Face Recognition using EigenFaces

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Abstract:
The goal of this mini project was to recognise static faces on the three datasets that were given- Yale,CMU-PIE and the SMAI students Dataset. The training set (using k=4 fold) was used to develop the Eigenfaces and then a classifier (either KNN or SVM) was used to carry out the different experiments. With this, up to 97% accuracy was obtained for some cases of the Yale Dataset. Also accuracy of 91% is reached for some cases of CMU-PIE dataset.

The aim was that of producing an effective face recognition system that could be of use in real time applications.

The various results we got is noted in this paper.

I Introduction

With the development of artificial intelligence and computer vision, face recognition has become a hot topic of pattern recognition. This paper presents implementation of face recognition using Eigenfaces, systematically classifying using KNN and SVM classifiers. In addition, some insights through which the same can be addressed more efficiently for further research in the area of face recognition are also pointed out at the end of this paper.

The field - History
Face recognition has received immense importance and this is evident from increases number of conferences for face recognition. AFGR, ABVPA.There can be two reasons for these:
Reason 1: Wide range of commercial and law enforcement applications
Reason 2: Availability of technology since there is ongoing research from over 30 years.

The Problem can be simply stated as this: Given still image of a person, identify him/her from the dataset we already have. Information such as gender, expressions, color etc may be used in narrowing down the search space. The solution in this paper involves, feature extraction(weight vector calculation), representing face in eigenspace, then identification and verification of a given test image.

In identification problems the input is an unknown face and the system outputs the predicted person from the information it has. In recognition problems, used in security systems these days system needs to reject or confirm the predicted identity of the face.

Interesting applications can be done if we can extend this to nail recognition etc. Recent algorithms are used to extract the local facial features. In addition, several major issues for further research in the area of face.

II Data sets description

Yale folder contains images of 38 human subjects(there are around 68 images for each subject). Each image is 168x192 pixels in size. And the filename of each image has details about the Azimuth and Elevation angle.

Hence, the dataset will contains 20x38 images. Then we divide this dataset into training and testing samples, and start with the First experiment. While following the Eigenface approach, initially resized the images from 168x192 pixels to 100x100 pixels or 80x80 pixels.

CMU-PIE data set: This is the dataset with illuminations and expressions. This contains 2586 images of 68 people. So there are 40 images of single person. The identification was required to be done.
Each image is 32x32.

Student dataset: 4-5 images of each individual in class is taken. These are all gray scale images.

III Experiments and Results

The EigenFace method:
In this we want to extract relevant information is a face image, and encode it as efficiently as possible and then compare one face encoding with a database of models encoded in similar way. To compare and classify two kinds are used - knn classifier and svm classifier.

Every image is a point or vector in a very high dimensional space. Eigenvectors of covariance matrix of the set of face images treating each image as point in high dimensional space.Each eigenvector accounts for a different amount of variation among the faces.

Identification task:
Fro each new image, pattern vector for it is calculated using above step and its distance to each known class is seen and is then classified as the known individual with least distance between pattern vectors or weight vectors.
Procedure:
1) Acquire an initial set of training face images.
2) Calculated eigen faces from training set keeping only M images that correspond to highest eigenvalues. These M define facespace.
3) For each individual calculate M-dimensional weight space for each known individual by projecting their face image onto facespace.

Results:
Result 1:
Expressions and illuminated images in decreases accuracies.

This is because variance of a class image from rest of its different expression images is sometimes more than distance between pattern vectors of it and another class.

Result 2:
Also, with kfold, accuracies decrease for students data or CMU-PIE data set,
Note 1:
For yale, for M’=9 the accuracy went as high as 97.89%.
Note 2:
For CMU-PIE for M’=13, the accuracy went as high as 91.1%. classified.

Result 3:
As the number of topk Eigenvalues increases, more information is retained and accuracies go high.

Graphs of topk eigenvalues considered vs accuracies for yale and CMU-PIE datasets are plotted:

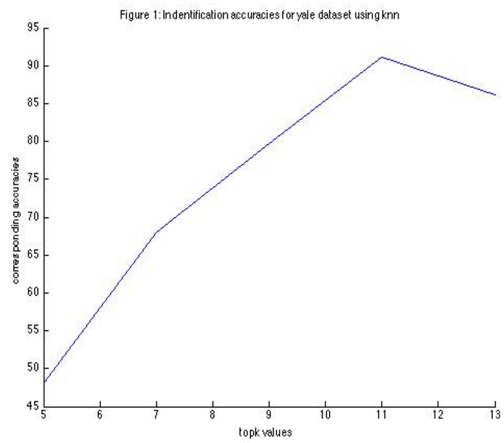
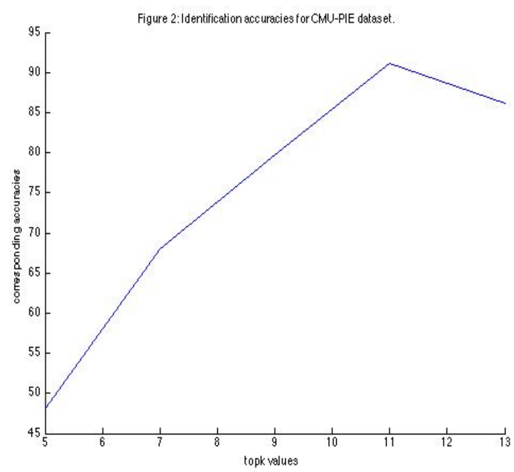


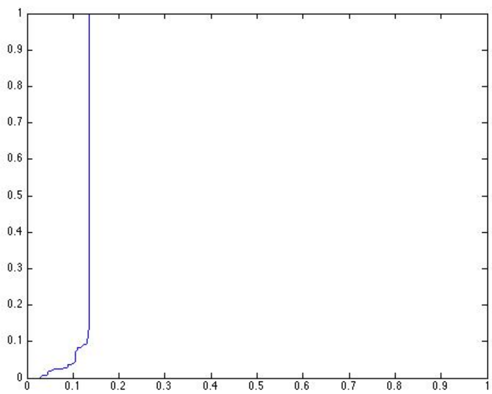
Figure 1: yale dataset acc Vs topk



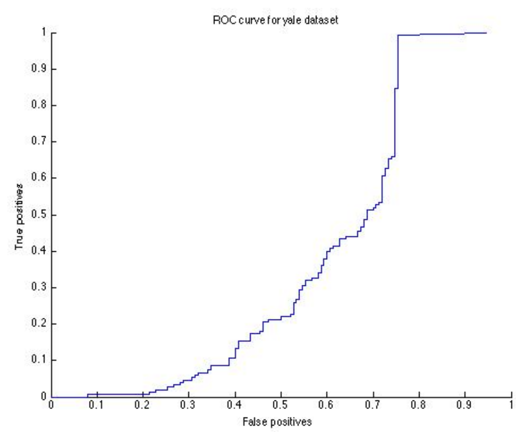
Result 5:
Highest accuracy for yale data set for M’=9 is 97.89%.
Accuracy for CMU-PIE data set for M’=11 is 81.57%.

Result 6:
With the above point said, there is always a trade off between time and accuracy. As eigenvalues number increases the time it takes for classification task also increases.

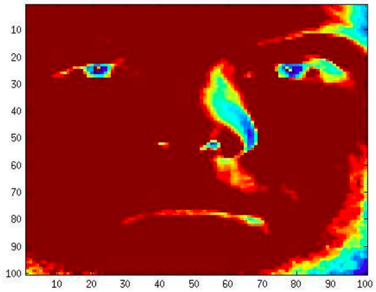
Result 7: ROC:
For CMU-PIE 1000 image pairs, 500 same and 500 different. For Yale 300 pairs, 150 same, 150 different.
The curve CMU-PIE below:

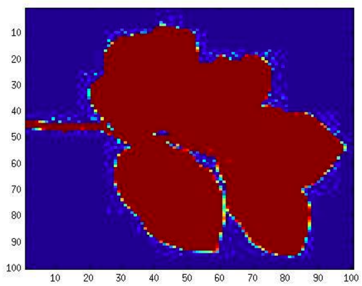


ROC for Yale:



Result 8:
Experiment 4: Reconstructed face and non-face images.





Discussions and Interesting observations:

1) The discriminative features in images are prominently dark in the datasets, so converting them into binary and then doing the identification task shouldn't make any difference in accuracies as is evident from accuracy values below and the performance curves are very similar too.

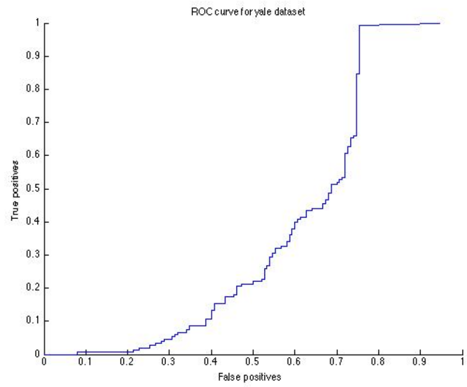
CMU-PIE dataset: Accuracies:

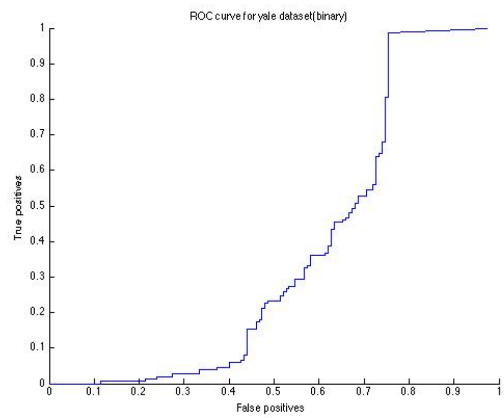
Normal Images	Binary Images
86.27%	86.27%

Yale dataset: Accuracies:

Normal Images	Binary Images
97.89%	81.57%

2) Interesting applications can be done if we can extend this to nail recognition etc.





How to make this better?

Instead of taking all the images towards calculating eigenvectors, we can design a mechanism through which we can only consider few images that contribute most to eigenvectors.

References:

"Eigenfaces for Recognition" by Turk and Pentland.
http://www.face-rec.org/algorithms/PCA/jcn.pdf

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