

A Review Paper on Real Time Face Detection Atracking

Sudipa Nag, Suyash Sangwan, Pooja Singh, Ekta Pandey, Pankaj Agrawal

Department, Electronics And Communication
SRM University, NCR Campus
ModiNagar, Ghaziabad

ABSTRACT:

In this article, Principal Component Analysis (PCA) algorithm is implemented for face detection. Face detection is mainly done by PCA algorithms. The algorithm is based on an Eigenfaces approach which represents a PCA method in which significant features like nose, eyes, lips, etc are used to describe the variation between face images. Eigen faces are also called as eigenvectors (Principal Component), they ignore the features such as eyes, ears, and noses. The projection operation is done by characterizing an individual face by a weighted sum of the Eigen faces features. Therefore, to detect a particular face comparison between these weights to those individuals is necessary.

KEYTERMS: Face detection, Principal Component Analysis algorithm (PCA), Eigen values, Eigenvectors.

INTRODUCTION:

Face recognition is one of the most useful techniques identifying a person. This is an attractive technology for identification and verification of identity. It is one of the most familiar functionality of visual surveillance systems. This technology has gained the attention due to its numerous potential applications. It is used in applications such as military, private security, national security, law enforcement and criminal investigation. Facial expression, illumination, cluttered background are some of the factors affecting the face recognition technology.

This process includes three steps capture, recapture and match. The algorithm begins with capturing the image as train database, then recapturing a new image and extracting only the face as the test image and then matching the test image to the trained image.

Face recognition by PCA analysis can be effectively done by using MATLAB programmes. Purpose of this article is to design an efficient

MATLAB program and to get the most accurate result for face recognition This technique is widely used because of its accuracy, speed, simplicity, insensitivity to small changes in the face.

FACE RECOGNITION:

Eigenface approach is one of the most effective and simplest approach used in face detection system. In this the face is divided into rows and columns, containing the special characteristics of the face, Eigenfaces. This is the trained set image. Recognition is done by recapturing a new image first. This image is then compared to all the other databases. The RGB values of the images are calculated. When the RGB value of the test image matches to any RGB value of trained image, then that is the resultant face. The disadvantage of the technique is that it is only limited to some number of databases and the illumination matters.

PRINCIPAL COMPONENT ANALYSIS:

PCA is an algorithm that transforms data obtained from correlated variables into a set of values of uncorrelated variables called principal components.

The purpose of PCA is to minimize the dimensions of the data by retaining only the special characteristics of the original image set. But problems arise when minimization of the dimensions result in loss of information. This can be overcome by using the best principal components.

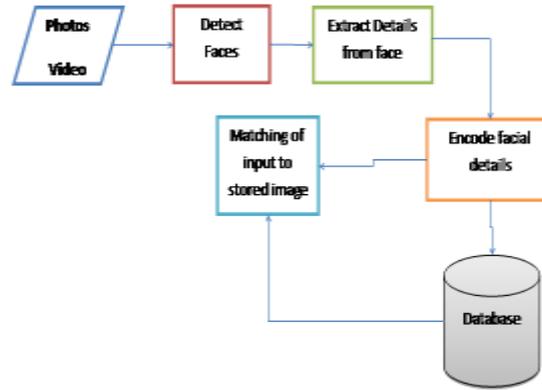
PCA uses the Eigenfaces approach which reduces the dimensionality of the database for the test image detection. This is the major advantage of the PCA algorithm. The database store the images as the feature vectors which compare each and every test image to the database.

Several steps are undertaken to perform PCA:

Stage 1: Mean of the data to be subtracted from each variable (our adjusted data)

Stage 2: Covariance Matrix is calculated and formed

Stage 3: Eigenvectors and Eigenvalues are calculated from the matrix.



WORK FLOW MODEL:

Stage 4: A Feature Vector is chosen.

Stage 5: Transposed Feature Vectors is multiplied to the transposed adjusted data.

STAGE 1: MEAN SUBTRACTION:

It is a fairly simple data and the calculation of the covariance matrix is made a simpler. Now the overall mean is not subtracted from each of the values because the matrix needs at least two dimensions of data. It is actually the mean of each row is subtracted from each element in that row.

STAGE 2: COVARIANCE MATRIX:

For two dimensional data the basic Covariance equation is:

$$covx = \frac{1}{n-1} \sum (y_i - \bar{y})^2$$

This is similar to the variance formula however, x changes in respect to the change in y. In this equation x is the mean of all x values and represents the pixel value and the total number of values is represented by n. How much the dimensions vary from the mean with respect to each other is represented by the covariance matrix.

Covariance matrix can be explained in an easy way by using an example of a 3x3 matrix.

$$C_{mat} = \begin{pmatrix} cov(x,y) & cov(x,y) & cov(x,z) \\ cov(y,x) & cov(y,y) & cov(y,z) \\ cov(z,x) & cov(z,y) & cov(z,z) \end{pmatrix}$$

$$\begin{matrix} 1 & 2 & 3 \\ 7 & 8 & 9 \end{matrix} \quad /1 = 4 \quad \begin{pmatrix} 5 & 6 \end{pmatrix}$$

$$C / 1 = \begin{pmatrix} cov(1,1) & cov(2,5) & cov(3,9) \\ cov(4,1) & cov(5,5) & cov(6,9) \\ cov(7,1) & cov(8,5) & cov(9,9) \end{pmatrix}$$

STAGE 3: EIGENVECTORS AND EIGENVALUES:

A non-zero vector that does not change its direction when linear transformation is applied to it, is called an eigen vector. In some special cases, eigen values are the product of matrices. When a covariance matrix is multiplied by a vector in 2D space, the product is an eigen value. This makes the transformation matrix equal to the covariance matrix. An example is illustrated below :

$$\text{Covariance Matrix} = \begin{pmatrix} 4 & 1 \\ 4 & 3 \end{pmatrix}$$

$$\text{Eigenvector} = \begin{pmatrix} 4 \\ 6 \end{pmatrix}$$

$$\text{Multiplied} = \begin{pmatrix} 4 & 1 \\ 4 & 3 \end{pmatrix} * \begin{pmatrix} 4 \\ 6 \end{pmatrix} = \begin{pmatrix} 22 \\ 17 \end{pmatrix}$$

Since scaling of eigenvectors is possible, so x/2 or x2 of the vector will produce the same results. As a vector is a direction, the scale will be changed and not the direction.

$$\begin{pmatrix} 4 & 1 \\ 4 & 3 \end{pmatrix} * \begin{pmatrix} 2 \\ 3 \end{pmatrix} = \begin{pmatrix} 11 \\ 17 \end{pmatrix}$$

STAGE 4: FEATURE VECTOR:

Usually Eigenvectors and Eigen values are not as accurate as in the example above. In most cases the results provided are scaled to a length of 1. Some example are illustrated using Matlab:

$$\text{Covariance Matrix} = \begin{pmatrix} 0.21 & 0.345 \\ 0.62 & 1.11 \end{pmatrix}$$

$$\text{Eigenvector} = \begin{pmatrix} 0.6271 \\ 0.3041 \end{pmatrix}$$

$$\text{Eigenvalues} = \begin{pmatrix} 0.6392 & -0.557 \\ 0.7691 & 0.3814 \end{pmatrix}$$

After Eigenvectors are found from the matrix, they are then ordered by the Eigenvalue, high to low.

$$\text{Resultant Eigenvalues} = \begin{pmatrix} 0.6392 \\ 0.7691 \end{pmatrix}$$

STAGE 5: TRANSPOSITION:

The fifth and the last stage in PCA is that the transposition of the feature vector matrix is multiplied to the transposed adjusted data set. The Eigen Object Recognizer performs all the process and feeds the data as the training set into the database. When an image is captured for recognition, PCA algorithm is performed and its Eigen values and Eigenvectors are compared to the ones from the training set. If the eigen values match to the training image, then that is the equivalent image else, it is unauthorised.

EXPERIMENTAL RESULTS:

An experiment was conducted using some database of faces. There's a training set containing 36 images of 18 persons (2 images per each person) and a test set having 38 images of different individuals (36 known and 2 unknown) with bright illuminated background.

The dimensions of photos are 92×112 . The images are grayscale. Fig. 1 shows the images from the training set. In this training base, about 10% of vectors have significant eigenvalues, while the remaining vectors are approximately equal to zero. We neglect the eigenvectors with small eigenvalues because they do not give efficient information about the image.



Fig. 1 – Pictures from the training base.

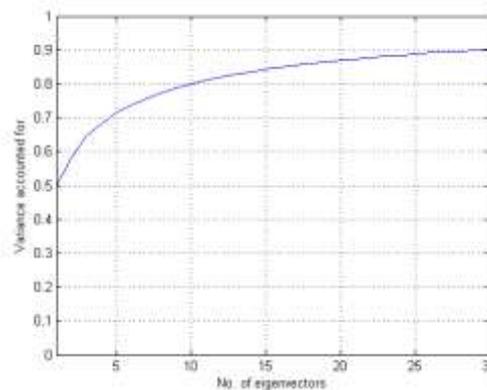


Fig. 2 – Eigenvalues

The first three and last three eigenfaces are shown in Fig.3 and 4, respectively. Fig. 3 resembles the faces, while those in Fig. 4 do not give any important information about the images.

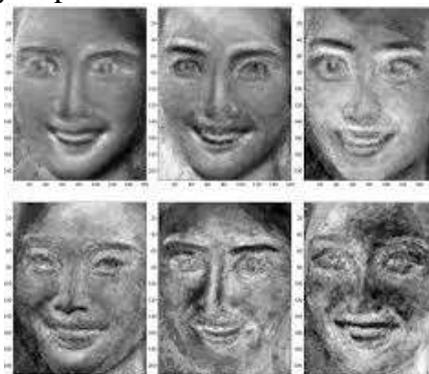
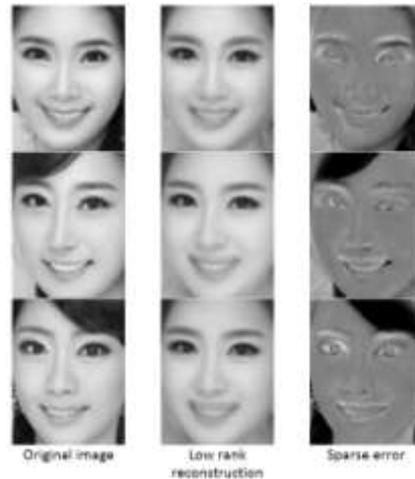


Fig:- 3

**Fig:- 4****CONCLUSION:-**

In this thesis, PCA approach was studied and implemented on face recognition system. The face detection system was based on eigenfaces approach. The technique has recognized the human faces successfully and have worked in different conditions of face orientation. The algorithm has been tested for the image database and implemented using MATLAB.

FUTURE PLANS:

In this research paper, we have worked with limited number of images but in future we have to make a system which will work for huge database. We want to eliminate the problems of light and different sizes of face image. We also have to compare the performance analysis of PCA based method with all other existing face recognition methods.

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