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Dedeblur Using PCA Correlation Technique in Multiscale Concordance Algorithm

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Abstract: Face recognition using Eigen faces is an approach to the detection and identification of human faces and describing, near real time face recognition system which tracks a subject's head and then recognizes the person by comparing characteristics of the face to those of known individuals. This approach treats face recognition as a two-dimensional recognition problem, taking advantage of the fact that face are normally upright and thus may be described by a small set of 2-D characteristics. Face images are projected on to a face space that best encodes the variation among known face images. The face space is defined by the "EIGEN FACES", which are the Eigen vectors of the set of faces. They don't necessarily correspond to isolated features such as eyes, ears, and noses. The framework provides the ability to learn a recognized new faces in an unsupervised manner.

Keywords: Eigen faces, 2-D

I. INTRODUCTION

An image may be defined as a two-dimensional function, f (x, y), where x and y are spatial coordinates, and the amplitude of 'f' at any pair of coordinates (x, y) is called the intensity or gray level of the image at that point. When x, y and the amplitude values of f are all finite, discrete quantities, we call the image a digital image.

The field of digital image processing refers to processing digital images by means of a digital computer. Note that a digital image is composed of a finite number of elements, each of which has a particular location and value. These elements are referred to as picture elements, image elements, pels and pixels. Pixel is a term widely used to denote the elements of a digital image.

Vision is the most advanced of our senses, so it is not surprising that images play the most important role in human perception. They can operate also on images generated by sources that include ultrasound, electron microscopy, and computer generated images.

Thus, digital image processing encompasses a wide and varied field of applications. There is no general agreement regarding where image processing stops and other related areas, such as image analysis and computer vision, starts. Sometimes a distinction is made by defining image processing as a discipline in which both the input and output of a process are images. We believe this to be a limiting and somewhat artificial boundary. For example, under this definition, even the task of computing the average intensity of an image would not be considered an image processing operation. On the other hand, there are field such as computer vision whose ultimate goal is to make interferences and take actions based on visual inputs. So it can be said that area of image analysis is in between image processing and computer vision.

An image may be defined as a two dimensional function, f(x, y), where x and y are spatial (plane) coordinates, and the amplitude off at any pair of coordinates (x, y) is called the intensity of image at that point. Color images are formed by a combination of individual 2-D images. For example, in the RGB color system, a color image consists of three (red, green, blue) individual component images as shown in Fig 1.1. For this reason, many of the techniques developed for monochrome images can be extended to color images by processing the three component images individually.

An image may be continuous with respect to the x, and y coordinates, and also in amplitude. Converting such an image to digital form requires that the coordinates, as well as the amplitude, be digitized. Digitizing the coordinate values is called sampling; digitizing the amplitude values is called quantization. Thus, when x, y and the amplitude values of f are all finite, discrete quantities, we call the image a digital image.

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Fig 1.1 - RGB Component of a Color Image

II. FACE RECOGNITION

Face Recognition Using Eigenfaces -Computer Vision and Pattern Recognition 1991. Proceedings CVPR'91., IEEE Computer by Matthew A. Turk and Alex P. Pentland . Our goal, which we believe is to develop a computational model of face recognition that is fast, reasonably simple, and accurate in constrained environments such as an office or a household. The scheme is based on an information theory approach that decomposes face images into a small set of characteristic feature images called eigenfaces, which may be thought of as the principal components of the initial training set of face images. Recognition is performed by projecting a new image into a subspace spanned by the eigenfaces (facespace) and then classifying the face by comparing its position in face space with the positions of known individuals.

Recognition under widely varying conditions is achieved by training on a limited number of characteristic views (e.g., a straight on view, pose variation and illumination variation). The approach has advantages over other face recognition schemes in its speed and simplicity, learning capacity, and insensitivity to small or gradual changes in the face. PCA – Principal Component Analysis is a statistical method for reducing the dimensionality of a data set while retaining the majority of the variation present in the data set.

The objective of the Principal Component Analysis (PCA) is to take the total variation on the training set of faces and to represent this variation with just some little variables. When we are working with great amounts of images, reduction of space dimension is very important. PCA intends to reduce the dimension of a group or to space it better so that the new base describes the typical model of the group.

The image space is highly redundant when it describes faces. This happens because each pixel in a face is highly correlated to the others pixels. The objective of PCA is to reduce the dimension of the work space. The maximum number of principal components is the number of variables in the original space. Even so to reduce the dimension, some principal components should be omitted. This means that some principal components can be discarded because they only have a small quantity of data, considering that the larger quantity of information is contained in the other principal components.

III. MATHEMATICAL ANALYSIS

3.1 STATISTICS

3.1.1 Mean

Mean is defined as the, ratio of summation of data set elements to number elements in a data set. Given by the formula,

3.1.2 Standard Deviation

To understand standard deviation, we need a data set. Statisticians are usually concerned with taking a sample of a population. To use election polls as an example, the population is all the people in the country, whereas a sample is a subset of the population that the statisticians measure. The great thing about statistics is that by only measuring (in this case by doing a phone survey or similar) a sample of the population, work out what is most likely to be the measurement if used the entire population. In this statistics section, we are going to assume that our data sets are samples of some bigger population. Here's an example set

$$X = \left(1\ 2\ 4\ 6\ 12\ 15\ 25\ 45\ 68\ 67\ 65 \right)$$

We could simply use the symbol X to refer to this entire set of numbers. If we want to refer to an individual number in this data set, we will use subscripts on the symbol X to indicate a specific number. E.g. X_3 refers to the 3rd number in X, namely the number 4. Note that X_1 is the first number in the sequence, X_0 not like you may see in

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some textbooks. Also, the symbol n will be used to refer to the number of elements in the Set.

The mean doesn't tell us a lot about the data except for a sort of middle point. For example, these two data sets have exactly the same mean (10), but are obviously quite different.

$$\begin{pmatrix} 0 & 8 & 12 & 20 \end{pmatrix} \text{ and } \begin{pmatrix} 8 & 9 & 11 & 12 \end{pmatrix}$$

So what is different about these two sets? It is the spread of the data that is different. The Standard Deviation (SD) of a data set is a measure of how spread out the data .Standard Deviation is "The average distance from the mean of the data set to a point". The way to calculate it is to compute the squares of the distance from each data point to the mean of the set, add them all up, divide by n-1, and take the positive square root. As a formula,

$$\sigma = \left(\frac{\Sigma^{n}_{i=1} (X_i - E[X])^2}{(n-1)} \right)^{1/2}$$

Where, σ is the usual symbol for standard deviation of a sample. Here we take (n-1) instead of n, our data set is a sample data set, i.e. We have taken a subset of the real-world (like surveying 500 people about the election) then We must use (n-1) because it turns out that this gives us an answer that is closer to the standard deviation that would result if we had used the entire population, than if we used n. If, however, we are not calculating the standard deviation for a sample, but for an entire population, then we should divide by n instead of (n-1).

IV. FACE RECOGNITION USING EIGENFACES

4.1 Initialization for Input Image

When a new face image is given as input to check for face recognition, then it can be classified in one of these image classes. Also it can be compared for match with any of the existing images in database. Say new image is Γ. This can be represented as column vector of dimension Nx1. This new image is mean centered by subtracting average face Ψ.

4.2 Projecting Input Face Image

Each of such new face submitted to the Face Recognition is projected into the face space, obtaining the vector, also known as face key (eigenvector) for this image, by using following equation.

$$\omega_k = u_k^T(\Gamma - \Psi)$$

$$\Omega^T = [\omega_1, \omega_2, \ \ldots\ldots\ , \omega_M]$$

4.3 Classification of Input Image

This vector with dimension (Mx1), is compared with each vector i representing face keys for each of class images. This Euclidean distance between two face key vectors can be calculated using square minimal method given by following equation.

$$\varepsilon_k = \left\| \Omega - \Omega_k \right\|^2$$

4.4 Face Recognition

The input face is considered to belong to a class if ε_k is below an established threshold θ_1. Then the face image is considered to be a known face. If the difference is above the given threshold, but below a second threshold, the image can be determined as a unknown face. If the input image is above these two thresholds, the image is determined not to be a face. If the image is found to be an unknown face, you could decide whether or not you want to add the image to your training set for future recognitions.

Eigenspace-based approaches approximate the face vectors (face images) with lower dimensional feature vectors. The main objective behind this procedure is that the face space (given by the feature vectors) has a lower dimension than the image space (given by the number of pixels in the image), and that the recognition of the faces can be performed in this reduced space. This approach considers training, where the face database is created and the feature vector, the one that achieve the dimensional reduction, is obtained from all the database face images. Also mean face is calculated and the reduced representation of each database image with respect to mean face is achieved. These representations are the ones to be used in the recognition process. The basic steps involved in Face Recognition using Eigenfaces Approach are as follows:

Initialization

1. Acquire initial set of face images known as Face set.
2. Calculate eigenfaces from face set keeping only M images that correspond to highest eigenvalues. These M images define the face-space.
3. Calculate distribution in this M-dimensional space for each known person by projecting their face images onto this face-space.

Recognition

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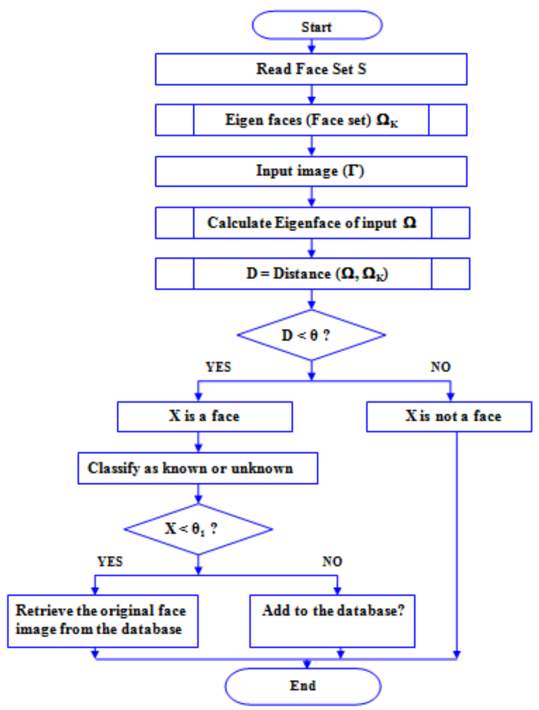
1. For given input image, calculate a set of weights based on M eigenfaces by projecting this new image onto each of eigenfaces.
2. Determine whether the image is face or not by checking if the image is sufficiently close to face-space.
3. If the image is face, then classify as either known or unknown person.
4. The weight pattern can be compared with known weight patterns to match faces.



Calculate Eigenvalues and Eigenvectors of Face set

As the dimension of this matrix is N x N, which means it will result in N eigenvalues and N eigenvectors. Since the value of N is very large, say 65536 as in above example, it would be better to reduce this overhead by considering matrix L = A^TA. The dimension of this matrix will be M x M.

$$\mathbf{L = A^{T}}$$

Since the covariance matrix is symmetric, it holds the property described in section 3.1.4.1. The N eigenvalues obtained from C are same as M eigenvalues with remaining N - M eigenvalues equals zero. Also if x is eigenvector obtained from C then the eigenvectors of L are given by,

$$\mathbf{y = A^{T} x}$$

We can make use of this relationship to obtain eigenvalues and eigenvectors of AA^T by calculating eigenvalues and eigenvectors for A^TA. The eigenvectors for C (Matrix U) are obtained from eigenvectors of L (Matrix V) as given below,

$$\mathbf{U = AV}$$

The matrix V, with dimension (M x M), is constituted by the M eigenvectors of L and matrix U, with dimension (N x M), is constituted by all the eigenvectors of C, and the matrix A is the image space, with dimension (N x M).

V. RESULT AND DISCUSSION

Acquiring Face Set

We are essentially using a for loop statement to read the images in the database. These face images will have numerical names as 1,2,3,…,M and will be in bitmapped format (bmp).

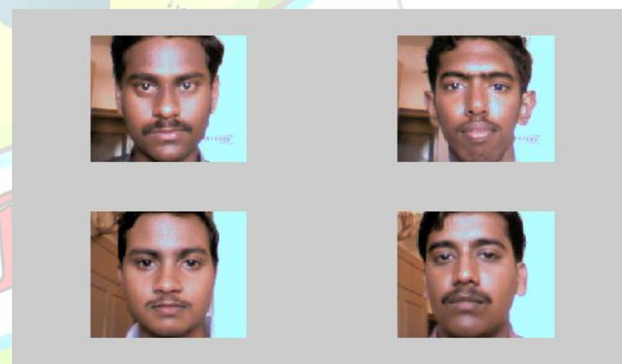


Fig 6.1 - Face Set Images

Changing the image matrix for manipulation

One of the first manipulation operations is to convert the color image that is read to gray scale so as to make it suitable for processing. This is because color image is 3-D and gray scale image is a 2-D one making it perfect for matrix manipulation operations.

Each of these gray face images will be in a form of matrix and we convert each matrix into a single column vector and then arrange all the column vectors in a big matrix (say S). Thus 'S' will be containing 'M' no. of columns each column representing one face image. This

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transformation is achieved using MATLAB command ‘reshape’ [6.1.d].

Also the images read are normally in the format of unsigned integer of 8 bits (uint8). This means that each pixel in the image is represented in integer values from 0 to 255 whereby 0 represents pure white and 255 counts for dark black. Now during our processing the pixel values can become fractional or go beyond the limit of 255. So we increase the scope of the image matrix by converting it into double format which can handle data limits of -10^{308} to 10^{308}. This enables us to perform operations like division, averaging etc on the image matrix

Calculating Mean

The mean of all the ‘M’ columns is found out and displayed by bringing the column vector back to a matrix like format. This can be shown as,

Fig 6.2 - Mean image

Normalization

Normalization is achieved by subtracting the respective mean and standard deviations from each column. This is done to minimize the variations due to lightning conditions. The normalized set will be as in Fig 6.3.

Fig 6.3 - Normalized Face Set

Calculating Eigenfaces

To obtain eigenfaces (eigenvectors) we first compute the covariance matrix as SS^T . The eigenvectors of this covariance matrix is calculated using the command eigs[6.1.g]. These eigenfaces looks like,

Distance Vector

The distance vectors (facespace) of face set and eigenfaces is achieved by computing the dot product between the two.

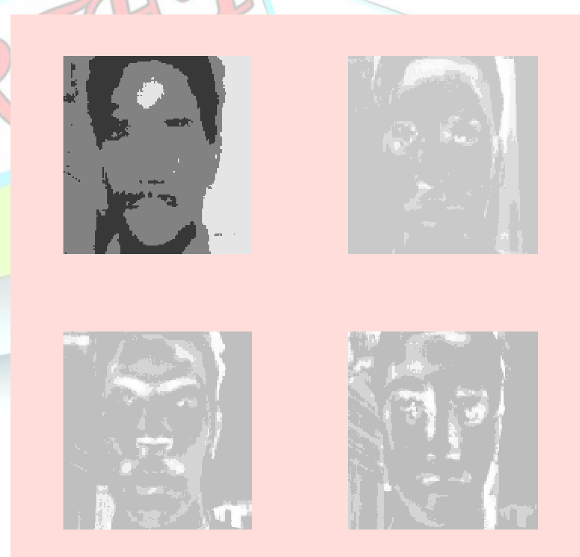

Fig 6.4 - Eigenfaces

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Euclidean Distance

After getting an input image similar steps are performed to extract the distance vector from the input image with respect to the eigenvectors of the face set. Then the Euclidean distance between both the distance vectors is found out and can be visualized as,

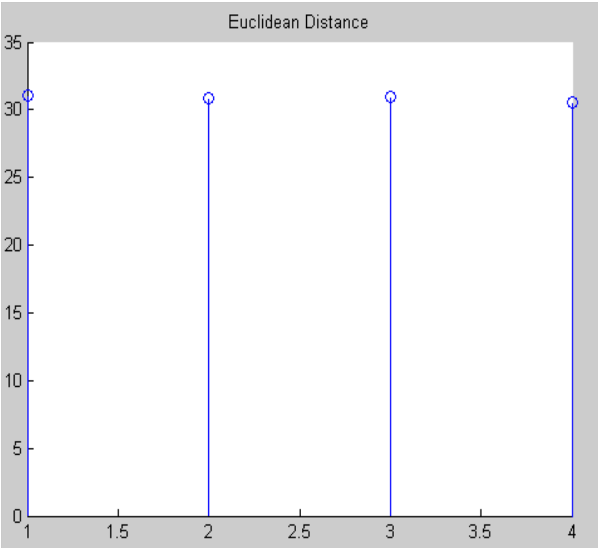

Fig 6.5 - Euclidean Distance

Recognition

Finally we retrieve the match from the database based on the minimum distance resulted. Also we may now classify the faces as known, unknown or nonface based on these distance.

VI. Conclusion

The eigenface approach for Face Recognition process is fast and simple which works well under constrained environment. It is one of the best practical solutions for the problem of face recognition. Many applications which require face recognition do not require perfect identification but just low error rate. So instead of searching large database of faces, it is better to give small set of likely matches. By using Eigenface approach, this small set of likely matches for given images can be easily obtained. For given set of images, due to high dimensionality of images, the space spanned is very large. But in reality, all these images are closely related and actually span a lower dimensional space. By using eigenface approach, we try to reduce this dimensionality. We have also seen that taking eigenvectors with higher M eigenvalues instead of all M eigenvectors, does not affect performance much. So even taking lower dimensional eigenspace for the images is acceptable as error rates in such cases are very low. The important part is making this choice of M, which will be crucial depending on type of application and acceptable error rate. More research needs to be done on choosing the best value of M. This value of M may vary depending on the application of Face Recognition. One of the limitations of eigenface approach is in the treatment of face images with varied facial expressions and with glasses. Also as images may have different illumination conditions. It is quite efficient and simple in preprocessing of image to verify the face geometry or the distances between the facial organs and its dimensions. The application of the normalization procedure improves the eigenface algorithm performance significantly, concerning images in unsuitable illumination conditions.

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