

Comparative Study of Face Recognition Techniques

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Abstract— The aim of this paper is to compare various methods for face recognition. In this paper we are going to discuss various techniques for face recognition. This paper includes a brief description of PCA (Principle Component Analysis), LDA (Linear Discriminant Analysis), LBP (Local Binary Pattern), Gabor filter, LGBP (Local Gabor Binary Pattern). Comparative study of various methods is discussed in this paper and from this study a suitable and more efficient technique is found out which will give more effective result.

Keywords— Face recognition, LDA (Linear Discriminant Analysis), PCA (Principle Component Analysis), LBP (Local binary pattern), Gabor Filter, LGBP (Local Gabor Binary Pattern).

I. INTRODUCTION

Face recognition is a very active area in the Computer Vision and Biometrics fields. It has been studied vigorously for 25 years and is now able to produce applications in security, robotics, human-computer-interfaces, digital cameras, games and entertainment, etc. Face recognition is carried out in two stages namely face identification and face verification.

There are different methods which have been studied for face analysis such as Eigenfaces (also called "Principal Component Analysis" or PCA [1]), Fisherface (also called "Linear Discriminant Analysis" or LDA [2]) etc.

II. PRINCIPLE COMPONENT ANALYSIS

Principle Component Analysis (PCA) is one of the most successful techniques that have been used in image recognition and compression [3]. Principal Component Analysis (PCA) is a statistical dimensionality reduction method. It has been used in a face recognition system and compression. The purpose of PCA is to reduce the large dimensionality of the data space into the smaller dimensionality of feature space, which is used to describe the data. PCA is used to compute set of a subspace vector, which is called Eigenfaces. The idea of using a PCA is that a 2-D image can be represented as 1-D vector of pixel, this can be called as a Eigenspace vector [4]. The covariance matrix derived from a set of facial images are used to calculate Eigenspace. PCA extract the relevant information in face image and encodes as effectively as possible.

Face recognition using PCA can be done in two phases:

- 1) Training phase: - In training phase large group of individuals faces are acted as a training set. In a training

phase the face image is pre-processed i.e. normalized the face image and you should extract a feature vector from each face image.

- 2) Recognition phase: - The image taken from the training phase i.e. normalized image is compared to a data base of known faces, to recognize the face.

Mathematics of PCA

Let us, consider X_j be N-element one-dimensional image and we have r such images i.e. $j=(1, \dots, r)$. By scanning all the elements of two-dimensional image row-by-row and writing them to column vector we obtain one-dimensional image-column X from two-dimensional image. From this, Mean vector(m)

$$m = \frac{1}{r} \sum_{j=1}^r X_j$$

Here, $m=(m_1, m_2, \dots, m_N)^T$

$$X=(X_1, X_2, \dots, X_N)^T$$

Centred vector(d_j)

$$d_j=X_j- m$$

Here, $d=(d_1, d_2, \dots, d_N)^T$ and covariance matrix(C)

$$C = \frac{1}{r} \sum_{j=1}^r d_j d_j^T$$

By calculating eigen vector μ_k and eigen value λ_k of covariance matrix C ($Cu_k = \lambda_k u_k$) we found principle axes.

Now any data X can be projected into eigenspace using following formula $Y=T(X-m)$.

In order to achieve better recognition result we must choose on appropriate distance measure

$$d(X, Y) = - \frac{\sum_{i=1}^n z_i x_i y_i}{\sqrt{\sum_{i=1}^m x_i^2 \sum_{i=1}^m y_i^2}}$$

Here,

X, Y = eigen feature vector of length n.

Following are the steps to perform PCA :

1. From each variable subtract the mean of the data.
2. Calculate the covariance matrix.
3. From the covariance matrix calculate Eigen vector and Eigen value.
4. Choose a feature vector.
5. Multiply the transposed feature vector by transposed adjusted data.

III. LINEAR DISCRIMINANT ANALYSIS

Linear Discriminant Analysis (LDA) gives effective performance in the Face Recognition tasks. As PCA encodes the information in an orthogonal linear space, the LDA encodes the information in linear separable space. The LDA can be used for the classification as well as for the dimensionality reduction, for e.g. LDA is used for reduction in speech recognition. LDA can be used for any kinds of classification problem e.g. Glasses recognition. The LDA is also called Fisherface [5] method. The Fisherface method for face recognition as described by Belhumeur [6], uses both principal component analysis and linear discriminant analysis. The strong argument in favour of using LDA method for dimensionality reduction is that we can perform the dimensionality reduction using linear projection and still preserve linear separability.

A. Algorithm used in LDA

Face recognition using a Linear Discriminant Analysis (LDA), we provide the following steps:

Step- I:

In the first step we require Training set which contain the database of a frontal face image. The database should also include different facial expression, different lighting and background condition. It is assumed that all images are already normalized to $m \times n$ arrays.

Step-II

We construct the vector expansion from two dimensional $m \times n$ array of intensity values $I(x, y)$. This vector corresponds to the initial representation of the face.

Step -III

Then we will find with-in class matrix and between class matrix. With-in class matrix (S_w)

$$S_w = \sum_{j=1}^c \sum_{i=1}^{N_j} (\Gamma_i^j - \mu_j)(\Gamma_i^j - \mu_j)^T \text{ ----- (1)}$$

Where

Γ_i^j = the i th samples of class j

μ_j = mean of class j

c = number of classes

N_j = number of samples in class j

Between class matrix (S_b)

$$S_b = \sum_{j=1}^c (\mu_j - \mu)(\mu_j - \mu)^T \text{ ----- (2)}$$

Where,

μ = the mean of all classes.

Then the subspace for LDA is spanned by a set of vector $W = [W_1, W_2 \dots W_d]$, satisfying

$$W = \arg \max = \text{mod} \left[\frac{W^T S_b W}{W^T S_w W} \right] \text{ ---- (3)}$$

The with-in class scatter matrix represents how the face images are distributed closely within classes.

The between class scatter matrix describe how classes are separated from each other. The discriminant vector (W) tries to minimize the denominator and maximizes the numerator in equation (3). LDA tries to discriminant the input data by dimension reduction.

IV. GABOR FILTER

Gabor filter is an image processing tool which is mostly used for feature extraction. Gabor Filter is used to filter the image with different spatial frequency, features and orientations. Fourier Transform is a way to analyse the spatial frequency content of an image, but the problem with this approach is that Fourier Coefficient is depend on the entire image and by this we lose the spatial information. To overcome this drawback the Gabor Filter is used as they have stronger response at points in an image where there are components that locally have a particular spatial frequency and orientation. Texture feature are obtained by calculating the mean and variation of Gabor Filter image.

V. LOCAL BINARY PATTERN

Out of the all feature extraction methods, texture feature extraction is one of most important and more efficient type used for feature extraction of images. The LBP operator [7] is mainly used for texture feature description and it was actually designed for texture description of the images to be analysed. Here in this method labels are assigned to every pixel of the image by thresholding 3 by 3 -neighbourhood of every pixel. The labels are in the binary form such as 0 or 1. According to the values obtained in the binary form, histograms are generated which are used as texture descriptor. To give the idea about the texture feature at different scales, an extension to the same was done by allowing to use different number of neighbourhoods [8].

A small example of how the labels are assigned to neighbours of central pixel is shown in the diagram. According to the value of the centre pixel values are assigned to the neighbouring pixels in the binary form. This pixel values are used to form the histograms.

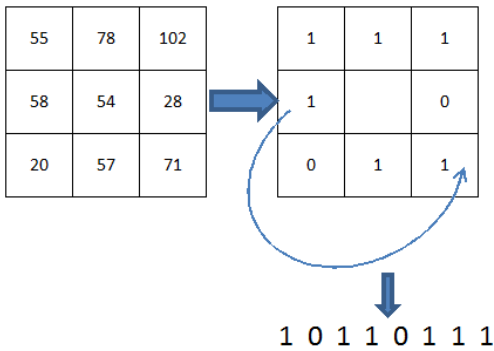


Fig. 1 The Basic LBP Operator

The formulae to obtain the above binary number can be given as:

$$S(f_s - f_c) = \begin{cases} 1, & f_s \geq f_c \\ 0, & f_s < f_c \end{cases}$$

Where, f_s = Value of surrounding pixel (0...8).
 f_c = Value of central pixel.

To express the LBP operator in decimal form the formulae can be given as:

$$LBP = \sum_{s=1}^8 S(f_s - f_c) 2^s$$

VI. LOCAL GABOR BINARY PATTERN

Although there are various methods which can be used for face recognition and detection, still it is an important topic to be discussed, due to the fact that faces can appear in various poses, backgrounds, illuminations etc. To overcome this issue, combination of different methods can be used to maximize the correctness of the result. The combination of Gabor filters and Local binary operators can produce better results as compared to the other methods. In this approach firstly Gabor filters are used to decompose the face image and hence the local binary operator is used for generation of the histograms [9][10].

The overall procedure to be followed for this approach is as follows: firstly the original image is normalized and later on this normalized image is passed to Gabor filters for further decomposition. Gabor filter generates Gabor magnitude pictures with different orientations and different scales. These gray-level images are the applied to LBP operators. LBP operator divides the images into many rectangular parts and further process on it to generate histograms of different parts. These histograms are combined to generate the final histogram sequence.

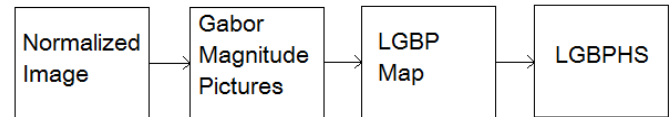


Fig. 2 Block Diagram of LGBP

VII. CONCLUSIONS

In this paper we have proposed various methods for Facial Recognition such as LDA (Linear Discriminant Analysis), PCA (Principle Component Analysis), Gabor Filters, LBP (Local Binary Pattern)

Operator and LGBP (Local Gabor Binary Pattern). Out of these all methods each has some drawbacks.

Using Gabor Filters or LBP Operator individually may not give as good results as would obtain by combining these two.

By comparing various methods we have concluded that combination of Gabor and LBP gives more efficient results. Hence we have concluded that LGBP (Local Gabor Binary Pattern) will be more effectively used than using them individually.

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