INTERNATIONAL JOURNAL OF RECENT TRENDS IN TECHNOLOGY AND ENGINEERING (IJRTTE)

Journal Home Page: https://ijrtte.com/

Dimensionality Reduction - Supervised and Unsupervised Approaches for Facial Image Recognition

Radha Seelaboyina[1] and Rajeev G Vishwakarma[2]

[1]*Research Scholar, Department of Computer Science and Engineering, Dr.A.P.J. Abdul Kalam University, Indore, Madhya Pradesh, India*

[2]*Professor,Department of Computer Science and Engineering, Dr.A.P.J. Abdul Kalam University, Indore, Madhya Pradesh, India*

[1]*radha.seelaboyina@gmail.com*, [2]*rajeev@mail.com*

Abstract. Nowadays Authentication of a person using biometric traits is very common. Number of Biometric features is used for authenticating person like fingerprint, iris, face etc. Among all of them facial recognition is very much popular for authenticating person. Number of algorithms is present but all have certain pros and cons. As facial image consists of number of features so dimensionality Reduction is important steps in any facial recognition algorithm. The main focus of this paper to apply principle component analysis techniques for face recognition process. PCA gives very good results in reducing dimension. Principle Component Analysis produces eigenvectors. One combines those eigenvectors into images and then visualizes the eigen faces.

Keywords: Eigen value, Eigen faces, hyper plane, Principle component analysis.

1. Introduction

Without any effort human beings perform face recognition every day .Although it seems to be very simple task for human, but for a computer it is proven as very complex task .The accuracy of face recognition depends on occlusion illumination variation, low resolution, etc. Recognizing person by face is principally the task of recognizing a person completely based on its facial features. Facial Recognition has one of the very popular in the last three decades, for remote authentication. One more reason of its popularity is price of videos/cameras decreases exponentially as well as advancement of high range and high quality camera every year. Face Recognition and Face Detection are two different tasks. Face detection is the first step having very steps in the bigger computer vision processes such as analyzing face and also its recognition. Face recognition is a more intricate process initializes with face detection and after that continues to set up that whether or not two or more faces matches, or not for the purposes of identification and authentication [1], [3], [4]. Every face is unique due to the presence of distinguishable landmarks, peaks and valleys features. Some of these features are measured by using numerical methods-

- Width of the nose
- Depth of eye socket
- Cheekbones Shapes
- Jaw line length
- Distance between eyes

All these are unique to each person and this is called nodal points. Approximately every human face has 80 nodal points. These nodal points can be measured and numerical code is created for further recognition and identification process [5], [6]. Facial recognition and identification are now becoming so advance day by day. Previously face recognition had done by using 2D image. After capturing image, it is compared with the database that consists of particular images. But the quality of image affected by little variance of

Volume: 01 Issue: 02 Year: 2022
Received: 05.04.2022 Received in revised form: 10.05.2022 Accepted: 15.06.2022
Available Online: 26.06.2022
Published by NTL Publisher

light and change of facial expression and it create problem when comparing with the image present in the database that reduces the effectiveness of the system. Because of this reason face recognition becomes a challenging area of research due to its non-meddling property. As the cost of camera and sensors are decreases day by day so it becomes very flexible to do research on facial recognition process [2], [7]. Number of algorithms are developed day by day out of these some are-

1. SURF i.e. Speed Up Robust Features
2. SIFT i.e. Scale Invariant Feature Transform
3. Fisher faces
4. Local Binary Patterns Histograms (LBPH)
5. Eigen faces
6. Algorithms for Facial Recognition [8], [10].

These are the steps involved for facial recognition process-

1) First, we have resized all P faces called N*N
2) Second step is removing average
3) After that create matrix called L of input faces each row N*N total size of L is (N*N) * P
4) Calculating average value for face
5) Average removing face from L
6) Computation the covariance for matrix C L'*L , C size is M*M
7) After wards compute Eigen vectors as well as Eigen values, for the computing of faces having higher dimension
8) Computation of the linear combination for each original face
9) After that for the given new face input it to Eigen face and then computes distance to individual Eigen face and this is the recognition [9], [11].

The main task of face recognition is to distinguish or divide input signals or image data into different classes. But the input signals obtained is highly noisy due to differing lighting conditions, mask, pose etc.), But there are certain patterns that are common among input images in spite of their differences those patterns which are common among different images observed in all input signals and is important domain of face recognition these objects are eyes nose mouth including distance between the objects [12], [13].

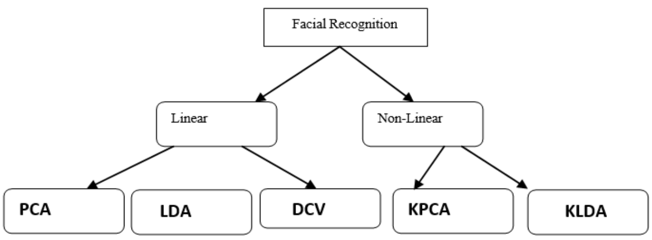

Figure 1: Different ways of dimensionality reduction.

PCA or principal component analysis and Linear Discriminant Analysis LDA come under linear approaches for dimensionality Reduction as shown in the Figure 1. A discriminative common vector is also a linear approach for two dimensional features. These features which are common among all faces are called Eigen faces. Eigen face recognition technique is very popular technique using eigenfaces. This is based on unsupervised method for reducing dimension of a feature space and called as Principal Component Analysis. In this paper we are going to apply these techniques for face recognition process. Principle Component Analysis produces eigenvectors. One can combine these eigenvectors into corresponding image and after that visualize the eigenfaces which is represent in the Figure 2.

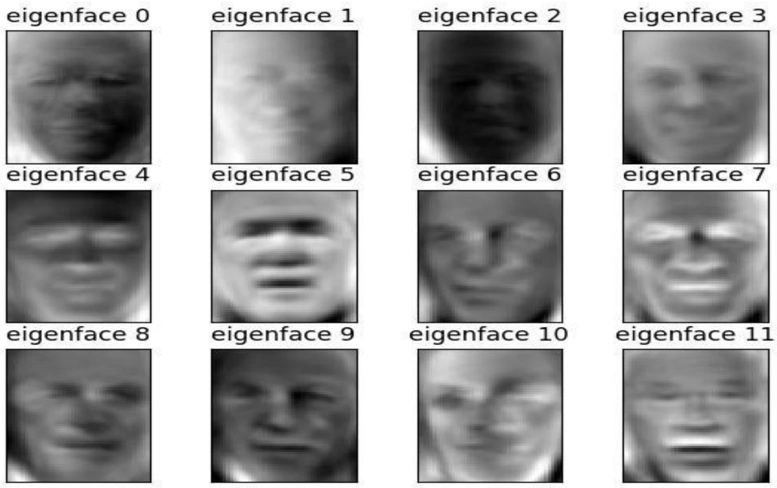

Figure 2: Different types of Eigen faces.

2. Dimensionality Reduction

The first important task is to decrease or reduce dimensions of the input images Dimensionality reduction is very important and is a type of unsupervised learning for which input is images of higher- dimensional data and to represent these images having lower-dimensional space. Figure 3 shows the diagram for different feature vector.

The main aim of dimensionality reduction is to find a hyperplane, a higher-dimensional line, for the projection of points present on it. One can see a projection by using a flashlight that is perpendicular to the hyperplane and plotting the area where the shadows fall on to that hyperplane. This is called a projection. We can visualize images in two dimensions (m and n) as points spreading in mn-dimensional space. To reduce space, Principal Component Analysis (PCA) is used to reduce space from mn into another much smaller space. This increases computation speed and becomes more robust to variation and noise [4], [19], [7], [15].

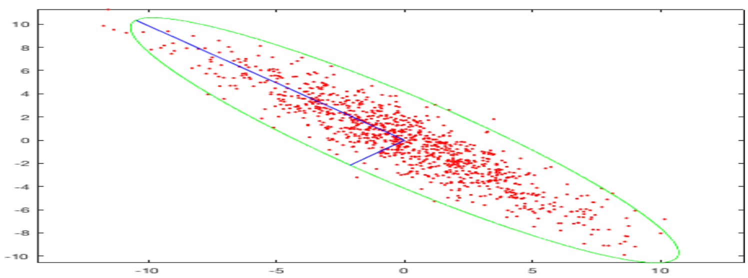

Figure 3: Diagram for different feature vector.

Eigen faces Code

To generate Eigen faces code

```
import matplotlib.pyplot
from learn1 open.datasets import fetch1_lfw_people1
from learn1open .metrics import classification1_report
from learn1open.decomposition import PCA
from learn1open.neural_network import MLPClassifier
```

 # Loading data

```
lfw_ dataset = fetch_lfw_people(mpp=150)
, h, w = lfw_dataset.images.shape
X = lfw_dataset.data
y = lfw_dataset.target
target names = lfw_dataset.target_names # split into a training as
well as testing set
1X_test, y_train, y_test = train_test_split (X, y, test size=0.4)
```

Now Principle component Analysis has to perform for the dimensionality reduction. For this select the number of eigenvectors to reduce the components output dimensionality that is the main objective. In these 150 components are used. To compute PCA following are the code 2.1.1 Computation of PCA

```
N components = 150
pca1 = PCA(N components = N components, whiten =
True).fit(X_training)
# apply Principal Component Analysis transformation
X_train1_pca = pca1.transform (X_train1)
X_test1_pca = pca1.transform(X_test1)
```

By using Principle Component Analysis one can easily transform each input original image belongs to training set into an equivalent eigenface.

An important characteristic of principle component analysis is the reconstruction of original image from the given set of training set data. Once combining the Eigen faces original image is created as Eigen faces are nothing less than attribute features of the faces. In the Figure 4 , graph over fitting starts as accuracy starts to decline for validation dataset. After that output is vector of reduce dimension, the next step is to train neural network, [16], [17], [20], [21] the code for which are

```
# Training of a neural network
Printing by using print(" To Fit the classifier in the training
set")
clf1 = MLP Classifier (hidden_layer_sizes1=1024, batch_size1=256,
verbose1 = 1, early_stopping=1).fit(X & Y train_pca)
```

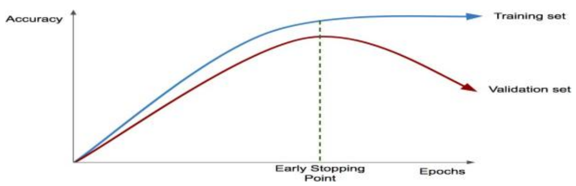

Figure 4: Over fitting Graph.

Training of dataset must stop when over fitting started

As training of classifier completed, one has to give few images for classification process- # Visualization

```
def plot1 .gallery (images1, titles, w, h, rows=4, cols=3):
pypyplt.figure1()
for value i in range1(cols * rows):
pyplt.subplot1(rows, cols, i + 1)
pyplt.imshow1(images[i]. reshape((h, w)), cmap=pyplt.cm.gray)
pyplt.title1(titles[i])
pyplt.xticks1(())
pyplt.yticks1(())
def titles1 (y_pred, y_test, target_names):
for i in range1(y_pred.shape[0]):
Pred_ name = target_names1 [y_pred[i]].split(' ')[-1]
true_name1 = target_names [y_test[i]].split(' ')[-1]
yield 'predicted: {0}\ntrue: {1}'.format(pred_name, true_name)
prediction_titles1 = list(titles(y_pred, y_test, target names))
plot_gallery1(X_test1, prediction_titles1, h, w)
```

For Accuracy precision, support f1-score, recall, are the parameters. The support is defined as a number of times truth table occur in test set, e.g., if there were actually 40 images of person xyz Using precision and recall scores f1 scores calculated. Precision and recall are most important measures compare to single accuracy score. Precision and Recall higher value are always better.

Classification, Clustering or Regression make use of training dataset for finding weight factors that can be used to find predictive results by seeing the nature of data. One can apply machine learning only after the necessary selection of relevant features called training dataset. Dimensionality reduction is the process to transforms a dataset for selecting only important features that is necessary to train the system. Linear Discriminant Analysis is also a one of the methods to reduce dimensionality of the data. The main aim of LDA is to uncover the feature subspace for optimizing class separability. As classes are present so, Linear Discriminant Analysis is a supervised machine learning algorithm. Learning LDA Models

3. Linear Discriminate Analysis makes simplifying assumptions the data:

If data is Gaussian, then every variable when plotted it shaped like a bell curve. Each attribute has same value for variance, and the nature is the values of every variable moves in the region of the mean value having average. Linear Discriminate Analysis model actually estimates variance and the mean using that will use data of each and every class. Easy always to reflect about this in the form of univariate means single input variable that consists of two classes.

The mean value of individual input for each class can be calculated in the simple way by dividing the all input sum of values by total number of values.

Using Equation (1), value of variance is calculated for all different classes and it is the value of average square and is the difference of each value from the mean [6], [18], [5], [22].

$$\sigma^2 = \frac{1}{(n-K)}\sum((x-M)^2)) \tag{1}$$

Where value of Sigma^2 is the variance across all inputs number of instances is n, K denotes total number of classes and M is the mean for input x .

4. Making Predictions with LDA

Linear Discriminate Analysis gives predictions by calculating the probability for every class a consists of new set of inputs. Highest probability class that is the output class thus prediction is made. For estimating probabilities Bayes Theorem are used.[16], [17], [9], [23].

5. Conclusion

In this paper we discussed the approach used for facial recognition having facial features of a image and recognizing those features There are numbers of algorithms present and also effective for performing face recognition process, example : Discrete Cosine Transform, Principal Component Analysis, Gabor Wavelets 3D acceptance methods, method etc. Our has centered on PCA Principal Component Analysis method for recognizing face in an efficient manner For Accuracy precision, f1-score, recall, and support are the parameters. The support is number of times truth table occurred in test set, e.g., if there were actually 40 images of person xyz the F1-Score computed from the precision and recall scores. Precision and recall are most important measures compare to single accuracy score. A higher value for precision and recall is always better [3], [14], [11].

References

1. Hiremath, Vinay, and Ashwini Mayakar. "Face recognition using Eigenface approach." IDT workshop on interesting results in computer science and engineering, Sweden. 2009.
2. Jalled, Fares. "Face Recognition Machine Vision System Using Eigenfaces." arXiv preprint arXiv: 1705.02782 (2017).
3. Torres, L., L. Lorente, and Josep Vila. "Automatic face recognition of video sequences using self-eigenfaces." In International Symposium on Image/video Communication over Fixed and Mobile Networks, Rabat (Morocco. 2000.
4. Turk, Matthew, and Alex Pentland. "Face recognition using eigenfaces." Proceedings. 1991 IEEE computer society conference on computer vision and pattern recognition. 1991.
5. Belhumeur, Peter N., João P. Hespanha, and David J. Kriegman. "Eigen faces vs. fisherfaces: Recognition using class specific linear projection." IEEE Transactions on pattern analysis and machine intelligence 19.7 (1997): 711-720.
6. Zhang, Jun, Yong Yan, and Martin Lades. "Face recognition: eigenface, elastic matching, and neural nets." Proceedings of the IEEE 85.9 (1997): 1423-1435.
7. Yang, M-H., Narendra Ahuja, and David Kriegman. "Face recognition using kernel eigenfaces." Proceedings 2000 International Conference on Image Processing (Cat. No. 00CH37101). Vol. 1. IEEE, 2000.
8. Yang, Ming-Hsuan. "Kernel Eigen faces vs. Kernel Fisherfaces: Face Recognition Using Kernel Methods." Fgr. Vol. 2. 2002.
9. Gunturk, Bahadir K., et al. "Eigenface-domain super-resolution for face recognition." IEEE transactions on image processing 12.5 (2003): 597-606.
10. Pentland, Alex, Baback Moghaddam, and Thad Starner. "View-based and modular eigenspaces for face recognition." (1994).
11. Tsalakanidou, Filareti, Dimitrios Tzovaras, and Michael G. Strintzis. "Use of depth and colour eigenfaces for face recognition." Pattern recognition letters 24.9-10 (2003): 1427- 1435.
12. Kshirsagar, V. P., M. R. Baviskar, and M. E. Gaikwad. "Face recognition using Eigen faces." 2011 3rd International Conference on Computer Research and Development. Vol. 2. IEEE, 2011.
13. Challa Esther Varma*, Dr. Adepu Sree Lakshmi, Radha Seelaboyina & Dr. Puja Sahay Prasad, “Tourist Behaviour Analysis And Managemnts Algorithm Using Machine Learing& Ai”, Editorial, vol. 54, no. 4, pp. 26–32, Mar. 2022.

14. Sophisticated Embedding of Artificial Intelligence Techniques in Biomedical Engineering, Radha Seelaboyina Dr puja S prasad ,Dr G.Somasekhar, 2021/3,ch.51,p.237,978-981-16-6406-9,ICMISC 2021.
15. Pathak, Rashmi, et al. "Normalization Techniques in Multi Modal Biometric." ICCCE 2019. Springer, Singapore, 2020. 425-431.
16. Kim, Kwang In, Keechul Jung, and Hang Joon Kim. "Face recognition using kernel principal component analysis." IEEE signal processing letters 9.2 (2002): 40-42.
17. Gottumukkal, Rajkiran, and Vijayan K. Asari. "An improved face recognition technique based on modular PCA approach." Pattern Recognition Letters 25.4 (2004): 429-436.
18. Yang, Jian, et al. "Two-dimensional PCA: a new approach to appearance-based face representation and recognition." IEEE transactions on pattern analysis and machine intelligence 26.1 (2004): 131-137.
19. Moon, Hyeonjoon, and P. Jonathon Phillips. "Computational and performance aspects of PCA-based face-recognition algorithms." Perception 30.3 (2001): 303-321.
20. Liu, Chengjun. "Gabor-based kernel PCA with fractional power polynomial models for face recognition." IEEE transactions on pattern analysis and machine intelligence 26.5 (2004): 572-581.
21. Perlibakas, Vytautas. "Distance measures for PCA-based face recognition." Pattern recognition letters 25.6 (2004): 711-724.
22. Yang, M-H., Narendra Ahuja, and David Kriegman. "Face recognition using kernel eigenfaces." Proceedings 2000 International Conference on Image Processing (Cat. No. 00CH37101). Vol. 1. IEEE, 2000.
23. Yambor, Wendy S., Bruce A. Draper, and J. Ross Beveridge. "Analyzing PCA-based face recognition algorithms: Eigenvector selection and distance measures." Empirica l evaluation methods in computer vision. 2002. 39-60.