ACCURATE FACE RECOGNITION USING PCA AND LDA

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Abstract:

Face recognition from images is a sub-area of the general object recognition problem. It is of particular interest in a wide variety of applications. Here, the face recognition is based on the new proposed modified PCA algorithm by using some components of the LDA algorithm of the face recognition. The proposed algorithm is based on the measure of the principal components of the faces and also to find the shortest distance between them. The experimental results demonstrate that this arithmetic can improve the face recognition rate. . Experimental results on ORL face database show that the method has higher correct recognition rate and higher recognition speeds than traditional PCA algorithm.

Keywords: Face recognition, PCA, LDA.

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I. INTRODUCTION:

A digital image is a discrete two-dimensional function f(x,y) which has been quantized over its domain and range . Without loss of generality, it will be assumed that the image is rectangular, consisting of x rows and y columns.[13] The resolution of such an image is written as x*y. By convention, f(0 0) is taken to be the top left corner of the image, and .w)f(x-1,y-1) the bottom right corner. This is summarized in Figure 1.

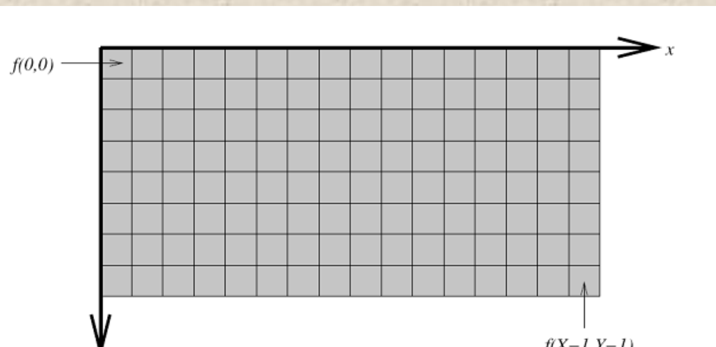

Figure 1: A rectangular digital image of resolution16*8.

Each distinct coordinate in an image is called a pixel, which is short for picture element. The nature of the output of f(x,y) for each pixel is dependent on the type of image. Most images are the result of measuring a specific physical phenomenon, such as light, heat, distance, or energy. The measurement could take any numerical form. A greyscale image measures light intensity only. Each pixel is a scalar proportional to the brightness. The minimum brightness is called black, and the maximum brightness is called white. A typical example is given in Figure 2.[15] A colour image measures the intensity and chrominance of light. Each colour pixel is a vector of colour components. Common colour spaces are RGB (red, green and blue), HSV (hue, saturation, value), and CMYK (cyan, magenta, yellow, black), which is used in the printing industry. Pixels in a range image measure the depth of distance to an object in the scene[30]. Range data is commonly used in machine vision applications.

Figure 2: A typical greyscale image of resolution 512*512.

For storage purposes, pixel values need to be quantized. The brightness in greyscale images is usually quantized to levels, so f(x,y) belongs to {0 1 …...z-1} .If z has the form 2^L the image is referred to as having L ¡bits per pixel. Many common greyscale images use 8 bits per pixel giving 256 distinct grey levels. This is a rough bound on the number of different intensities the human visual system is able to discern. For the same reasons, each component in a colour pixel is usually stored using 8 bits[17].

Medical scans often use 12-16 bits per pixel, because their accuracy could be critically important. Those images to be processed predominantly by machine may often use higher values to avoid loss of accuracy throughout processing. Images not encoding visible light intensity, such as range data, may also require a larger value of z to store sufficient distance information.

There are many other types of pixels. Some measure bands of the electromagnetic spectrum such as infra-red or radio, or heat, in the case of thermal images. Volume images are actually three dimensional images, with each pixel being called a voxel. In some cases, volume images may be treated as adjacent two-dimensional image slices.[43] Although this thesis deals with grayscale images, it is often straightforward to extend the methods to function with different types of images.

II. Recognition:

Face recognition from images is a sub-area of the general object recognition problem. It is of particular interest in a wide variety of applications. Applications in law enforcement for mugshot identification, verification for personal identification such as driver's licenses and credit cards, gateways to limited access areas, surveillance of crowd behavior are all potential applications of a successful face recognition system. The environment surrounding a face recognition application can cover a wide spectrum − from a well controlled environment to an uncontrolled one. In a controlled environment, frontal and profile photographs of human faces are taken, complete with a uniform background and identical poses among the participants.[16] These face images are commonly called mug shots. Each mug shot can be manually or automatically cropped to extract a normalized subpart called a canonical face image, as shown in Fig. In a canonical face image, the size and position of the face are normalized approximately to the predefined values and the background region is minimized. Face recognition techniques for canonical images have been successfully developed by many face recognition systems.

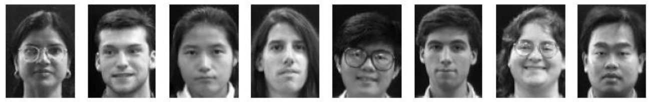

Figure 3: A few examples of canonical frontal face images.

General face recognition, a task which is done by humans in daily activities, comes from a virtually uncontrolled environment. Systems to automatically recognize faces from uncontrolled environment must first detect faces in sensed images. A scene may or may not contain a set of faces; if it does, their locations and sizes in the image must be estimated before recognition can take place by a system that can recognize only canonical faces. A face detection task is to report the location, and typically also the size, of all the faces from a given image. Figure 3. gives an example of an image which contains a number of faces. From figure 3, we can see that recognition of human faces from an uncontrolled environment is a very complex problem, more than one face may appear in an image; lighting condition may vary tremendously; facial expressions also vary from time to time; faces may appear at different scales, positions and orientations; facial hair, make-up and turbans all obscure facial features which may be useful in localizing and recognizing faces; and a face can be partially occluded.[5],[23],[39] Further, depending on the application, handling facial features over time (e.g., aging) may also be required. Given a face image to be recognized, the number of individuals to be matched against is an important issue.[11] This brings up the notion of face recognition versus verification: given a face image, a recognition system must provide the correct label (e.g., name label) associated with that face from all the individuals in its database. A face verification system just decides if an input face image is associated with a given face image. Since face recognition in a general setting is very difficult, an application system typically restricts one of many aspects, including the environment in which the recognition system will take place (fixed location, fixed lighting, uniform background, single face, etc.), the allowable face change (neutral expression, negligible aging, etc.), the number of individuals to be matched against, and the viewing condition (front view, no occlusion, etc.).

Figure 4: An image that contains a number of faces.

The task of face detection is to determine the position and size (height and width) of a frame in which a face is canonical. Such a frame for a particular face is marked in the image.[15]

III. FACE DETECTION:

Face Detection is a part of a wide area of pattern Detection technology. Detection and especially face Detection covers a range of activities from many walks of life. Face Detection is something that humans are particularly good at and science and technology have brought many similar tasks to us. Face Detection in general and the Detection of moving people in natural scenes in particular, require a set of visual tasks to be performed robustly. That process includes mainly three-task acquisition, normalisation and Detection. By the term acquisition we mean the detection and tracking of face-like image patches in a dynamic scene. Normalisation is the segmentation, alignment and normalisation of the face images[3], and finally Detection that is the representation and modelling of face images as identities, and the association of novel face images with known models.

IV. Principal Component Analysis:

On the field of face Detection most of the common methods employ Principal Component Analysis. Principal Component Analysis is based on the Karhunen-Loeve (K-L), or Hostelling Transform, which is the optimal linear method for[9] reducing redundancy, in the least mean squared reconstruction error sense. 1. PCA became popular for face Detection with the success of eigenfaces.

The idea of principal component analysis is based on the identification of linear transformation of the co-ordinates of a system. “The three axes of the new co-ordinate system coincide with the directions of the three largest spreads of the point distributions.”

In the new co-ordinate system that we have now the data is uncorrected with the data we had in the first co-ordinate system. [2]

For face Detection, given dataset of N training images, we create N d-dimensional vectors, where each pixel is a unique dimension. The principal components of this set of vectors is computed in order to obtain a d x m projection matrix, W. Approximates the original image where μ is the mean, of the χ_i and the reconstruction is perfect when m = d.

For the comparison we are going to use two different PCA algorithms. The first algorithm[11] is computing and storing the weight of vectors for each person's image in the training set, so the actual training data is not necessary. In the second algorithm each weight of each image is stored individually, is a memory-based algorithm. For that we need more storing space but the performance is better.

In order to implement the Principal component analysis in MATLAB we simply have to use the command prepca. The syntax of the command is

ptrans,transMat = prepca(P,min_frac)

Prepca pre-processes the network input training set by applying a principal component analysis. This analysis transforms the input data so that the elements of the input vector set will be uncorrected. In addition, the size of the input vectors may be reduced by retaining[10] only those components, which contribute more than a specified fraction (min_frac) of the total variation in the data set.

Prepca takes these inputs the matrix of centred input (column) vectors, the minimum fraction variance component to keep and as result returns the transformed data set and the transformation matrix.

a) Algorithm

Principal component analysis uses singular value decomposition to compute the principal components. A matrix whose rows consist of the eigenvectors of the input covariance matrix multiplies the input vectors. This produces transformed input vectors whose components are uncorrected and ordered according to the magnitude of their variance.

Those components, which contribute only a small amount to the total variance in the data set, are eliminated. It is assumed that the input data set has already been normalised so that it has a zero mean.

In our test we are going to use two different "versions' of PCA. In the first one the centroid of the weight vectors for each person's images in the training set is computed and stored. On the other hand in PCA-2 a memory based variant ofPCA, each of the weight vectors in individually computed and stored.

Eigenfaces

Human face Detection is a very difficult and practical problem in the field of pattern Detection. On the foundation of the analysis of the present methods on human face Detection, [12]a new technique of image feature extraction is presented. And combined with the artificial neural network, a new method on human face Detection is brought up. By extraction the sample pattern's algebraic feature, the human face image's eigenvalues, the neural network classifier is trained for Detection. The Kohonen network we adopted can adaptively modify its bottom up weights in the course of learning. Experimental results show that this method not only utilises the feature aspect of eigenvalues but also has the learning ability of neural network. It has better discriminate ability compared with the nearest classifier. The method this paper focused on has wide application area. The adaptive neural network classifier can be used in other tasks of pattern Detection.

In order to calculate the eigenfaces and eigenvalues in MATLAB we have to use the command eig. The syntax of the command is

d = eig(A)

V,D = eig(A)

V,D = eig(A,'nobalance')

d = eig(A,B)

V,D = eig(A,B)

d = eig(A) returns a vector of the eigenvalues of matrix A. V,D = eig(A) produces matrices of eigenvalues (D) and eigenvectors (V) of[13] matrix A, so that A*V = V*D. Matrix D is the canonical form of A, a diagonal matrix with A's eigenvalues on the main diagonal. Matrix V is the modal matrix, its columns are the eigenvectors of A. The eigenvectors are scaled so that the norm of each is 1.0. Then we use W,D = eig(A'); W = W' in order to compute the left eigenvectors, which satisfy W*A = D*W.

V,D = eig(A,'nobalance') finds eigenvalues and eigenvectors without a preliminary balancing step. Ordinarily, balancing improves the conditioning of the input matrix, enabling more accurate computation of the eigenvectors and eigenvalues. However, if a matrix contains small elements that are really due to round-off error, balancing may scale them up to make them as significant as the other elements of the original matrix, leading to incorrect eigenvectors. We can use the no balance option in this event.

d = eig(A,B) returns a vector containing the generalised eigenvalues, if A and B are square matrices. V,D = eig(A,B) produces a diagonal matrix D of generalised eigenvalues and a full matrix V whose columns are the corresponding eigenvectors so that A*V = B*V*D. The eigenvectors are scaled so that the norm of each is 1.0.

Euclidean distance

One of the ideas on which face Detection is based is the distance measures, between to points. The problem of finding the distance between two or more point of a set is defined as the Euclidean distance. The Euclidean distance is usually referred to the closest distance between two or more points.

IV. IMPLEMENTATION:

The first component of our system is a filter that receives as input a 20x20 pixel region of the image, and generates an output ranging from 1 to -1, signifying the presence or absence of a face, respectively. To detect faces anywhere in the input, the filter is applied at every location in the image. To detect faces larger than the window size, the input image is repeatedly reduced in size (by subsampling), and the filter is applied at each size. This filter must have some invariance to position and scale. The amount of invariance determines the number of scales and positions at which it must be applied. For the work presented here, we apply the filter at every pixel position in the image, and scale the image down by a factor of 1.2 for each step in the pyramid. The filtering algorithm is shown in . First, a preprocessing step, adapted from , is applied to a window of the image. The window is then passed through a neural network, which decides whether the window contains a face. The preprocessing first attempts to equalize the intensity values in across the window. We fit a function which varies linearly across the window to the intensity values in an oval region inside the window. Pixels outside the oval may represent the background, so those intensity values are ignored in computing the lighting variation across the face. The linear function will approximate the overall brightness of each part of the window, and can be subtracted from the window to compensate for a variety of lighting conditions. Then histogram equalization is performed, which non-linearly maps the intensity values to expand the range of intensities in the window. The histogram is computed for pixels inside an oval region in the window. This compensates for differences in camera input gains, as well as improving contrast in some cases. For the experiments which are described later, we use networks with two and three sets of these hidden units. Similar input connection patterns are commonly used in speech and character recognition tasks .The network has a single, real-valued output, which indicates whether or not the window contains a face. The network has some invariance to position and scale, which results in multiple boxes around some faces. To train the [14]neural network used in stage one to serve as an accurate filter, a large number of face and nonface images are needed. Nearly 1050 face examples were gathered fromface databases at CMU, Harvard2, and from the World Wide Web. The images contained faces of various sizes, orientations, positions, and intensities. The eyes, tip of nose, and corners and center of the mouth of each face were labelled manually. These points were used to normalize each face to the same scale, orientation, and position, as follows:

Table 1: Methodology

a.) Use LDA and Fishers Face Algorithm.
b.) Take Training data base.
c.) Take Test image.
d.) Implementation of the PCA and LDA.
e.) Checking the test image on training data.
f.) Compilation and Performance graph generation on the ease of steps b, c, d, and e.

Now the algorithm for the proposed technique is as follows:

Step1. Align a set of face images say T

Step 2. Create training database (ORL Face database) of M rows and N columns of each image.

P=M x N

Step3. Reshapes: 2D images into 1D column vectors.

Step 4. Create database

W=26 % number of folders in database

for i=1: w %for each unit of database

if DB=1 Then % where DB is the database means database exists

DB= 1: i

Find Components

Ti is mapped onto a (P-C) mapping

if D_{min} == 0 then %where D_{min} is the minimum value of the %mean distance between test image and trained image

Proceed

Else

Goto step 4 again;

Endif

End For

Step 5. Calculating Discriminant for Fisher Linear (P-C)(C-1)

for DB=1: w

Projected Images Fisher

for 1: (C-1)*P

%Training images from 1 to w

End for

End for

Show the Matched Output with Success rate

V. RESULTS:

The database of images is having the images of 10 different peoples and we are performing our test on 3 of them. The following results were found.

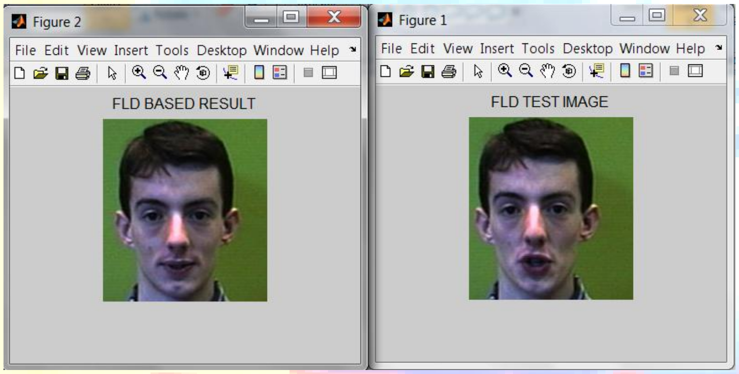

Figure 6: Test image for FLD testing (image 1/10).

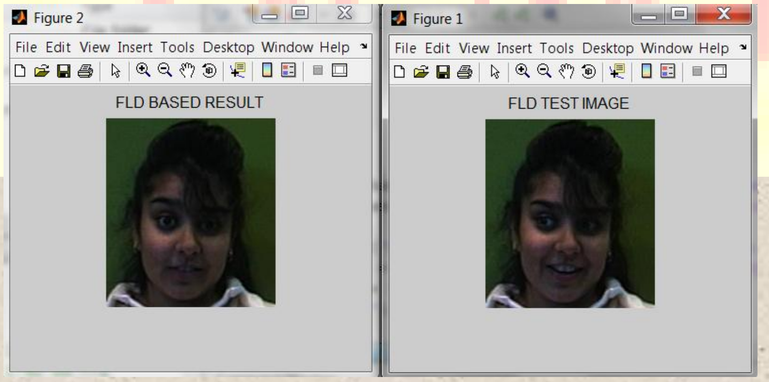

Figure 7: Test image for FLD testing (image 2/10).

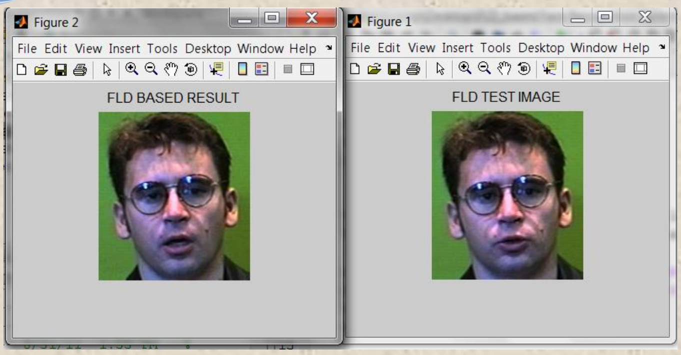

Figure 8: Test image for FLD testing (image 3/10).

Approach	**No. of correct outputs out of 100**	**Accuracy Rate (%)**
PCA	90	90
Proposed PCA along with linear distance finding method	99	99

The ORL Database of Facial Images [19] is used for performing the experiments. The database consists of 400 facial images of 40 individuals with 10 images of each. For performing the experiments we have taken 100 images of 10 individuals with 10 images of each. The training set consists of 50 images from these with 5 images of each individual.

The experiment is performed first by recognizing images of each individual using PCA and then PCA with linear distance finding algorithm. Then, the accuracy rate for both the approaches is calculated, by finding out, how many results are found correct.

VI. Conclusion:

The propose work shows the robust performance for the give test images the achieved output is 99% in our case. The system performance may vary machine to machine. In our system, we perform the test on i3 machine with 4GB Ram in less than 5 sec. The speed performance and accuracy outperforms the available methods till date. Our system is better than the all available methods of face recognition.

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