# Automatic clusters to face recognition

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## Abstract

*In this paper we consider to study the distribution of the vectors of face in the dimensional space (n x m pixels of the image), and we have developed a face recognition that works under varying pose dealing with N different individual given under M different view/ poses and illumination. We construct an automatic algorithm that computes and finds clusters within the training group preserving intrinsic human face characteristics. The algorithm named K-PCA applies a SOM neural network in the cluster stage and applies the PCA method into each cluster, that is, each cluster forms an eigenface.*

## 1. Introduction

Though most of the algorithms achieve good recognition rates with the frontal views of faces, they fail when the pose of the face in the database and that in the query are different. Some authors have presented methods to recognize human faces with variations in rotation (or pose). The most significative works are Beymer and Poggio [1], Vetter [8], Lu and Jain [5], Huang et al. [3], Nayar et al. [6], Graham and Allinson [2], Pentland and Moghaddam [7].

The PCA technique based on face recognition finds eigenvectors that constitute the face sub-space bases (eigenspace) that are gotten through the covariance matrix formed by the correlation between pixels. In summary, each image of a human face in the training set can be represented in terms of a linear combination of eigenvectors, and the coefficients of this combination will be the new face represented in the eigenspace.

The SOM nets are auto-organized maps constituted by neurons on a flat structures either 1-D or 2-D. The learning method is based on ”competitive learning”, whose purpose is to discover patterns into input data. An input vector of arbitrary dimension is taken in a discrete neuron map in accordance with the proximity of the patterns in the original dimension [4].

## 2. Methodology

To construct the sub-spaces of eigenfaces, we trained the SOM neural net with the training faces. After that, we defined the region of clusters and finally separated the training face that is similar for each cluster computing the eigenface independent for each eigenspace (figure 1). In the identification, the first step is to determine the best one cluster to classify the input image. This is reached calculating the face projection into each eigenspace, doing the reconstruction of image and calculating the error between the reconstructed and original image. The eigenspace that presents the lesser error in the image reconstruction will be used to make the recognition.

The Algorithm K-PCA is an extension of PCA with the advantage to simplify the calculations of the eigenvectors, because it parallels the process when applied in big database.

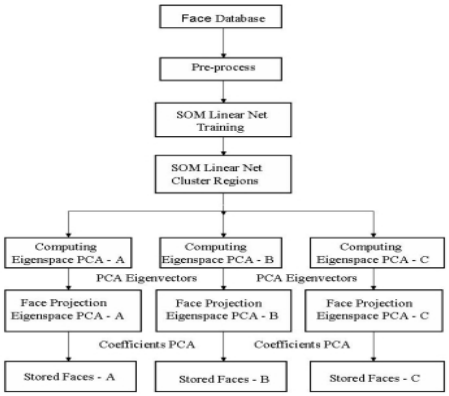


**Figure 1. Flowchart of training to K-PCA.**

The face database Umist [1] and Essex [2] had been used separately to evaluate the algorithm K-PCA.

Umist database has 20 different people covering a scale of poses from profile to frontal view. For the test, 20 faces

[1] http://images.ee.umist.ac.uk/danny/database.html
[2] http://www.essex.ac.uk/allfaces/faces94.html

of each person had been selected and flipped horizontally to produce more 20 images. The images was divided in a set of training images (12 for each person) and another set of test images (28 for each person). Essex database has 132 individuals with 20 faces for each person had been selected, and this set was divided in 10 faces for training and 10 for test (figure 2).

**Figure 2. Exemples of faces in the database.**

SOM neural net has been trained with 21 neurons distributed in a linear map. The weight distribution of neurons converges to the characteristics of illumination and pose with relation to the average faces of the set however it does not converge to the faces of each person. After SOM training, three regions (clusters) were established applying the K-means algorithm. Figure 3 shows the vectors related to each neuron and transformed into faces for the database Umist and Essex.

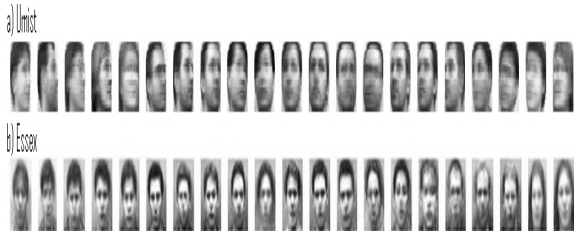


**Figure 3. SOM's neurons after training.**

In the test phase, the faces of testing set images are presented to the algorithm to effect the recognition. Figure 4 shows the recognition rate for the two databases.

The results presented for the database Essex are better than the presented ones for the database Umist, because this last one presents great variations with relation to the illumination and rotation.

## 3. Conclusions

The experiment that we report appeals an efficient method to brighten up the variations of rotation and illumination, and to parallel the PCA algorithm applied in the face recognition. The algorithm forms training sets with relation to the rotation, illumination or scales automatically separating the training face in accordance with these characteristics.

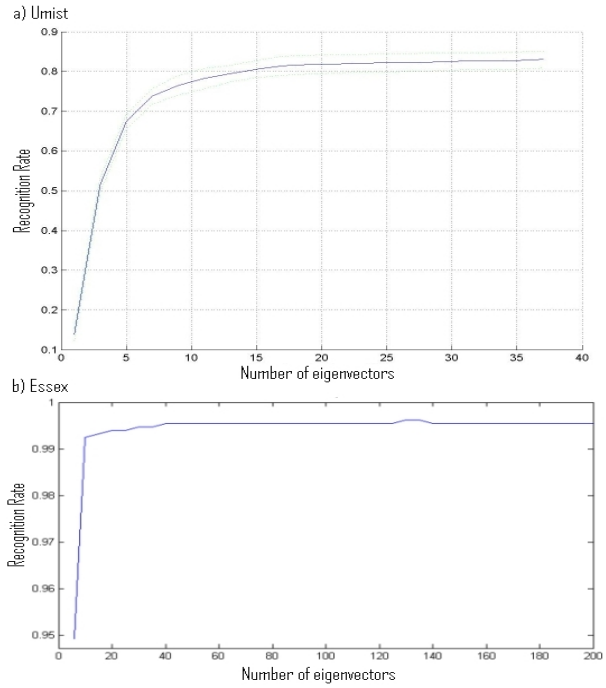


**Figure 4. Recognition rate for K-PCA.**

SOM neural net revealed efficient in the identification of the position of face rotation, and distribution of the illumination in the face databases. It makes possible a study of the scattering vectors of faces in dimensional space n x m.

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