Using PCA for Dimensionality Reduction from Facial Images

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Abstract*— Face Recognition is a typical issue in AI. This innovation has just been generally utilized in our lives. For instance, Facebook can consequently label individuals' countenances in pictures, and furthermore a few cell phones use face acknowledgment to secure private security. Face pictures accompanies diverse foundation, variation brightening, diverse outward appearance and impediment. There are countless methodologies for the face acknowledgment. Various methodologies for face acknowledgment have been explored different avenues regarding explicit databases which comprise of single kind, organization and piece of picture. Doing as such, these methodologies sometimes fall short for with various face databases. One of the fundamental face acknowledgment systems is eigenface which is very basic, proficient, and yields by and large great outcomes in controlled conditions. In this way, this paper displays an exploratory exhibition correlation of face acknowledgment utilizing Principal Component Analysis (PCA). The tests are completed on the AT&T database images. The outcomes got for this technique have been thought about by fluctuating the quantity of preparing pictures. MATLAB is utilized for executing calculations.

I. INTRODUCTION

Dimension reduction is a process of reducing the number of variables under observation. The need for dimension reduction arises when there is a large number of univariate data points or when the data points themselves are observations of a high dimensional variable. The key observation is that although face images can be regarded as points in a high-dimensional space, they often lie on a manifold (i.e., subspace) of much lower dimensionality, embedded in the high-dimensional image space. The main issue is how to properly define and determine a low-dimensional subspace of face appearance in a high-dimensional image space. Dimensionality reduction techniques using linear transformations have been very popular in determining the intrinsic dimensionality of the manifold as well as extracting its principal directions. Dimensionality reduction is an effective approach to downsizing data. In statistics, dimension reduction is the process of reducing the number of random variables under consideration and can be divided into feature selection and feature extraction

II. METHODS

Principal Component Analysis (PCA) produces the optimal linear least-square decomposition of a training set. The PCA approach is applied to reduce the dimension of the data. The advantage of this reduction in dimensions is that it specifically decomposes the structure of face into components known as Eigen faces. Each image of face may be stored in a 1D array which is the representation of the weighted sum (feature vector) of the Eigen faces. Next the classification step which makes use of Euclidean Distance for comparing/matching of the test and trained images. Now project the test image into the same eigenspace as defined during the training phase. This projected image is now compared with projected training image in eigenspace. Images are compared with similarity measures. Relative Euclidean distance is calculated between the testing image and the reconstructed image, the minimum distance gives the best match.

Other effective methods include N-PCA (Normalized PCA) where it has been developed to give better results in terms of efficiency. N-PCA is an extension over linear PCA in which firstly normalization of images is done in order to remove the lightning variations and background effects and singular value decomposition (SVD) is used instead of eigen value decomposition (EVD), followed by the feature extraction steps of linear PCA.

III. RESULTS AND DISCUSSION

Considering the Facial dataset from the AT&T database we performed MATLAB PCA algorithm to certain face data. In this algorithm we have converted the face image to data pixels data and stored it in the form of matrix and then computed the covariance matrix for the data and Later on determined the Eigen values and Eigen vectors for that covariance matrix. Based on the obtained eigen values we found the following variance proportion for multiple K-values and the results are shown below.

Table illustrates the results obtained on using Principal Component Analysis (PCA) on AT&T dataset images			
Eigval = [9.8808, 1.6513, 1.3221, 1.1098, 0.9452, 0.8169, 0.7581, 0.6023, 0.5400, 0.4580, 0.4284, 0.2993, 0.2294, 0.2203, 0.1744, 0.1244, 0.1210, 0.0901, 0.0610, 0.0333, 0.0211, 0.0080, 0.0027, 0.0000] * 1.0e+03 >0 Where λ_1= 9.8808 * 1.0e+03 , λ_2=1. 6513 * 1.0e+03 …. so on			
Determining the proportion of variance for K-Values k = [3, 6, 9]			
K-Value	3	6	9
Sum (eigval) = λ_{total}	λ_{total} = 19.9051 * 1.0e+03	λ_{total} = 19.9051 * 1.0e+03	λ_{total} = 19.9051 * 1.0e+03
Sum(K-Values)	$\lambda_1+\lambda_2+\lambda_3$	$\lambda_1+\lambda_2+\lambda_3+\lambda_4+\lambda_5+\lambda_6$	$\lambda_1+\lambda_2+\lambda_3+\lambda_4+\lambda_5+\lambda_{6+}\lambda_7+\lambda_8+\lambda_9$
Sum (K- eigen values)	12.8542 * 1.0e+03	15.7261 * 1.0e+03	17.6265 * 1.0e+03
Proportion of variance = sum(k-eigen values)/sum(eigval)	$(\lambda_1+\lambda_2+\lambda_3 / \lambda_{total})$	$(\lambda_1+\lambda_2+\lambda_3+\lambda_4+\lambda_5+\lambda_6 / \lambda_{total})$	$(\lambda_1+\lambda_2+\lambda_3+\lambda_4+\lambda_5+\lambda_{6+}\lambda_7+\lambda_8+\lambda_9/ \lambda_{total})$
Proportion of variance	0.64577	0.7903	0.8858

IV. CONCLUSION

Use of PCA i.e. Eigenface approach is one the best practical solutions for the problem of face recognition. From the detailed analysis on certain images of AT&T database we have conducted so far using MATLAB PCA algorithm shows very significant and effective results rather than any other methodologies. In our experiment we carried out we used 3 different K-values for test purpose and we have come to know that based on the K-value we take the proportion of variance differs and Our experiment depicted an upward trend i.e. increase in proportion with increase of K-value. From the above table we can clearly see that, when the K-Value is increasing the proportion of variance is also increasing for the obtained eigen values for the face images dataset. It is clear that the proportion of variance is increasing for the given K-values as {3,6,9} as {0.64577, 0.7903, 0.8858) respectively.

REFERENCES

[1] “Principal Component Analysis in the Eigenface Technique for Facial Recognition”, Kevin Huang Trinity College.

[2] “Face Recognition Using Principal Component Analysis”, Ningthoujam Sunita Devi1 1, K. Hemachandran 2, Research Scholar, Department of Computer Science.

[3] “Face Recognition Using Principal Component Analysis Method”, Liton Chandra Paul 1, Abdulla Al Sumam 2, Electronics and Telecommunication Engineering.

[4] “Patch-Based Principal Component Analysis for Face Recognition”, Tai-Xiang Jiang, Ting-Zhu Huang, Xi-Le Zhao, and Tian-Hui Ma School of Mathematical Sciences, University of Electronic Science and Technology of China.

[5] “Face Recognition using Principle Component Analysis”, Kyungnam Kim, Department of Computer Science University of Maryland, College Park.

[6] ”Age Dependent Face Recognition using Eigenface.” International Journal of Modern Education and Computer Science 5.9 (2013): 38. Tin, Hlaing Htake Khaung.

[7] ”Face Recognition Using Eigenfaces.” International Journal of Emerging Technology and Advanced Engineering 3.5 (2013): 90-93. Saha, Rajib, and Debotosh Bhattacharjee.