A Survey on Machine Learning Algorithms for Face Recognition

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Abstract - *A Facial Recognition is a most important technology now a days. In this review paper, we will discuss different algorithms used for Face Recognition so far. The most popularly used algorithms are Eigenfaces, Fisherfaces, Local Binary Patterns (LBP), Scale Invariant Feature Transform (SIFT), Speed-Up Robust Features (SURF).*

Key Words: Face Recognition, Eigenfaces, Fisherfaces, Local Binary Patterns (LBP), Scale Invariant Feature Transform (SIFT), Speed-Up Robust Features (SURF).

1. INTRODUCTION

Face Recognition is the ability of a system to recognize person by their facial characteristics. It is a type of biometric programming application that can recognize a particular individual in a computerized picture by breaking down and comparing patterns, recognition of a face has become popular in the recent years. It will identify people by their facial characteristics from the inputs in the form of image or videos. Generally, Face recognition incorporates feature extraction which includes feature reduction and recognition.

2. FACE RECOGNITION SYSTEM

The face recognition system consist of three significant advances, Data acquisition in the form of face image, Feature extraction and Face recognition. Image acquisition is the initial steps in the face recognition system. Next the feature is extracted from the image and finally it is given for the recognition purpose.

2.1 Acquisition of Face Data

It is the initial step in the face recognition system. Initially, it well collects the face images from different sources like images or live videos in real-time or static-time. Those collected images have different features such as illumination, expression and pose etc. The accuracy of any face recognition system may vary due to these features. The performance of face recognition systems may be influenced by the adjustment in the brightening condition foundation camera separation lighting conditions and the size and direction of the head.

2.2 Feature Extraction

Feature Extraction is a procedure of making an insignificant arrangement of best Feature from the current ones. Feature extraction is an attribute decrease process. The following are a portion of the benefits of Feature Extraction procedures.

- Accuracy improvements.
- Overfitting risk reduction.
- Reduce the training time.
- Improved Data Visualization.
- Increase in explain ability of our model.

2.3 Recognition of Face

Face recognition is a technique for identifying or verifying the identity of an individual utilizing their face. Face recognition can be utilized to recognize individuals in photographs, video, or in real-time. The face image is compared with the stored image. In the face picture is matched with the stored image, at that point the face is recognized.

3. ALGORITHMS FOR FACE RECOGNITION SYSTEM

There are different types of algorithm that can be used for face recognition. Some of them are listed below.

3.1 Eigenfaces.
3.2 Fisherfaces.
3.3. Local Binary Patterns (LBP).
3.4 Scale Invariant Feature Transform (SIFT)
3.5 Speed-Up Robust Features (SURF)

3.1 Eigenfaces

Eigenfaces is based on Principal Component Analysis (PCA). The Principal Component Analysis is a factual methodology utilized for decreasing the quantity of factors in face recognition. Eigenface is utilized to reduce dimensionality in facial space. Here recognition rate increments with the increment in the quantity of Eigen value and doesn't rely upon picture size. The eigenface algorithm is able to recognize human faces with high accuracy. It can even recognize faces in more challenging cases such as facial expressions, recognize real faces and after surgery, can even be combined with reconstruction of damaged facial images [1]. To make a lot of eigenfaces, we have to do the following steps.

1. Prepare a training set of face images. The training set should have been taken under the same lighting conditions, it must be normalized to have the eyes and mouths aligned across all images. Each image is treated as one vector, resulting in a single column with $r \times c$ elements. It is assumed that all images of the training set are stored in a single matrix **T**, where each column of the matrix is an image.

2. Subtract the mean. The average image has to be calculated and then subtracted from each original image in **T.**

3. Calculate the eigenvectors and eigenvalues of the covariance matrix **S.** Each eigenvector has a similar dimensionality (number of parts) as the original images, the eigenvectors of this covariance framework are in this way called eigenfaces.

4. Choose the principal components. Sort the eigenvalues in descending order and arrange eigenvectors accordingly. The number of principal components k is determined arbitrarily by setting a threshold ε on the total variance. Total variance
$\vartheta = (\lambda 1 + \lambda 2 + \lambda 3 \ldots. + \lambda n)$,
Where, n = number of components.

5. k is the smallest number that satisfies,
$\frac{(\lambda 1+\lambda 2+\lambda 3 \ldots.+\lambda k)}{n} > \epsilon$

These eigenfaces can now be used to represent both existing and new faces. The eigenvalues associated with each eigenface represent how much the images in the training set vary from the mean image in that direction.

3.2 Fisherfaces

The Fisherface approach is also one of the most generally utilized techniques for feature extraction in face images. The Fisherface algorithm is a refinement of the eigenface algorithm to provide the brightening variation. Bulhumeur reported that Fisherface algorithm performs better than eigenface in a situation where the lighting condition is changed. For it requires additionally training images for each faces [4]. The fisherface is improved in better classification of different classes image. The fisherface strategy for face recognition utilizes both principal component analysis and linear discriminant analysis to deliver a subspace projection matrix not at all like eigenface technique which utilizes just principal component analysis. Within-class differences can be estimated using the within-class scatter the matrix, given by.

$$S_w = \sum_{i=1}^{c} \sum_{x_j \in x_i} (x_j - \mu_i)(x_j - \mu_i)^T$$

Where, $\mathbf{x}_{ij}$ is the i^{th} sample of class j, μ_j is the mean of class j, n_j the number of samples in class j and C is the number of classes. Likewise, the between class differences are computed using the between-class scatter.

$$S_B = \sum_{i=1}^{c} N_i(\mu_i - \mu)(\mu_i - \mu)^T$$

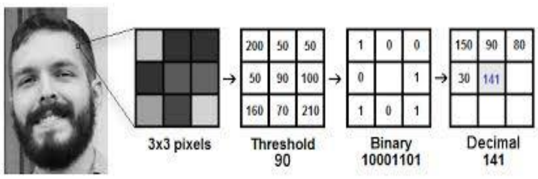
Where, μ represents the mean of all classes. S_B is maximized while S_w is minimized for the classification to be done [2].

3.3 Local Binary Patterns (LBP)

The LBP is a very efficient texture operator. It considers center pixel as a threshold value and computes neighboring pixel values. It considers the result in the form of binary numbers. The result is then encoded into a local binary pattern (LBP) to achieve fast and memory efficient processing. Initially, face image is divided into several regions and the features are extracted over the region. These features are concatenated to form face descriptor [3]. The original LBP operator was 3*3 matrix form. The central pixel value as the threshold of the matrix. Those thresholds it compares the threshold value with the gray-scale values of neighboring or adjacent 8 pixels. After comparing the value of neighbourhood pixel, if value is greater than or equal to the central pixel value, the value of pixel position is marked as 1 or otherwise marked as 0.

$$s(x) = \begin{Bmatrix} 1 & x \geq 0 \\ 0 & x < 0 \end{Bmatrix}$$

This operation can be described in the below figure.it shows initially the LBP generate 3*3 pixels the center of the matrix is known as threshold then this values compare with the above statement to get a 8-bit binary sequence and at the end it will converted into a decimal forms.



The obtained LBP values of central pixel points of the window, which is used to reflect the texture features of the region. The improved circular LBP operator is used in the current LBPH algorithm as represented in the below figure.

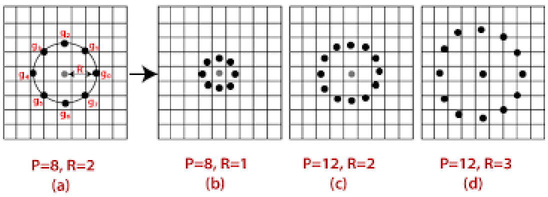


Figure: The LBP operator in circle form

The histograms of LBP are used for face recognition since LBP histograms contain information about the distribution of local micro patterns.

$$LBP_P^R = \sum_{p=0}^{p=1} s(g_p - g_r)2^p$$

g_p is the gray value of P neighborhoods of the pixel C, the radius of which is R. g_c is the gray value of the pixel C(xc,yc) This algorithm makes the LBP operator not at this point constrained to a fixed radius and neighborhood, and can meet the needs of more different size and texture features[5]. The LBPH algorithm utilizes the histogram of LBP characteristic spectrum as the feature vector for classification. It will divide image into several sub regions, then extracts LBP feature from each pixel of sub region, establishing a statistical histogram of LBP characteristic spectrum in each sub region, so that each sub region can use a statistical histogram to describe the whole picture by a number of statistical histogram components.

3.4 Scale Invariant Feature Transform

The detection of human faces from images plays a significant job in Computer vision. The different computational and scientific models, for arranging face including Scale Invariant Feature Transform (SIFT) have been proposed to yield better performance.

The Scale Invariant Feature Transform (SIFT) proposed by David G. Lowe. Some works on the use of SIFT features, such as SIFT_GRID proposed by M. Bicego and SIFT_CLUSTER proposed by Jun Luo.

SIFT is utilized in applications including scaling of an image and further more to identify corners, circles, blobs, and so on. The initial step is to scale space extreme direction. Once the image is blurred using Difference of Gaussian (DoG) blurring, the pixel is compared with nine pixels in the following and past scales. If it is the local extrema, it is a potential key point. The subsequent advance is key point localisation in which if intensity is less than the threshold esteem, they are rejected. Edges are evacuated utilizing eigen esteems and their proportions. At that point expulsion of low contrast key points and edge key points will be the strong interest points and coordinating sets can be acquired.

A direction is then allotted to each key point. At that point direction histograms will be created. The highest peak above 80% is considered. The extracted features are invariant to scale and direction which at that point makes key points with same area and scale, but with the different direction. At that point descriptor are the vector of size by (number of key points is *128) measurement accomplished from the direction histogram. At long last, the key point coordinating is between two images, and it is finished by distinguishing the closest neighbors. Moreover, the proportion examination among nearest and second nearest is finished.

3.5 Speed-Up Robust Features (SURF)

Speed-Up Robust Features (SURF) was first published by HerbertBay, Tinne Tuytelaars, and Luc Van Gool. The algorithm has three main parts: interest point detection, local neighborhood description, and matching. SURF is a patented local feature detector and descriptor with comparable or even better performance with SIFT.

1. Detection

In computer vision, the concept of interest points, also called key points or feature points. These key points has been to a great extent used to tackle numerous issues in object recognition, picture registration, visual tracking, 3D remaking, and more. SURF could then decide key point features utilizing Hessian-matrix. The estimation of a determinant of Hessian-matrix is figured for each pixel in steady time utilizing incorporated images. It is utilized for both interest point localisation and scale location.

$$H(x,\sigma) = \begin{bmatrix} L_{xx}(x,\sigma) & L_{xy}(x,\sigma) \\ L_{xy}(x,\sigma) & L_{yy}(x,\sigma) \end{bmatrix}$$

Where x is the pixel location, σ is the scale of computation $L_{xx}(x,\sigma)$, $L_{xy}(x,\sigma)$, $L_{yy}(x,\sigma)$ are the convolutions of the Gaussian second order partial derivatives with the image I in point x respectively.

The box filter of size 9×9 is an approximation of a Gaussian with σ=1.2 and represents the lowest level (highest spatial resolution) for blob-response maps. Scale spaces are usually implemented as image pyramids. The images are repeatedly smoothened with Gaussian and subsequently sub-sampled. Due to use of box filters and integral image, we can apply filter of any size directly on the original image.

2. Descriptor

The descriptor describes the features of the interest points and builds the feature vectors of the interest points. To think about two identified key point they should be lined up with one another. Be that as it may, the relating identified key point and the various images probably won't have a same orientation, so it is important to adjust the region before comparing them.

The initial step is to discover the orientation by considering the round about area around the interest point. At that point use Haar Wavelets responses to process the element of an interest point. Then compute descriptor vector in the dominant orientation by square region and extract the surf descriptor key point from it.

3. Matching

After obtaining the key point descriptor from different images, it is then compared and finally matching pairs can be obtained.

4. PROS AND CONS OF FACE RECOGNITION SYSTEM

- **Pros Of Face Recognition System**

1. Improved Security
2. High Accuracy
3. Fully Automated
4. More user friendly

- **Cons of Face Recognition system**

1. Data Storage
2. Camera Angle

5. CONCLUSION

After discussing the above different algorithm for face recognition, we would like to make a comparison. Between eigenface and fisherface, we get a better result with eigenface using PCA. On the other hand, eigenface algorithm is best for representation of the set of data where as fisherface is best for classification of data and pattern recognition. One of the oldest and more popular face recognition algorithms Local Binary Patterns Histograms (LBPH). Each method has a different approach to extract the image information and perform the matching with the input image. However, the methods Eigenfaces and Fisherfaces have a similar approach as well as the SIFT and SURF methods.

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