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FACE RECOGNITION USING PRINCIPAL COMPONENT ANALYSIS

Anand Singh[1], Erarica Mehra[2], Saundarya Dorle[3]

[1,2,3,4] *Computer Department, D.Y.P.I.E.M.R Pune,(India)*

ABSTRACT

Face recognition is an important and interesting feature of Image Processing. Face recognition involves the three main stages:detecting face- like images, feature extraction and identification or recognition of an unknown face.. Face recognition has become more and more popular due to the increasing crime rate and terrorism. Face Recognition has its applications in many fields such asauthentication and security systems where access is allowed only to authorized persons, forensic department, etc. Our paper focusses on the use of face recognition system to identify suspects/criminals in order to meet the requirements of the police department.The project is developed after studying the efficiencies as well as the weaknesses of several methods such as perceptual hash function, SIFT, ORB algorithm, etc. SIFT uses key points for image comparison and ORB is an enhancement over the SIFT algorithm. Perceptual hash, on the other hand converts the two images into hash values and then compares these hash values in order to find a match. Even after continuous research, a truly efficient system with 100% accuracy rate still does not exist. Most face recognition algorithm suffer from the disadvantage that variations in images of the same subject due to difference in pose, orientation, etc. produce different result.Our project focusses on PCA (Principal Component Analysis) algorithm for face recognition with better accuracy and efficiency.

Keywords:Covariance matrix, dimensionality reduction, Eigen vectors, normalization, training set

I. PRINCIAL COMPONENT ANALYSIS

The proposed paper uses Principal Component Analysis for feature extraction. Each face to be analyzed is converted into a vector and projected into the face vector space. A k-nearest-neighbor approach is used for classification. This technique projects the training data into face vector space, normalizes the face vectors and finallygenerates Eigen faces with reduced dimensionality. PCA evaluates the input image by projecting it into the face vector space and comparing it with the training data.

The two main steps involved in the PCA algorithm are 1) Training the Recognizer, 2) Recognizing an unknown face.

II. TRAINING THE RECOGNIZER

Step 1: Create a training set.

A training set consists of total M face images, say M=100 face images (Refer Fig.1). Each face image will be of size N*N, say 50*50 that is 2500 pixels or dimensions. In order to train the recognizer, each of the faces in the training set is converted into a vector form. As we know, PCA does not work on the images directly but converts the images into a vector form.

Γ_i = i^{th} face vector ...(1)

Step 2: Normalize the face vectors.

Once all the images in the training set have been converted to their vector form, the next step is to normalize these face vectors. Normalization means to remove all common features that these faces share so that each face vector is left behind with only its unique features.

First we find out the common features which is given by average face vector Ψ. Average face depicts the average features of the whole training set. The average face vector is subtracted from each face vector to get the normalized face vectors using the formula

$\phi_i = \Gamma_i - \Psi$ ...(2)

Step 3: Calculate the Eigen Vectors

Once we have the normalized face vectors, we need to calculate the Eigen vectors. First we need to calculate the Covariance matrix.(Refer Fig.1)

$C= A\ A^T$ ...(3)

Where A is $\{\phi_1, \phi_2, \ldots, \phi_M\}$ and A^T is the transpose of A.

PCA requires decomposition of the Covariance matrix. In a Covariance matrix each column has normalized face vectors where A is of dimensions $N^2 * M$.

Obviously

$C = A\ A^T$...(3)

$= N^2*M \quad . \quad M*N^2$ by matrix formula

$= N^2*N^2$

Example 2500*2500(Refer Fig.1).

Covariant matrix will generate 2500 Eigen vectors, each of dimensions 2500*1 that is as big as the image itself.

The idea behind PCA is to train each image in the training set as a linear combination of k Eigen faces where k<M. So if M=100, the k Eigen faces selected should be 100or below 100. So to select 100 Eigen vectors from 2500 Eigen vectors, require huge amount of calculations due to which, the system may slow down terribly or may run out of memory. The solution to this problem is dimensionality reduction.

Step 4: Calculate Eigen vectors from a Covariance matrix with reduced dimensionality.

The purpose behind this step is to reduce the calculations and the effect of noise on the needed Covariance matrix.

$C= A^T . A$

$= M*N^2 \quad . \quad N^2*M$

$= M*M$

Example if M=100, C = 100*100

Now we can see a difference in the number of Eigen vectors that are calculated. So C here is the Covariance matrix of reduced dimensionality. It will give 100 Eigen vectors each with 100*1 dimensionality. Obviously it is easier to find k Eigen vectors since the size of the matrix is smaller since $M << N^2$. (Refer Fig.1)

Step 5: Select k best Eigen vectors such that k <M and can represent the whole training set.

Selected k Eigen faces must be in the original dimensionality of the face vector space.

$\mu_i = A\, v_i$ …(4)

Where μ_i represents the Eigen vectors in the higher dimension space and v_i represents the Eigen vectors in the lower dimension space.

Each Eigen vector is multiplied by A. The k Eigen vectors are mapped backed to their original dimensionality that is 2500*2500 ($N^2 * N^2$).

Step 7: Represent each face image as a linear combination of all k Eigen vectors.

Each face from the training set can be represented as a weighted sum of the k Eigen faces + the Average face. There are k weights associated with the k Eigen faces each of weight w_i(Refer Fig.2). These weights represent the proportion or percentage it contributes to represent the original face. A weight vector Ω, is the Eigen face representation of the i^{th}face weight vector is calculated.

III. RECOGNIZING AN UNKNOWN FACE

The steps involved in recognizing the unknown face are:(Refer Fig.3)

Step 1: Input the image of the unknown person.

Step 2: Convert the input image to a face vector.

Step 3: Normalize this face vector that is remove all common features the face vector is left behind with only its unique features.

Step 4: Calculate Eigen vectors and project them into Eigen space.

Step 5: Represent the face as a weight vector of the input image. There are k weights associated with the k Eigen vectors.

Step 6: Calculate distance between the weight vector of the input image and the weight vector of the training set. If the distance is less than some threshold value.

IV. FIGURES

Fig. 1 shows the Eigen vectors calculated from a Covariance Matrix with reduced dimensionality

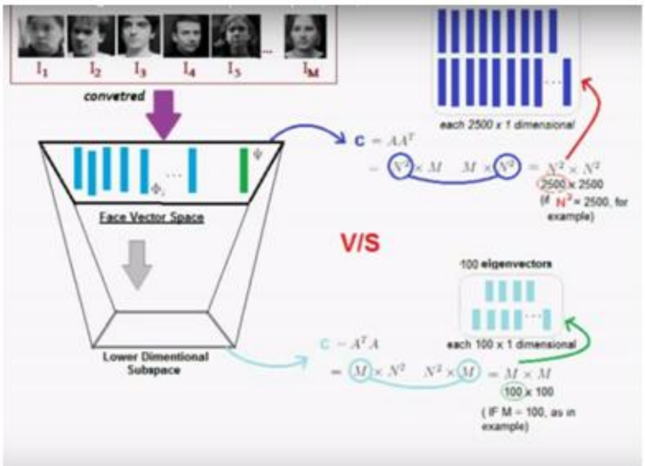


Fig. 2represents each face image as a linear combination of all k Eigen vectors.

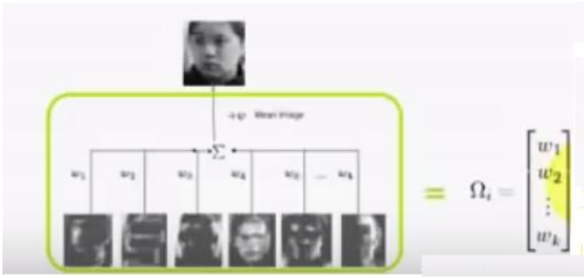
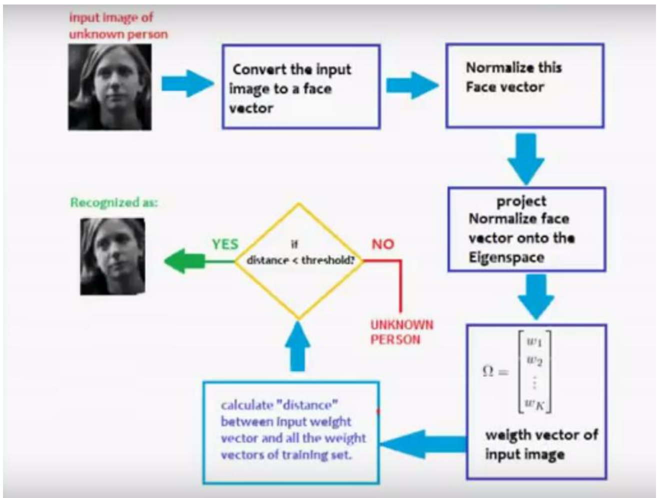


Fig. 3 shows the steps involved in recognizing an unknown face



V. CONCLUSION

PCA is extremely beneficial in case of criminal investigations. It does not require computation of large datasets. PCA's key advantages are its reduction of noise, the reduced memory requirements, and increased efficiency as compared to other existing algorithms. PCA requires smaller database representation since only the trainee images are stored in the database in the form of their projections onto the face vector space. The only disadvantage offered by PCA is that the Covariance matrix is difficult to be calculated efficiently.

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REFERENCES

[1] Geoffrey M Henebry, Department of Biological Sciences, Rutgers University, 07102 Newark, NJ, USA Advantages of principal components analysis for land cover segmentation from SAR image series.

[2] An Overview of Principal Component Analysis Sasan Karamizadeh1, Shahidan M. Abdullah1, Azizah A. Manaf1, Mazdak Zamani1, Alireza Hooman2

[3] Department of Computer Science and Engineering National Institute of Technology Rourkela Rourkela – 769008, IndiaFace Recognition Using PCA and Eigen Face Approach by Abhishek Singh and Saurabh Kumar