



Face Recognition Using Raspberry Pi

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Abstract: Since lot of forgeries occur in our day to day life, security and surveillance has become a mandatory aspect. Over the last few decades, face recognition has become a popular area of research in computer vision. This system may be implemented in real time systems requiring user authentication such as attendance systems, ATM security, Electronic Passports and Network security. Our project aims in developing precise way of detecting faces using an algorithm called "Eigen face detection" which uses Principal Component Analysis(PCA). The algorithm involves comparison of trained samples with the query images. If the trained samples matches with the query images, then the detected face is a "known face". If there is a mismatch, then the detected face is a "new face". PCA extracts the eigen values and eigen vectors for the given set of samples in the PCA-sub space and compares it with the new values during run time. Then the threshold value is calculated from these eigen faces. If the new face value is less than the threshold, then it is a "known face". Otherwise, he/she must be a new user. This algorithm is implemented using python on a Raspberry pi module in which the raspberry camera is used to extract the face values. The Face values are displayed on a 659M10 LCD so that it could act as an alarm in door security system.

Keywords: Arduino, Touchless Interface, Micro Controller, Capacitive Sensing

I. INTRODUCTION

Biometrics is used in the process of authentication of a person by verifying or identifying that a user requesting a network resource is who he, she, or it claims to be, and vice versa. It uses the property that a human trait associated with a person itself like structure of finger, face details etc. By comparing the existing data with the incoming data we can verify the identity of a particular person, There are many types of biometric system like fingerprint recognition, face detection and recognition, iris recognition etc., these traits are used for human identification in surveillance system, criminal identification. Advantages of using these traits for identification are that they cannot be forgotten or lost. These are unique features of a human being which is being used widely. Generally, there are three phases for face recognition, mainly face representation, face detection, and face identification.

Face representation is the first task, that is, how to model a face. The way to represent a face determines the successive algorithms of detection and identification. For the entry-level recognition (that is, to determine whether or not the given image represents a face), a face category should be characterized by generic properties of all faces; and for the subordinate-level recognition (in other words, which face class the new face belongs to), detailed features of eyes, nose, and mouth have to be assigned to each individual face. There are a variety of approaches for face representation, which can be roughly classified into three categories: template-based, feature-based, and appearance-based.

The simplest *template-matching* approaches represent a whole face using a single template, i.e., a 2-D array of intensity, which is usually an edge map of the original face image. In a more complex way of template-matching, multiple templates may be used for each face to account for recognition from different viewpoints. Another important variation is to employ a set of smaller facial feature templates that correspond to eyes, nose, and mouth, for a single viewpoint. The most attractive advantage of template-matching is the simplicity, however, it suffers from large memory requirement and inefficient matching. In *feature-based* approaches, geometric features, such as position and width of eyes, nose, and mouth, eyebrow's thickness and arches, face breadth, or invariant moments, are extracted to represent a face. Feature-based approaches have smaller memory requirement and a higher recognition speed than template-based ones do. They are particularly useful for face scale normalization and 3D head model-based pose estimation. However, perfect extraction of features is shown to be difficult in implementation [5]. The idea of *appearance-based* approaches is to project face images onto a linear subspace of low dimensions. Such a subspace is first constructed by principal component analysis on a set of training images, with eigenfaces as its eigenvectors. Later, the concept of eigenfaces were extended to eigenfeatures, such as eigeneyes, eigenmouth, etc. for the detection of facial features. More recently, fisherface space and illumination subspace have been proposed for dealing with recognition The touch screens itself are of two types- Capacitive and Resistive. While capacitive is the more preferred one due to its smooth and flowing interface but a resistive one needs to be there for any kind of stylus interaction. It's hard to believe that just a few decades ago; touch screen technology could only be found in science fiction books and film. These days, it's almost unfathomable how we once got through our daily tasks without a trusty tablet or smart phone nearby, but it doesn't stop



there. Touch screens really are everywhere. Homes, cars, restaurants, stores, planes, wherever—they fill our lives in spaces public and private. The main feature which motivated me for making this project was to create something useful by using simple materials and circuitry. I'm well aware there are better ways to do capacitive distance sensing, but I wanted to make something as simple as possible that's still functional under varying illumination.

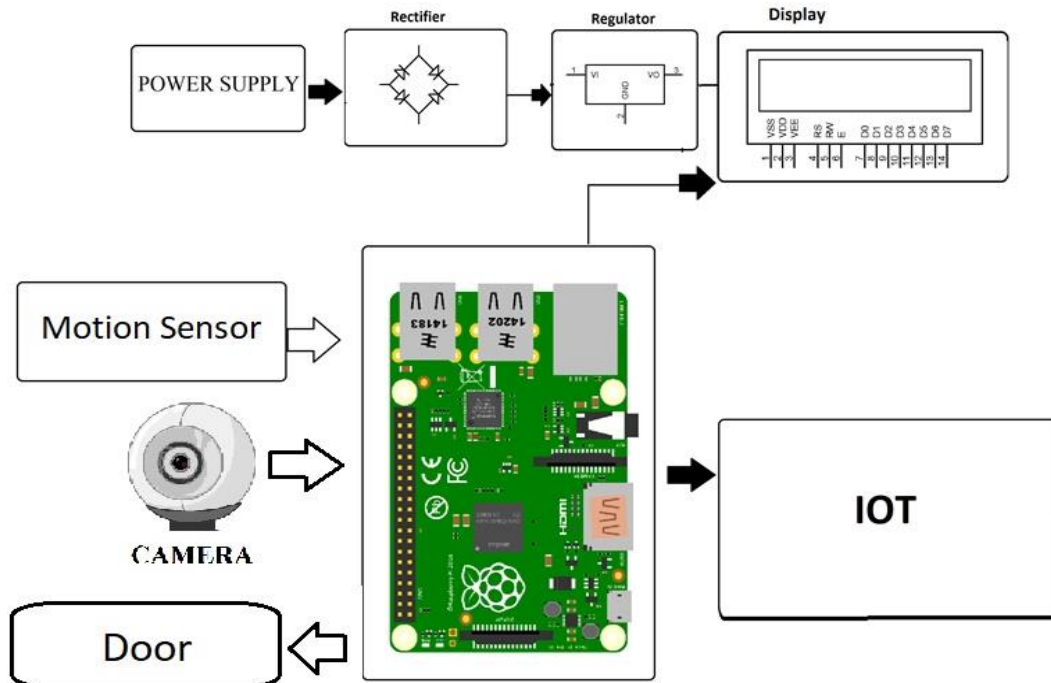


Fig 1.1 Face Recognition Model Block Diagram

II. PROJECT ANALYSIS

2.1 Feature Extraction:

In face alignment, facial components, such as eyes, nose, and mouth, and facial outline are located, and thereby the input face image is normalized in geometry and photometry. The following are the methods by which the features of the particular face can be extracted and can be used to create a data model from the given set of data trials.

- Principal Component Analysis (PCA)
- Linear Discriminant Analysis (LDA)
- Independent Component Analysis (ICA)

2.2 Linear Subspace Analysis

Three classical linear appearance-based models: PCA, LDA and ICA

- Each model has its own representation (basis vectors) of a high-dimensional face vector space based on different statistical viewpoints.
- All the three representations can be considered as a linear transformation from the original image vector to a projection feature vector.

$$Y=W^T X$$

Where $Y - (d \times 1)$, $X - (n \times 1)$ and $W - (n \times d)$, $d \ll n$

2.2.1 Principal Component Analysis:

Principal component analysis (PCA) was invented in 1901 by Karl Pearson. PCA is a variable reduction procedure and useful when obtained data have some redundancy. This will result into reduction of variables into smaller number of variables which are called Principal Components which will account for most of the variance in the observed variable. Problems arise when we wish to perform recognition in a high-dimensional space. Goal of PCA is to reduce the dimensionality of the data by retaining as much as variation possible in our original data set. On the other hand, dimensionality reduction implies information loss. The best low-dimensional space can be determined by best principal components. The major advantage of PCA is using it in eigenface approach which helps in reducing the size of the database for recognition of a test images. The images are stored as their feature vectors in the database which are found out projecting each and every trained image to the set of Eigen faces obtained. PCA is applied on Eigen face approach to reduce the dimensionality of a large data set.

2.2.2 Eigen Face Approach

It is adequate and efficient method to be used in face recognition due to its simplicity, speed and learning capability. Eigen faces are a set of Eigen vectors used in the Computer Vision problem of human face recognition. They refer to an appearance based approach to face recognition that seeks to capture the variation in a collection of face images and use this information to encode and compare images of individual faces in a holistic manner. The Eigen faces are Principal Components of a distribution of faces, or equivalently, the Eigen vectors of the covariance matrix of the set of the face images, where an image with N by N pixels is considered a point in N -dimensional space. Previous work on face recognition ignored the issue of face stimulus, assuming that predefined measurements were relevant and sufficient. This suggests that coding and decoding of face images may give information of face images emphasizing the significance of features. These features may or may not be related to facial features such as eyes, nose, lips and hairs. We want to extract the relevant information in a face image, encode it efficiently and compare one face encoding with a database of faces encoded similarly. A simple approach to extracting the information content in an image of a face is to somehow capture the variation in a collection of face images. We wish to find Principal Components of the distribution of faces, or the Eigen vectors of the covariance matrix of the set of face images. Each image location contributes to each Eigen vector, so that we can display the Eigen vector as a sort of face. Each face image can be represented exactly in terms of linear combination of the Eigen faces. The number of possible Eigen faces is equal to the number of face image in the training set. The faces can also be approximated by using best Eigen face, those that have the largest Eigen values, and which therefore account for most variance between the set of face images. The primary reason for using fewer Eigen faces is computational efficiency.

2.2.3 Eigen Values and Eigen Vectors

In linear algebra, the eigenvectors of a linear operator are non-zero vectors which, when operated by the operator, result in a scalar multiple of them. Scalar is then called Eigen value (λ) associated with the eigenvector (X). Eigen vector is a vector that is scaled by linear transformation. It is a property of matrix. When a matrix acts on it, only the vector magnitude is changed not the direction. $AX = \lambda X$, where A is a vector function. $(A - \lambda I)X = 0$, where I is the identity matrix. This is a homogeneous system of equations and form fundamental linear algebra. We know a non-trivial solution exists if and only if $\text{Det}(A - \lambda I) = 0$, where det denotes determinant. When evaluated becomes a polynomial of degree n . This is called characteristic polynomial of A . If A is N by N then there are n solutions or n roots of the characteristic polynomial. Thus there are n Eigen values of A satisfying the equation. $AX_i = \lambda_i X_i$, where $i=1,2,3,\dots,n$. If the Eigen values are all distinct, there are n associated linearly independent eigenvectors, whose directions are unique, which span an n dimensional Euclidean space.

2.2.4 Face Image Representation

Training set of m images of size $N \times N$ are represented by vectors of size N^2 . Each face is represented by $\Gamma_1, \Gamma_2, \Gamma_3, \dots, \Gamma_M$.



Fig 2.2.4 Face Image Representation

Feature vector of a face is stored in $N \times N$ matrix. Now, this two-dimensional vector is changed to one dimensional vector.



For Example-

$$\begin{pmatrix} 1 & 2 \\ 2 & 1 \end{pmatrix} = \begin{pmatrix} 1 \\ 2 \\ 2 \\ 1 \end{pmatrix}$$

Each face image is represented by the one dimensional vector Γ_i .

$$\Gamma_1 = \begin{pmatrix} 1 \\ -2 \\ 1 \\ -3 \end{pmatrix} \quad \Gamma_2 = \begin{pmatrix} 1 \\ 3 \\ -1 \\ 2 \end{pmatrix} \quad \Gamma_3 = \begin{pmatrix} 2 \\ 1 \\ -2 \\ 3 \end{pmatrix} \quad \dots \quad \Gamma_M = \begin{pmatrix} 1 \\ 2 \\ 2 \\ 1 \end{pmatrix}$$

2.2.5 Mean and Mean Centered Images

Average face image is calculated by

$$\Psi = (1/M) \sum_{i=1}^M \Gamma_i$$

$$\begin{pmatrix} 1 \\ -2 \\ 1 \\ -3 \end{pmatrix} + \begin{pmatrix} 1 \\ 3 \\ -1 \\ 2 \end{pmatrix} + \begin{pmatrix} 2 \\ 1 \\ -2 \\ 3 \end{pmatrix} + \dots + \begin{pmatrix} 1 \\ 2 \\ 2 \\ 1 \end{pmatrix} \rightarrow \begin{pmatrix} -1 \\ -1 \\ 2 \\ -3 \end{pmatrix}$$

$\Psi = (\Gamma_1 + \Gamma_2 + \Gamma_3 + \dots + \Gamma_M)/M$. Each face differs from the average by $\Phi_i = \Gamma_i - \Psi$ which is called mean centered image.

$$\Phi_1 = \begin{pmatrix} 2 \\ -1 \\ -1 \\ 0 \end{pmatrix} \quad \Phi_2 = \begin{pmatrix} 2 \\ 4 \\ -3 \\ 5 \end{pmatrix} \quad \Phi_3 = \begin{pmatrix} 3 \\ 2 \\ -4 \\ 6 \end{pmatrix} \quad \dots \quad \Phi_M = \begin{pmatrix} 2 \\ 3 \\ 0 \\ 4 \end{pmatrix}$$

Then we have to find **Eigen Value and Eigen Vectors** with the help of Co-variance Matrix. The Co-variance Matrix can be found as follows:

2.2.6 Covariance Matrix

A covariance matrix is constructed as: $C = AA^T$, where $A = [\Phi_1, \Phi_2, \dots, \Phi_M]$ of size $N \times N$

$$A = \begin{pmatrix} 2 & 3 \\ -1 & -2 \\ -1 & 1 \\ 0 & 2 \end{pmatrix} \quad A^T = \begin{pmatrix} 2 & -1 & -1 & 0 \\ 3 & -2 & 1 & 2 \end{pmatrix}$$

Size of covariance matrix will be $N^2 \times N^2$ (4×4 in this case). Eigen vectors corresponding to this covariance matrix is needed to be calculated, but that will be a tedious task therefore, For simplicity we calculate $A^T A$ which would be a 2×2 matrix in this case.

2.2.7 Eigen Face Space

The Eigen vectors of the covariance matrix AA^T are AX_i which is denoted by U_i . U_i resembles facial images which look ghostly and are called Eigen faces. Eigen vectors correspond to each Eigen face in the face space and discard the faces for which Eigen values are zero thus reducing the Eigen face space to an extent. The Eigen faces are ranked according to their usefulness in characterizing the variation among the images.

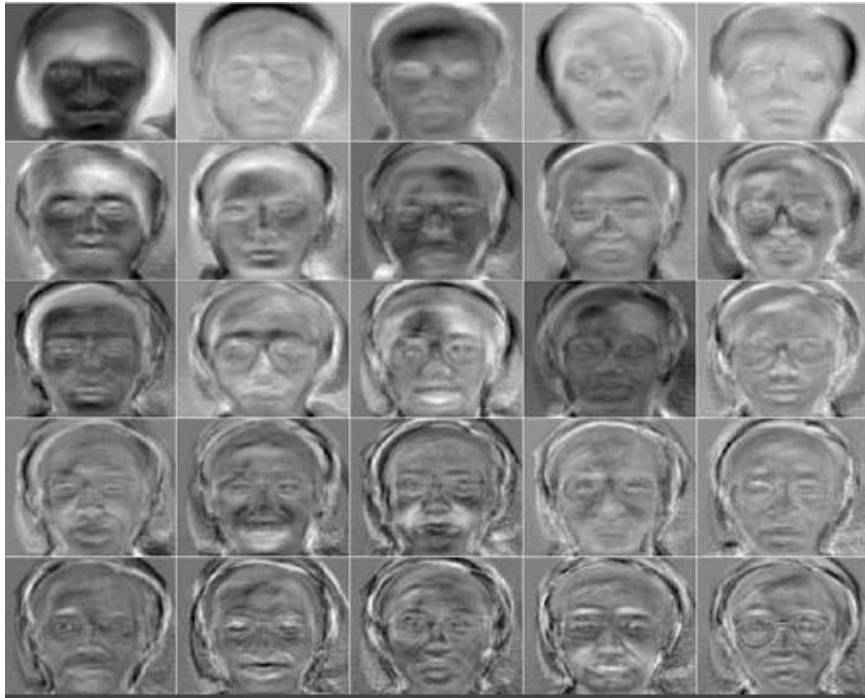


Fig 2.5 Eigen Faces

A face image can be projected into this face space by $\Omega_k = U^T(\Gamma_k - \Psi)$; $k=1, \dots, M$, where $(\Gamma_k - \Psi)$ is the mean centered image.

Hence projection of each image can be obtained as Ω_1 for projection of *image1* and Ω_2 for projection of *image2* and hence forth.

2.3.8 Recognition Step

The test image, Γ , is projected into the face space to obtain a vector, Ω as

$$\Omega = U^T(\Gamma - \Psi)$$

The distance of Ω to each face is called Euclidean distance and defined by

$$e^{2k} = \|\Omega - \Omega_k\|^2$$

$k = 1, \dots, M$ where Ω_k is a vector describing the k th face class.

A face is classified as belonging to class k when the minimum e_k is below some chosen threshold Θ_c . otherwise the face is classified as unknown.

Θ_c , is half the largest distance between any two face images:

$$\Theta_c = (1/2) \max_{j,k} \|\Omega_j - \Omega_k\|; j, k = 1, \dots, M$$

We have to find the distance between the original test image Γ and its reconstructed image from the Eigen face Γ_f
 $e^2 = \|\Gamma - \Gamma_f\|^2$, where $\Gamma_f = U * \Omega + \Psi$

If $e \geq \Theta_c$ then input image is not even a face image and not recognized.

If $e < \Theta_c$ and $e_k \geq \Theta$ for all k then input image is a face image but it is recognized as unknown face.

If $e < \Theta_c$ and $k < \Theta$ for all k then input images are the individual face image associated with the class vector Ω_k .

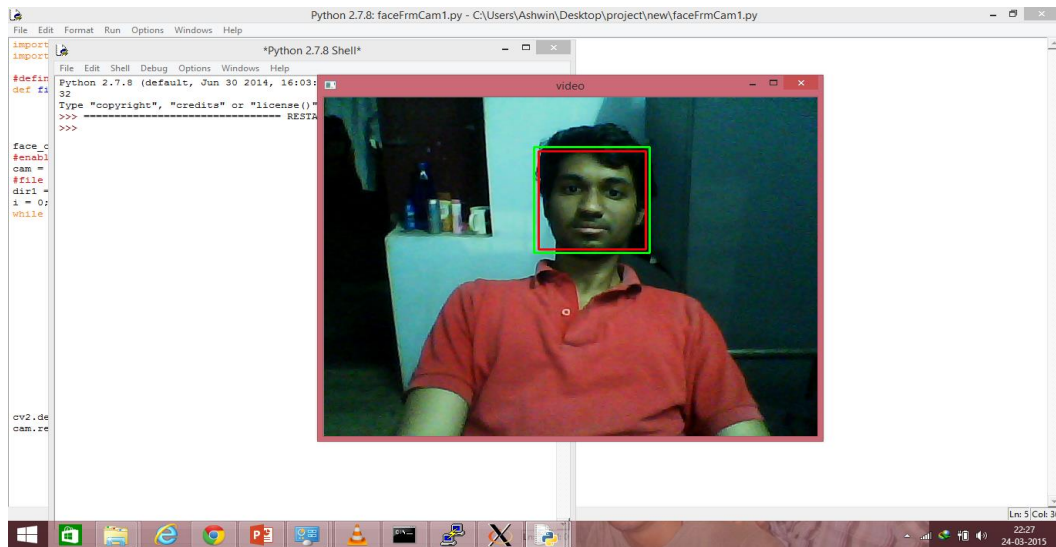


Fig 2.3.8 Sample Detection of Face Object

III. SYSTEM SPECIFICATION

3.Implementation on Raspberry Pi

3.1 Description

The Raspberry Pi is a small, powerful and lightweight ARM based computer which can do many of the things a desktop PC can do. The powerful graphics capabilities and HDMI (High Definition Multiplexed Input) video output make it ideal for multimedia applications such as media centers and narrowcasting solutions. The Raspberry Pi is based on a Broadcom BCM2835 chip. It does not feature a built-in hard disk or solid-state drive, instead relying on an SD card for booting and long-term storage.

3.2 Model

Raspberry Pi Model B is used for our implementation.



Fig 3.1 Raspberry Pi Model B

4.3.1 Specifications

Chip	Broadcom BCM2835 SoC
Core architecture	ARM11
CPU Clock	700 MHz
GPU	Dual Core VideoCore IV
Memory	512MB SDRAM
Operating System	Raspbian
Dimensions	85.6 x 53.98 x 17mm
Power	Micro USB socket 5V, 1.2A (1)

4.3.2 Connectors

Ethernet	10/100 BaseT Ethernet Sockets
Video Output	HDMI
Audio Output	3.5mm jack
USB 2.0	Dual USB Connector

GPIO Connector

26-pin 2.54 mm (100 mil) expansion header: 2x13 strip. Providing 8 GPIO pins plus access to I²C, SPI & URAT as well as +3.3 V, +5 V and GND supply lines

Camera Connector Memory Card Slot

15-pin MIPI Camera Serial Interface
SDIO

4.3.3 Terminal Requirements

Putty, Xming are required to launch R-Pi home screen in Windows Operating System.

4.4 Raspberry Pi Camera

The Raspberry Pi camera module can be used to take high-definition video, as well as stills photographs. You can also use the libraries we bundle with the camera to create effects. The module has a five megapixel fixed-focus camera that supports 1080p30, 720p60 and VGA90 video modes, as well as stills capture. It attaches via a 15cm ribbon cable to the CSI port on the Raspberry Pi.

The camera works with all models of Raspberry Pi 1 and 2. It can be accessed through the MMAL and V4L APIs, and there are numerous third-party libraries built for it, including the Picamera Python library. The camera module is very popular in home security applications, and in wildlife camera traps.

4.5 Setting up Raspberry Pi

The Raspberry Pi Camera is mounted on the Raspberry pi board with SD card loaded with Raspbian OS. We can either use a HDMI cable as a video output through devices like Television, projector etc. We can also use Ethernet Cable to access our R-Pi Kit through laptop. The steps involved are as follows.

Step 1: Change the network adapter settings to share Wi-Fi connection via Ethernet.

Step 2: Open “Command Prompt” (Run as administrator) and type `arp -a`

Step 3: A Dynamically generated IP Address will be displayed on the screen. Note that we can also configure static IP Address for user’s convenience

Step 4: Open Putty Terminal and type the configured IP address. In order to view the raspberry pi home page, we have to enable X11 Forwarding in SSH settings.

Step 5: Now Open Xlaunch and type `startlxde` to enable a new lxsession

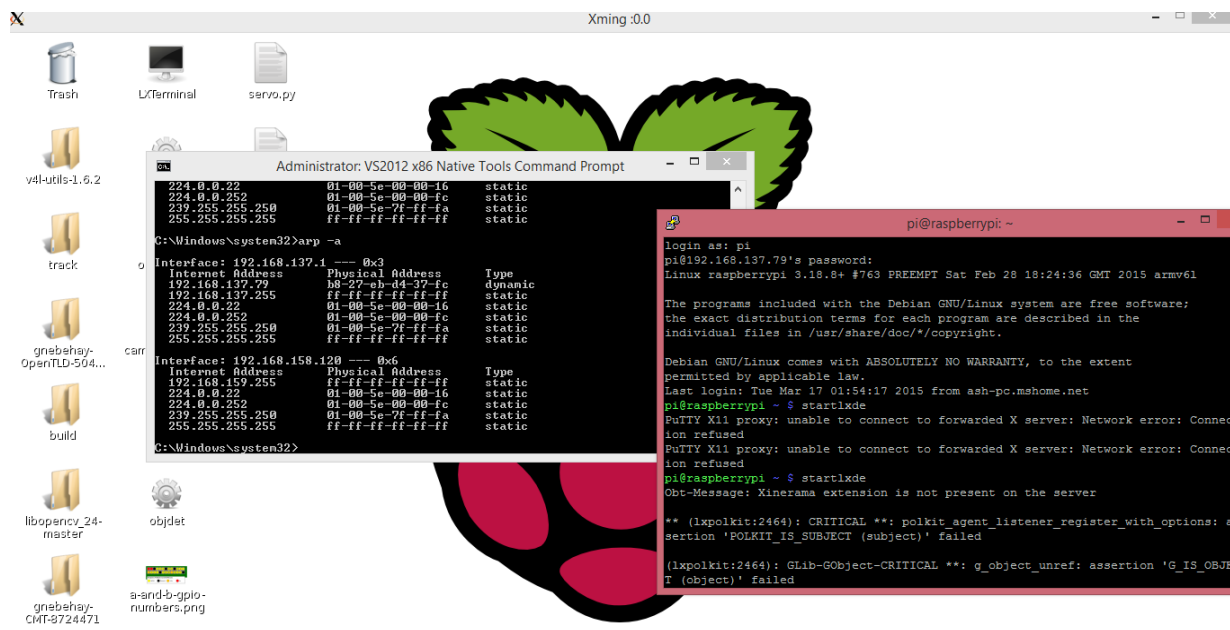


Fig 4.2 Getting Started with Raspbian OS

Click on lxterminal to execute various functionalities of the R-Pi Modules.

V. INFERENCE

The following results are obtained based on the implementation on the R-Pi board

4.6.1 Detecting a Known Face

After image acquisition, the PCA algorithm is implemented and threshold value is calculated accordingly. When a new query image is acquired, it compares the values with the stored values and matches it. The message “Known Face” will be displayed only if the value is within a certain threshold value range. If not, the message “Unknown user” is displayed.

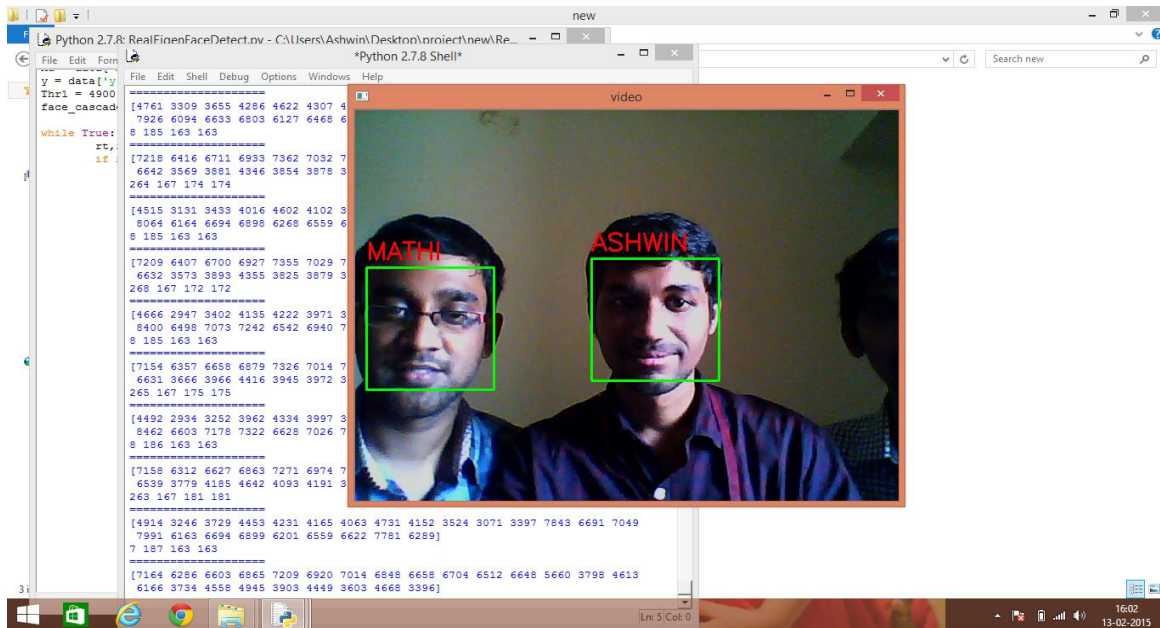


Fig 4.6.1 Implementation Model of Known face pattern.

4.6.2 Detecting a New User

Consider the next case, where a new user is trying to access the system. It must display a message “I can't recognize you” once the user's face gets recognized. The values obtained as a result of image acquisition are compared with the new query image and since it doesn't match any stored values, the message new face is displayed.

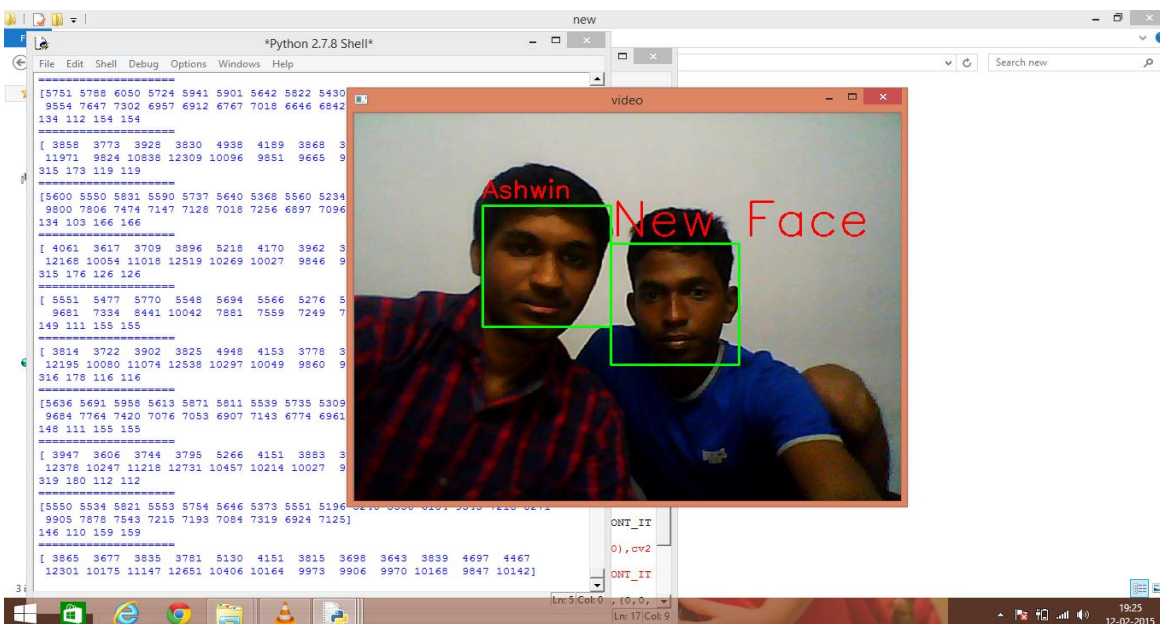


Fig 4.6.2 Implementation Model of New face pattern



4.6.3 No Face Condition

By including the haar cascade XML file, it is evident that it will detect only if a face is found. In case, if there is no clear view of the face, the message “Sorry! No Face Found is Displayed”

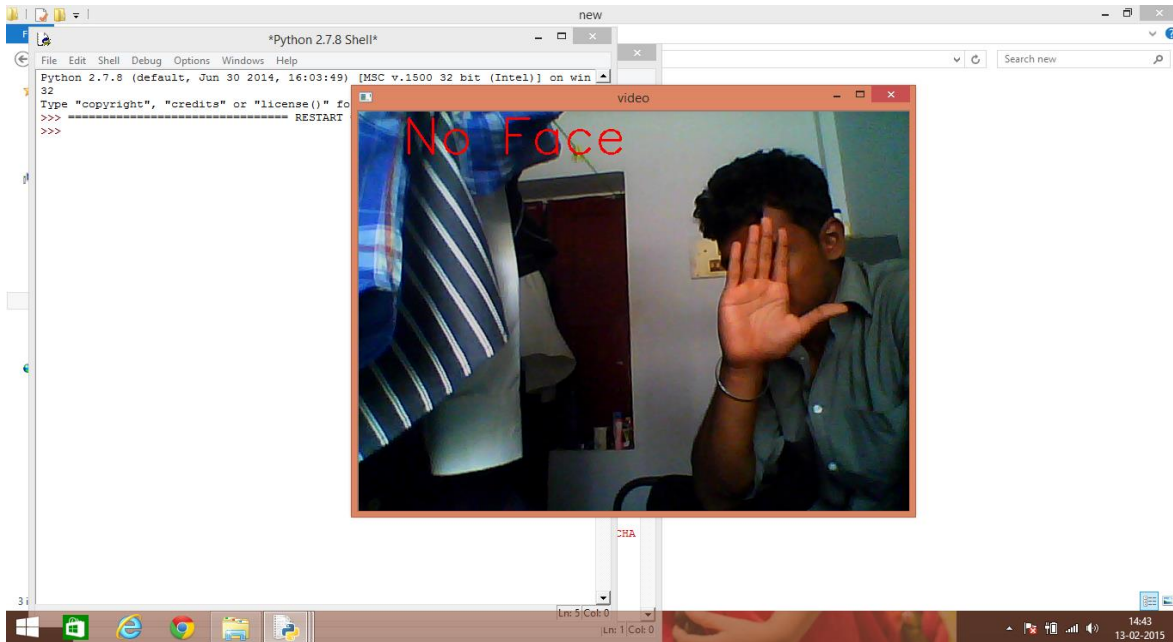


Fig 4.6.3 Implementation Model of No face pattern

4.6.5 Threshold Value Calculation

```
>>>
A (1).jpg
A (10).jpg
A (11).jpg
A (12).jpg
A (2).jpg
A (3).jpg
A (4).jpg
A (5).jpg
A (6).jpg
A (7).jpg
A (8).jpg
A (9).jpg
B (1).jpg
B (10).jpg
B (11).jpg
B (12).jpg
B (2).jpg
B (3).jpg
B (4).jpg
B (5).jpg
B (6).jpg
B (7).jpg
B (8).jpg
B (9).jpg
(24, 22500)
[ 4109 4638 5002 4215 5186 4761 4199 4416 3505 4036 4780 5999
 12586 10121 11208 12874 10296 10078 9943 9810 9959 10187 9672 10076]
[ 3505 4036 4109 4199 4215 4416 4638 4761 4780 5002 5186 5999
 9672 9810 9943 9959 10076 10078 10121 10187 10296 11208 12586 12874]
[ 8 9 0 6 3 7 1 5 10 2 4 11 22 19 18 20 23 17 13 21 16 14 12 15]
>>>
```

Fig 4.7 Threshold value Calculation

The values above represent the threshold values (Θ). It is clear that first set of images has a certain range which deviates from the next set of values. Since, the threshold value Θ_c , is half the largest distance between any two face images, the value in between the two sets of faces can be set as threshold.

**VI. CONCLUSION**

Thus over the past few decades with the growing need to secure information, face recognition has become an essential need. Further enhancement can be done by extracting the key features or point detection over face matrix. But Eigen Face Algorithm has got its unique importance since it can recognise 'n' faces in a single frame. With an easy computational method and relatively simple algorithm, Principal Component Analysis Technique can be used for variety of real time applications.

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