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PCA Technique for Recognition of Face

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ABSTRACT

The face is a complex multidimensional structure which needs a good computing technique for recognition. Our present approach treats face recognition as two-dimensional recognition problem. In this scheme, face recognition is done by Principal Component Analysis (PCA). Face images are projected onto a face space that encodes the best variation among known face images. The face space is needed by eigenface which are eigenvectors of the set of faces, which may not correspond to general facial features such as eyes, nose, and lips. The eigenface approach uses the PCA for recognition of the images. The system performs by projecting pre extracted face image onto a set of face space that represents significant variations among known face images. The face will be categorized as a known or unknown face after matching with the present database. If the user is new to the recognition system then his/her template will be stored in the database else matched against the templates stored in the database. The variable reducing theory of PCA accounts for the smaller face space than the training set of the face.

Keywords: *Principal Component Analysis (PCA), Eigen faces, Database.*

1. INTRODUCTION

Biometrics is used in the process of authentication of a person by verifying or identifying that a user requesting a network resource is who he, she, or it claims to be, and vice versa. It uses the property that a human trait associated with a person itself like the structure of finger, face details etc. By comparing the existing data with the incoming data we can verify the identity of a particular person [1].

There are many types of a biometric system like fingerprint recognition, face detection, and recognition, iris recognition etc., these traits are used for human identification in a surveillance system, criminal identification. Advantages of using these traits for identification are that they cannot be forgotten or lost. These are unique features of a human being which is being used widely [2].

2. FACE RECOGNITION

Face recognition can be applied to a wide variety of problems like image and film processing, human-computer interaction, criminal identification etc. This has motivated researchers to develop computational models to identify the faces, which are relatively simple and easy to implement. The model developed in [1] is simple, fast and accurate in constrained environments. Our goal is to implement the model for a particular face and distinguish it from a large number of stored faces with some real-time variations as well.

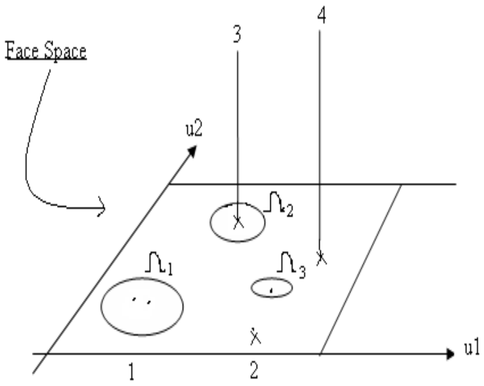
The scheme is based on an information theory approach that decomposes face images into a small set of characteristic feature images called 'eigenfaces', which are actually the principal components of the initial training set of face images. Recognition is performed by projecting a new image into the subspace spanned by the eigenfaces ('face space') and then classifying the face by comparing its position in the face space with the positions of the known individuals.

Recognition under widely varying conditions like the frontal view, a 45° view, scaled frontal view, subjects with spectacles etc. are tried, while the training data set covers limited views. Further, this algorithm can be extended to recognize the gender of a person or to interpret the facial expression of a person. The algorithm models the real-time varying lighting conditions as well. But this is out of the scope for the current implementation. [1]

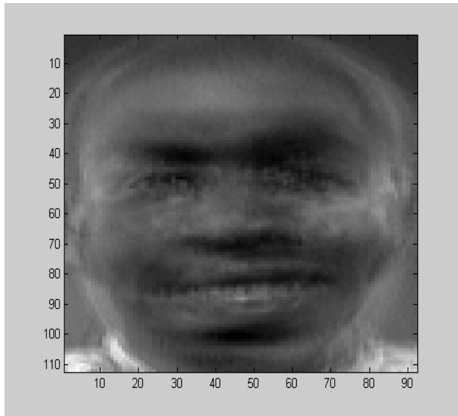
3. EIGEN FACE APPROACH

The information theory approach of encoding and decoding face images extracts the relevant information in a face image, encode it as efficiently as possible and compare it with a database of similarly encoded faces. The encoding is done using features which may be different or independent than the distinctly perceived features like eyes, ears, nose, lips, and hair. Mathematically, principal component analysis approach will treat every image of the training set as a vector in a very high dimensional space. The eigenvectors of the covariance matrix of these vectors would incorporate the variation amongst the face images. Now each image in the training set would have its contribution to the eigenvectors (variations). This can be displayed as an '*eigenface*' representing its contribution in the variation between the images. These eigenfaces look like ghostly images and some of them are shown in figure 2.In each eigenface, some sort of facial variation can be seen which deviates from the original image.

The high dimensional space with all the eigenfaces is called the image space (feature space). Also, each image is actually a linear combination of the eigenfaces. The amount of overall variation that one eigenface counts for, is actually known by the eigenvalue associated with the corresponding eigenvector. If the eigenface with small eigenvalues is neglected, then an image can be a linear combination of reduced no of these eigenfaces. For example, if there are M images in the training set, we would get M eigenfaces. Out of these, only M' eigenfaces are selected such that they are associated with the largest eigenvalues. These would span the M'-dimensional subspace 'face space' out of all the possible images (image space).
When the face image to be recognized (known or unknown), is projected on this face space (figure 1), we get the weights associated with the eigenfaces, that linearly approximate the face or can be used to reconstruct the face. Now, these weights are compared with the weights of the known face images so that it can be recognized as a known face in used in the training set. In simpler words, the Euclidean distance between the image projection and known projections is calculated; the face image is then classified as one of the faces with minimum Euclidean distance.



(a)



(b)

Figure1: (a) the Face Space and the Three Projected Images on it. Here u1 and u2 ARE the Eigen Faces. (b)The Projected Face from the Training Database

Mathematically Calculations

Let a face image *I(x, y)* be a two dimensional N by N array of (8-bit) intensity values. An image may also be considered as a vector of dimension N^2 so that a typical image of size 256 by 256 becomes a vector of dimension 65,536 or equivalently a point in a 65,536-dimensional space. An ensemble of images, then, maps to a collection of points in this huge space. The principal component analysis would find the vectors that best account for the distribution of the face images within this entire space.
Let the training set of face images be T_1, T_2, T_3 ...TM. This training data set has to be mean adjusted before calculating the covariance matrix or eigenvectors. The average face is calculated as $\Psi = (1/M)\ \Sigma_1^M T_i$. Each image in the data set differs from the average face by the vector $\Phi = T_i - \Psi$. This is actually mean adjusted data. The covariance matrix is

$$C = (1/M)\ \Sigma_1^M \Phi_i \Phi_i^T \tag{1}$$

$$= AA^T$$

Where $A = [\ \Phi_1, \Phi_2 \dots \Phi_M]$. The matrix C is an N^2 by N^2 matrix and would generate N^2 eigenvectors and eigenvalues. With image sizes like 256 by 256, or even lower than that, such a calculation would be impractical to implement.

A computationally feasible method was suggested to find out the eigenvectors. If the number of images in the training set is less than the no of pixels in an image (i.e., $M < N^2$), then we can solve an M by M matrix instead of solving an N^2 by N^2 matrix. Consider the covariance matrix as A^TA instead of AA^T. Now the eigenvector v_i can be calculated as follows,

$$A^TAv_i = \mu_i v_i \tag{2}$$

Where μ_i is the eigenvalue. Here the size of covariance matrix would be M by M. Thus we can have m eigenvectors instead of N^2.
Pre-multiplying equation 2 by A, we have

$$AA^TAv_i = \mu_i Av_i \tag{3}$$

The right-hand side gives us the M eigenfaces of the order N^2 by 1.All such vectors would make the image space of dimensionality M.
Face Space

As the accurate reconstruction of the face is not required, we can now reduce the dimensionality to M’ instead of M. This is done by selecting the M’ eigenfaces which have the largest associated eigenvalues. These eigenfaces now span a M’-dimensional subspace instead of N^2.

Recognition

A new image T is transformed into its eigenface components (projected into ‘face space’) by a simple operation,

$$w_k = u_k^T (T - \psi) \tag{4}$$

Here k = 1, 2….M’. The weights obtained above form a vector $\Omega^T = [w_1, w_2, w_3 \ldots w_{e'}]$ that describes the contribution of each eigenface in representing the input face image. The vector may then be used in a standard pattern recognition algorithm to find out which of a number of predefined face class, if any, best describes the face. The face class can be calculated by averaging the weight vectors for the images of one individual. The face classes to be made depending on the classification to be made like a face class can be made of all the images where the subject has the spectacles. With this face class, classification can be made if the subject has spectacles or not. The Euclidean distance of the weight vector of the new image from the face class weight vector can be calculated as follows,

$$\varepsilon_k = \| \Omega - \Omega_k \| \tag{5}$$

Where Ωk is a vector describing the k^{th} face class. Euclidean distance formula can be found in [2]. The face is classified as belonging to class k when the distance ε_k is below some threshold value θε. Otherwise, the face is classified as unknown. Also, it can be found whether an image is a face image or not by simply finding the squared distance between the mean adjusted input image and its projection onto the face space.

$$\varepsilon^2 = \| \Phi - \Phi_f \| \tag{6}$$

Where Φ_f is the face space and $\Phi = T_i - \Psi$ is the mean adjusted input.
With this, we can classify the image as a known face image, unknown face image and not a face image.

4. RECOGNITION EXPERIMENTS

24 images were trained with four individuals having 6 images per individual. The 6 images had different lighting conditions, orientations, and scaling. These images were recognized successfully with the accuracy of 100% for lighting variations, 90% for orientation variations, and 65% for size variations. The lighting conditions don’t have any effect on the recognition because the correlation over the image doesn’t change. The orientation conditions would affect more because of the image would have more hair into it than it had for training. Scaling affects the recognition significantly because the overall face data in the image changes. This is because the background is not subtracted for training. This effect can be minimized by background subtraction.

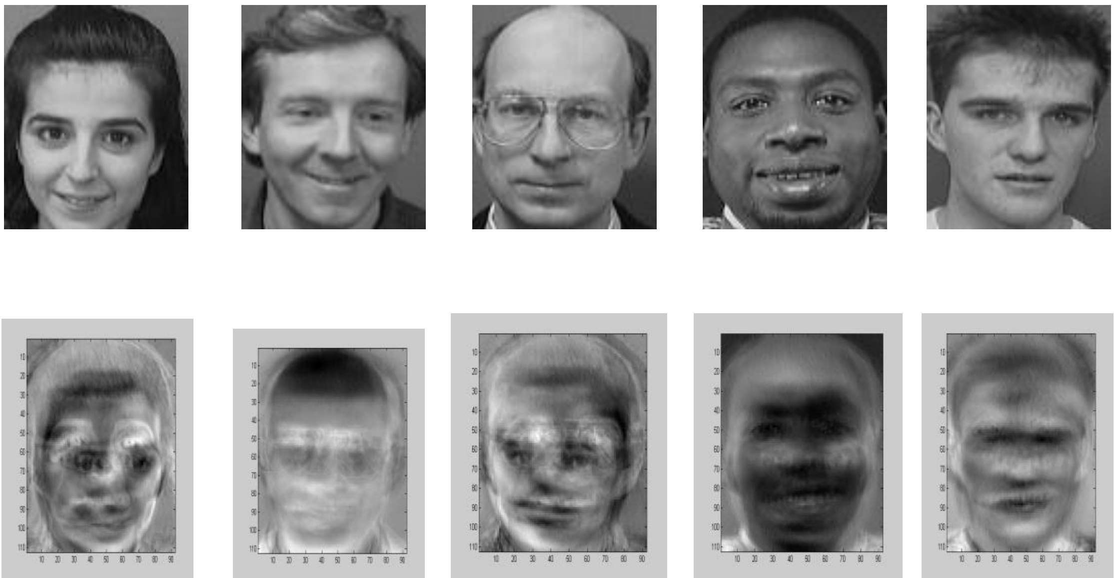


Figure2: The First Row is some of the Images used for Training While the Second Row Shows the Eigen faces with Significant Eigenvectors.

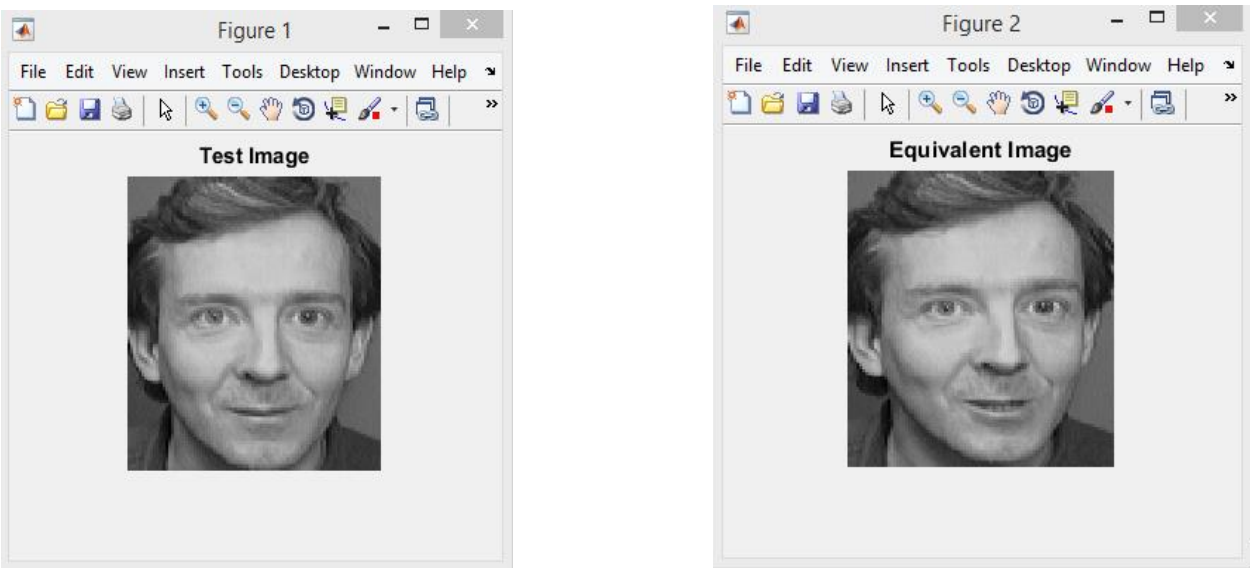


Figure 3: The First Image is the Test Image That we want to recognize, while the Second Image is the Equivalent Image.

5. CONCLUSION

The approach is definitely robust, simple, and easy and fast to implement compared to other algorithms. It provides a practical solution to the recognition problem. We are currently investigating in more detail the issues of robustness to changes in head size and orientation. Also, we are trying to recognize the gender of a person using the same algorithm.

6. REFERENCES

[1] Matthew A. Turk and Alex P. Pentland. "*Eigenfaces for recognition*". Journal of cognitive neurosciences, Volume 3, Number 1, Nov 27, 2002.
[2] Dimitri PISSARENKO. "*Eigen face-based facial recognition*". Dec1, 2202.
[3] Matthew A. Turk and Alex P. Pentland. "*Face recognition using eigenfaces*". Proc. CVPR, pp 586-591. IEEE, June 1991.
[4] L.I.Smith. "*A tutorial on principal component analysis*". Feb 2002.
[5] M.Kirby and L.Sirovich. "*Application of the karhunen-loeve procedure for the characterization of human faces*". IEEE Trans. on Pattern analysis and machine intelligence, Volume 12, No.1, Jan 1990.