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A new approach for real time Face Recognition System using a modified Eigenfaces with Edge Tracking

نهج جديد للتعرف على الوجوه في الوقت الحقيقي بواسطة

المعدله وتتبع الحافه (Eigenfaces)

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Authorization Statement

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Dedication

I dedicate this work to my dear father, dear mother, sisters, my friends, and friends at work; for their love, understanding and support, they were the light in my path. Without them nothing of this would have been possible. Thank you all.

Table of Content

Authorization Statement I
Examination Committee Decision II
Acknowledgements III
Dedication IV
Table of Content V
Table of Figures VII
Table of Tables VIII
Abstract IX
Abstract In Arabic X
Chapter 1 1
1. Introduction 1
1.1 Face Recognition 3
1.1.1 What is Face Recognition? 3
1.1.2 Why Face Recognition? 5
1.1.3 Face Recognition Model 7
1.1.4 Face Detection 8
1.1.4 Challenges for Face Detection and Recognition 12
1.2 Problem Statement 14
1.3 Objectives of Study 15
1.4 Significance of Study 15
1.5 Limitations of Study 16
1.6 Thesis Organization 16
Chapter 2 17
Literature review 17
2. Introduction 17
2.1 Eigenfaces 17
2.1.1 Eigenfaces Definition 18
2.1.1.1 Principal Component Analysis (PCA) 19
2.1.2 Eigenfaces Approach Methodology 21
2.1.2.1 Calculating Eigenfaces 23
2.1.2.2 Using Eigenfaces to Classify a Face Image 26
2.1.3 Eigenfaces Approach Related Work 30
2.2 Skin Color Segmentation 33
2.2.1 RGB Color Model 37
2.2.2 HSV Color Model 38
2.2.3 YCbCr Color Model 40
2.2.4 Skin Color Detection Related Work: 41
2.2.5 Eigenfaces with Skin Color Detection Related Work: 41
2.3 Hough Transforms 43
2.4 Sobel Detection Method 46
Chapter 3 47
Methodology 47
3. Modified Eigenface Approach 47
3.1 Acquiring and Dividing Dataset 53

3.2 Face Detection Phases 55
3.2.1 Phase 1: Skin segmentation 56
3.2.1.1 Skin segmentation using Hue component 56
3.2.1.2: Skin segmentation using YCbCr color space 57
3.2.2 Phase 2: Finding edges of the face using Sobel edge detection 59
3.2.3 Phase 3: Finding edges of the face using Hough transform 60
3.2.4 Phase 4: Finding edges of the face using statistical methods 62
3.3 Face recognition phase 66
Chapter 4 69
Evaluation and experiments results 69
4. Evaluation and experiments results 69
4.1 Testing dividing (grouping) data set with variation of training images number 73
4.1.1 Testing using only one training image for each individual 74
4.1.2 Testing using two training images for each individual 76
4.1.3 Testing using three training images for each individual 78
4.1.4 Testing using four training images for each individual 80
4.2 Testing for undivided data set 83
4.3 Testing changing of Threshold value on recognition results 83
4.4 Testing on face segmentation hue color component: 85
4.5 Testing on Standard dataset: 86
4.5.1 Comparison with Standard dataset: 88
4.6 Testing recognition time 90
4.7 comparing with literatures: 90
Chapter 5 93
Conclusion and recommendations 93
5. Conclusion and recommendations: 93
References 94
Annex A 98

Table of Figures

Figure 1.3: Face recognition systems model. 7
Figure 1.4: Face detection classifications. 11
Figure 1.5: Individual with different illumination, facial expressions and head positions. 14
Figure 2.1: PCA representation for the image-space and face-space coordinate system for face recognition (Gottumukkal, Asari, 2004, 430). 21
Figure 2.2: Principle of the eigenface-based facial recognition algorithm (Pissarenko, 2002, 3). 29
Figure 2.3: General representation for RGB color model (Georgieva, et al, 2005, 2). 37
Figure 2.4: HSV color model (Georgieva, et al, 2005, 2). 38
Figure 2.5: Block diagram of the face recognition system using color information (Yoo, et al, 2007, 107). 43
Figure 2.5: The normal parameters for a line in General Hough transform (Duda, Hart 1972, 12). 45
Figure 2.6: Projection of colinear points onto a line (Duda, Hart 1972, 12). 46
Figure 3.1: sample of FERRT database faces (Geng, Jiang, 2009, 601). 48
Figure 3.2: Sample of training set for African origin male actor with different head position and different scaling. 49
Figure 3.3: Sample of training set for Arabic origin female singer with different head position and different head profile. 50
Figure 3.4: Sample of training set for Asian origin female actor with different head position and different head size 50
Figure 3.4: Proposed face recognition approach. 51
Figure 3.5: Manipulating training data set. 54
Figure 3.6: Face detection chart 55
Figure 3.7: Test images with resulted image for skin segmentation areas 58
Figure 3.8: Segmented image with resulted image after applying edge detection. 60
Figure 3.9: Hough transform applied for the edge detected image giving all the peaks found 61
Figure 3.10: Hough transform filtered by variance. 62
Figure 3.11: Filtered Hough transform. 63
Figure 3.12: The geometrical face model (Lu , et al, 2003, 168). 64
Figure 3.13: A frontal face view with distance measuring relations (Tin,2012, 32). 64
Figure 3.15: Face recognition chart. 68
Figure 4.1: Snapshot from training data set 69
Figure 4.2: individual training images 70
Figure 4.3: Tested image result after executing 70
Figure 4.4: Individual training images. 71
Figure 4.5: Tested image result after executing. 71
Figure 4.6: Individual training images. 72
Figure 4.7: Test result after executing with 2 different test images. 72
Figure 4.9: Sample of Faces 94 dataset. 87
Figure 4.10: Samples of testing on Faces 94 dataset. 87
Figure 4.11: Results comparing for two testing different datasets chart. 89

Table of Tables

Table 2.1: Results for appearance-based face recognition projection methods (Pathak *et al,* 2011,8). 31
Table 2.2: Results for eigenfaces algorithm for real time face recognition (Arora, 2012, 196) 31
Table 4.3: Results for testing training set with 1 image. 74
Table 4.4: Summary Results for testing training set with 1 image. 75
Table 4.5: Results for testing training set with 2 image. 76
Table 4.5: Summary of results for testing training set with 2 image. 77
Table 4.6: Results for testing training set with 3 image. 78
Table 4.7: Summary results for testing training set with 3 image. 79
Table 4.8: Results for testing training set with 4 image. 80
Table 4.9: Summary of results for testing training set with 4 image. 81
Table 4.10: Summary of all test results for testing training sub-sets. 81
Table 4.2: Results for testing division effect on recognition 83
Table 4.1: Results for testing threshold variation. 84
Table 4.11 a: Results foe test on hue segmentation hue color component 85
Table 4.11 b: Results for test on hue segmentation hue color component 85
Table 4.12: Comparison between Faces 94 dataset and proposed dataset. 88
Table 4.13: Results comparing for two testing different datasets. 88

Abstract

This thesis presents Real-time Face Recognition using modified Eigenfaces technique and color segmentation with Edge tracking for face detection. Eigenfaces is a fast and simple method for face recognition which is considered as a remarkable feature for eigenfaces, but the face recognition accuracy drops severely when head position changes which needs to feed the training set with large number of face images in different head position. Proposed approach in this thesis intent to implement eigenfaces technique with skin color segmentation and Hough transforms edge detection and tracking to enhance the results of face recognition in different head position, face profile and head scale. This will be implemented with a data set that have only three images for each individual, images will have unconstrained background for different environments for any given image to find the face and recognize the person in the image, where unconstrained background increase the complexity of the detection and recognition process, that requires these condition must be solved for real time implementation.

Results have been showed that increasing of both number of training images and the number of individuals in the sub-set group (found that) was three training images per each, and three individuals for each sub-set group which is found as the optimal choice training for this approach. Comparison with standard dataset of faces has been done for verifying proposed work assumption; results were fair and approving for developed work.

Key words: Eigenfaces, Training sub-setting, Hue, CbCr, Euclidian distance.

Abstract In Arabic

تقدم هذه الأطروحة تقنية التعرف على الوجه في الوقت الحقيقي باستخدام تقنية (Eigenfaces) المعدله ولون البشره مع تتبع حافة الوجه لتحديد موقعه في الصوره . تعتبر تقنية (Eigenfaces) سريعة وبسيطة للتعرف على الوجوه ،حيث تعد ميزة ملحوظة لهذه التقنيه، الا ان دقة التعرف على الوجوه تنحدر بشدة عند تغير موقع الراس واتجاه الوجه في الصوره مما يتطلب تغذية مجموعة التدريب (Training set) بعدد كبير من الصور للشخص الواحد لمواقع مختلفة للراس.

لتحقيق الهدف من هذه الاطروحة سيتم استخدام مجموعة تدريب تحتوي على ثلاثة صور فقط لكل فرد، و تكون هذه الصور غير محدده بخلفية معينه، مما سيجعل هذه العملية امرا معقداً مما يتطلب ايجاد حلول لتنفيذ هذه العمليات في الوقت الحقيقي.

أظهرت نتائج الدراسة ان استخدام ثلاثة صور لكل شخص مع وجود ثلاث اشخاص في المجموعات الفرعية هو الخيار الامثل لعينة التدريب وفقاً لهذا النهج المقترح. وبمقارنة نتائج النهج المقترح مع مجموعة التدريب لقواعد البيانات القياسية العالمية للوجوه تبين ان هذه النتائج كانت متوافقة مع نتائج النهج المقترح في هذه الاطروحة

Chapter 1

Introduction

1. Introduction

People used to recognize any person throw different ways: face, body weight, voice and finger print. Finger print needs specialist to do the job. A person can be recognized from his body shape from back seen with very low percentage of correct recognition, voice can be stronger indicator for recognizing some one's identity but also can be risky, but can't mistaken someone known with frontal seen, face gives so much information about person and personality. The past few decades witnessed huge developments in modern life style that influenced by information technologies revolution that turned the whole world into a small village "such as common", this development influenced all human life aspect from making a phone call to manufacturing plains, rockets and satellites. Security field is one of these fields that developed a great deal national security, police, banks security, companies and even home security has computer systems that ensures the job is well be done. Determining the Identity of person in these systems and determining the authority category for this person with high accuracy to avoid the danger of false identification (Thepade, *et al*, 2012, 156), (Abul-Kashem, et al, 2011, 36).

Researchers are trying to develop automated computer systems that can exactly imitate human brain remarkable ability in identifying and recognizing human faces, this aim still a big challenge for these researches, although much work have been done and good results have been achieved in this field, human brain ability still a dilemma where it can recognize human's face in almost all head positions, facial expression, head rotation and different illumination conditions, even through aging with face changing appearance. Machine face recognition systems still need much work in developing a system that can do the job to get 100% correct identification results as human dose in a glance (Tin, 2012,31), (Yang, et al, 2005, 64).

Slavkovic and Jevtic (2012) think that human faces are extremely complex and dynamic structure because of its characteristics that significantly change with time. They describe face social impact as the primary focus of attention in social relationships and play a major role in the transmission of identity and emotions, for the detection and recognition field they say that development of facial recognition systems is difficult because of face powerful features (page 121).

Face recognition complexity is justified by the complexity of its rich geometry that each technique has to read and analyze to get correct result, face geometry describes the physical structure of human face: eyes, nose, mouth, ears, cheek bones, chin and the skin, these components determined by the shape and vertices that surround them which can be read by machine from a face photo, the variation in shapes and colors of these components are the key for face detection and recognition. These components vary in structure complexity; eyes for example are rich component structure recent studies are focusing on iris recognition.

The variation in face component structure is reflected on the color and this color intensity of each component in the face image, this variation in color intensity is the key for determining how each pixel in face image is represented in the testing system to determine if this given image has a face or not.

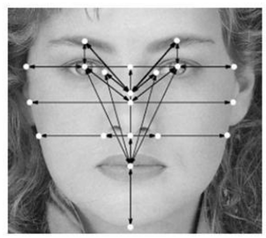


Figure 1.1: Face geometry with its determinant points that are used to detect and recognize individual face (Arora, 2012, 191)

1.1 Face Recognition

Face recognition in general can be defined as interrelated multi process techniques starting with image processing or image analyzing to detect and locate human face in a given image, then compare it with known faces in the database to recognize person identity in that image.

1.1.1 What is Face Recognition?

Georgescu, (2011) defined face recognition by: Face recognition system is expected to identify faces present in images and video automatically. It can operate in either or both of two modes: face identification and face verification. Identification mode used when the identity of the individual is not known in advance. The entire template database is then search for a match to the individual concerned, in one-to-many search. If a match is made, the individual is identified. Verification mode is used when the person provides an alleged identity. The system then performs a one-to-one search, comparing the captured biometric characteristics with the biometric template stored in the database. If a match is made the identity of the person is verified.

Arora (2012) defined face recognition system as one of the successful and important applications in image analysis (which is known as image processing), where computer application used for automatically identifying or verifying a person from a digital image or a video frame from a video source, comparing selected facial features from the image and a facial database, where human face plays a major role in conveying identity and emotion. “Face recognition is a holistic approach towards the technology and has potential applications in various areas in modern life style which need the type of applications” (Arora, 2012).

Facial features are extracted and implemented through algorithms which are efficient with some modifications done to improve the existing algorithm models. Face recognition techniques gained good accuracy in personal identification when they are provided with large set of training images (Ramesha, 2009).

Thepade, *et al* (2012) defined face recognition term by the process to identifying and verifying a face image. It is basically the process of classifying a face as ‘known’ or ‘unknown’, based on training a set. The computer systems store the faces in such way that the important contents of the face image they store, can be used efficiently for recognizing the face (page 156).

Tsalakanidou, *et al* (2003) define face recognition as complex task this complexity is due to the set of processes starting with detecting and locating faces in a cluttered background then this process is followed by normalization and recognition then face within a given image (page 1427).

Manyam, *et al*, (2011) say Face recognition systems largely identify individuals independently, where the recognition decision of one face does not influence the decision of the second face for controlled imaging conditions. In unconstrained setting, the face recognition problem is harder. There is an emerging area that addresses this setting and evaluates performance on unconstrained data sets. Most methods operating in constrained settings have been based on aligning gallery and probe images in some way, including cross pose.

1.1.2 Why Face Recognition?

With modern life style where automated systems plays an important role in daily life activities, the need for face recognition systems and applications has increased where many fields need to use face detection and recognition techniques. This type of technologies are used in either to verify the claimed identity for authentication as database access, access control or bank transactions, in this case the comparison takes search process to verify the person’s identity considered as one to one search process, or one-to-many search process which is known as searching for unknown person if he/ she exist in the database and give the identity for the target person in this search (Georgescu, 2011, 194).

An advantage that must be taken in consideration for face recognition that it's unlike finger print and iris recognition which are considered as intrusive biometrics technologies that need physical contact with human body, face recognition doesn't need it where it can be done from fair distance for personal identification and authentication (Arora, 2012).

Mentioning some fields where face recognition use can be mandatory or secondary depending on the field needs and requirements from different literatures (Thepade, *et al*, 2012), (Georgescu, 2011, 194), (Chellappa etal, 1995, 705).

Face recognition can play an important role in various fields like:

1. Security: the main reason this type of systems where developed is security and surveillance issues access control for homes, companies, stores, banks, ect.
2. Law enforcement: Finger print was the strongest evidence can convict a criminal in crime scene, or in borders check point, now face recognition can offer important role for criminals identification investigations, airports security to recognize forbidden person from traveling and watching terrorist.
3. Authentication: investigating the identity of a person for certain condition, tasks, permissions access control.
4. Banking: banking field requires high level of accuracy in systems for authentications and security system, face recognition helps great deal in these purposes.

5. Military: where no mistakes are allowed most existing technologies now where developed to serve military field in the first place and permitted later for civil and commercial use.
6. Commercial: human interaction with products that has face recognition system could raise their desire to buy such product, taking smart phones as example that has interaction applications face recognition is one of these applications.
7. Smart technologies: the whole word is directed toward smart phones, smart electronic boards in class room, smart cars, smart, etc, even smart home access person don't need a key or pin code to get into his house.
8. Human machine interaction.

1.1.3 Face Recognition Model

Face recognition model can be summarized by following points:

1. The face detection to locate the face in given image.
2. Extraction of face features and feature matching.
3. Identification: search and matching image with saved dataset.

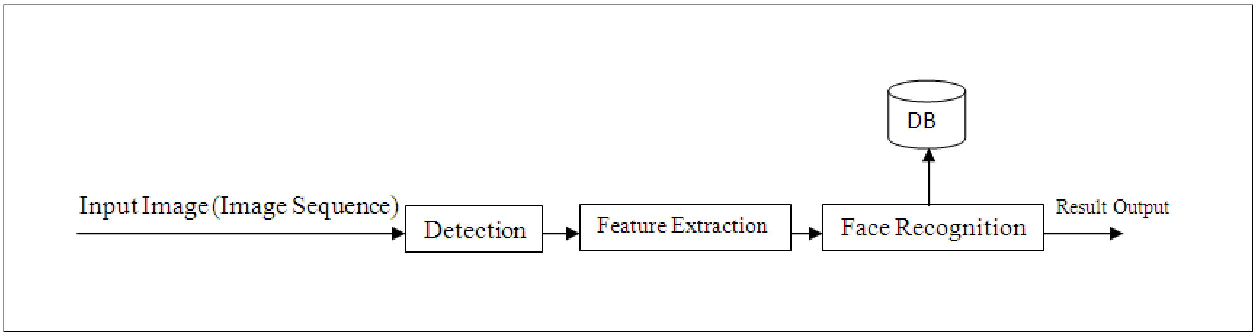


Figure 1.3: Face recognition systems model.

1.1.4 Face Detection

Corner stone for all face recognition techniques is the face detection technique used, face detection purpose can simply described by finding the human’s face in a given image from any source of photos used to capture them: still photos from database or digital camera that provide the system with still images or video camera as input stream. Finding humans face in a given photo and separate or cut the face part from the original image has specific steps to be done, starting with dimension reduction for data of face image because face has complex structure, and image may have complex back ground, then analyze the image to locate a face to determine face structure to be detected. Each detection technique has its own methodology, restrictions and determents in searching for the face features that may be not suitable for other ones that make the comparison between different algorithms limited, where no standards for testing the algorithms or evaluating their results are available, on the other hand this variation enrich recognition field and forces competition in results percentage for researchers. Even the calcification for these techniques varies according to the researchers point of view in their study (Hjelm, Low, 2001, 236).

Since most of the recognition techniques such as Eigenfaces for example assume the face images normalized in terms of scale and rotation, their performance depends heavily upon the accuracy of the detected face position within the image. This makes face detection a critical step in the process of face recognition in other words face detection affects recognition rate (Tin, 2012, 31).

Researchers have different ways in classifying face detection approaches, some of them think that calcification of face detection methodologies falls in four categories of detection approaches according to the way these approaches study the structure of the face and locate these features to determine if the given image has a face in it or not with pointing to their cons and pros (Anila, Devarajan, 2010, 54), (Tin, 2012, 31).

Different Approaches of face detection calcification:

1. Knowledge-based methods: where these methods studies the patterns shape of faces that gives the information of the face structure component and the relation between these components.
2. Feature invariant or feature based approaches: this approach try to find facial features which are invariant to pose, lighting condition or rotation. Studying the face geometry by extracting the face features, these structural components are tested in different conditions of illumination and position factors which affect detection and recognition results, feature based is relatively fast in detection because it require low memory space than other approaches.
3. Template matching: one of the simplest approaches for face detection and recognition, this approach follows saved templates for facial features structure, calculate the correlation between a test image and pre-selected facial templates , maybe use one template or more for better results, where one template maybe considered insufficient which needs high memory resources.

4. Appearance-based methods: unlike the template matching this approach methodology is to teach the system using training sets of face images to help it to find the facial features structure, relatively fast in detection and recognition with higher accuracy than template matching, eigenfaces subject of this thesis is following this category.

Other researcher followed another standards in classifying face detection and recognition approaches can be said as in more general standards, they classified face detection into two approaches: knowledge based (feature base) approaches and image based approaches (Wang, Tieniu, 2000), (Hjelm, Low, 2001):

1. Knowledge Based: these types of methods study the structure of the face by using information about features of the face and skin color or use face template matching. These factors are used to find face components: eyes, mouth, nose or other facial features to detect the human faces. Color detection and edge detection are some examples for knowledge base.
2. Image based: Image based approaches apply in a window scanning technique for detecting faces. The window scanning algorithm is just an exhaustive search of the input image for possible face locations at all scales, but there are variations in the implementation of this algorithm for almost all the image-based systems. Typically the size of the scanning window, sub-sampling rate, step size and the number of iterations vary depending on the method proposed and the need for a

computationally efficient system. Strong techniques follows image based approach such as neural network, liner method like PCA and statistical approaches.

The following figure summaries the face detection approaches and examples of the methods that follows these approaches classification followed by some examples of some approaches:

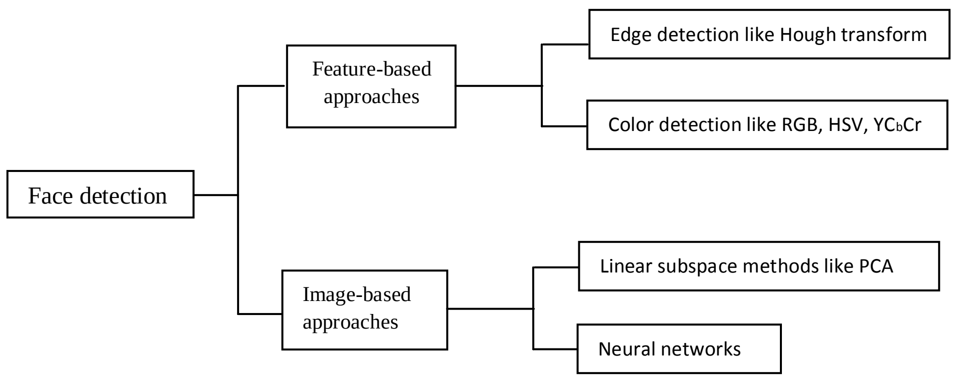


Figure 1.4: Face detection classifications.

Color detection information of image colors can be an efficient tool for identify facial areas and specific facial features, when the skin color model can be adapted properly for different lighting environments results gain good accuracy (Zhang, Zhang, 2009, 111).

Hough transform for edge detection is an important transform method used to detect the occurrence of figure points lying on a straight line and possessing some specified property of the point-to-curve transformation (Duda, Hart, 1972, 14).

Neural networks is a multi-layer neural model architecture with a learning algorithm that receives input information to process the desired output, where the size of neural network is *n-m-p,* i.e. *n* nodes in the input layer, *m* nodes in the hidden layer and *p* nodes in the output layer. The sigmoid function is used as the signal transfer function for each neuron in the model (Manyam, etal, 2011). Neural networks have been applied, with considerable success, to the problem of face detection and recognition, neural network apply small windows on image and examined this image to decided whether each window contained a face or not (Lu , et al, 2003,175).

Liner method PCA called Principal Component Analysis, in mathematical concept PCA is mathematical procedure that does dimensionality reduction by transforming a number of possibly correlated variables into a number of uncorrelated variables called principal components related to the original variables by an orthogonal transformation (Arora, 2012).

1.1.4 Challenges for Face Detection and Recognition

To gain accurate results in simulating human brain in recognizing faces many conditions should be taken in consideration when developing any system that do detecting and recognizing faces, listing below some of these conditions that could severely affect the face detection and recognition process (Chitra , Balakrishnan, 2012, 4230), (Samal, Iyengar, 1992, 65):

1. Illumination: any photo taken by any type of camera is affected by the surrounded illumination and where the light coming from, where face recognition is handling photos of image this factor should be taken in account.
2. position of the head: how the face position is determined in the image frontal view position which is the best case scenario for the face image and simplest case, head in given image can be positioned as left or right view, 45 degree profile, upside and down these different head position must be detected and calculated, Out-of Plane Rotation could cause false recognition result or could cause unknown face result while the face dose exist in the database.
3. Presence of beards, mustaches and glasses.
4. Analysis of facial expressions: face appearance is completely affected by a person's facial expression, a sad face or angry face expression is completely different view from a laughing one.
5. Occlusion on the face image: faces may be partially occluded by other objects.
6. Camera’s characteristics: optical axis, sensor response, gains control, resolution and colors intensity.

Giving a real example for previous challenges with real data photos for the same person (celebrity actor), challenges in the example: different illumination condition affect the color of the skin, facial expression that also vary and head rotation and extreme change in head position which affect the recognition results.

Figure 1.5: Individual with different illumination, facial expressions and head positions.

Sinha (2006) says extensive research effort that has gone into computational face recognition algorithms, the reason for these researches is to deployed recognition systems effectively in an unconstrained setting, with all of the attendant variability in imaging parameters such as sensor noise, viewing distance, and illumination. So far the only system that does seem to work well in the face of these challenges is the human visual system.

1.2 Problem Statement

Eigenfaces method utilizes PCA (Principle Component Analysis) that reduces the computational complexity to find the face in a given image. Although eigenfaces approach is a fast and simple calculation method for face recognition which is considered a remarkable feature for eigenfaces, but also the face recognition accuracy drops severely when head position changes (Turk & Pentland, 1991), eigenfaces approach needs to feed the training set with large number of face images in different head position (Ramesha, 2009).

Proposed approach in this thesis intent to implement eigenfaces technique with (1) skin color segmentation (2) Hough transforms for edge detection and tracking to enhance the results of face recognition in different head position, different face profile and different head scale. This will be implemented with a data set that have three images for each individual, images will have unconstrained background for different environments to any given image to find the face and identify the person in that image. Unconstrained background increases the complexity of the detection and recognition process, for a real time implementation these complications must be solved.

1.3 Objectives of Study

The objectives of this study can be briefly listed by:

1. Find the optimal number of sub group size to enhance the recognition results.
2. Find the significance of using one or more detection techniques.
3. Testing the optimal threshold for Eigen vector.

1.4 Significance of Study

The significance of this study can be an optimizing technique for face recognition which became one of the hottest topics in the last decades for its major applications for security and commercial field's implementations.

1.5 Limitations of Study

Proposed work was implemented and run on MatLab 2012a, but it was noticed that it is slow for huge data. Unfortunately, MatLab simulator is one of the best common used for this kind of researches.

1.6 Thesis Organization

This thesis will be organized as follows:

Chapter 1: Introduction.

Chapter 2: Detailed information for literature reviews for basic concepts of face detection and face recognition. 3 major approaches to the face detection and one major approach for face recognition problem are reviewed.

Chapter 3: Based on the details of the proposed face recognition method and the actual system developed.

Chapter 4: Dedicated to face recognition software that was developed to demonstrate the eigenfaces approach.

Chapter 5: conclusion and recommendations.

Chapter 2

Literature review

2. Introduction

Face detection and recognition had a huge number of researches due to its important applications in all fields of human life. So it’s impossible to review all literatures related to it. So in this chapter the focus will be on the main research methodologies which are most related to the proposed work.

2.1 Eigenfaces

Eigenfaces is known as ghostly faces appearance image of the face as described by Turk and Pentland in their approach research that was developed in 1991, the ghostly appearance is an impact of using PCA concept which can be simply described as dimension reduction concept, PCA based on information theory was invented back in 1901 by Person, because of its simplicity and speed eigenfaces gained much attention from researchers among huge number of recognition techniques for that reason. Eigenfaces approach was able to detect and recognize faces under constrained environment, this approach is suitable for real time face recognition system because of this remarkable advantage of speed and simplicity due of using PCA (Arora, 2012), (Turk & Pentland, 1991).

2.1.1 Eigenfaces Definition

Slavkovic and Jevtic (2012) defined eigenfaces by being one of the simplest and most effective approaches used in face recognition systems, eigenface approach transforms faces into a small set of essential characteristics, eigenfaces, which are the main components of the initial set of learning images also called (training set). Recognition of faces is done by projecting a new image (test image) in the eigenface subspace, after which the person is classified by comparing its position in eigenface space with the position of known individuals. Advantage of this approach over other face recognition systems is in its simplicity, speed and insensitivity to small or gradual changes on the face. The problem of this approach is the images must be vertical frontal views of human faces (pages 121,122).

Eigenfaces is classified as image base approaches, where its goal is to find out the eigenvectors of the covariance matrix of the distribution, the eigenvectors resulted from projecting training set of face images into linear subspace with lower dimensional space where the dimensionality reduction is achieved this subspace is the implementation of PCA concept on the face image appearance, eigenfaces doesn't analyze the face feature variation (Turk & Pentland, 1991).

Belhumeur, et al (1997) considered eigenfaces approach as one of the best solutions that have been developed up-to-date, using dimensionality reduction for faces by considering each face as a vector in the face space where vector comparison is much easier and faster than matrices comparison. The training set of face images where every face is represented by 2 dimensional matrix is now a matrix with every face image is a vector, this vector is the face image after projecting to face space.

This train set has constraints on the face image must be the same size to be calculated and to be frontal view to line-up most important facial features: eyes, mouth and nose these face features are analyzed and transferred into unrelated components known as orthogonal component named by eigenfaces (Arora, 2012), another constraint lighting where image background is the wall or any object behind the face that affect the recognition, must be aware of is the background where PCA face recognition is sensitive to the changes in these factors (Kondo & Yan, 1998).

2.1.1.1 Principal Component Analysis (PCA)

PCA based on information theory concept where the use of Eigenfaces is commonly called as Principal Component Analysis, in mathematical concept **PCA** is mathematical procedure that does dimensionality reduction by transforming a number of possibly correlated variables into a number of uncorrelated variables called principal components related to the original variables by an orthogonal transformation. This transformation is defined in such a way that the first principal component has as high variance as possible (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it be orthogonal to the preceding components. PCA is sensitive to the relative scaling of the original variables (Arora, 2012).

Simply PCA can be describe as a projection technique that finds a set of projection vectors designed such that the projected data retains the most information about the original data. The most representative vectors are eigenvectors corresponding to highest eigenvalues of the covariance matrix. This method reduces the matrices dimension by projecting data from *M*-dimensional space to *P*-dimensional space, where $P < M$ *(*Slavkovic & Jevtic, 2012).

PCA Requires full frontal display of face and considers every face in the database as a different image where faces of the same person are not classified in classes (Sirovich, Kirby, 1978), (Turk, Pentland, 1991).

Tin (2012) Said that PCA is a suitable strategy for face recognition because it identifies variability between human faces, which may not be immediately obvious. PCA does not attempt to categorize faces using familiar geometrical differences, such as nose length or eyebrow width. Instead, a set of human faces is analyzed using PCA to determine which 'variables' account for the variance of faces. In face recognition, these variables are called eigenfaces because when plotted they display a ghostly resemblance to human faces (page 33). In other words PCA doesn’t study the structure of facial features it finds the differences between faces with are caused be features variations between different faces.

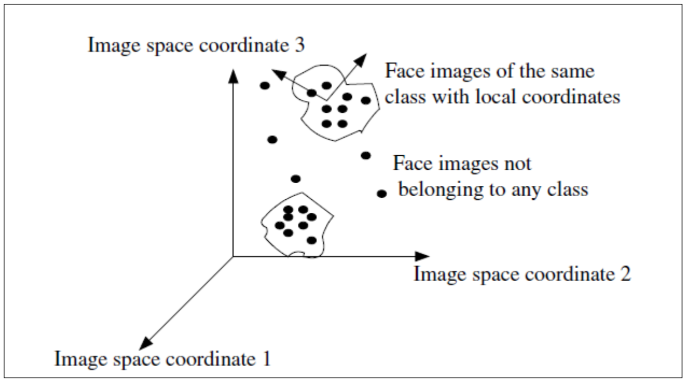


Figure 2.1: PCA representation for the image-space and face-space coordinate system for face recognition (Gottumukkal, Asari, 2004, 430).

2.1.2 Eigenfaces Approach Methodology

Eigenfaces as Turk and Pentland explained their approach which developed back in 1991 by algorithmic concept and mathematical equations the used in their research to develop the following approach (Turk, Pentland, 1991, 73-76):

In the language of information theory, the objective is to extract the relevant information in a face image, encode it as efficiently as possible, and compare one face encoding with a database of models encoded in the same way. A simple approach to extract the information contained in a face image is to somehow capture the variation in a collection of face images, independent of any judgments of features, and use this information to encode and compare individual face images.

In mathematical terms, the objective is to find the principal components of the distribution of faces, or the eigenvectors of the covariance matrix of the set of face images. These eigenvectors can be thought of as a set of features which together characterize the variation between face images. Each image location contributes more or less to each eigenvector, so that it can display the eigenvector as a sort of ghostly face called an eigenface. Each face image in the training set can be represented exactly in terms of a linear combination of the eigenfaces. The number of possible eigenfaces is equal to the number of face images in the training set. However, the faces can also be approximated using only the "best" eigenfaces those that have the largest eigenvalues, and which therefore account for the most variance within the set of face images. The primary reason for using fewer eigenfaces is computational efficiency. The most meaningful M eigenfaces span an M-dimensional subspace (face space) of all possible images. The eigenfaces are essentially the basis vectors of the eigenface decomposition (Turk, Pentland, 1991).

The idea of using eigenfaces was motivated by a technique for efficiently representing pictures of faces using principal component analysis. It is argued that a collection of face images can be approximately reconstructed by storing a small collection of weights for each face and a small set of standard pictures. Therefore, if a multitude of face images can be reconstructed by weighted sum of a small collection of characteristic images, then an efficient way to learn and recognize faces might be to build the characteristic features from known face images and to recognize particular faces by comparing the feature weights needed to (approximately) reconstruct them with the weights associated with the known individuals.

2.1.2.1 Calculating Eigenfaces

Let a face image Γ(x,y) be a two-dimensional *N* by *N* array of intensity values. An image may also be considered as a vector of dimension N^2, so that a typical image of size 256 by 256 becomes a vector of dimension 65,536, or equivalently, a point in 65,536-dimensional space. An ensemble of images, then, maps to a collection of points in this huge space (Turk, Pentland, 1991).

Images of faces, being similar in overall configuration, will not be randomly distributed in this huge image space and thus can be described by a relatively low dimensional subspace. The main idea of the principal component analysis is to find the vector that best account for the distribution of face images within the entire image space. These vectors define the subspace of face images, which we call "face space". Each vector is of length N^2, describes an *N* by *N* image, and is a linear combination of the original face images. Because these vectors are the eigenvectors of the covariance matrix corresponding to the original face images, and because they are face-like in appearance, they are referred to as "eigenfaces" (Turk, Pentland, 1991).

Let the training set of face images be $\Gamma_1,\ \Gamma_2,\ \Gamma_3,\ \ldots,\ \Gamma_M$. The average face of the set if defined by $\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n$. Each face differs from the average by the vector $\Phi_n = \Gamma_n - \Psi$.

This set of very large vectors is then subject to principal component analysis, which seeks a set of M orthonormal vectors, μ_n, which best describes the distribution of the data. The kth vector, μ_k is chosen such that:

$$\lambda_k = \frac{1}{M}\sum_{n=1}^{M}(\mu_k^T \Phi_n)^2 \qquad (1)$$

is a maximum, subject to:

$$\mu_l^T \mu_k = \begin{cases} 1, l = k \\ 0, otherwise \end{cases} \qquad (2)$$

The vectors μ_k and scalars λ_k are the eigenvectors and eigenvalues, respectively, of the covariance matrix:

$$C = \frac{1}{M}\sum_{n=1}^{M}\Phi_n \Phi_n^T = AA^T \qquad (3)$$

Where the matrix $A = [\Phi_1 \Phi_2 ... \Phi_M]$. The matrix C, however, is N^2 by N^2, and determining the N^2 eigenvectors and eigenvalues is an intractable task for typical image sizes. Computationally feasible method is needed to find these eigenvectors (Turk, Pentland, 1991).

If the number of data points in the image space is less than the dimension of the space ($M < N^2$), there will be only $M-1$, rather than N^2, meaningful eigenvectors (the remaining eigenvectors will have associated eigenvalues of zero). Fortunately, the solution of N^2-dimensional eigenvectors in this case by first solving for the eigenvectors of and M by M matrix—e.g., solving a 16 x 16 matrix rather than a 16,384 x 16,384 matrix—and then taking appropriate linear combinations of the face images Φ_n. Consider the eigenvectors v_n of $A^T A$ such that

$$A^T A v_n = \lambda_n v_n \qquad (4)$$

(Turk, Pentland, 1991).

Pre-multiplying both sides by *A*:

$$AA^T A v_n = \lambda_n A v_n \qquad (5)$$

From which we see that $A v_n$ are the eigenvectors of $C = AA^T$.

Following this analysis, time to construct the *M* by *M* matrix $L = A^T A$, where $L_{mn} = \Phi_m^T \Phi_n$, and find the *M* eigenvectors v_n of *L*. These vectors determine linear combinations of the *M* training set face images to form the eigenfaces μ_n:

$$\mu_n = \sum_{k=1}^{M} v_{nk} \Phi_k = A v_n, n = 1,......, M \qquad (6)$$

(Turk, Pentland, 1991).

With this analysis the calculations are greatly reduced, from the order of the number of pixels in the images (N^2) to the order of the number of images in the training set (*M*). In practice, the training set of face images will be relatively small ($M < N^2$), and the calculations become quite manageable. The associated eigenvalues allows ranking the eigenvectors according to their usefulness in characterizing the variation among the images (Turk, Pentland, 1991).

2.1.2.2 Using Eigenfaces to Classify a Face Image

The eigenface images calculated from the eigenvectors of L span a basis set with which to describe face images. As mentioned before, the usefulness of eigenvectors varies according their associated eigenvalues. This suggests picking only the most meaningful eigenvectors and ignore the rest, in other words, the number of basis functions is further reduced from M to M' ($M'<M$) and the computation is reduced as a consequence (Turk, Pentland, 1991).

The eigenfaces span an M' dimensional subspace of the original N^2 image space. The M' most significant eigenvectors of the L matrix are chosen as those with the largest associated eigenvalues (Turk, Pentland, 1991).

A new face image Γ is transformed into its eigenface components (projected onto "face space") by a simple operation:

$$\omega_n = \mu_n(\Gamma - \Psi) \qquad (7)$$

for n=1,……,M'. This describes a set of point-by-point image maltiplications and summations.

The weights form a vector $\Omega^T = [\omega_1, \omega_2, ..., \omega_{M'}]$ that describes the contribution of each eigenface in representing the input face image, treating the eigenfaces as a basis set for face images. The vector may then be used in a standard pattern recognition algorithm to find which of a number of predefined face classes, if any, best describes the face. The simplest method for determining which face class provides the best description of an input face image is to find the face class *k* that minimizes the Euclidian distance:

$$s\,\varepsilon_k^2 = \left\|(\Omega - \Omega_k)^2\right\| \quad (8)$$

(Turk, Pentland, 1991).

where Ω_k is a vector describing the kth face class. The face classes Ω_k are calculated by averaging the results of the eigenface representation over a small number of face images (as few as one) of each individual. A face is classified as "unknown", and optionally used to create a new face class (Turk, Pentland, 1991).

Because creating the vector of weights is equivalent to projecting the original face image onto to low-dimensional face space, many images (most of them looking nothing like a face) will project onto a given pattern vector. This is not a problem for the system, however, since the distance ε between the image and the face space is simply the squared distance between the mean-adjusted input image $\Phi = \Gamma - \Psi$ and $\Phi_f = \sum_{i=1}^{M'} \omega_i \mu_i$, its projection onto face space:

$$\varepsilon^2 = \left\|\Phi - \Phi_f\right\|^2 \quad (9)$$

(Turk, Pentland, 1991).

Thus there are four possibilities for an input image and its pattern vector:

1. Near face space and near a face class

2. Near face space but not near a known face class

3. Distant from face space and near a face class

4. Distant from face space and not near a known face class.

In the first case, an individual is recognized and identified. In the second case, an unknown individual is present. The last two cases indicate that the image is not a face image. Case three typically shows up as a false positive in most recognition systems; in this framework, however, the false recognition may be detected because of the significant distance between the image and the subspace of expected face images(Turk, Pentland, 1991).

Eigenfaces recognition algorithm can be summarized in the following diagram according to Pissarenko (2002) described it in his research:

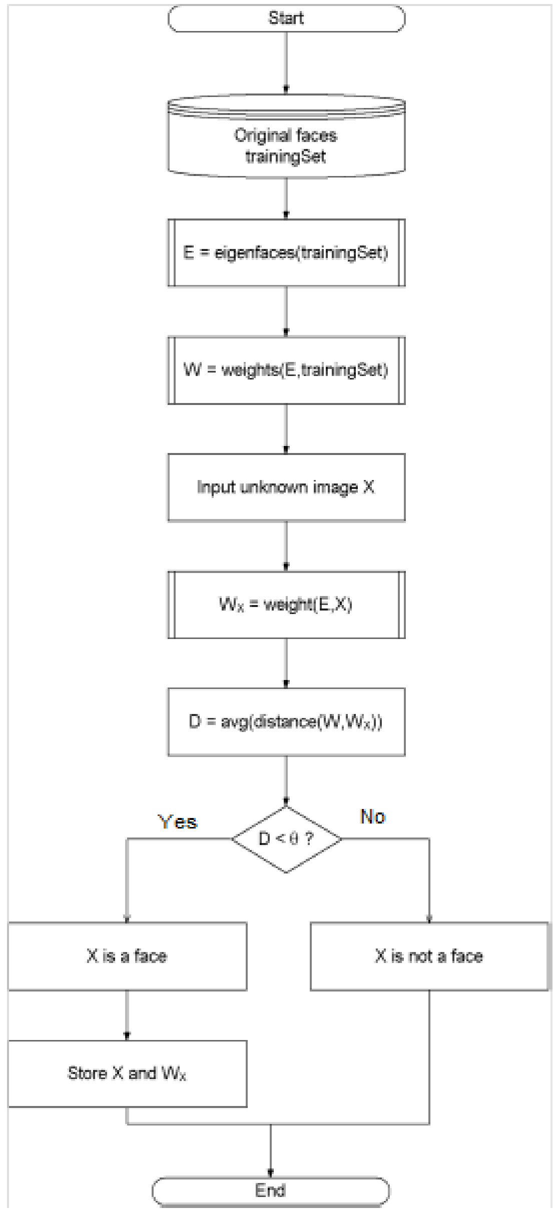


Figure 2.2: Principle of the eigenface-based facial recognition algorithm (Pissarenko, 2002, 3).

2.1.3 Eigenfaces Approach Related Work

As mentioned before eigenfaces based on PCA, a comparison made by Pathak *et al* (2011) for three popular appearance-based face recognition projection methods (PCA, LDA and ICA), these methods were tested in equal working conditions regarding preprocessing and algorithm implementation on the FERET standard data set. The three methods reduce the high dimension image space to smaller dimension subspace which is more appropriate for presentation of the face images (page 5).

LDA method finds the vectors in the underlying space that best discriminate among classes. For all samples of all classes it defined two matrices: between class scatter matrix SB and the within-class scatter matrix SW. SB represents the scatter of features around the overall mean for all face classes and SW represents the scatter of features around the mean of each face class (Pathak *et al*, 2011,6).

ICA minimizes both second order and higher-order dependencies in the input data and attempts to find the basis along which the projected data are statistically independent. For the face recognition task they proposed two different architectures: Architecture I - has statistically independent basis images (ICA I) and Architecture II assumes that the sources are independent coefficients (ICA II), these coefficients give the factorial code representation. They test all the projection-metric combinations. Since implementation four projection methods (PCA, LDA, ICA1 and ICA2) and three distance measures (L1, L2 and

COS) The best performance on each data set for each method is bolded (Pathak *et al,* 2011,6). Results of their experiment are shown in Tables 2.1.

	PCA	LDA	ICA1	ICA2
L1	**41.2%**	37.2%	**37.5%**	17.5%
L2	34.2%	40.1%	29.2%	27.2%
COS	32.5%	**57.3%**	30.5%	**41.9%**

Table 2.1: Results for appearance-based face recognition projection methods (Pathak *et al,* 2011,8).

Arora (2012) implemented eigenfaces recognition algorithm for real time face recognition using laptop computer and web camera, Arora considered video frames as still picture, his experiment examined changing or variation in illumination and head size, he considered the experiment quite successful.

Results of Arora’s experiment where registered as following:

Face condition	recognition accuracy	recognition error
Normal	83%	17%
Light variation	61%	39%
Size of face variation	55%	45%

Table 2.2: Results for eigenfaces algorithm for real time face recognition (Arora, 2012, 196)

From the previous table results shows that eigenfaces method is stable with fair recognition rate in normal condition (frontal head view, normal light condition, fixed head size), but unfortunately recognition rate drops when light conditions changed and the drop became worse when the scale vary which is bad impact on this technique.

Li and Tang (2002) studied the relationship between eigenface recognition performance and different training data sets. Using the Multilevel Dominant Eigenvector Estimation (MDEE) method, they were able to compute eigenfaces from a large number of training samples. They focus more on the results of short feature lengths since they illustrate how efficient the transformation compresses the large face vector. As the length of the feature vector increases, it becomes more like the original face vector. The effect of the transformation is largely lost if the original face image directly was used for face recognition, they got an accuracy of 74.9%; their experimental results show that increasing the number of people benefits the recognition performance more than increasing the number of images per person. The gallery used for their research contains 72*10 face images of 72 different persons.

Abdullah, et al, (2012) in their research tried to minimize the participated eigenvectors which consequently decreases the computational time. They conduct a study to optimize the time complexity of PCA (eigenfaces) that does not affects the recognition performance. Their algorithm was tested on standard dataset: face94 face database experiments conducted using MatLab.

They conduct three experiments: The first experiment is used to adjust the best number of images for each individual to be used in the training set that gives a highest percentage of recognition. They choose 19 individual with 6 images for each in the training because the result of the first experiment shows that this number of images gives 100% recognition.

Second experiment tested 28 persons in the test database with 6 images for each person in the training database as given by experiment one. They changed the threshold trying to make a decision of the best matching. In this experiment we reduce the eigenfaces for the PCA algorithm where eigenvalues are sorted and those who are less than a specified threshold are eliminated.

Third experiment decreased the number of eigenvectors and consequently this decrease the time of computation. The results of this experiment give the same recognition result as the second experiment but with less time. The recognition time is reduced by 35%.

2.2 Skin Color Segmentation

Color is important characteristic for face detection and localization is the speed of processing time for such algorithms, which is great benefit in video tracking the moving objects, this benefit for detection and recognition process comes from that color processing time is fast when compared to facial features variation processing time, another important characteristic for skin color detection is that it can overcome scaling and occlusion, also strong and stable to face geometry variations, in spite these great features color face detection is so sensitive to illumination which could cause drop in detecting accuracy (Singh, et al, 2003,1).

Zhang and Zhang (2009) said that people from different raises have different skin color nature, several studies have been done and found that the major difference lays in the variation between their skin color intensity rather than their chrominance(page 110).

Tathe, Narote (2012) defined skin color based detection by: technique that used to separate skin pixels from the rest of colors in a given image, this technique is simple and requires less computation, but it is difficult to locate face in the presence of complex background and poor illuminations.

Color information can be an efficient tool for identify facial areas and specific facial features when the skin color model can be adapted properly for different lighting environments. But such skin color model are not effective where spectrum of the light source varies significantly, in other words color appearance is often unstable due to changes in both background and foreground lighting. To solve this problem the analysis of the features like color intensity and color saturation using color channel analysis base method instead of using the existing color space (Zhang, Zhang, 2009, 111).

Süsstrunk, et al (1999) analyzed color space, they mentioned that for any type of color space it is considered as a geometric representation of colors in space of three dimensions where the basis functions are color matching functions. Spectral spaces are spaces spanned by a set of spectral basis functions. The set of color spaces is therefore a subset of the set of spectral spaces (page 1).

Most face detection techniques are based on skin color detection because this helps to decrease searching area influencing to increase the accuracy result. Detecting faces using color of skin uses different color models: RGB (red, green, blue) which is highly correlated components, HSI (hue, saturation , intensity), HSV(hue, saturation , value) both works on properties used to describe color, YCbCr mainly used for video processing for television transmission, YUV,YIQ and many other color models (Kjeldsen, Kender,1996).

From previous literatures skin color detection advantages and features can be summarized as following:

1. Faster processing than feature and pattern approaches.
2. Geometric variations doesn't affect on its results.
3. Can handle partial occlusion.
4. Resolution changes are critical challenge for testing images.

Detecting a face using any skin color segmentation is simple and easy, to do that there are some common steps these techniques follows (Singh, et al, 2003):

1. Starting by scanning the given or test image to determine skin region in this image.
2. Apply the threshold to detect face region to eliminate other skin regions in the image like: nick, arms, legs and any uncovered skin exist in the image.

3. A rectangle is drawn around the face.

Figure 2.2: Example of skin color segmentation for face detection (Tripathi, etal, 2011, 7)

Most of face recognition systems are based on the evaluation or analyzing two dimensional images intensity or color images. Extraction of reliable features from two dimensional images is difficult and is subject to a variety of possible interpretation errors, where the recognition accuracy of such systems is limited on a small set of individuals (Tsalakanidou, *et al*, 2003, 1428), a combination of different based approaches could decrease this interpretation errors rate.

Yoo ,et al (2007) think that most of face recognition systems have used only luminance information because these systems convert the color input images to grayscale images by discarding the color information and use only luminance information. And think that the colored image recognition method is better than grayscale image recognition approaches (page 1).

2.2.1 RGB Color Model

RGB (red, green, blue) color space or color model consist of the three additive primaries: red, green and blue. Spectral components of these colors combined additively to produce a resultant color (Singh, et al, 2003, 2). Tathe and Narote (2012) said that images are captured in RGB space, but the skin pixel detection in RGB space is difficult as it is not perceptually uniform and the color components are very sensitive to the intensity (page 182). RGB is highly correlated color components (Kjeldsen, Kender, 1996).

Color detection for skin segmentation using RGB technique mostly gives poor detection results due to its sincerity to illumination intensity despite its simplicity and fast process, the solution for this disadvantage is to increase tolerance toward intensity changes in images is to transform the RGB image into a color space whose intensity and chromaticity are separate and use only chromaticity part for detection (Singh, et al, 2003, 1).

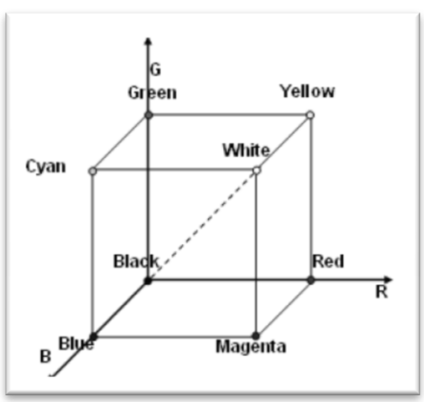


Figure 2.3: General representation for RGB color model (Georgieva, et al, 2005, 2).

2.2.2 HSV Color Model

According to Georgieva et al (2005) HSV color model (Hue, Saturation, value), also called HSB (Hue, Saturation, Brightness), defines a color space in terms of three ingredient components as shown with their values in figure 1.9:

- *Hue:* is the color type (such as red, magenta, blue, cyan, green or yellow). Hue ranges from 0-360 deg.
- *Saturation:* refers to the intensity of specific hue. Saturation ranges are from 0 to 100%.
- *Value* refers to the brightness of the color.

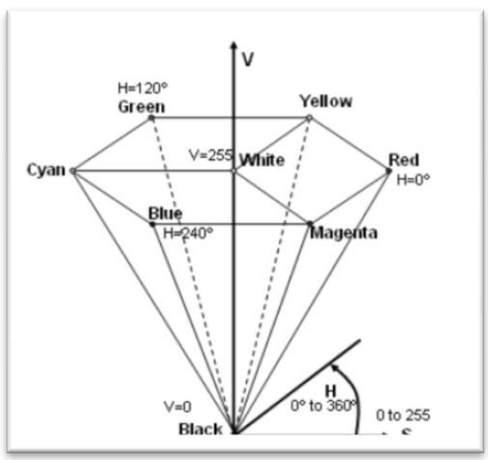


Figure 2.4: HSV color model (Georgieva, et al, 2005, 2).

Hue (H) is color depth a measure of the spectral composition of a color and represented as an angle, which varies from 0 to 360. Saturation (S) refers to the purity of colors and intensity of pixel is defined by the value (V), which values ranges from 0 to 1.

HSV model is related to human color perception. Tathe and Narote (2012) in their research made conversion from RGB to HSV color system is done using following equations by using RGB values in the image (page 183):

$$H_1 = \cos^{-1} \frac{0.5[(R-G)+(R-B)]}{\sqrt{(R-G)^2+(R-B)(G-B)}} \tag{1}$$

$$H = H_1 \quad if \quad B \leq G \quad H = 360^0 - H_1 \quad if \quad B > G \tag{2}$$

$$S = \frac{Max(R,G,B) - Min(R,G,B)}{Max(R,G,B)} \tag{3}$$

$$V = \frac{Max(R,G,B)}{255} \tag{4}$$

(Chakraborty, 2012) thinks that the most used algorithm for skin color detection is HSI model with high rate of correct result (accuracy), where HSI has a significant feature that study color characteristic and the information that carried in intensity component that carry the information of hue and saturation of colors of colored image the that helps to analyze the depth variation where this variation affect the color reading number like blue code is different from light blue code, depth variation help to give better results in detecting face features process. HSI, HSV, HSL (hue, saturation, intensity/value/luminance) carry the same features.

2.2.3 YCbCr Color Model

Tathe, Narote (2012) said that the mostly used color space is YCbCr, because of its high quality and stability; they identify these color space components by:

- Y is luminance component
- Cb is blue chrominance and Cr is red chrominance.

Where the chroma component is represented only by blue and red as the sum of chroma value of red, green and blue component is always constant. The separate luma and chroma component makes this model illumination invariant. They converted from RGB color space to YCbCr color space is done using the RBG values in the image by the following equations (Tathe, Narote, 2012, 183):

$$Y = 0.299R + 0.587G + 0.114B \tag{5}$$

$$C_b = 128 + (-0.169R + 0.331G + 0.5B) \tag{6}$$

$$C_r = 128 + (0.5R - 0.419G - 0.081B) \tag{7}$$

YCbCr are has color components like Luminance, blue minus Luminance, red minus Luminance as YCbCr is the digital version color space. It has more advantage than the RGB & HSV model and extracts the skin portion of an image using chrominance values (Chitra, Balakrishnan, 2012, 4231).

Chitra and Balakrishnan think that even though it is the best approach for face detection using skin segmentation it gives low accuracy due to some reasons other color spaces challenges. They found that the skin portion of an image should satisfy as follows

140 <= Cr <= 165; 140 <= Cb <= 195

(Chitra , Balakrishnan, 2012, 4231).

2.2.4 Skin Color Detection Related Work:

Singh, et al, (2003) in their research compared the face detection results between 3 color models (color space) RGB, HSI and YCbCr without eliminating any components of mentioned color models based on detailed experimental study of face detection algorithms based on Skin Color, RGB color space gained accuracy result of 56.46%, and YCbCr gained 83.91% which is considered very high comparing to RGB model, HSI model gained 82.27% which is comparatively so close to results YCbCr. So this comparison showed that model is the best for skin detection (page 232).

The second part of their experiment was mixing the three color detection techniques to enrich the work and improve the detection rate, their algorithm combined the 3 color models in their skin detection algorithm, and the examined face detection algorithm gained accuracy 95.18% with complex background and detection for different head position (Singh, et al, 2003, 234), which make fair to say that they had a robust algorithm.

2.2.5 Eigenfaces with Skin Color Detection Related Work:

Yang *et al* (2005) presented complex eigenface method; their method combines saturation and intensity components in the form of matrix to represent the faces, where intensity component is sensitive to illumination. The remarkable development for their work is that they showed that multi-variable principle component analysis (PCA) method outperforms traditional grayscale eigenface methods, The experimental result demonstrates that the proposed color image based complex Eigenfaces method is more robust to illumination variations than the traditional grayscale image based Eigenfaces (pages 64).

Yoo and his colleagues (2007) evaluated the eigenface face recognition algorithm in diffrent color spaces and analyzed their performance in terms of the recognition rate applied the eigenface method to each color component independently and combine the results to make the final decision for 3 color space (domain): RGB, HSV, YCbCr and YCg'Cr', the data set used for their test was colored FERET (Yoo, et al, 2007, 107).

For RGB domain they used **x***R*, **x***G*, and **x***B* are *N**1 vectors, denoting red, green, and blue components of an input face image, respectively. First, these components of RGB are converted to three other components **xC1**, **x***C*2, and **x***C*3. At the second stage, the eigenface analysis is performed for each component, independently. And then, the three distance vectors, **d C1**, **d C2**, and **d C3** are combined with weighting factors and the person of the face image is identified at the end. Following figure shows the block diagram of the used face recognition system for multi-spectral face images:

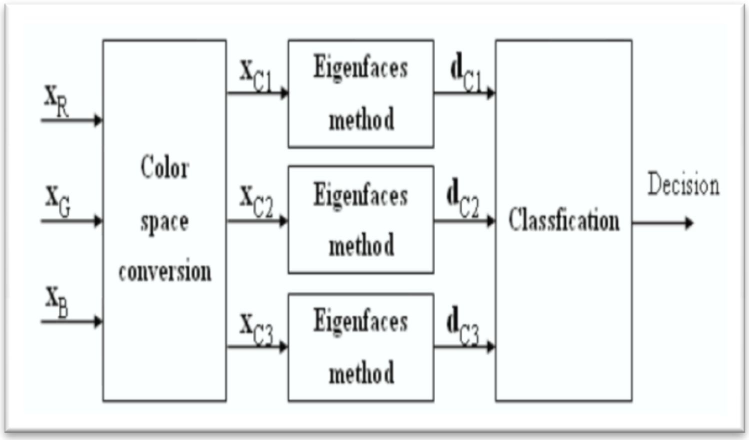


Figure 2.5: Block diagram of the face recognition system using color information (Yoo, et al, 2007, 107).

For the rest of color space domain the same test was applied after calculating each component value that reflect RGB value for that color space. Their experimental results face images showed that color information is beneficial for face recognition as following: RGB was (0.876), HSV was (0.881) and finally YCbCr was (0.923), so that the YCbCr space is the most appropriate spaces for face recognition. The YCbCr space is shown to be effective to facial expression variation (Yoo, et al, 2007, 109).

2.3 Hough Transforms

Hough transforms will be overviewed according to Duda and Hart (1972) in their research. Hough transforms defined by parameterization specifies a straight line by the angle θ of its normal and its algebraic distance ρ from the origin, the set of all straight lines in the picture plane constitutes a two-parameter family, if the parameterization for the family can be fixed, then an arbitrary straight line can be represented by a single point in the parameter space. (page 12).

The equation of a line corresponding to this geometry is:

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

Hough transforms has interesting properties of the point-to-curve transformation:

1. A point in the picture plane corresponds to a sinusoidal curve in the parameter plane.
2. A point in the parameter plane corresponds to a straight line in the picture plane.
3. Points lying on the same straight line in the picture plane correspond to curves through a common point in the parameter plane.
4. Points lying on the same curve in the parameter plane correspond to lines through the same point in the picture plane.

Duda, Hart (1972) mintioned that Hough uses the slope intercept parameterization. However, this parameterization has the disadvantage of being sensitive to the choice of coordinate axes in the picture plane.

If several figure points lie on a nearly vertical line, for example, both the slope and the intercept may be arbitrarily large. Thus the entire two-dimensional parameter plane must be considered. It could be done twice, interchanging the x- and y-axes, but this would introduce additional complications. The normal parametrization avoids these disadvantages, fundamentally for the same reasons that make it useful in integral geometry: It allows us to place an invariant measure on the set of all straight lines. An important special use of the transform method is to detect the occurrence of figure points lying on a straight line and possessing some specified property (page 14).

Duda, Hart (1972) said that General Hough transform approach can be extended to curves other than straight lines. To detect circular configurations of figure points, a parametric representation for the family of all circles (within a retina) and transform each figure point must be chosen. If, as a parametric representation, it is described as circle in the picture plane by (x- a) 2-+- (y- b) 2 = c ~, then an arbitrary figure point (x~, y~) will be transformed into a surface in the *a-b-c* parameter space defined by *(Xi* -- a) 2 -q- *(yi -- b)* ~ *= c 2* (Page 15).

The following figures show the difference normal parameters for a line and Projection of collinear points onto a line (Duda, Hart 1972, 12).

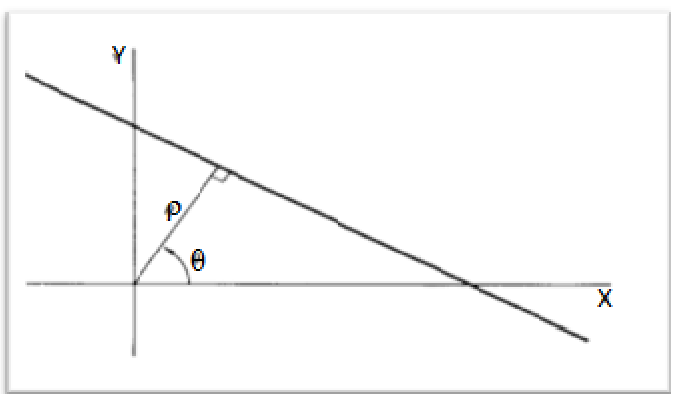


Figure 2.5: The normal parameters for a line in General Hough transform (Duda, Hart 1972, 12).

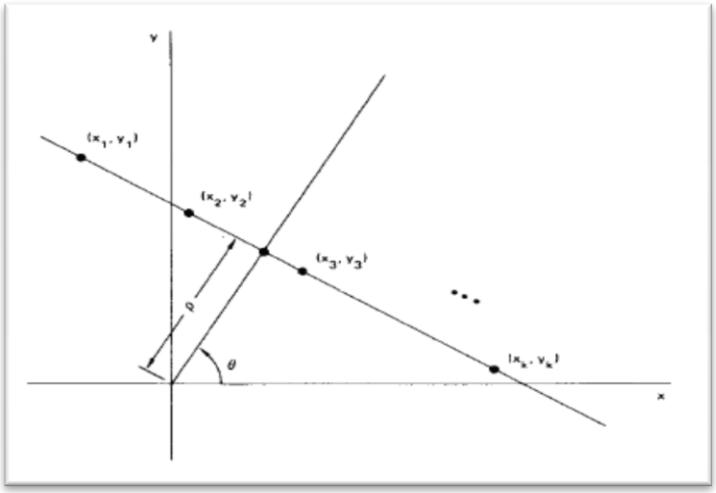


Figure 2.6: Projection of colinear points onto a line (Duda, Hart 1972, 12).

2.4 Sobel Detection Method

Sobel is a face detection technique with operator is a kind of orthogonal gradient operator. Gradient corresponds to first derivative, and gradient operator is a derivative operator. For a continuous function f (x, y), in the position (x, y), its gradient can be expressed as a vector (the two components are two first derivatives which are along the X and Y direction respectively.

Sobel has two main features: it has some smoothing effect to the random noise of the image, and elements of the edge on both sides has been enhanced, because it is the differential of two rows or two columns, so that the edge seems thick and bright.(Gao, et al, 2010, 68)

Chapter 3

Methodology

3. Modified Eigenface Approach

This chapter has detailed view for the proposed approach for modified Eigenfaces using color segmentation and edge detection for real time face recognition using real data with low restriction on training and testing data to simulate real environment, the purpose of this modification is to overcome some challenge for eigenfaces approach the challenge of recognizing faces in images having variation in head position, rotation and head scaling.

Most of the studies used standard faces database (data set) like FERRT, Yale, ORL, MIT and many others that can be downloaded from the internet with referencing conditions enforced by data set providers. Researchers used these databases as training sets and test sets for faces images contain only the head in standard head scale meeting most needed face status in standard tests condition, they do this in order to eliminate the error rate for testing results due to face recognition limitations: illumination, face position, facial expression, facial occlusion (where part of the face is occluded by glasses, scarves or hats) and image background, which force restriction applies on the testing images to fit certain head size and certain background, where this kind of databases where prepared for this type of studies.

Figure 3.1: sample of FERRT database faces (Geng, Jiang, 2009, 601).

Face recognition systems gained high rate of accuracy when the learning set is large where each person have fair number of images that satisfies different head positions and facial expressions for better recognition results. Eigenfaces approach recognition results are affected by the training data set images condition where unwanted (unconstrained) face image can defect the whole set recognition results (Ramesha, 2009).

Many of the current face recognition techniques assume the availability of frontal faces of similar sizes. In reality, this assumption may not hold due to the various nature of face appearance and environment conditions (Hjelm, Low, 2001, 237). PCA is the core of eigenfaces approach (subject of this study) requires full frontal display of face, considers every face in the database as a different image. Faces of the same person are not classified in classes (Sirovich, Kirby, 1978), (Turk, Pentland, 1991).

As mentioned before eigenfaces utilize PCA which is a classical feature extraction and data representation technique widely used in pattern recognition. It is one of the most successful techniques in face recognition. But it has drawback of high computational especially for big size database (Abdullah, et al, 2012, 23).

The proposed approach seeks to manage having less restricted training database to these detection and recognition constraints in testing face images for real time recognition, challenges for real time recognition increase due to background and scaling factors, with reducing the number of images for three images of each person in the training set this will increase this type of challenges because eigenfaces need fair number of images for each individual, and the test images will be from another data set (there will be no common images between training and test set).

Tests will be done on training set for some well known celebrities from different origins, where this type of images is public. For an example, figure 3.2 is a sample from the train set that has 3 training images for American actor named Will Smith, as noticed the back ground is not standard, with different head position and head profile staring from left to right: frontal profile with head rotation with around 80 degrees to X axes, semi left profile, full frontal view. Also images have different scaling where the head size in the three images not standard.

Figure 3.2: Sample of training set for African origin male actor with different head position and different scaling.

Figure 3.3: Sample of training set for Arabic origin female singer with different head position and different head profile.

Figure 3.4: Sample of training set for Asian origin female actor with different head position and different head size

The used training set observed that the chosen images satisfying condition for face recognition, and to have training images with factors that considered to be challenging for the results of face recognition:

1. Persons in the training set are from various origins.
2. Chosen images have different head position and face profile.
3. Different scaling where head sizes vary from image to another.
4. Satisfies different head rotation.
5. Face expression variation.
6. Unrestricted background.

Proposed approach was developed using MatLab 2012a software for its powerful feature in manipulating matrices where this types of systems built on these matrices.

Proposed face recognition approach in this thesis for Eigenfaces in general overview is summarized in the figure 3.4.

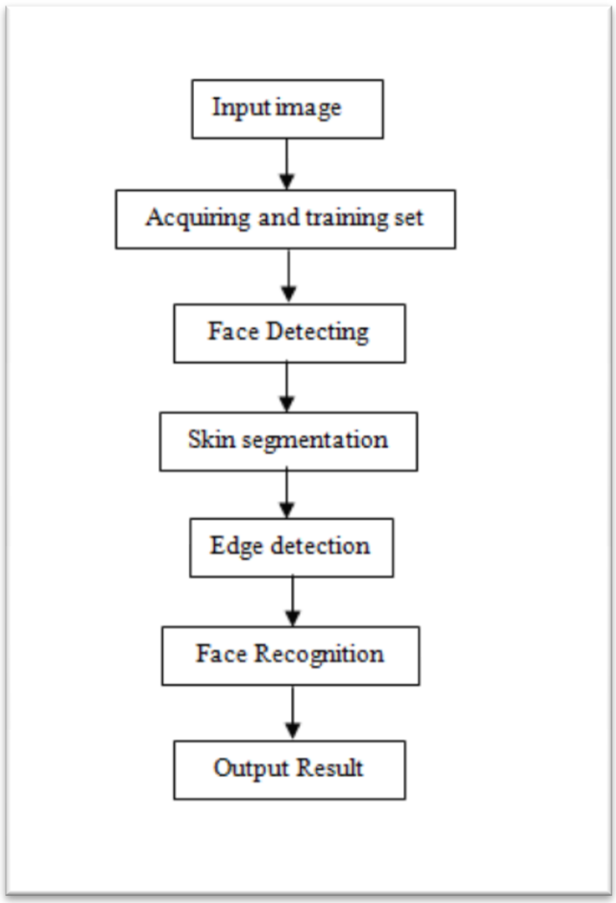


Figure 3.4: Proposed face recognition approach.

The proposed approach methodology based on:

1. Acquiring the training dataset and split it into groups to enhance the recognition percentage for such training set that have less number of images for each individual proved by testing phase. Managing the training set by splitting images into groups

to enhance the recognition accuracy for such training set which have only three images for each individual.

2. Detection phase where the images for both test image and training set are forced to face detection techniques with skin segmentation and edge detection:
    - Using hue component from HSV color model (hue, saturation and value) where hue color component will be used to determine skin existing in the image; hue component will be used and calculated.
    - In parallel with using hue use CbCr from the YCbCr color space for skin segmentation to mange using the RGB color space by converting RGB components value in to YCbCr.
    - Using General Hough transformation technique to determine the location of eyes which are considered important face features.
    - Cropping detected face area from the test image to be recognized by eigenfaces.
3. Applying eigenfaces approach on the train set and test image:
    - Projecting test image to face space and find its eigenvalues, and eigenvectors called (eigenfaces).
    - Comparing the transformed test image with both centered image eigenfaces sub-set which is the reflection of the training set.
    - Determine if the given image face has a matching known individual or not, comparison will be done using two Euclidian distances.

3.1 Acquiring and Dividing Dataset

Proposed technique suggest reducing the number of training images for each individual, as mentioned in the beginning of this chapter according to previous studies eigenfaces needs fair number of training images (10 images for each individual), this reduction of data will influence the recognition accuracy by decreasing it, this drop in accuracy can be justified by projecting the train set to the sub space to generate the eigenfaces, when the image is converted into vector distortion to its structure which results the ghostly appearance face, and the correlation between these faces causes more complexity to recognition with small number of data set.

The problem arises when the test image is projected to this sub space for comparing it with these eigenfaces, the accuracy for this process depends on the quality and quantity of the used data set, quality refers to type of constrains on that images. In addition to the number of images for each individual the constraints on the training set images is less restricted in this proposed work.

How the reduction of number of training images will be determined? This will be done starting by using only 1 training image for each individual ending by using 4 images for each individual, results of recognition will score dropping in recognition, another source of challenge beside decreasing training images number is having unconstrained type of images. Solution for these challenges will be by dividing the training data set into subsets, each subset has a number of individuals, and the best practice for the number of individuals for each subset is number of persons, which will be proven by experiments.

Data set is acquired and divided into sub-sets; the data set must have the training images for each person in a sequence order to ensure that his/here training images will be in the same sub group where the division will be in a sequence order.

The eigenfaces approach will be implemented and to find images eigenvalues and eigenfaces mentioned in chapter 2 (Turk, Pentland, 1991, 74) as in the following summary:

1. Calculate the matrix *L*, find its eigenvectors and eigenvalues, and choose the *M'* eigenvectors with the highest associated eigenvalues.
2. Combine the normalized training set of images produce the eigenfaces $\mu_k, k = 1, \ldots\ldots, M'$.
3. Sub-setting the normalized training set of eigenfaces.
4. For each known individual, calculate the class vector Ω_k by averaging the eigenface pattern vectors Ω calculated from the original images of the individual.

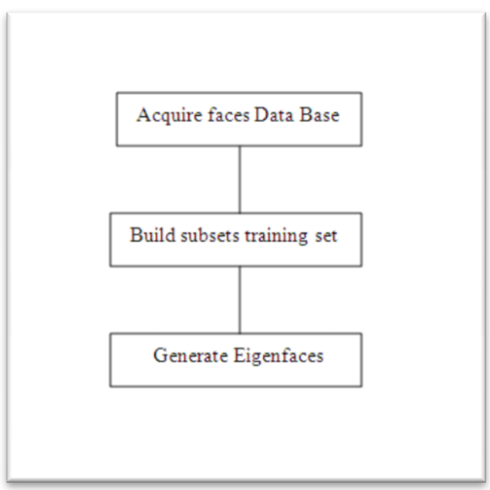


Figure 3.5: Manipulating training data set.

3.2 Face Detection Phases

Eigenfaces approach implement detecting using PCA technique. PCA determines the variables that make the variance of faces from each others; this feature gives it the benefit of speed and insensitivity to small or gradual changes on the face. The problem of this approach is the images must be vertical frontal views of human faces (Slavkovic, Jevtic, 2012, 122). Meaning PCA will not be functional to the type of images used in this work that was mentioned in the introduction of this chapter, that what justify applying face different detection techniques in this approach. The following figure represents the detection phases for proposed approach.

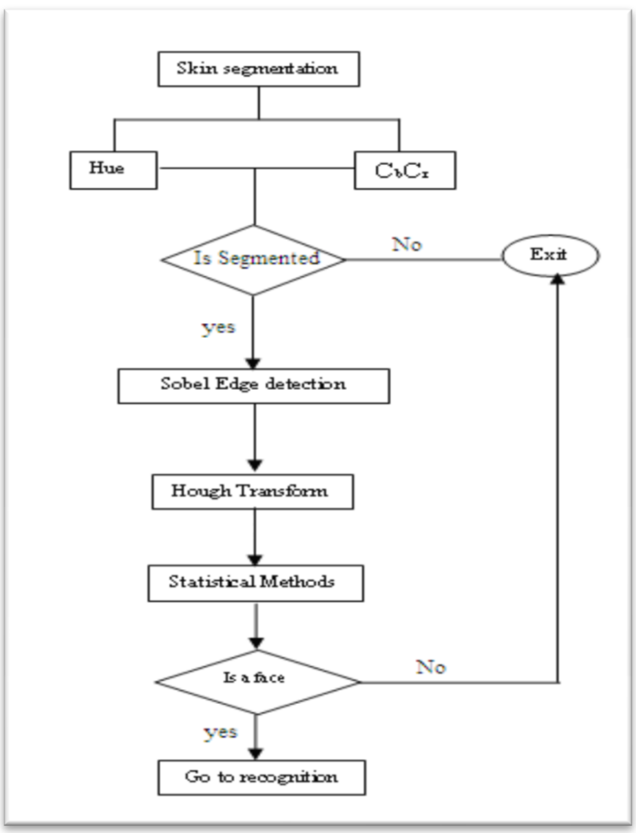


Figure 3.6: Face detection chart

3.2.1 Phase 1: Skin segmentation

Colored images are RGB format by default; the given image must be analyzed to find the color characteristic for each color component that is represented in its own value: red, blue, and green component to find the skin color combination of the 3 components. Because RGB detection has poor results in face detection color handling must be done with powerful techniques (or color space) YCbCr and HSV, using Hue component from HSV and CbCr components from YCbCr.

3.2.1.1 Skin segmentation using Hue component

HSV color space is used for better presentation of skin color, so RGB model will be replaced with HSV color space a robust color model for face detection (Singh, et al, 2003, 232), hue component is the targeted element for this transformation for better skin segmentation process, where the illumination is a challenge for face detection and recognition using powerful color components can solve this challange, HSV is a strong technique to handle this challenge. To do that the RGB color space will be converted using MatLab function rgb2hsv( ) which converts each component of RGB to its equivalent HSV color component, the hue component will be used for manipulating the image where:

$$0.01<=\text{hue}<=0.1$$

(Georgieva, et al, 2005, 2).

3.2.1.2: Skin segmentation using YCbCr color space

Using YCbCr color space for it high performance in face detection according to previous literatures (Singh, et al, 2003, 234), to convert from RGB to YCbCr the following equations were used:

$$Cb = 0.148*red - 0.291*green + 0.439*blue + 128;$$

$$Cr = 0.439*red - 0.368*green - 0.071*blue + 128;$$

(Yoo, et al, 2007, 107)

Determining skin segments that vary from white skin to dark brown (Chitra , Balakrishnan, 2012, 4231), the image in YCbCr format skin color fall in the range of:

$$140 <= Cb, Cr <= 195$$

And for the best presentation of human skin color should match two conditions for hue values and CbCr values in parallel:

$$140 <= Cb, Cr <= 195 \quad \& \quad 0.01 <= hue <= 0.1$$

By applying the formula on each pixel in the image that determine skin segment skin will be located, any existing of colors out of the skin color range will be set to zero value for that pixel, green color for example doesn’t belong to the normal range for human skin color segment, pixels belonging to the defined range will be given the value of 1, resulting normalized image will in black and white, and have the shape of the face with empty spaces for eyes hole , mouth, nose, ears and neck. This step challenge is the existence of the neck and ears which match the color segmentation of the face.

The following examples (a,b) show the result for detecting the skin color segmentation areas with the value of one and non skin color with value of zero where skin area is limited and hair color is not near to skin color in this example.

Example a

Example b

Figure 3.7: Test images with resulted image for skin segmentation areas

The first example (a) shows the result for detecting the skin segmentation areas that have good concentration on faces area, and distortion from back ground is also limited, the second example (b) shows the result for detecting the skin segmentation areas where the wide area of skin color segmentation and the hair color degree close to the segmentation range with light effect is highly noticed, that is considered to be complication on processing to locate the face in this given image, on the left the test image that must be detected and recognized, on the left the result imaged after running Hough transform test on it.

3.2.2 Phase 2: Finding edges of the face using Sobel edge detection

Now to find the face boundaries by eliminating unwanted part like neck, ears and hair in case hair color is close to skin segmentation range, this will be done by finding the human’s face edges using edges detection using Sobel method and General Hough transformation method then do statistical method calculation.

Sobel will find the faces edges in the images that will look for the edges between black and white color in the segmented image, according to the segmentation condition to separate it from the rest of the image but yet this process will not remove non face boundaries, this process will be done using.

The following figure shows the result image for the result of applying Sobel edge detection on the segmented image, the white lines have the value of one represents the edge between different colors.

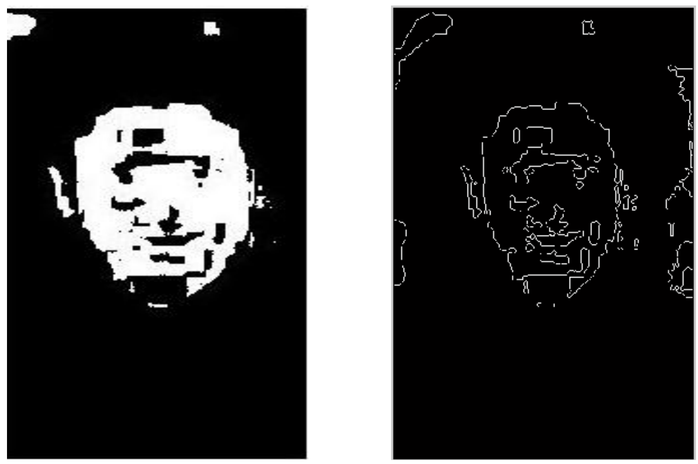


Figure 3.8: Segmented image with resulted image after applying edge detection.

3.2.3 Phase 3: Finding edges of the face using Hough transform

Detecting face boundaries by row will be done using Hough transform (Hough transformation for image processing) after that column boundaries will be determind, Hough transform determine the location of eyes by allocate the peak value of variances about one point, where it looks for the collection of ones values in a group of pixels and zeroes collection in another areas in the image, in other words it scans the image searching patterned value in the image and extract the of value in order to locate them, the black spots of the mouth, nose and eyes considered as variation points because they carry the value of zeroes where the surrounding pixels skin have ones values, this peak or set of peaks was found is represented in curved coordinates by θ (theta) and ρ (rho).

$$x \cos \theta + y \sin \theta = \rho.$$

(Duda, Hart 1972, 12).

Hough Transform used to find lines in an image. Hough space output is matrix with the ρ axis and θ axis vectors. Peak values in the matrix represent potential lines in the input image, these peaks are the concerned to find eyes position. So it will find all the peaks in the Hough space matrix in order to identify potential lines, as the peaks that have highest values of the face matrix position refers to position of eyes in terms of ρ and θ and calculated.

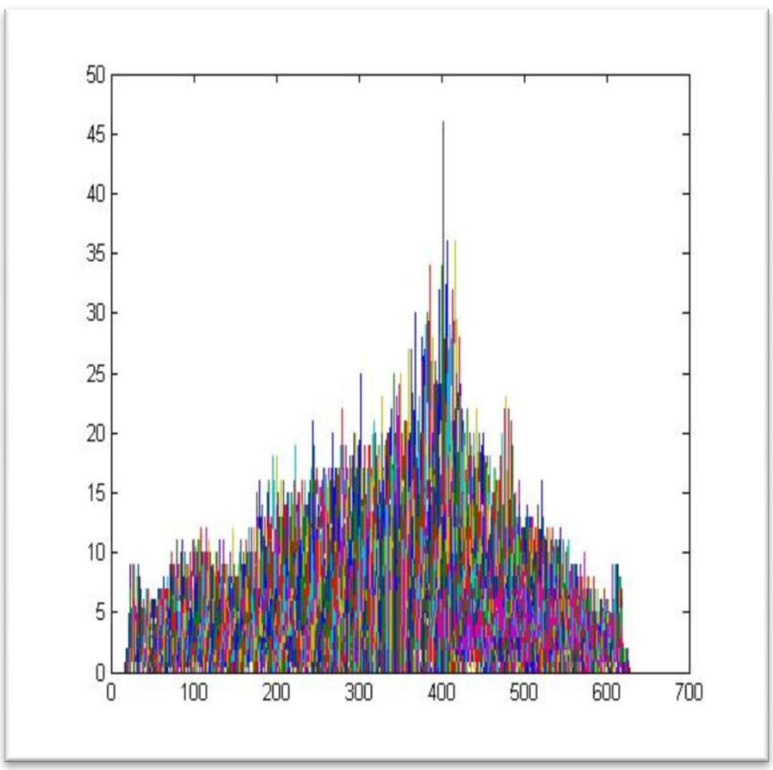


Figure 3.9: Hough transform applied for the edge detected image giving all the peaks found

3.2.4 Phase 4: Finding edges of the face using statistical methods

Finding the face boundaries demands to allocate these edges by row and columns, the use of statistical methods such as variance and mean function will eliminate non face pixels. Variance function is applied on the segmented and Hough transformed image to find the variance of ones in each column where the variance measures how the data (the distribution for zeros and ones) is spread out, then mean value will be used for of each column is subtracted from its variance, these calculation will determine the beginning of the face and end ones values from the beginning to the end of the segmented image.

Hough is applied on the image to find all the peak values in the image as showed in figure 3.9, now to find the location o eyes some statistical calculation were needed to distinguish eye peaks (Islam, et al, 2003, 1), first calculate variance of Hough result to find the relation between the columns as flirting factor on Hough transformation to get one matrix, then find its max and, the result will be as shown in figure 3.10.

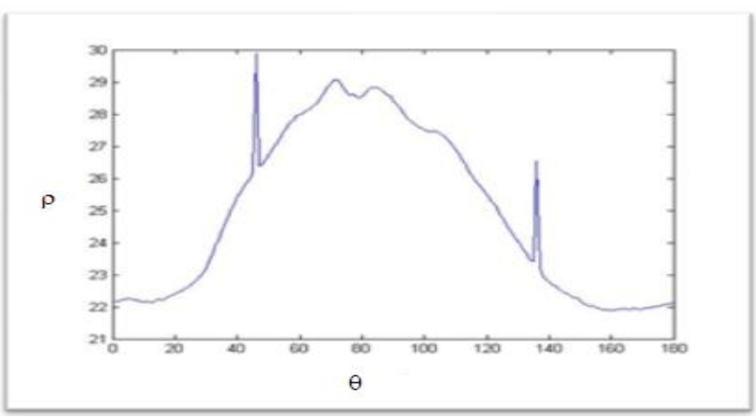


Figure 3.10: Hough transform filtered by variance

Eyes area represented the most (extreme or max variation) variance values in the image because of the structure of eyes where the pupil in the eye is brown color falls in the range of skin segmentation, so they represent the peaks as shown in Figure 3.10, left eye peak is represented at θ= 45 and ρ~= 30 and right eye peak is represented at θ ~= 140 and ρ~= 27.

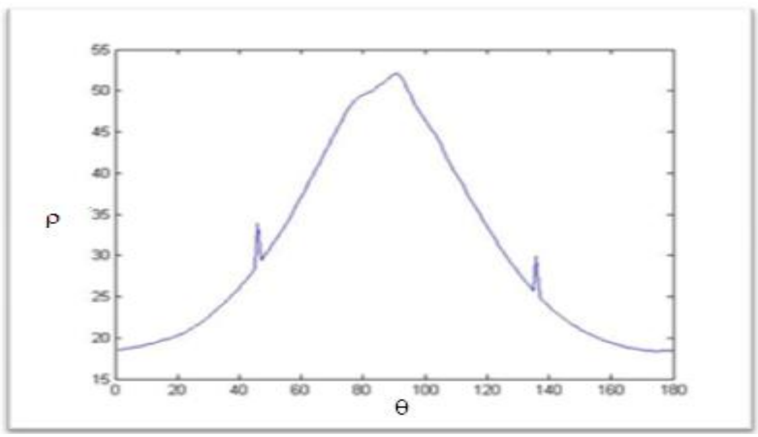


Figure 3.11: Filtered Hough transform

Now calculating the position of the eyes proposed as found by Hough peak results at θ for eye1=46, and θ for eye2 = 136.

After calculating the eye position using θ and ρ finding face detection by row will be done, where the relation between facial features is standard based on the fact that human faces are constructed in the same geometrical configuration. This model was constructed to evaluate which combination of feature blocks measures the distance between these features, according to the average proportion between each facial organ obtained by estimating several real faces. Facial symmetry is another geometrical characteristics for this technique (Lu , et al, 2003, 168).

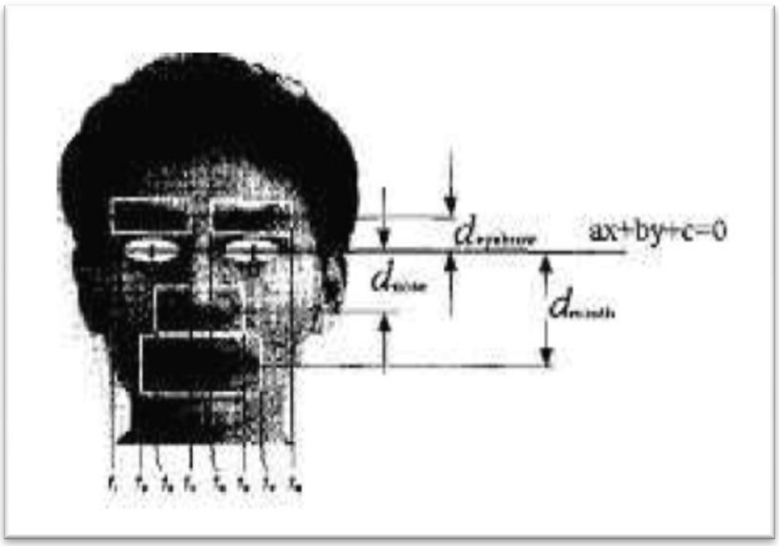


Figure 3.12: The geometrical face model (Lu , et al, 2003, 168).

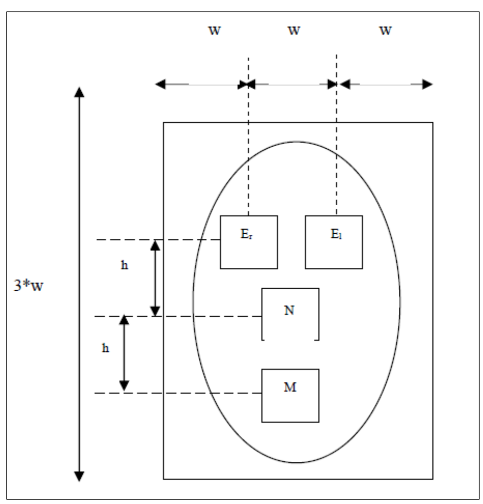


Figure 3.13: A frontal face view with distance measuring relations (Tin,2012, 32).

This step finalizes face detection process it, then the detected face is cropped and sent to recognition. The following an example that summarizes the detection phases:

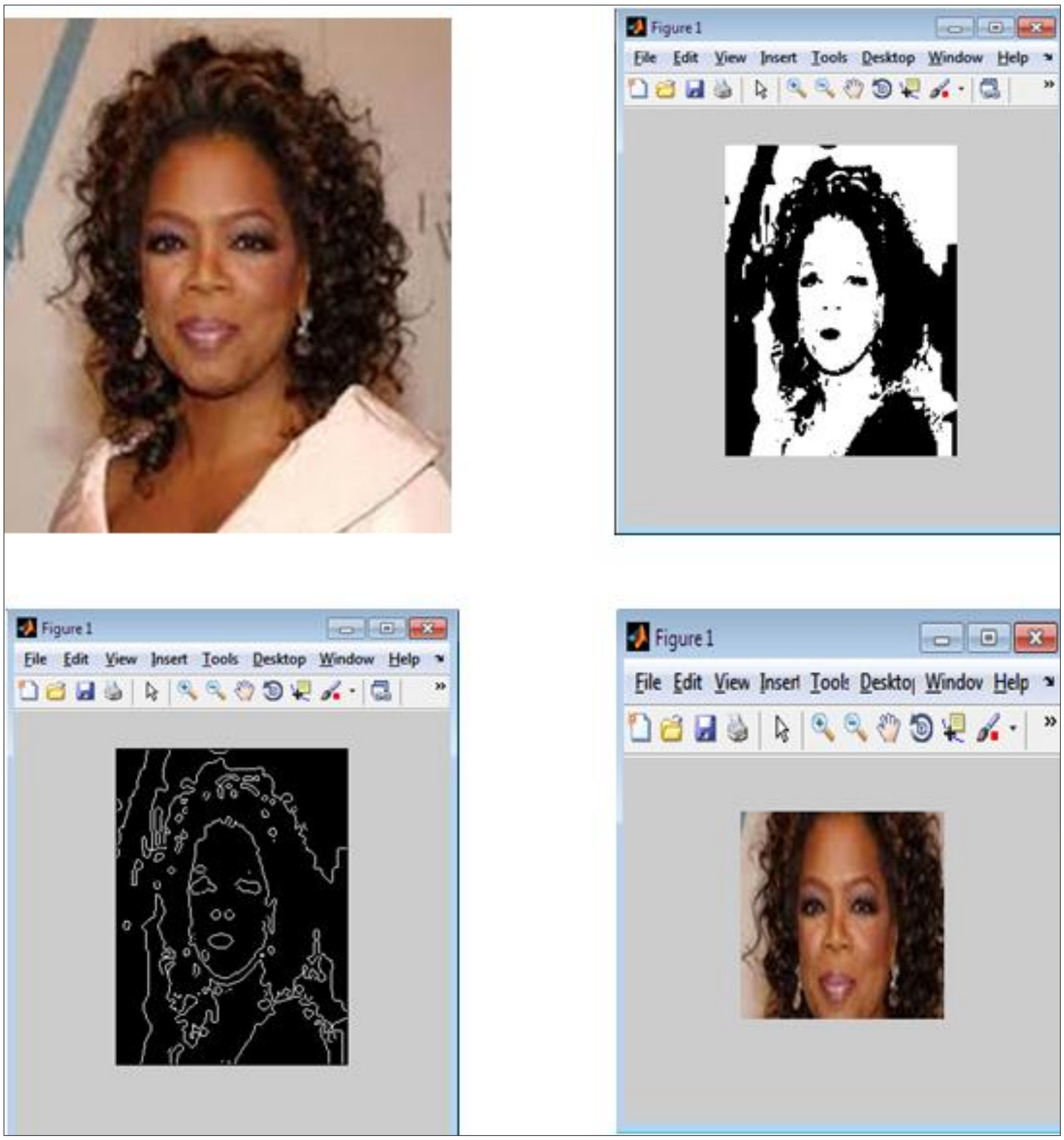


Figure 3.14: Example of detection phases.

3.3 Face recognition phase

Recognition phase depends on using eigenfaces approach with modification by the sub-setting that was done on acquiring the training set and comparison process; eigenfaces will be implemented on both test image and sub-set of training data, where this sub-setting comparison with test image as follows:

First: After acquiring the subsets groups of eigenfaces and their eigenvalues, find the centered images for each sub-set:

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

These centered images will be projected by multiplying Eigenfaces transposed by the array of all images vector.

$$\text{Projected images} = \Phi i * A^T$$

Second: The comparing for image is done on projected images (eigenfaces) and for centered images, that will be done for the following reason: eigen image is distorted due to projecting it to the sub space, this distortion with big number of images gives false recognition, this is solved by sub-setting the training set and with comparing with both projected image and centered image has its own group properties which give in the comparison results, where the centered image is the product of multiplying eigenfaces value with difference from mean value.

Euclidian distance for comparison where two Euclidian distances will be found and this is the modification in eigenfaces that is promoted in this work:

- Find the Euclidian distance for centered images in each group and between eigenfaces; defend the minimum distance within the sub-set ε_{ki}, which means the number of resulted Euclidian distance is equal to the number of sub-set groups. Comparison within the eigenfaces sub-set is easier than comparing with the whole set of eigenfaces.
- Then comparing test image with the general features in each group, where this Euclidian distance ε is the distance between test image with each Euclidian distance of sub-group ε_k to find the match for that image.

The proposed work based on eigenfaces recognition had new technique in recognizing faces by using a combination of detection and recognition methods: starting by using hue and CbCr for skin segmentation, then used three different edge detection techniques : Sobel, Hough transform and statistical method to allocate the face in the given image. The reason for using these techniques is to find the face in colored image because eigenfaces works on gay scale level, in addition to this issue the type of used training and testing images has challenges to eigenfaces that was the reason for these modification. Reducing the number of training images was the reason for splitting training set into sub-sets to overcome the distortion appearance of the face in projected images to eigenfaces sub space.

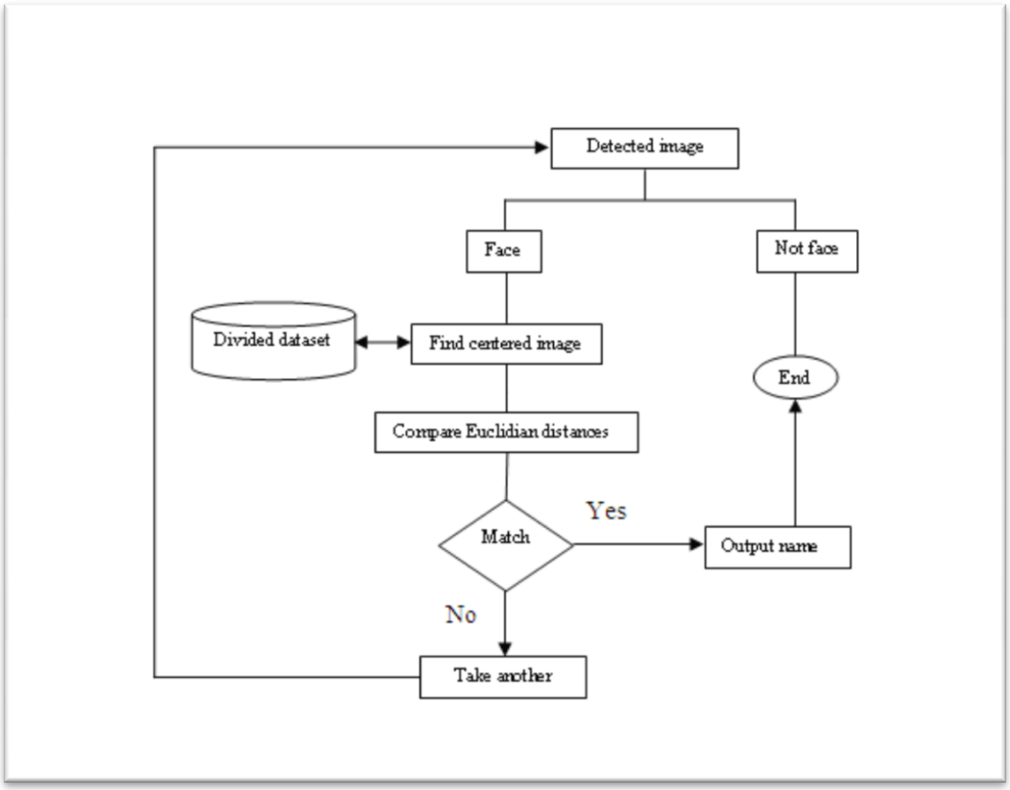


Figure 3.15: Face recognition chart.

Chapter 4

Evaluation and experiments results

4. Evaluation and experiments results

Software used for implementation is MatLab 2012a, training data set has images up to four training images for each individual, the number of individual is 26, the testing images for these individual is not included their training set. Recognition results are influenced by different training data sets. However, most researches simply choose a small number of training samples randomly for computation of the eigenfaces without much justification (Li, Tang, 2002, 1); proposed dataset has no limtations or constraint on head position, head size or backgroun, figure (4.1) shows a collection of images from training data set.

Figure 4.1: Snapshot from training data set

Example is given for test on female image testing the accuracy to recognize individual with left side view for the test image, and having head rotation, the test scored true recognition. Figure 4.2 showing the equivalent image.

Figure 4.2: individual training images

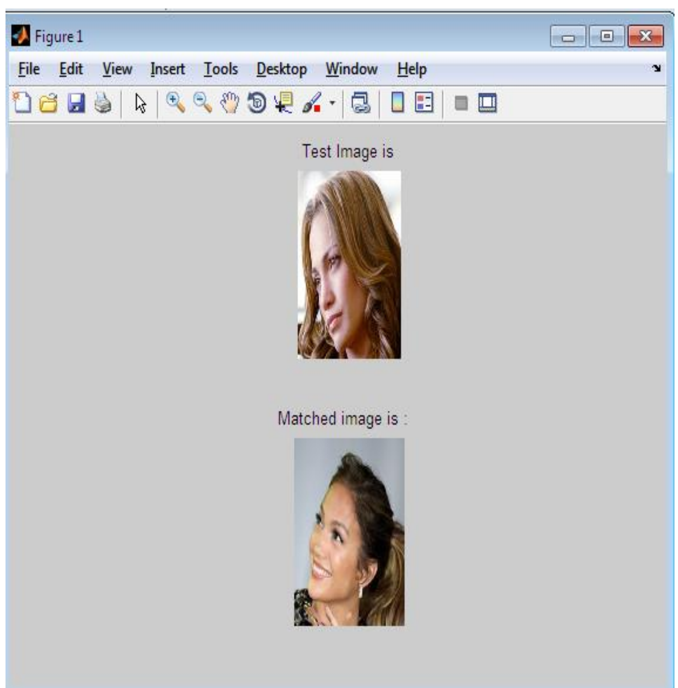


Figure 4.3: Tested image result after executing

Example is given for test on male image testing the accuracy to recognize individual with left frontal face view for the test image, and having head rotation with the hand position beneath the chin, the test scored true recognition. Figure 4.4 showing the equivalent image.

Figure 4.4: Individual training images.

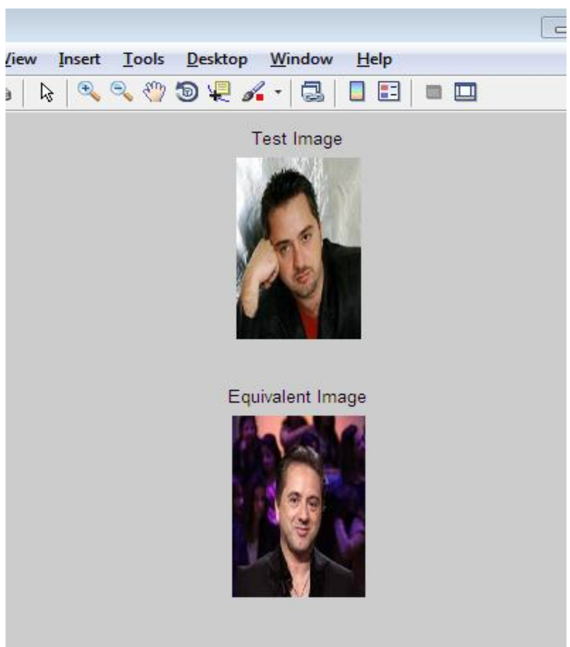


Figure 4.5: Tested image result after executing.

Figure 4.6: Individual training images.

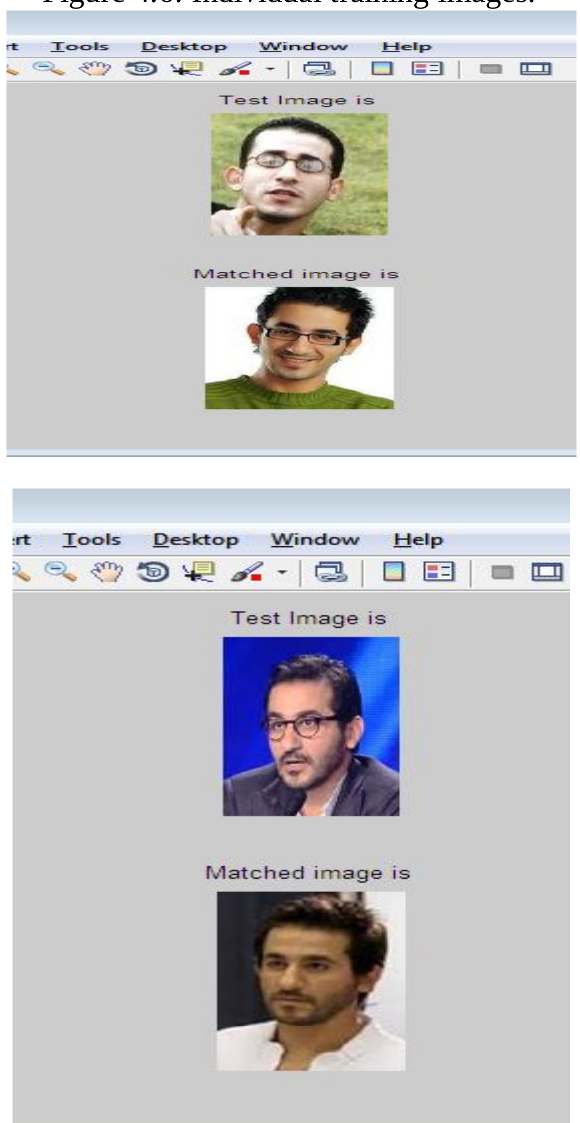


Figure 4.7: Test result after executing with 2 different test images.

4.1 Testing dividing (grouping) data set with variation of training images number

This test will be implemented in phases as following: where the data set is available for 26 persons and dividing technique into sub-set for the training set is implemented, plus the aim of the proposed approach to decrease the number of the training images for each individual, this type of challenge need excessive testing.

Testing will find the effect of both factors:

First: decreasing the number of images for each individual, starting with minimum number of training images for each individual and increment this number (starting by 1 for each ending by 4) and observe the results.

Second: sub-setting training data set, in parallel with changing training images numbers sub-setting the training set will be tested also (starting by 2 individual in each sub-set ending by 7).

Detailed testing results will be listed in the following section, tests will be categorized according to the number of training images for each individual, results of recognition will be listed in tables with recognition result for each individual, correct recognition result will be marked with (✓) sign. This will be followed by summarized table of results for easier observing recognition accuracy and analyzing these results.

4.1.1 Testing using only one training image for each individual

Phase 1: Data set of 26 person, training images are (1) image per each individual, where groups in each sub-set has vary 2, 3,4,5,6,7 respectively.

Image no	training image = 1 Number of individual in each sub-set					
	2	3	4	5	6	7
1						
2	✓					
3	✓	✓	✓			
4		✓	✓		✓	
5			✓	✓	✓	✓
6	✓					
7	✓	✓	✓	✓	✓	✓
8						
9	✓	✓	✓	✓	✓	✓
10		✓	✓	✓	✓	
11						
12	✓		✓	✓		✓
13			✓			
14	✓					
15	✓					
16						
17	✓	✓	✓	✓	✓	✓
18		✓	✓	✓	✓	✓
19	✓	✓				
20		✓		✓	✓	✓
21						
22	✓	✓	✓	✓	✓	✓
23	✓	✓				
24						
25	✓					
26						✓

Table 4.3: Results for testing training set with 1 image.

result	Table summary training image = 1 Number of individual in each sub-set 2-7					
	2	3	4	5	6	7
correct	13	11	11	9	9	9
false	13	15	15	17	17	17

Table 4.4: Summary Results for testing training set with 1 image.

Using only 1 test image for each individual gained poor results, even with small sub-sets of training dataset accuracy is low.

4.1.2 Testing using two training images for each individual

Phase 2: Now increasing the data training images: set of 26 person, training images are (2) per each individual, where groups in each sub-set has vary 2, 3,4,5,6,7 respectively.

Image no	Training images = 2 Number of individual in each sub-set (2-7)					
	2	3	4	5	6	7
1	✓	✓	✓			
2	✓	✓	✓	✓	✓	✓
3	✓	✓	✓	✓	✓	
4	✓	✓	✓	✓	✓	
5	✓	✓	✓	✓	✓	✓
6	✓	✓			✓	
7	✓	✓	✓	✓	✓	
8	✓	✓	✓	✓	✓	✓
9	✓	✓		✓		
10		✓	✓		✓	✓
11						
12	✓	✓	✓	✓		✓
13	✓	✓	✓		✓	
14	✓	✓	✓	✓	✓	✓
15	✓		✓	✓	✓	✓
16	✓					
17	✓	✓			✓	
18	✓	✓	✓	✓	✓	✓
19	✓	✓	✓	✓	✓	✓
20	✓	✓	✓	✓		✓
21	✓		✓			✓
22	✓	✓	✓	✓	✓	✓
23	✓	✓				✓
24	✓	✓	✓	✓	✓	
25	✓	✓	✓	✓	✓	✓
26	✓	✓	✓			✓

Table 4.5: Results for testing training set with 2 image.

result	Table summary training images = 2 Number of individual in each sub-set increasing					
	2	3	4	5	6	7
correct	23	22	20	17	17	17
false	3	4	6	9	9	9

Table 4.5: Summary of results for testing training set with 2 image.

As can be observed the small number of persons gives higher accuracy for recognition.

4.1.3 Testing using three training images for each individual

Now increasing the data training images: set of 26 person, training images are (3) per each individual, where groups in each sub-set has vary 2, 3,4,5,6,7 respectively.

Image no	training images = 3 Number of individual in each sub-set increasing					
	2	3	4	5	6	7
1	✓	✓				✓
2	✓	✓	✓	✓	✓	✓
3	✓	✓	✓	✓		
4	✓	✓	✓	✓	✓	
5	✓	✓	✓	✓	✓	✓
6	✓	✓			✓	
7	✓	✓	✓	✓	✓	✓
8	✓	✓	✓	✓	✓	✓
9	✓	✓		✓	✓	✓
10		✓	✓		✓	✓
11			✓	✓		✓
12	✓	✓	✓	✓	✓	✓
13	✓	✓	✓		✓	
14	✓	✓	✓	✓	✓	✓
15	✓		✓	✓	✓	✓
16	✓	✓	✓	✓	✓	✓
17	✓	✓			✓	
18	✓	✓	✓	✓	✓	✓
19	✓	✓	✓	✓	✓	✓
20	✓	✓	✓	✓		
21	✓	✓	✓			✓
22	✓	✓	✓	✓	✓	
23	✓	✓				✓
24	✓	✓				
25	✓	✓	✓	✓	✓	✓
26						

Table 4.6: Results for testing training set with 3 image.

result	Table summary training images = 3 Number of individual in each sub-set increasing					
	2	3	4	5	6	7
correct	23	23	19	16	18	17
false	3	3	7	10	8	9

Table 4.7: Summary results for testing training set with 3 image.

4.1.4 Testing using four training images for each individual

Now increasing the data training images: set of 26 person, training images are (4) per each individual, where groups in each sub-set has vary 2, 3,4,5,6,7 respectively.

Image no	training images = 4 Number of individuals in each sub-set increasing					
	2	3	4	5	6	7
1	✓	✓	✓	✓	✓	✓
2	✓	✓	✓	✓	✓	✓
3	✓	✓	✓	✓		
4	✓	✓	✓	✓	✓	
5	✓	✓	✓	✓	✓	✓
6	✓	✓	✓	✓		
7	✓	✓			✓	✓
8	✓	✓	✓	✓	✓	✓
9	✓	✓		✓	✓	✓
10		✓	✓		✓	✓
11			✓			
12	✓	✓	✓	✓	✓	✓
13	✓	✓	✓		✓	
14	✓	✓	✓	✓	✓	✓
15	✓		✓	✓	✓	✓
16	✓	✓	✓	✓	✓	✓
17	✓					
18	✓	✓	✓	✓	✓	✓
19	✓					
20	✓	✓	✓	✓	✓	✓
21		✓			✓	✓
22	✓	✓	✓	✓	✓	✓
23	✓	✓				
24	✓	✓				
25	✓	✓	✓		✓	
26	✓	✓	✓			

Table 4.8: Results for testing training set with 4 image.

result	Table summary training images = 4 Number of individual in each sub-set increasing					
	2 in G	3 in G	4 in G	5 in G	6 in G	7 in G
correct	23	22	19	11	18	15
false	3	4	7	15	8	11

Table 4.9: Summary of results for testing training set with 4 image.

Summary for this test for all the previous tables is represented with recognition percentage for each case

training image	result	Table summary Number of individual in each sub-set groups increasing					
		2	3	4	5	6	7
1 image per each person	recognized	50%	42.4%	42.4%	34.6%	34.6%	34.6%
	unrecognized	50%	57.6%	57.6%	65.3%	65.3%	65.3%
2 images per each person	recognized	88.4%	84.6%	76.9%	65.3%	65.3%	65.3%
	unrecognized	11.6%	15.4%	23.1%	34.6%	34.6%	34.6%
3 images per each person	recognized	88.4%	88.4%	73.0%	61.5%	69.3%	65.3%
	unrecognized	11.6%	11.6%	27.0%	38.4%	30.7%	34.6%
4 images per each person	recognized	88.4%	84.6%	73.0%	42.4%	69.3%	57.6%
	unrecognized	11.6%	15.4%	27.0%	57.6%	30.7%	42.4%

Table 4.10: Summary of all test results for testing training sub-sets.

Figure 4.8: Chart of comparing sub-sets recognition results.

Increasing the number of training images from 1 to 2 images for each individual increased the recognition results remarkably, but then from 2 to 3 to four it has less effect on the recognition. Although sub-setting the training data set solved the problem of having small number of training set for each person, on the other hand, increasing the number of individual more than 3 individual in each sub-set effects in decreasing the recognition results.

The highest result from previous work with increasing both training images and the number of individuals in the sub-set group was (3 training images per each and 3 individual for each sub-set group) the is the optimal choice training for this approach as proposed in chapter three, this (sample) will be chosen to do some test to change other variables.

4.2 Testing for undivided data set

A test will be implemented on this approach without dividing the data set into sub set using only face detection any eigenfaces:

Data set	Number of recognized faces	Number of error in recognition
Divided data set	23	3
Un-Divided data set	14	12

Table 4.2: Results for testing division effect on recognition

It can be easily noticed that the recognition had been severely because using only 3 training images of eigenfaces features where it requires frontal head view but sensitive to head position changing and illumination condition and scaling change the accuracy severely drop (Turk, Pentland, 1991).

4.3 Testing changing of Threshold value on recognition results

Testing the impact for reducing the threshold for sorting and eliminating eigenvalues,

Where if the number of data points in the image space is less than the dimension of the space ($M < N^2$), there will be only $M-1$, rather than N^2, meaningful eigenvectors (the remaining eigenvectors will have associated eigenvalues of zero).

And to construct the M by M matrix $L = A^T A$, where $L_{mn} = \Phi_m^T \Phi_n$, and find the M eigenvectors v_n of L. These vectors determine linear combinations of the M training set face images to form the eigenfaces μ_n. The associated eigenvalues allows ranking the eigenvectors according to their usefulness in characterizing the variation among the images (Turk, Pentland, 1991, 74-75).

D refers to diagonal elements of the eigenvalues for $L = A^T A$.

Threshold D	Number of recognized faces	Number of error in recognition
D > 3	23	3
D > 2	23	3
D > 1	23	3
D > 0.5	19	4
D > 0.1	19	4
D > 0	19	4

Table 4.1: Results for testing threshold variation.

With changing D (threshold) values the optimal values for D started from D >1, this test was implemented on data set of 26 person, each person has 3 training images, this data set was divided into sub-sets where each sub set has training images for 3 persons. The reason for choosing this calcification will be explained by the following tests will be done on sub-setting the dataset.

4.4 Testing on face segmentation hue color component:

Testing on detecting phase, test on face segmentation hue color component by changing the values:

Range for hue values	recognized face	error in recognition
0.00<=hue <=0.1	20	6
0.01<=hue <=0.1	23	3
0.02<=hue <=0.1	21	5
0.03<=hue <=0.1	21	5
0.04<=hue <=0.1	21	5
0.05<=hue <=0.1	16	10

Table 4.11 a: Results foe test on hue segmentation hue color component

Range for hue values	recognized face	error in recognition
0.01<=hue <=0.1	23	3
0.01<=hue <=0.2	18	8
0.01<=hue <=0.3	19	7
0.01<=hue <=0.4	19	7

Table 4.11 b: Results for test on hue segmentation hue color component

From the previous test with changing the lowest value parameter and the largest value parameter, the condition of optimal hue range from literatures was proven by experiments. When the hue component was not used the approach was able to recognize only 18 persons from 26, in other words the proposed approach accuracy dropped from 88.4% to 69.8%.

4.5 Testing on Standard dataset:

This test is done to compare the results of changing the data set, before any test is done the expected result must gain very high where the dataset that intended to be used in standard, which have the features that where mentioned in chapter 3.

The colored faces dataset is used to this test is called Faces 94 (Spacek, 2007) where the images have (jpg) format the same format for the developed system dataset, 3 training images will be used for each individual, number of participants in the test is 27 individuals: male and female,3 person in each sub-set, features will be tested is impact of sub-setting the dataset, then compared with results of un-standard dataset results. Following figure has a sample of Faces 94 set.

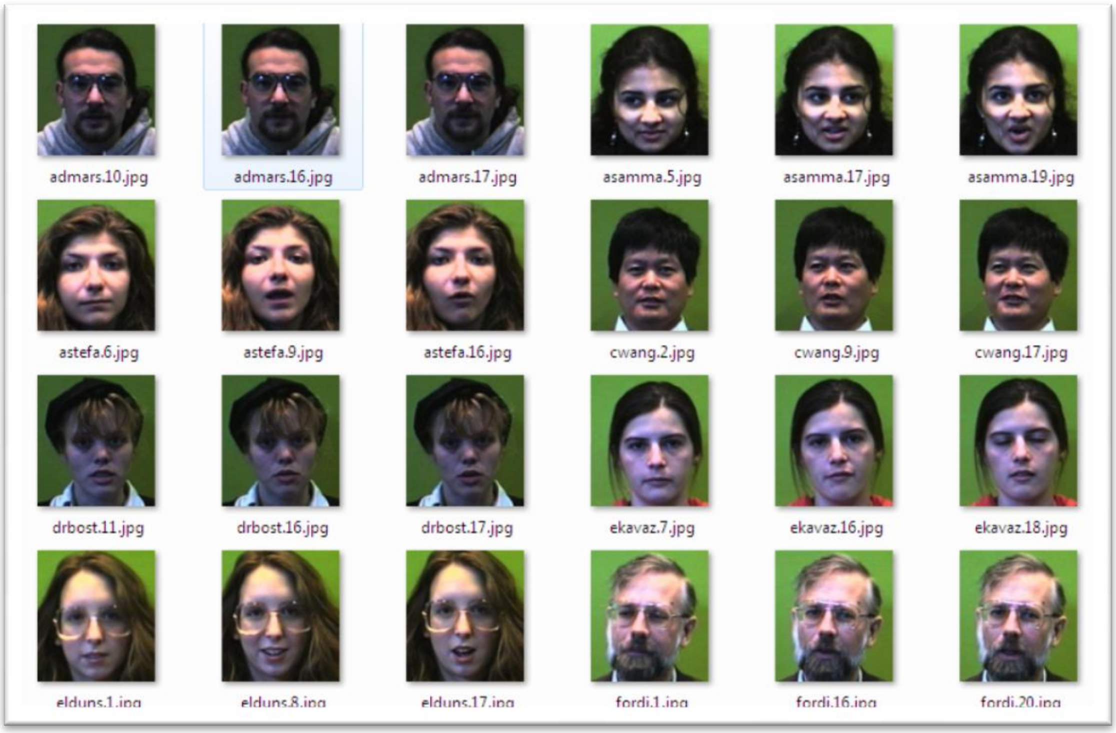
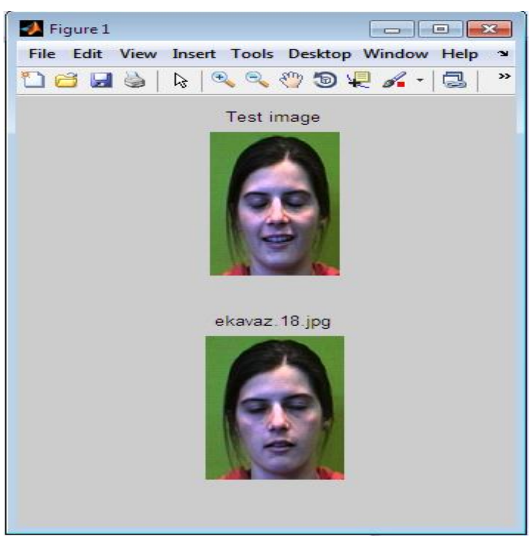


Figure 4.9: Sample of Faces 94 dataset.



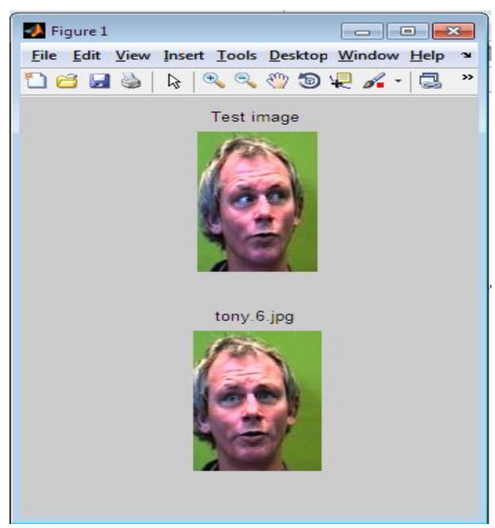


Figure 4.10: Samples of testing on Faces 94 dataset.

4.5.1 Comparison with Standard dataset:

Following table has brief comparison between Faces 94 dataset and proposed dataset:

Data set	Images type	Images dimensions	Images background	Head sizes	Head position
Faces 94	Jpg format	Fixed 180*200	Uniformed (green)	Uniformed	Uniformed
Proposed data set	Jpg format	No limitation	No limitation	Different Scaling	Vary significantly

Table 4.12: Comparison between Faces 94 dataset and proposed dataset.

From the previous table a conclusion can be made that the standard dataset which are prepared for this type of experiments have high accuracy due to its high restriction, less restriction on data set cause execution complexity due to several challenge caused by the manipulated data. Lower rate of accuracy in this case can't be considered as con for the developed system; it can be counted as pros in the existence of all mentioned challenges. Now time to test the results of testing with numbers, the following table has the result for testing the two datasets.

Data set	**Recognized faces Rate**	**Error in recognition Rate**
Faces 94 Sub-setting	92.6%	1.4%
Proposed data set sub-setting	88.4%	11.6%
Faces 94 without Sub-setting	85.2%	14.8%
Proposed data set without sub-setting	53.8%	46.2%

Table 4.13: Results comparing for two testing different datasets.

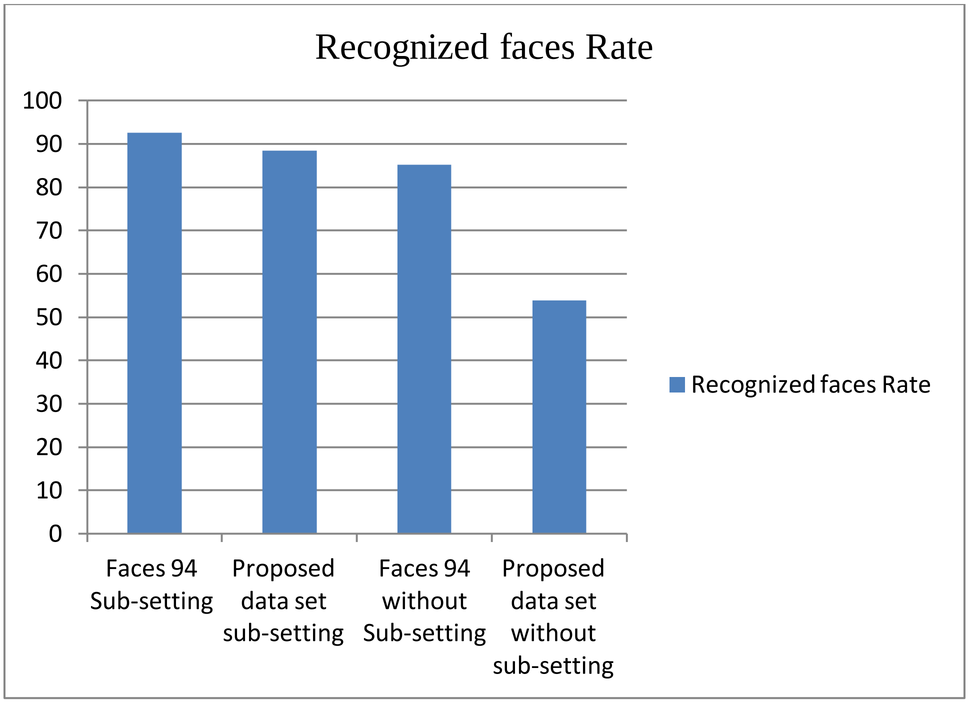


Figure 4.11: Results comparing for two testing different datasets chart.

As noticed Faces 94 dataset had higher accuracy in testing results (92.6%) than the proposed data set for the developed system, and the accuracy dropped to (85.2%) when the sub-setting part was ignored, proposed of this work was approved by results on another dataset with higher restriction on training and testing images.

4.6 Testing recognition time

For a real-time face recognition system testing time consumed for recognition process is important feature, time that will be measured is image recognition, average of face images recognition. As time will be documented system specification must be listed down as follows:

Operating system: Windows 7, 32 bit, professional version, service Pack 1.

Software used for development: MatLab 2012a.

Processor: AMD Turion(tm) mobile technology TL-62, 2.10 GHz.

RAM memory: 2.00 GB.

The result of testing time is the average time for recognition execution for each image, without calculating the time of GUI interacting.

Avg-time= 0.0039 sec

4.7 comparing with literatures:

Li and Tang (2002) studied the relationship between eigenface recognition performance and different training data sets. Using the Multilevel Dominant Eigenvector Estimation (MDEE) method, they were able to compute eigenfaces from a large number of training samples. They focus more on the results of short feature lengths since they illustrate how efficient the transformation compresses the large face vector. As the length of the feature vector increases, it becomes more like the original face vector. The effect of the transformation is largely lost if the original face image directly was used for face recognition, they got an accuracy of 74.9%; their experimental results show that increasing the number of people benefits the recognition performance more than increasing the number of images per person. The gallery used for their research contains 72*10 face images of 72 different persons.

Li and Tang (2002) had recognition result of 74.9% by applying MDEE on eigenfaces using 10 training images pre individual, and increased the length of eigenvector. Proposed work used 3 images for each individual, and comparison based on using 2 Euclidian distances due to sub-setting.

Abdullah, et al, (2012) in their research tried to minimize the participated eigenvectors which consequently decreases the computational time. They conduct a study to optimize the time complexity of PCA (eigenfaces) that does not affects the recognition performance. Their algorithm was tested on standard dataset: face94 face database experiments conducted using MatLab.

They conduct three experiments: The first experiment is used to adjust the best number of images for each individual to be used in the training set that gives a highest percentage of recognition. They choose 19 individual with 6 images for each in the training because the result of the first experiment shows that this number of images gives 100% recognition.

Second experiment tested 28 persons in the test database with 6 images for each person in the training database as given by experiment one. They changed the threshold trying to make a decision of the best matching. In this experiment we reduce the eigenfaces for the PCA algorithm where eigenvalues are sorted and those who are less than a specified threshold are eliminated.

Third experiment decreased the number of eigenvectors and consequently this decrease the time of computation. The results of this experiment give the same recognition result as the second experiment but with less time. The recognition time is reduced by 35%.

Abdullah, et al, (2012) work focused on reducing decreases the computational time beside recognition rate, they gained 100% when standard dataset was used and 6 images for each individual. They edited on number of people in the group and changing threshold in comparison phase. Again proposed work used 3 images for each individual, and comparison based on using 2 Euclidian distances due to sub-setting.

Chapter 5

Conclusion and recommendations

5. Conclusion and recommendations:

From experiments and results found that with increasing both training images and the number of individuals in the sub-set group were three training images per each and three individual for each sub-set group which is found as the optimal choice training for this approach. For future work this approach will be implemented on bigger data set, and implantation using object oriented software for higher speed for big data

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Annex A

Main Function where the path is specified and importing the train ant test images part is done:

```
clc
close all

cont=1;
used=0;
Tall=[];
mall=[];
Aall=[];
inTall=[];
Eigenfacesall=[];
while cont==1

if used~=1
   folnm=uigetdir;
   files=dir(folnm);
   Nods=inputdlg('Enter No. of data set per person');
   Nods=str2num(cell2mat(Nods));

   lngfls=length(files);
   Noper=(lngfls-2)/Nods;
   Nogrp=inputdlg('Enter No. of person per group');
   Nogrp=str2num(cell2mat(Nogrp));

   j=0;
   for i=1:floor(Noper/Nogrp)
      k=Nods*Nogrp*(i-1);
      subfiles=files(3+k:3+k+(Nods*Nogrp-1));

      [T inT] = CreateDB (folnm,subfiles,Nogrp,Nods);
      [m, A, Eigenfaces] = calc_Eigenfaces(T);
      used=1;
      j=j+1;
      Tall{j}= T;
      mall{j}=m;
      Aall{j}=A;
      inTall{j}=inT';
      Eigenfacesall{j}=Eigenfaces;
```

```
    end
end

[name,pt] = uigetfile('*.*');
f=fullfile(pt,name);
ip = importdata(f);

TestImage = face_det(ip);

im = ip;
TestImage=imresize(TestImage,[100 100]);

[gr inx bsub] = Recognizefaces(TestImage, mall, Aall,inTall, Eigenfacesall);
intt=inTall{gr};
subinx=inx(gr);
index=intt(subinx);
OutputName=index+Nods*Nogrp*(gr-1)+2;

tstco=0;
initst=0;
TestImg=name;
lntst=length(TestImg);
TestImgName=TestImg(1:lntst-4);
RecImg=files(OutputName).name;
lnrec=length(RecImg);
RecImgName=RecImg(1:lnrec-8);
if lntst-4==lnrec-8
    tstres=TestImgName-RecImgName;
    res=find(tstres);
    if isempty(res)
        f=fullfile(folnm,files(OutputName).name);
        SelectedImage = importdata(f);
        tstco=1;
    else
        initst=1;
    end
else
    initst=1;

end

Nogrps=length(inTall);
```

```
if initst==1
   for i=1:Nogrps
      intt=inTall{i};
      subinx=inx(i);
      index=intt(subinx);
      SbIn=index+Nods*Nogrp*(i-1)+2;
      SubName=files(SbIn).name;
      lnsbrec=length(SubName);
      SubImgName=SubName(1:lnsbrec-8);
      if lntst-4==lnsbrec-8
         tstres=TestImgName-SubImgName;
         res=find(tstres);
         if isempty(res)
            f=fullfile(folnm,files(SbIn).name);
            RecImgName=SubImgName;
            SelectedImage = importdata(f);
            tstco=1;
            break
         end
      end
   end
end

if tstco==1
   im=imresize(im,[640 400]);
   SelectedImage=imresize(SelectedImage,[300 200]);
   subplot(2,1,1)
   imshow(im)
   title(TestImgName);
   subplot(2,1,2)
   imshow(SelectedImage);
   title(RecImgName);
else
   choice = questdlg('No Reconigtion for this Image.Would you like to choose another
picture?','Continue?','Yes','No','No');
end
if tstco==1
   choice = questdlg('Would you like to choose another
picture?','Continue?','Yes','No','No');
end
switch choice
   case 'Yes'
```

```
        cont=1;
    case 'No'
        cont=0;
end
end
```

%%%The following part is used to create the training set and divide it into sub-set according to the user choice.

```
function [T inT] = CreateDB(fol,files,Nogrp,Nods)
TrainFiles = files;
Tcount = 0;
T = [];
temp_faces=[];

for tr = 1 : length(TrainFiles)

    f=fullfile(fol,TrainFiles(tr).name);
    ip = importdata(f);
    img=ip;
    [avgr avgc]=size(rgb2gray(img));
    TrainFiles(tr).name

    I1=imresize(img,[avgr avgc]);
    I=double(I1);
    [hue,s,v]=rgb2hsv(I);
    red_lay=I(:,:,1);
    green_lay=I(:,:,2);
    blue_lay=I(:,:,3);
    cb=0.148*red_lay-.291*green_lay+0.439*blue_lay+128;
    cr=0.439*red_lay-0.368*green_lay-.071*blue_lay+128;
    segment=0;

    for i=1:avgr
        for j=1:avgc

if(140<=cr(i,j))&(cr(i,j)<=195)&(140<=cb(i,j))&(cb(i,j)<=195)&(0.01<=hue(i,j))&(hue(i,j)
<=0.1)
                segment(i,j)=1;
            else
                segment(i,j)=0;
```

```
        end
    end
end

ped=edge(segment,'log');

vr1=var(ped);
ref1=vr1-mean(vr1)/5;
for i=1:avgc
    if ref1(i)<0
        ref1(i)=0;
    end
end
ref1=ref1(1:floor(avgc*.8));
c1=find(ref1>0,1,'first');
c2=find(ref1>0,1,'last');
d=c2-c1;
cv=floor((c1+c2)/2);
d1=ceil(.8*d);
d2=ceil(.2*d);

H=hough(ped(:,c1:c2));

convr=var(H);
mx=max(convr);
mn=mean(convr);
cc=mean([c1 c2]);
convr=max(max(H))*convr/mx;

mx1=max(convr);
re1=convr(46);
re2=convr(136);
e1=abs((re1/cos(46*pi/180)));
e2=abs((re2/cos(136*pi/180)));
me=mean([e1 e2]);
fc1=mx1/me;
fc2=max([e1 e2])/min([e1 e2]);
ra=me*fc1;

r1=floor(ra);
r2=floor((avgr-ra)*.9);
```

```
    pic_face=I1(r1:r2,c1:c2,:);
    img=pic_face;

    img = rgb2gray(img);
    [a1 a2]=size(img)
    img=imresize(img,[100 100]);
    [irow icol] = size(img);
    temp =reshape(img,10000,1);
    T = [T temp];
end

Tmn =min(T);
[Tmns inT]=sort(Tmn);
for ii=1:Nods*Nogrp
    temp_faces =[temp_faces T(:,inT(ii))];
end

T=temp_faces;
```

%%% Face detection part where hue and C_bC_r, color segmentation and edge detection is processed the result of this stage will be cropped face from the image.

```
function [prop]  =face_det(ip)
[rr cc]=size(rgb2gray(ip));
I=double(ip);
[hue,s,v]=rgb2hsv(I);
red_lay=I(:,:,1);
green_lay=I(:,:,2);
blue_lay=I(:,:,3);
cb=0.148*red_lay-0.291*green_lay+0.439*blue_lay+128;
cr=0.439*red_lay-0.368*green_lay-0.071*blue_lay+128;
segment=0;

for i=1:rr
    for j=1:cc
        if
(140<=cr(i,j))&(cr(i,j)<=195)&(140<=cb(i,j))&(cb(i,j)<=195)&(0.01<=hue(i,j))&(hue(i,j)<
=0.1)
            segment(i,j)=1;
        else
            segment(i,j)=0;
        end
```

```
    end
end

ped=edge(segment,'log');
H=hough(ped);
convr=var(H);

mx=max(convr);
convr=max(max(H))*convr/mx;
mx1=max(convr);
re1=convr(46);
re2=convr(136);
e1=abs((re1/cos(46*pi/180)));
e2=abs((re2/cos(136*pi/180)));
me=mean([e1 e2]);
fc1=mx1/me;
fc2=max([e1 e2])/min([e1 e2]);
ra=me*fc1;

r1=floor(ra);
r2=floor((rr-ra)*.9);
vr1=var(ped(r1:r2,:));
c1=find(vr1>mean(vr1),1,'first');
c2=find(vr1>mean(vr1),1,'last');
d=c2-c1;
cv=floor((c1+c2)/2);
d1=ceil(.8*d);
d2=ceil(.2*d);

cv1=floor(d1/2);
c1=cv-cv1;
c2=cv+cv1;

I1=ip;
I1(floor(1*ra),:,1)=255;
I1(floor(1*ra),:,2)=0;
I1(floor(1*ra),:,3)=255;

pic_face=ip(r1:r2,c1:c2,:);

prop=pic_face;
```

```
%%%calculating Eigenfaces part

function [m, A, Eigenfaces] = calc_Eigenfaces(T)

m = mean(T,2);
Tcount = size(T,2);

A = [];
for i = 1 : Tcount
   tempfaces = double(T(:,i)) - m;
   A = [A tempfaces];
end

L = A'*A;
[V D] = eig(L);

neweigenfaces = [];
for i = 1 : size(V,2)
   if( D(i,i)>1 )
      neweigenfaces = [neweigenfaces V(:,i)];
   end
end
Eigenfaces = A * neweigenfaces;
```

%% Recognition phase of the program where the Euclidian distance comparison is done:

```
function [grps inx bsub] = Recognizefaces(TestImage, mall, Aall,inTall, Eigenfacesall)
Euc_dist1all=[];
Euc_dist2all=[];
Nogrp=length(inTall);
ProjTst=[];
for bb=1:Nogrp
   Eigenfaces=Eigenfacesall{bb};
   A=Aall{bb};
   m=mall{bb};
   ProjectedImages = [];
   Tcount = size(Eigenfaces,2);
   for i = 1 : Tcount;
      tempfaces = Eigenfaces'*A(:,i);
      ProjectedImages = [ProjectedImages tempfaces];
   end
   InputImage = TestImage;
   tempfaces=rgb2gray(InputImage);


   [irow icol] = size(tempfaces);
   InImage = reshape(tempfaces,irow*icol,1);

   Difference = double(InImage)-m;
   ProjectedTestImage = Eigenfaces'*Difference;
   ProjTst=[ProjTst ProjectedTestImage];


   Euc_dist1 = [];
   Euc_dist2 = [];

   for i = 1 : Tcount
      q = A(:,i);
      p = ProjectedImages(:,i);

      temp1 = norm( Difference - q )^2;
      temp2 = norm( ProjectedTestImage-p)^2;
      Euc_dist1 = [Euc_dist1 temp1];
      Euc_dist2 = [Euc_dist2 temp2];

   end
```

```
    po1=length(int2str(ceil(Euc_dist1(1))));
    po2=length(int2str(ceil(Euc_dist2(1))));
    Euc_dist1=(Euc_dist1/10^(po1-1));
    Euc_dist2=(Euc_dist2/10^(po2-1));
    Euc_dist1all=[Euc_dist1all Euc_dist1];

    Euc_dist2all=[Euc_dist2all Euc_dist2];

    [Va1 In1]=min(Euc_dist1);
    [Va3 In3]=min(Euc_dist2);
    Va(bb)=Euc_dist1(In1);
    inx(bb)=In1;
    Va2(bb) =(Euc_dist2(In1));

    mngr(bb)=mean((Euc_dist2));

end

Va3=min(abs(ProjTst))./max(max(abs(ProjTst)));
subst1=Va3./Va2;
[a b]=sort(subst1);
grs1=floor(Nogrp/3)+1;
bsub=b(1:grs1);
subst2=mngr(bsub);
[ag bg]=min(subst2);
grps=bsub(bg);
```