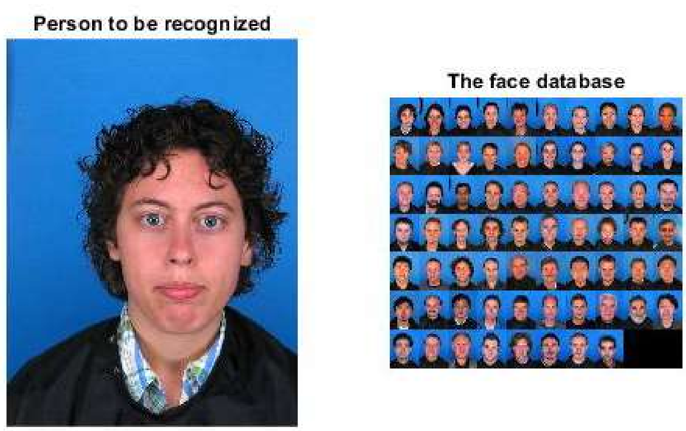

Figure 5.11: Test image to be recognized

The classifier find a true positive match in the training set with similarity score of 101.826, the output is shown in figure 5.12.

Figure 5.12: True positive match

Demonstration with Pain expressions 2D Face set

Pain expressions 2D Face set is a collection of 2d face images that is collected from the university of Stirling.

1. **Loading the images:** Pain expressions 2D Face set contains color images of 23 different subjects, the first step is to load the training images from the database. The images are resized and grayscaled in proprocessing stage. Face part of each person has to be detected to create the training set of the classifier.

   The database contains 25 different images each of 23 different subjects. In figure 5.13 a illustration of the database is shown after loading the training images.

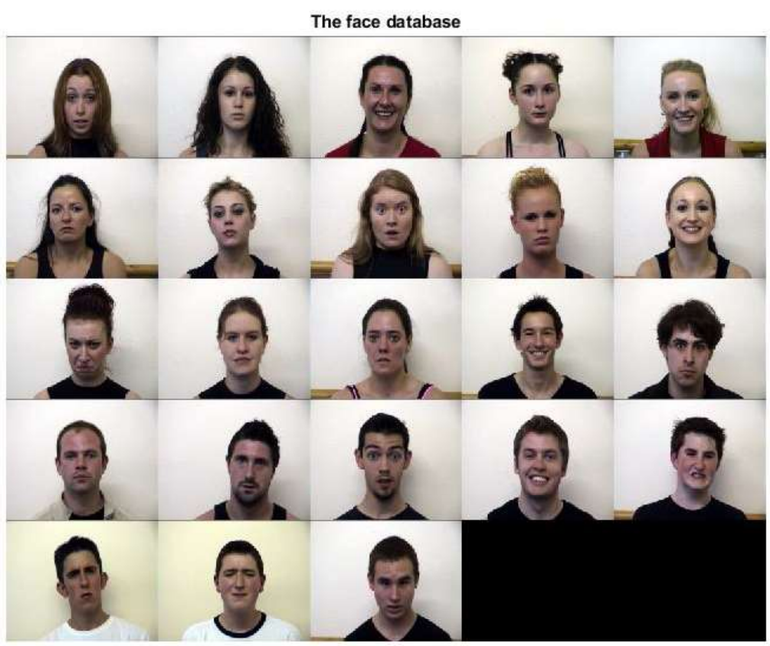

Figure 5.13: Pain expressions 2D Face set

Different images of an individual subject from training set is shown in figure 5.14.

Figure 5.14: Images of first subject

2. **Training phase:** In the training phase the database is split into around 85:15 partition, 22 images is used to train the classifier and 3 image is used to test the classifier. The feature vectors i.e. the eigenfaces are generated in the training phase. The selection of the discriminant best eigenfaces are also done in the training phase.

3. **Classifying an unknown face image:** Selected a face image with unknown face from the dataset that is not trained, as the input of the classifier for testing purpose. In figure 5.15 it is shown that an untrained face image of a subject is selected classify.

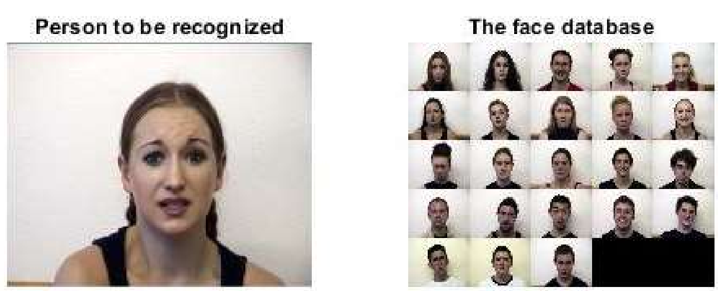

Figure 5.15: Test image to be recognized

The classifier find a true positive match in the training set with similarity score of 454.051, the output is shown in figure 5.16.

Figure 5.16: True positive match

Demonstration with Aberdeen 2D Face set

Aberdeen 2D Face set is a collection of 2d face images that is collected from the university of Stirling.

1. **Loading the images:** Aberdeen 2D Face set contains color images of 42 different subjects, the first step is to load the training images from the database. The images are resized and grayscaled in proprocessing stage in the steps to recognition. Face part of each person has to be detected to create the training set of the classifier.

   The database contains 5 to 11 different images each of 42 different subjects. In figure 5.17 a illustration of the database is shown after loading the training images.

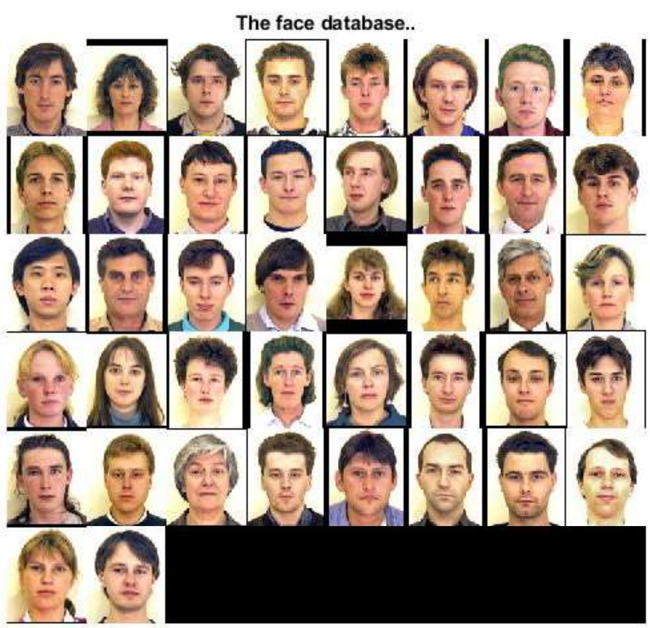

Figure 5.17: Aberdeen 2D Face set

Different images of an individual subject from training set is shown in figure 5.18.

Figure 5.18: Images of first subject

2. **Training phase:** In the training phase the database is split into around 80:20 partition, 4 to 8 images is used to train the classifier and 1 or 2 images is used to test the classifier. The feature vectors i.e. the eigenfaces are generated in the training phase. The selection of the discriminant best eigenfaces are also done in the training phase.

3. **Classifying an unknown face image:** Selected a face image with unknown face from the dataset that is not trained, as the input of the classifier for testing purpose. In figure 5.19 it is shown that an untrained face image of a subject is selected classify.

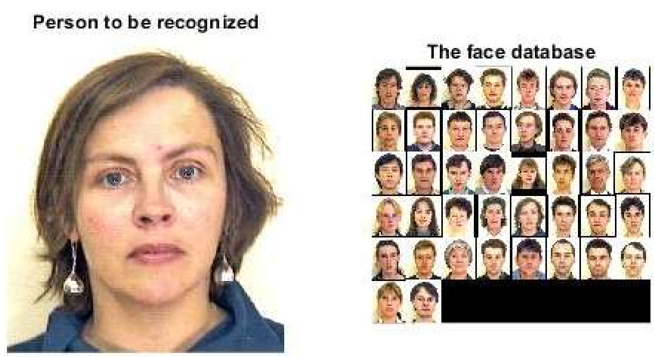

Figure 5.19: Test image to be recognized

The classifier find a true positive match in the training set with similarity score of 1075.185, the output is shown in figure 5.20.

Figure 5.20: True positive match

Demonstration with Stirling faces database

Stirling faces database is a collection of 2d face images that is collected from the university of Stirling.

1. **Loading the images:** Stirling faces database contains color images of 35 different subjects, the first step is to load the training images from the database. The images are resized and in proprocessing stage in the steps to recognition. Images are in monochrome format so gray scaling is skipped. images are only containing the face part of each person, face detection is not needed to create the training set of the classifier.

   The database contains 7 to 8 different images each of 35 different subjects. In figure 5.21 a illustration of the database is shown after loading the training images.

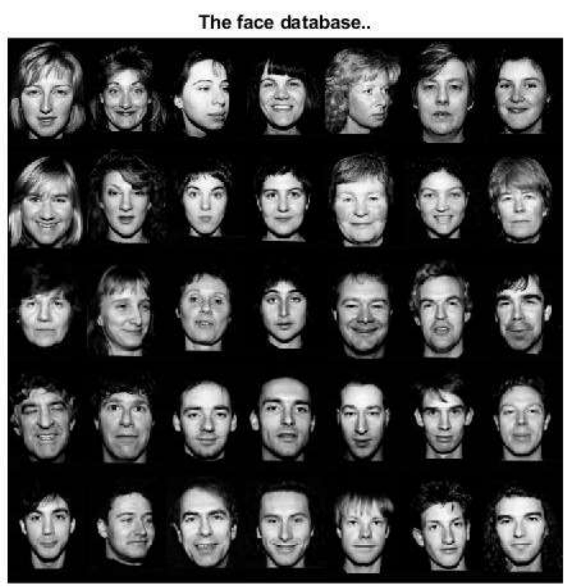

Figure 5.21: The Stirling faces database

Different images of an individual subject from training set is shown in figure 5.22.

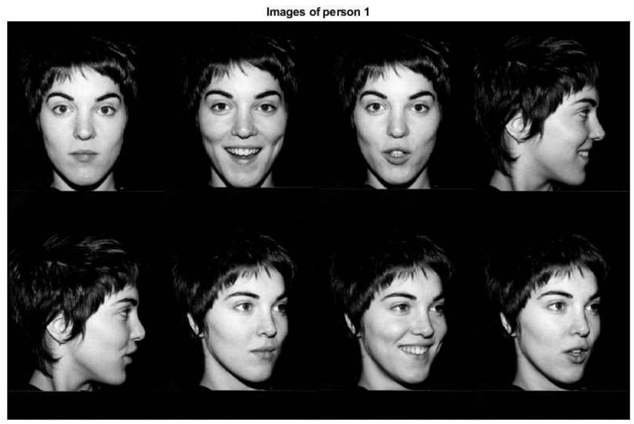

Figure 5.22: Images of first subject

2. **Training phase:** In the training phase the database is split into around 80:20 partition, 6 to 7 images is used to train the classifier and 1 or 2 images is used to test the classifier. The feature vectors i.e. the eigenfaces are generated in the training phase. The selection of the discriminant best eigenfaces are also done in the training phase.

3. **Classifying an unknown face image:** Selected a face image with unknown face from the dataset that is not trained, as the input of the classifier for testing purpose. In figure 5.23 it is shown that an untrained face image of a subject is selected classify.

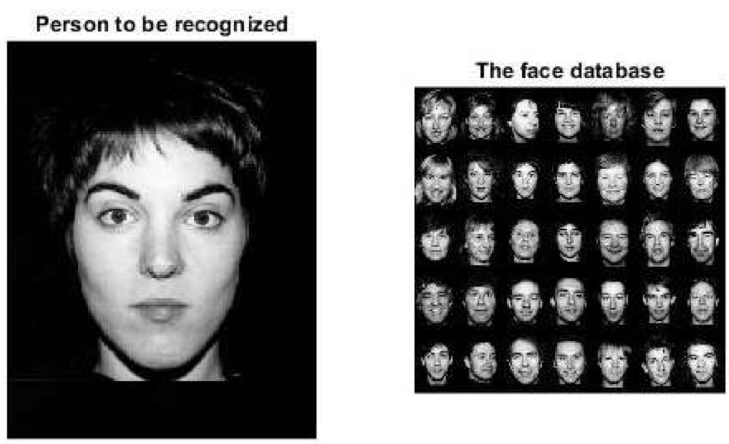

Figure 5.23: Test image to be recognized

The classifier find a true positive match in the training set with similarity score of 290.556, the output is shown in figure 5.24.

Figure 5.24: True positive match

5.1.2 Face Recognition from real-time video

The face recognition process in real-time video stream is not similar as the process followed to recognize faces from static face ImageSet. Real-time video is acquired from hardwares (e.g. security camera, webcam) that is read by OS generic video interface of MATLAB. From the real-time video the image dataset is comprised and that dataset is split into training set and testing set. To classify a unknown test the recognition system initialize the video player and takes the test image as the input of the classifier.

1. Loading the images:

   To load the image dataset the recognition system initialize the video player to acquire video. The acquired video is read and sliced into frame by frame and captured slice of single frame is like a static image. After a constant time interval the recognition system takes a single frame and cuts a picture and saves the image file.

2. Training phase:

   The real-time recognition system detects the face portion from the video player by detecting the face features and takes 10 images of each training subject. The images of each subject is saved in different single sub directory.

   The detected face is highlighted in figure 5.25.

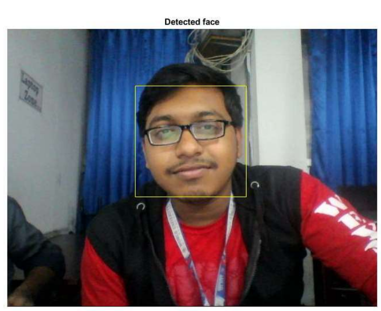

Figure 5.25: Real-time face detection

The detected features of face is shown in figure 5.26, the features are highlighted by green color plus ('+') signs.

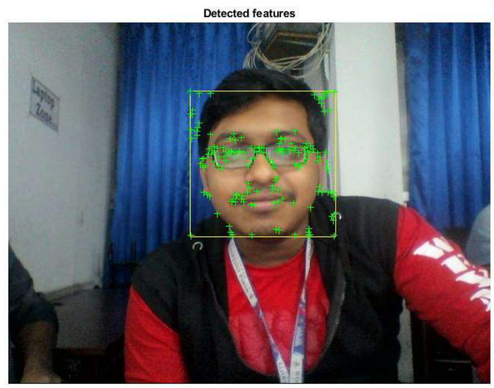

Figure 5.26: Detected face features

In real-time recognition there is no need of splitting the image data set. The test image will be taken during the initialization of the video player in testing period. The feature vectors i.e. the eigenfaces are generated in the training phase. The selection of the discriminant best eigenfaces are also done in the training phase.

3. Classifying an unknown face:

   To recognize an unknown face the recognition takes the test image during the initialization of the video player and the classifier takes this image as input and finds for an equivalent match from the training set, if the person is trained before then the classifier finds a true positive match otherwise the person remains unknown or unregistered for the real-time face recognition system.

   In figure 5.27 it is shown that the video player is initialized and found a test face, detected with red color plus ('+') signs.

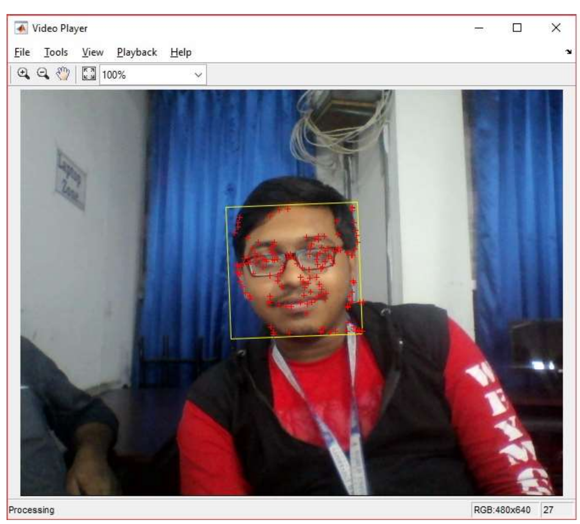

Figure 5.27: Detected the unknown test face

The classifier detects the face with the face features marked with green color plus ('+') is shown in figure 5.28 and cuts the test face surrounded by yellow bounding box. The

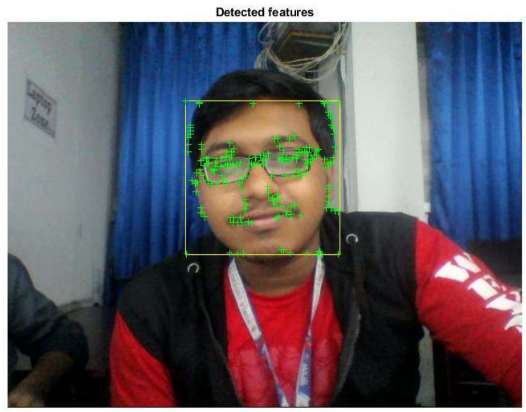

Figure 5.28: Detected the test face features

person in figure 5.29 is found in the training set as the person is known and registered to the real-time face recognition system.

Figure 5.29: Recognized test face as known

Chapter :6 Conclusion

6.1 Conclusion

As science is evolving the use of advanced technologies increased to solve many issues. In the age of globalization of information, personal verification and validation is the challenge to face. Biometric solution is the proper solution for this challenge. Biometric is a unique, measurable characteristic of a human being that can be used to automatically recognize an individual or verify an individual's identity. Among other biometric verification, face recognition is currently most accurate and efficient way.

In this paper, face recognition has been approached with eigenface method based on principle component analysis (PCA). In this method, a given face image is transformed into the eigenspace to obtain a feature projection vector. The Euclidean Distance between the projection vector of a given face and the class projection vectors are used to determine a correct or false recognition. In this paper, a approach to select minimum number of eigenvectors which can represent and maintain highest percentage of variance to create eigenfaces has been proposed. This approach has been applied to multiple face image data set to find maximum of 98.75% accuracy. The real time face recognition approach has achieved 90% accuracy.

6.2 Limitations

The challenges of face recognition with eigenface method were many. In this paper, the accuracy rate has been increased with a proposed technique. But few limitation still remains.

- This system cannot recognize multiple face on same image frame.
- The system needs to restart for the new training data set to classify test image.

6.3 Future works

The future works should be focused on increasing accuracy even farther. Researches can be done to find a solution to the problem of not recognizing multiple face on same image frame. Farther research can be done on detection algorithm to detect face on low intensity light, high noise environment and huge distracting background. Another must do thing is improve the training method, each to test a new face the previous trained data need to be loaded. In future dynamic training method is going to be applied to improve the performance of the real-time face recognition system.

- In future the recognition method will be developed to be able to recognize multiple faces in a single image frame.
- Dynamic training technique will be applied to build a more robust face recognition system.

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