Face Recognition using Eigenvectors from Principal Component Analysis

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Abstract

There are many biometrics methods used nowadays for the identification of a person. People in computer vision and pattern recognition have been working on automatic recognition of human faces for the last 20 years. Computer can outperform human in many face recognition through the development technique "eigenfaces." Particularly those in which large database of faces must be searched. We use principal component analysis with "Eigenface" approach due to its simplicity, speed and learning capability. The design of the face recognition system is based upon "eigenfaces." The original images of the training set are transformed into a set of eigenfaces E. Then, the weights are calculated for each image of the training set and stored in the set W. Upon observing an unknown image Y, the weights are calculated for that particular image and stored in the vector WY. Afterward, WY is compared with the weights of images, of which one knows for certain that they are facing.

Keywords: Principal component analysis, Eigen Vector, Eigen Value

Introduction

Until Kirby and Sirovich [4] applied the Karhunen- Loeve Transform to faces, face recognition systems utilized either feature-based technique, template matching or neural networks to perform the recognition. PCA technique which is provided by Kirby and Sirovich not only resulted in a technique that efficiently represents pictures of faces, but also laid the foundation for the development of the "eigenface" technique of Turk and Pentland [1]. Such patterns, which can be observed in all signals, could be - in the domain of facial recognition - the presence of some objects (eyes, nose, mouth) in any face as well as relative distances between these objects. These characteristic features are called eigenfaces in the facial recognition domain .out of original image data these characteristics can be extracted with the help of a mathematical tool called Principal Component Analysis (PCA). The face space is described by a set of eigenfaces. By projecting a face onto the space expanded by eigenfaces is efficiently represented. Principal component analysis is applied to find the aspects of face which are important for identification. Eigenvectors (eigenfaces) are calculated from the initial face image set. New faces are projected onto the space expanded by eigenfaces and represented by weighted sum of the eigenfaces. To identify faces, we make uses of these weights.

Eigenvectors and Eigen values

We make use of Eigenvectors and Eigenvalues for face recognisition with PCA. So we prepare an initial set of face images [X1, X2, ..., Xn]. The average face of the whole face distribution is

$$X = (X1 + X2 + \ldots + Xn)/n$$

Then the average face is subtracted from each face, Xi' = Xi - X, i = 1, 2, ... , n [Y1, Y2, ..., Yn] eigenvectors are calculated from the new image set [X1', X2', ... Xn'].

[Y1, Y2, ..., Yn] eigenvectors are calculated from the new image set [X1', X2', ... Xn']. These eigenvectors are orthonormal to each other. These eigenfaces look like sort of face they do not correspond directly to any face features like eyes, nose and mouth. They are a set of important features which describe the variation in the face image set.

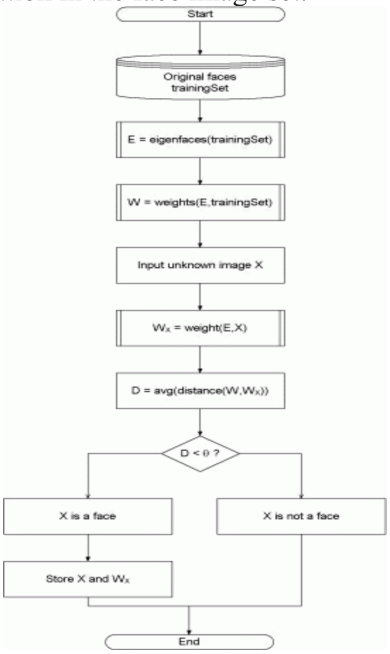

Figure no. 1

Each eigenvector has an eigenvalue associated with it. Eigenvectors on face variation with bigger eigenvalues provide more information than those with smaller eigenvalues. After the eigenfaces are extracted from the covariance matrix of a set of faces, each face is projected onto the eigenface space and represented by a linear combination of the eigenfaces, or has a new descriptor corresponding to a point inside the high dimensional space with the eigenfaces as axes. If we use all the eigenfaces to represent the faces, those in the initial image set can be completely reconstructed. But these eigenfaces are used to represent or code any faces which we try to learn or recognize.

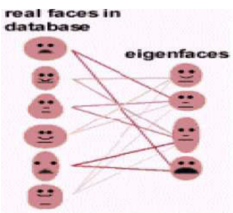

Figure no. 2

An important feature of PCA is that by combining the eigenfaces, one can reconstruct any original image from the training set. Remember that eigenfaces are nothing less than characteristic features of the faces. Therefore original face image can be reconstructed from eigenfaces if one adds up all the eigenfaces (features) I the right proportion. Starting with a preprocessed image makes the task of determining N eigenvectors and Intensity values. This may be considered a vector of dimension N2.

A database of M images can, therefore, map to a collection of points in this high dimensional "face space" as Γ1, Γ2, Γ3…..ΓM. (1)

Each face can be mean normalized and be represented as deviations from the average face by Φi=Γi-Ψ. The covariance matrix, defined as the expected value of ΦΦT can be calculated by the equation T (2)

Set of very large vectors is subject to PCA, which seeks a set of M ortho-normal vectors, un, which best describes the distribution of the data. The kth vector, UK is chosen such that (3)

Is a maximum, subject to !" # (4)

Given the covariance matrix C, we can now proceed with determining the eigenvectors u and eigenvalues Λ of C in order to obtain the optimal set of principal components, a set of eigenfaces that characterize the variations between face images.

$$\lambda_i = u_i^T C u_i$$

$$= \frac{1}{M} u_i^T \sum_{n=1}^{M} \Phi_n \Phi_n^T u_i$$

$$= \frac{1}{M} \sum_{n=1}^{M} u_i^T \Phi_n \Phi_n^T u_i$$

$$= \frac{1}{M} \sum_{n=1}^{M} (u_i \Phi_n^T)^T (u_i \Phi_n^T)$$

% &
%)* +,-%)
.-/%) (5)

Consider an eigenvector ui of C satisfying the equation 00' (6)

Turk and Pentland thus suggest [1] that by selecting the eigenvectors with the largest corresponding eigenvalues as the basis vector, the set of dominant vectors that express the greatest variance are being selected. Recall, however, that an N-by-N face image treated as a vector of dimension N2 is under consideration. Therefore, if we use the approximated equation derived in Eq. 5, the resultant covariance matrix C will be of dimensions N2 by N2. A typical image of size 256 by 256 would consequently yield a vector of dimension 65,536, which eigenvalues intractable and computationally unfeasible.

Recalling that A= [Φ1, Φ2….. ΦM], the matrix multiplication of ATA results in an M-by-M matrix. Since M is the number of faces in the database, the eigenvectors analysis is reduced from the order of the number of pixels in the images (N2) to the order of the number of images in the training set (M). In practice, the training set is relatively small (M<< N2) [1], making the computations mathematically manageable.

The simplified method calculates only M eigenvectors while previously it was proven that there are mathematically N2 possible eigenvectors. Only the eigenvectors with the largest corresponding eigenvalues fFrom the N2 set are selected as the principal components. Thus, the eigenvectors calculated by the alternative algorithm will only be valid, if the resulting eigenvectors correspond to the dominant eigenvectors

Consider the eigenvectors, vi, of ATA such that 0 0. 1.
Pre-multiplying both sides by A and using Eq. (5), we obtain

00' 0.% 1% 0.%

.% 1% 0.%

Following this analysis, we construct the M by M matrix L- ATA, where and find the M eigenvectors, vi of L. these vectors determine linear combinations of the M training set face images to form the eigenfaces ui 4_5 $65_{7\ 8}$

With this analysis, the calculations are greatly reduced If the no of data points in face space is less than the dimension of space itself, which in our case is true since M<< N2, it follows logically that there will only be M – 1, rather than N2, meaningful eigenvectors and so calculation becomes quite manageable. Where M is no of images in the training set and N2 is number of pixels in the image. Thus rather than calculating the N^2 eigenvectors of AA^T, ^TA we can instead compute the eigenvectors of, and multiply the results with A in order to obtain the eigenvectors of the covariance matrix, C = AA^T Recalling that, the $A = [\Phi_1, \Phi_2 \ldots \Phi_M]$, A^TA matrix multiplication of results in an M-by-M matrix.

Since M is the number of faces in the database, the eigenvectors analysis is reduced from the order of the number of pixels in the images (N^2) to the order of the number of images in the training set (M). In practice, the training set is relatively small (M<< N^2) [1], making the computations mathematically manageable. The simplified method calculates only M eigenvectors while previously it was proven that there are mathematically N^2 possible eigenvectors.s demonstrated In Eq. (5) Only the eigenvectors with the largest corresponding eigenvalues from the set are selected as the principal components. Thus, the eigenvectors calculated by the alternative algorithm will only be valid, if the resulting eigenvectors correspond to the dominant eigenvectors selected from the N^2 set.

Conclusion

An overview of the design and development of a real- Time face recognition system has been presented in this thesis. Although some aspects of the system are still under experimental development, the project has resulted in overall success, being able to perform reliable recognition in a constrained environment. Under static mode, where recognition is performed on single scaled images without rotation,a recognition accuracy of 96% has been achieved. Face location and normalization were performed in real-time and consistent accuracy in face detection is recorded with video input.

Future Work

In a research area that is under vigorous investments and major developments, opportunities for future work are abundant. Improvements in the design and implementation of the face detection and normalization modules or any extensions that could aid in the speed and robustness of the face recognition system are continually in demand.

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