Facial Detection and Recognition on RaspberryPi: Security can be Cheap and Smart

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Abstract

The development of this project will be vertical in nature to demonstrate proof of concept rather than extensibility. In short, the Group 3 project team has developed a smart security system on the RaspberryPi at minimal cost. The system will use a motion sensor and camera to gather data, a convolutional neural network for facial detection and recognition, and finally a push notification based output. The targeted use case of this technology is a household security system. A homeowner will point the system at the door, and the system will notify the homeowner via push notification that they have a guest as well as the system's best guess at the guest's name. For this particular implementation, facial data will be manually created for demonstration purposes. Future implementations of the system may include but are not limited to: Facebook profile data, LinkedIn profile data, Google Photos image data, etc. The end goals of this project may be analyzed on a few different planes. In the meta-educational plane, this project will serve to demonstrate Group 3's competence in Machine Learning techniques, basic circuitry, and comfort with the Internet of Things. In terms of practical application, this project may serve to demonstrate the potential effectivity of machine learning with simple and cost effective components like the RaspberryPi.

1 Introduction

The document is a report on the final project for Facial Detection and Recognition on Raspberry Pi. It involved building a system for face detection and face recognition using several classifiers available in the open computer vision library(OpenCV). Face recognition is a non-invasive identification system and faster than other systems since multiple faces can be analyzed at the same time. The difference between face detection and identification is, face detection is to identify a face from an image and locate the face. Face recognition is making the decision "whose face is it ? ", using an image database. In this project both are accomplished using different techniques and are described below. The report begins with an Experimentation setup. This is followed by the explanation of HAAR-cascades, Eigenface, Fisher face and Local binary pattern histogram (LBPH) algorithms. Next, the experimentation and the results of the project are described. A discussion regarding the challenges and the resolutions are described. Finally, a conclusion is provided with limitations and future works for betterment.

2 The History of Face Recognition

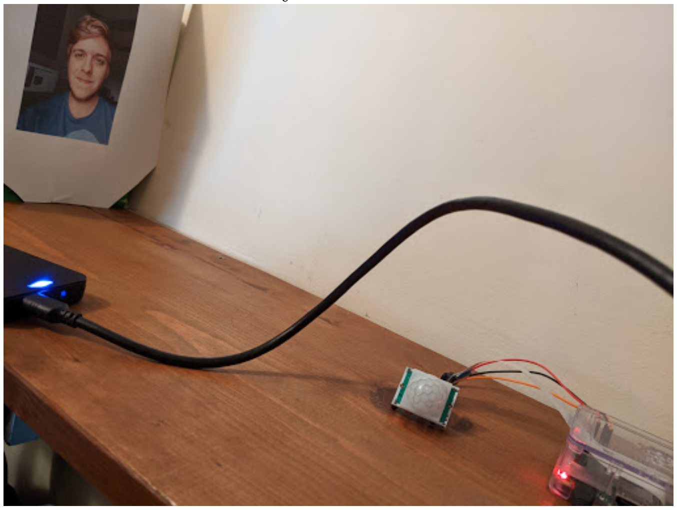
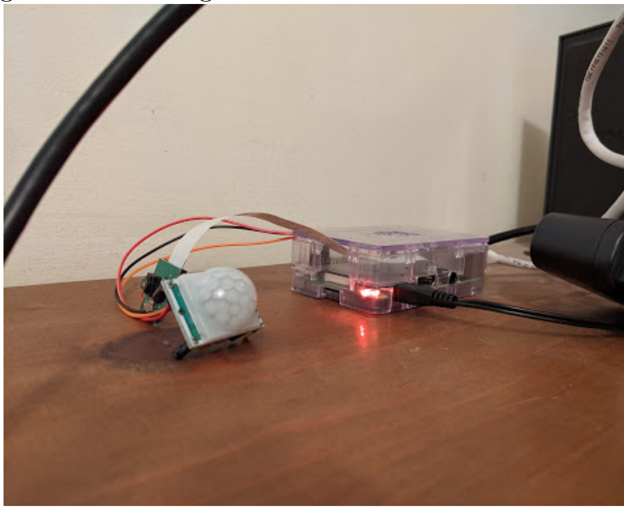
Face recognition began as early as 1977 with the first automated system being introduced By Kanade using a feature vector of human faces [1]. In 1983, Sirovich and Kirby introduced the principal component analysis(PCA) for feature extraction [2]. Using PCA, Turk and Pentland Eigenface was developed in 1991 and is considered a major milestone in technology [3]. Local binary pattern analysis for texture recognition was introduced in 1994 and is improved upon for facial recognition later by incorporating Histograms(LBPH) [4], [5]. In 1996 Fisherface was developed using Linear discriminant analysis (LDA) for dimensional reduction and can identify faces in different illumination conditions, which was an issue in Eigenface method [6]. Viola and Jones introduced a face detection technique using HAAR cascades and ADABoost [7]. In 2007, A face recognition technique was developed by Naruniec and Skarbek using Gabor Jets that are similar to mammalian eyes [8], [9]. In This project, HAAR cascades are used for face detection and Eigenface, Fisherface and LBPH are used for face recognition.

3 Architecture

This is Architecture Place holder.

4 Face Detection using Haar-Cascades

A Haar wavelet is a mathematical fiction that produces square-shaped waves with a beginning and an end and used to create box shaped patterns to recognise signals with sudden transformations. An example is shown in figure 1. By combining several wavelets, a cascade can be created that can identify edges, lines and circles with different colour intensities. These sets are used in Viola Jones face detection technique in 2001 and since then more patterns are introduced [10] for object detection as shown in figure 1. To analyse an image using Haar cascades, a scale is selected smaller than the target image. It is then placed on the image, and the average of the values of pixels in each section is taken. If the difference between two values pass a given threshold, it is considered a match. Face detection on a human face is performed by matching a combination of different Haar-like-features. For example, forehead, eyebrows and eyes contrast as well as the nose with eyes as shown below in figure A single classifier is not accurate enough. Several classifiers are combined as to provide an accurate face detection system as shown in the block diagram below in figure 3.

5 Face Recognition

The following sections describe the face recognition algorithms Eigenface, Fisherface, Local binary pattern histogram and how they are implemented in OpenCV.

5.1 Eigenface

Eigenface is based on PCA that classify images to extract features using a set of images. It is important that the images are in the same lighting condition and the eyes match in each image. Also, images used in this method must contain the same number of pixels and in grayscale. For this example, consider an image with n * n pixels as shown in figure 4. Each raw is concatenated to create a vector, resulting a 1*n2 matrix. All the images in the dataset are stored in a single matrix resulting a matrix with columns corresponding the number of images. The matrix is averaged (normalised) to get an average human face. By subtracting the average face from each image vector unique features to each face are computed. In the resulting matrix, each column is a representation of the difference each face has to the average human face. A simplified illustration can be seen in figure 4.

images goes here

The next step is computing the covariance matrix from the result. To obtain the Eigen vectors from the data, Eigen analysis is performed using principal component analysis. From the result, where covariance matrix is diagonal, where it has the highest variance is considered the 1st Eigen vector. 2nd Eigen vector is the direction of the next highest variance, and it is in 90 degrees to the 1st vector. 3rd will be the next highest variation, and so on. Each column is considered an image and visualised, resembles a face and called Eigenfaces. When a face is required to be recognised, the image is imported, resized to match the same dimensions of the test data as mentioned above. By projecting extracted features on to each of the Eigenfaces, weights can be calculated. These weights correspond to the similarity of the features extracted from the different image sets in the dataset to the features extracted from the input image. The input image can be identified as a face by comparing with the whole dataset. By comparing with each subset, the image can be identified as to which person it belongs to. By applying a threshold detection and identification can be controlled to eliminate false detection and recognition. PCA is sensitive to large numbers and assumes that the subspace is linear. If the same face is analysed under different lighting conditions, it will mix the values when distribution is calculated and cannot be effectively classified. This makes to different lighting conditions poses a problem in matching the features as they can change dramatically.

5.2 Fisherface

Fisherface technique builds upon the Eigenface and is based on LDA derived from Ronald Fishers' linear discriminant technique used for pattern recognition. However, it uses labels for classes as well as data point information [6]. When reducing dimensions, PCA looks at the greatest variance, while LDA, using labels, looks at an interesting dimension such that, when you project to that dimension you maximise the difference between the mean of the classes normalised by their variance [6]. LDA maximises the ratio of the between-class scatter and within-class scatter matrices. Due to this, different lighting conditions in images has a limited effect on the classification process using LDA technique. Eigenface maximises the variations while Fisherface maximises the mean distance between and different classes and minimises variation within classes. This enables LDA to differentiate between feature classes better than PCA and can be observed in figure 5 [12]. Furthermore, it takes less amount of space and is the fastest algorithm in this project. Because of these PCA is more suitable for representation of a set of data while LDA is suitable for classification.

image goes here.

5.3 Local Binary Pattern Histogram

Local binary patterns were proposed as classifiers in computer vision and in 1990 By Li Wang [4]. The combination of LBP with histogram oriented gradients was introduced in 2009 that increased its performance in certain datasets [5]. For feature encoding, the image is divided into cells (4 x 4 pixels). Using a clockwise or counter-clockwise direction surrounding pixel values are compared with the central as shown in figure 6. The value of intensity or luminosity of each neighbour is compared with the centre pixel. Depending if the difference is higher or lower than 0, a 1 or a 0 is assigned to the location. The result provides an 8-bit value to the cell. The advantage of this technique is even if the luminosity of the image

image goes here is changed as in figure 7, the result is the same as before. Histograms are used in larger cells to find the frequency of occurrences of values making process faster. By analysing the results in the cell, edges can be detected as the values change. By computing the values of all cells and concatenating the histograms, feature vectors can be obtained. Images can be classified by processing with an ID attached. Input images are classified using the same process and compared with the dataset and distance is obtained. By setting up a threshold, it can be identified if it is a known or unknown face. Eigenface and Fisherface compute the dominant features of the whole training set while LBPH analyse them individually.

image goes here:

6 Methodology

Below are the methodology and descriptions of the applications used for data gathering, face detection, training and face recognition. The project was coded in Python using a mixture of IDLE and PYCharm IDEs.

6.1 Face Detection

First stage was creating a face detection system using Haar-cascades. Although, training is required for creating new Haar-cascades, OpenCV has a robust set of Haar-cascades that was used for the project. Using face-cascades alone caused random objects to be identified and eye cascades were incorporated to obtain stable face detection. The flowchart of the detection system can be seen in figure 8. Face and eye

image goes here classifier objects are created using classifier class in OpenCV through the cv2.CascadeClassifier() and loading the respective XML files. A camera object is created using the cv2.VideoCapture() to capture images. By using the CascadeClassifier.detectMultiScale() object of various sizes are matched and location is returned. Using the location data, the face is cropped for further verification. Eye cascade is used to verify there are two eyes in the cropped face. If satisfied a marker is placed around the face to illustrate a face is detected in the location.

6.2 Face Recognition Process

For this project three algorithms are implemented independently. These are Eigenface, Fisherface and Linear binary pattern histograms respectively. All three can be implemented using OpenCV libraries. There are three stages for the face recognition as follows: 1. Collecting images IDs 2. Extracting unique features, classifying them and storing in XML files 3. Matching features of an input image to the features in the saved XML files and predict identity.

6.2.1 Collecting the image data

Collecting classification images is usually done manually using a photo editing software to crop and resize photos. Furthermore, PCA and LDA requires the same number of pixels in all the images for the correct operation. This time consuming and a laborious task is automated through an application to collect 50 images with different expressions. The application detects suitable expressions between 300ms, straightens any existing tilt and save them. The Flow chart for the application is shown in figure 9.

image goes here

Application starts with a request for a name to be entered to be stored with the ID in a text file. The face detection system starts the first half. However, before the capturing begins, the application check for the brightness levels and will capture only if the face is well illuminated. Furthermore, after the face is detected, the position of the eyes are analysed. If the head is tilted, the application automatically corrects the orientation. These two additions were made considering the requirements for Eigenface algorithm. The Image is then cropped and saved using the ID as a filename to be identified later. A loop runs this program until 50 viable images are collected from the person. This application made data collection efficient.

6.2.2 Training the Classifiers

OpenCV enables the creation of XML files to store features extracted from datasets using the FaceRecognizer class. The stored images are imported, converted to grayscale and saved with IDs in two lists with same indexes. FaceRecognizer objects are created using face recogniser class. Each recogniser can take in parameters that are described below: cv2.face.createEigenFaceRecognizer() 1. Takes in the number of components for the PCA for crating Eigenfaces. OpenCV documentation mentions 80 can provide satisfactory reconstruction capabilities. 2. Takes in the threshold in recognising faces. If the distance to the likeliest Eigenface is above this threshold, the function will return a -1, that can be used state the face is unrecognisable 6 cv2.face.createFisherfaceRecognizer() 1. The first argument is the number of components for the LDA for the creation of Fisherfaces. OpenCV mentions it to be kept 0 if uncertain. 2. Similar to Eigenface threshold. -1 if the threshold is passed. cv2.face.createLBPHFaceRecognizer() 1. The radius from the centre pixel to build the local binary pattern. 2. The Number of sample points to build the pattern. Having a considerable number will slow down the computer. 3. The Number of Cells to be created in X axis. 4.

The number of cells to be created in Y axis. 5. A threshold value similar to Eigenface and Fisherface. if the threshold is passed the object will return -1 Recogniser objects are created and images are imported, resized, converted into numpy arrays and stored in a vector. The ID of the image is gathered from splitting the file name, and stored in another vector. By using FaceRecognizer.train(NumpyImage, ID) all three of the objects are trained. It must be noted that resizing the images were required only for Eigenface and Fisherface, not for LBPH. Next, the configuration model is saved as a XML file using FaceRecognizer.save(FileName). In this project, all three are trained and saved through one application for convenience. The flow chart for the trainer is shown in figure 10.

images goes here.

6.2.3 The Face Recognition

Face recogniser object is created using the desired parameters. Face detector is used to detect faces in the image, cropped and transferred to be recognised. This is done using the same technique used for the image capture application. For each face detected, a prediction is made using FaceRecognizer.predict() which return the ID of the class and confidence. The process is same for all algorithms and if the confidence his higher than the set threshold, ID is -1. Finally, names from the text file with IDs are used to display the name and confidence on the screen. If the ID is -1, the application will print unknown face without the confidence level. The flow chart for the application is shown in figure 11.

image goes here:

7 result

The collected images are shown below. Each face has 50 images. Three applications were written to iter- ate through the parameters of each algorithm. On each iteration, the algorithm is trained using different parameters and tested against a photo. The resulting data is plotted at the after finishing the tests. The applications are :

result goes here.

8 Conclusions, Limitations and Future Works

This paper describes the final project for Facial Detection and Recognition on Raspberry Pi. It also explains the technologies and methodology used. At the end, it shows the results, and conclusion which also discuss the challenges and how they were resolved followed. Using Haar-cascades for face detection worked extremely well even when subjects wore spectacles. Images captured by phones had to be scaled down profoundly into standard 1920x1080. Face detection performance decreased rapidly if face was more than a 45-degree angle off facing the camera directly. if camera was upside down, facial detection did not work at all. Motion sensor sensitivity had to be decreased and sampling delay increased to get motion sensor to work with normal use case (someone walking into view of the camera). If moving objects in shot while image captured, facial detection performance decreased by about half 1) To combat this, a slight wait was added between the motion capture and image capture process. 2) This is to mimic the future application case of someone coming to and stopping at a user's front door. With all these limitations, we came up with few enhancements need to make it a better solution which are described as below. This device can be integrated with a smart lock system.