FACE DETECTION & FACE RECOGNITION USING OPEN COMPUTER VISION CLASSIFIRES

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ABSTRACT

Identifying a person with an image has been popularised through the mass media. However, it is less robust to fingerprint or retina scanning. This report describes the face detection and recognition mini-project undertaken for the visual perception and autonomy module. It reports the technologies available in the Open-Computer-Vision (OpenCV) library and methodology to implement them using Python. For face detection, Haar-Cascades were used and for face recognition Eigenfaces, Fisherfaces and Local binary pattern histograms were used. The methodology is described including flow charts for each stage of the system. Next, the results are shown including plots and screen-shots followed by a discussion of encountered challenges. The report is concluded with the authors' opinion on the project and possible application.

INTRODUCTION

Following project 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 analysed 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 a brief history of face recognition. This is followed by the explanation of HAAR-cascades, Eigenface, Fisherface and Local binary pattern histogram (LBPH) algorithms. Next, the methodology and the results of the project are described. A discussion regarding the challenges and the resolutions are described. Finally, a conclusion is provided on the pros and cons of each algorithm and possible implementations.

Face Detection using Haar-Cascades

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 recognize signals with sudden transformations. 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 for object detection. 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 single classifier is not accurate enough. Several classifiers are combined as to provide an accurate face detection system.

(A Haar wavelet and resulting Haar-like features)

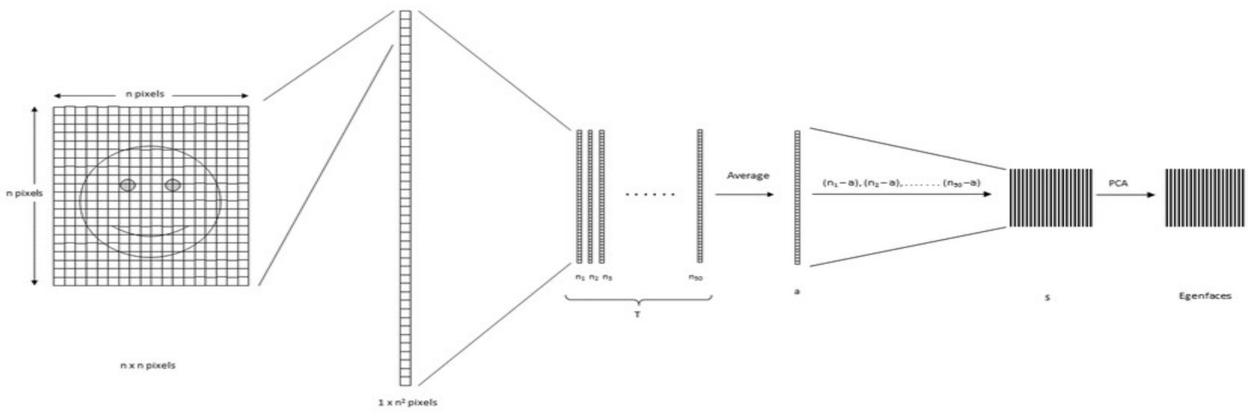
In this project, a similar method is used effectively to by identifying faces and eyes in combination resulting better face detection. Similarly, in viola Jones method, several classifies were combined to create stronger classifiers. ADA boost is a machine learning algorithm that tests out several week classifiers on a selected location and choose the most suitable. It can also reverse the direction of the classifier and get better results if necessary. Furthermore, Weight-update-steps can be updated only on misses to get better performance. The cascade is scaled by 1.25 and re-iterated in order to find different sized faces. Running the cascade on an image using conventional loops takes a large amount of computing power and time. Viola Jones used a summed area table (an integral image) to compute the matches fast. First developed in 1984, it became popular after 2001 when Viola Jones implemented Haar-cascades for face detection. Using an integral image enables matching features with a single passover the image.

Face Recognition

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

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 x n pixels as shown in figure 4. Each raw is concatenated to create a vector, resulting a 1×n2matrix. 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.



(Pixels of the image are reordered to perform calculations for Eigenface)

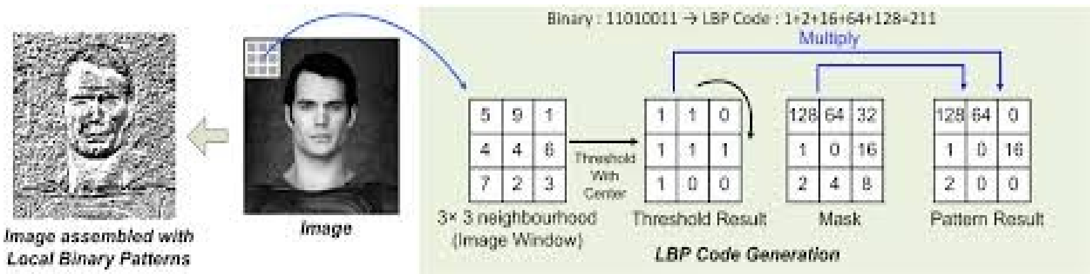
The next step is computing the covariance matrix from the result. To obtain the Eigen vectors from the data, Eigen analysis is performed using principal component analysis. From the result, where covariance matrix is diagonal, where it has the highest variance is considered the 1st Eigen vector. 2nd 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 im 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.

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 . 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. 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. 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.

Local Binary Pattern Histogram :

Local binary patterns were proposed as classifiers in computer vision and in 1990 By Li Wang. The combination of LBP with histogram oriented gradients was introduced in 2009 that increased its performance in certain datasets. 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. 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 is changed, 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.

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.

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. Face and eye 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.

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:
-> Collecting images IDs
-> Extracting unique features, classifying them and storing in XML files
-> Matching features of an input image to the features in the saved XML files and predict identity

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 in a folder.

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 for me.

Training the Classifiers :

OpenCV enables the creation of XML files to store features extracted from datasets using the ***FaceRe-cognizer*** 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.

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.