Face Recognition With EigenFaces

Tahrima Mustafa, Upama Nakarmi
Final Project Report for CS5341: Pattern Recognition
Texas Tech University
Spring 2016

1. Introduction

An approach to the recognition and identification of human faces has been presented and described for a face recognition system that identifies a person by comparing characteristics of the face to those of individuals in the training dataset. In this approach, face images are projected into a feature space that best encodes the variation among known face images. The face space is defined by the Eigen faces which are eigenvectors of the set of faces.

The Eigenfaces method takes a holistic approach to face recognition: A facial image is a set of points having a high-dimension. Hence, a lower-dimensional representation is found where classication becomes easy. The lower-dimensional subspace is found with Principal Component Analysis, which identies the axes with maximum variance. While this kind of transformation is optimal from a reconstruction standpoint, it doesnt take any class labels into account. The basic idea for this approach is to minimize the variance within a class, while maximizing the variance between the classes at the same time.

The main motivation behind using eigenfaces for face recognition was implementing PCA, the dimensionality reduction technique. However, eigenfaces have advantages over other techniques available, such as the recognizer's speed and efficiency. With PCA, a system can represent many subjects with a relatively small set of data. As a face recognition system it is also fairly invariant to large reductions in image sizing, however it begins to fail considerably when the variation between the seen images and probe image is large.

2. Eigenfaces for Recognition

In the language of information theory, the relevant information was extracted from a face image, encoded and compared to an instance of an encoded face with a database of models encoded similarly. In mathematical terms, this approach finds the principal components of the distribution of faces or the eigenvectors of the covariance matrix of the set of face images. The eigenvectors can be thought of as a set of features which together characterize the variation between face images. The faces can also be approximated using the best eigenfaces: those that have the largest eigenvalues, so they have the most variance within the set of images.

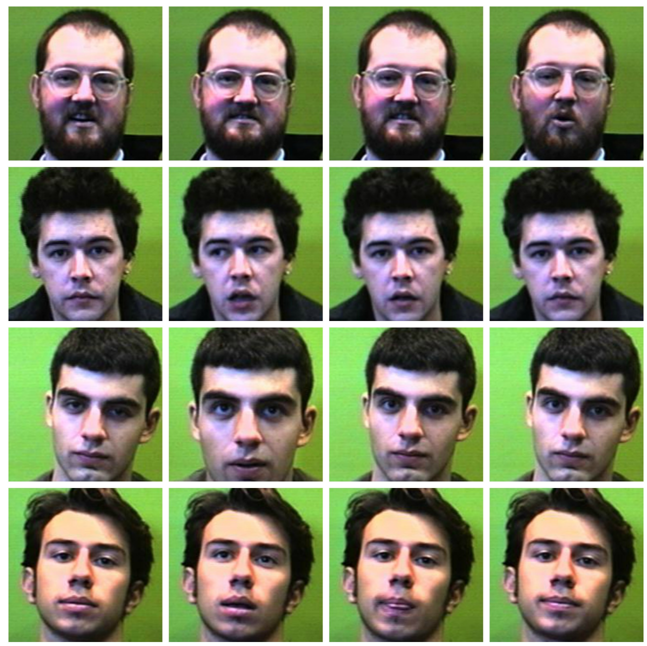

Figure 1. Images used as training set for face recognition

The problem with the image representation was the high dimensionality. Two-dimensional mn images span a P =mn dimensional vector space, so an image with 100100 pixels lies in a 10,000-dimensional image space already. In order to make the process efficient and quick, PCA was used. A high-dimensional dataset is often described by correlated variables and therefore only a few meaningful dimensions account for most of the information. The PCA method nds the directions with the greatest variance in the data, called principal components.

Dataset: In this project, a dataset of 60 images from this database (faces94) was used. A subset of the total dataset was used. Hence the dataset for this project has 60 pictures of 5 persons having different emotions like laughing, not laughing, with glasses, without glasses, happy, sad, mouth open, mouth closed etc. 50 images were used for training the recognizer and 10 images were used as test set.

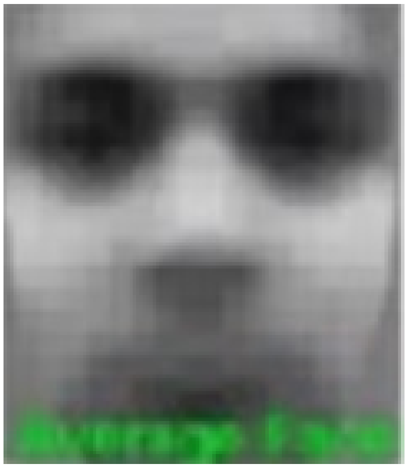

Figure 2. Average Mean Face

2.1. Algorithmic Description

Below is the step by step description of how the process works. Let the training set of face images be $\Gamma_1, \Gamma_2, \Gamma_3, ..., \Gamma_M$

1. Compute the mean

$$\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n$$

Each face differs from the average by the vector

$$\Phi_i = \Gamma_i - \Psi$$

2. Compute the Covariance Matrix $C = AA^T$, where $A = [\Phi_1, \Phi_2, ..., \Phi_M]$. The matrix C is N^2 by N^2 and determining N^2 eigenvectors and eigenvalues requires a lot of calculation. So, we are going to use the solution of M by M matrix and taking linear combination of the resulting vectors.

3. The K significant eigenvectors are chosen from the largest associated eigenvectors where K<M. There were 50 eigenvectors in total and the first computation was done with all 50 eigenvectors, then with 40, then 30 and at last with 10 eigenvectors. But even 10 eigenvectors give good reconstruction of the original image. Hence, just 10 eigenvectors have been used for further processing.

4. A new face image is transformed into its eigenface components by the operation:

$$\omega = \mu_K^T(\Gamma - \Psi)$$

The weight vectors form the vector

$$\Omega^T = [\omega_1, \omega_2, ..., \omega_K]$$

5. Next step is finding the class K that maximizes the Euclidian distance $\epsilon_K = [\Omega - \Omega_K]$, where Ω_K is the vector from the kth face class. A face is classified as belonging to a class k when the minimum ϵ_K is below the chosen threshold t. Otherwise the face is classified as unknown. The threshold value has been decided by a hit and trial method.

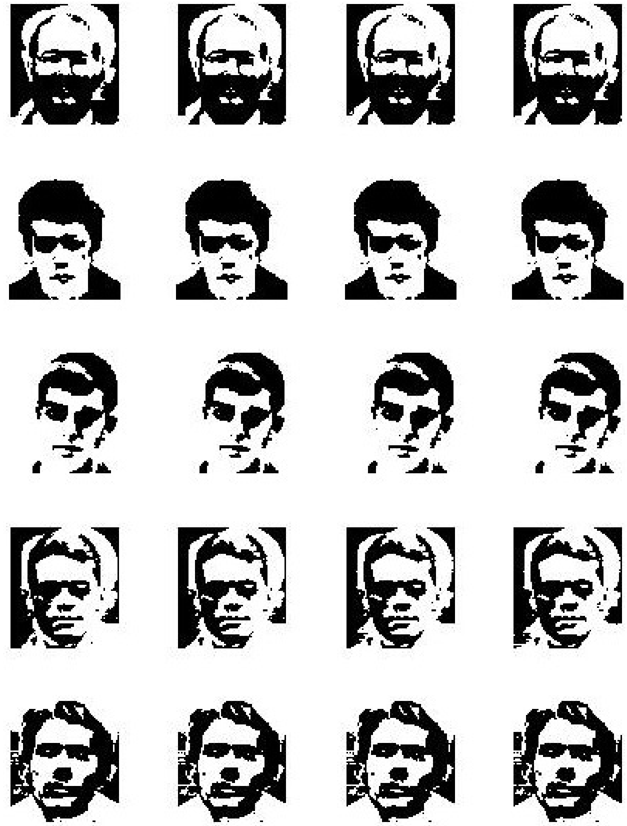

Figure 3. Eigen faces from the training dataset

2.2. Performance Evaluation

For this project, the training set was used in 3 different types. At first only one image per person was used and being tested. The success rate was 40

Then 5 images per person was used and being tested again with known and unknown face. The success rate for this case was almost 80

Next 10 images of same person were used as training set and being tested with completely different expression of the same person. This time the success rate was almost 99

3. Conclusion

Face recognition is a very high level task for which computational approaches can currently only suggest broad constraints on the corresponding neural activity. We therefore focused our project towards developing a very basic pattern recognition capability that is fast, simple and accurate in constrained environments. It is a very basic technique for recognizing an unknown face independent of lighting and expression of the face. The success rate of this process says that the Eigenface method is a very good technique for face recognition.

References

[1] *Eigenfaces for Recognition*, Matthew Turk Vision and Modeling Group, The Media Laboratory Massachusetts, Institute of Technology; Alex Pentland Vision and Modeling Group, The Media Laboratory Massachusetts, Institute of Technology

[2] *Dataset 1*, http://cswww.essex.ac.uk/mv/allfaces/index.html

[3] *Dataset 2*, http://cvc.yale.edu/projects/yalefaces/yalefaces.html

[4] *Face Recognition with Python by Philipp Wagner*

[5] http://www.pages.drexel.edu/ sis26/Eigenface