

Performance Comparison of Face Recognition Algorithm Based on Accuracy Rate

Rashmi Ravat¹, Namrata Dhanda²

Department of Computer Science, Uttar Pradesh Technical University Lucknow, India¹

Head of Department of Computer Science, Goel Institute of Technology & Management, Lucknow, India²

Abstract: This paper presents an overview of different face recognition techniques, study and analysis of the face recognition rate, failure rate, training time and recognition time of various face recognition algorithms like PCA, LDA, SVM, ICA and SVD. We analyzed from the results that the performance of SVD in terms of accuracy was better when no. of images increased on ORL database whereas the performance of PCA was the lowest. Also SVD took more recognition time than other algorithms. Training time of SVM is lowest and PCA, LDA and ICA consume marginal time.

Keywords: Face Recognition, PCA, LDA, ICA, SVM&SVD, ORL Database.

I. INTRODUCTION

In biometrics recognition of image perception was difficult for both local and global information. Pattern recognition and Computer vision is innovative for developing face recognition technique. Here introduce two types of recognition first is intrusive other one is non-intrusive recognition also proposed emerging techniques of feature extraction process [2]. Also attention on how to reduce dimensions. Most difficulty encountered in face recognition techniques was how to handle various poses in human face i.e. recognition of face in arbitrary in –depth rotations [3]. Pose tracking problem was handled by many applications dealing with uncooperative, but still problem intractability in 3D face modeling. Whenever identifies person face then because facial expression or poses difficult in distinguishing identities. Lots of researcher was compared performance of various face recognition algorithms (PCA, LDA, ICA and SVM) on AT&T and IFD database to study their performance in terms of accuracy, training time, testing time, total execution time and model size for more detailing information see [4]. For comparing four existing algorithms tried to finding out which one was best in accuracy and also finding testing time of all those. Several of face recognition algorithms have been developed in last attempt. In 2013 was attempt review in wide range of methods used for face recognition. This was include PCA, LDA, ICA, SVM, Gabor wavelet soft computing tool like ANN for recognition and various combinations of techniques [5]. A different approach towards face recognition techniques can be based on models or [6] to derive their Active Appearance Model. The Class information is captured by these models however many constraints are encountered while dealing with variation in appearance. On the other hand exemplars are also used for recognition. In Some methods like ARENA [7] all trainings are simply stored and are individually matched with task image. Generally exemplars are not used by present methods employing models and vice versa. A new method using the combination of models and exemplars was recently proposed by [8]. In this method additional training images

are synthesized using the models, which are then used as exemplars in the learning stage. Considering the aspect of pose invariance, the recognition approaches can be categorized as: 1) Global approach and 2) Component-based approach. In the global approach a single feature vector representing the whole face is used as input to the classifier.

The performance of global techniques is better when used for classifying the frontal views of faces. However being highly sensitive towards translation and rotation of faces, these are not consistent in situation involving pose changes. Alignment stage is usually added before classifying the face for avoiding this problem. Alignment of input face image and reference face image requires computing correspondence between the two of prominent points of the face e.g. eyes, nose etc. The input image is warped to the reference image by using these correspondences.

II. ALGORITHMS

A. Principal Component Analysis (PCA)

In Principal Component Analysis (PCA) estimates 2-D facial image as 1-D vector by concatenating each row (or column) into a long thin vector.

These basis vectors are representation of an images which is named eigenfaces. Eigenfaces compressed images use for easily comparison in database. Follow these steps :

- Assume we have M vectors of size N (= rows of image × columns of image) representing a set of sampled images.
- Mean centered subtracting by the mean image from each image vector. Find the eigenvectors and eigenvalues of the covariance matrix.
- Rearrange the eigenvectors and eigen values. Compute the cumulative energy content for each eigenvector.
- Select a subset of the eigenvectors as basis vectors.
- Project the z-scores of the data onto the new basis.

B. Linear Discriminant Analysis

It is difficult to analyzed human facial components like features. All of component has a different discrimination for identifying a person. Linear discriminant group images of the same class and separates images of different classes of the images. Follows these steps:

- First, we acquire training set composed of a relatively large set of images with diverse facial characteristics.
- Second, appropriate selection of training set support to find out final result. So that we considered that images have already normalized to $m \times 3 \times n$ arrays only face region.
- Each image and subimage, starting with the two-dimensional $m \times 3 \times n$ array of intensity values $I(x, y)$, then we construct the lexicographic vector expansion $f \in \mathbb{R}^{m \times 3 \times n}$.
- Third, by defining one class for all instances of the same person's face and the faces of different subjects as being in different classes for all subjects in the training set, we establish a framework for performing a cluster separation analysis in the feature space. having labeled all instances in the training set and having defined all the classes, we compute the within- and between-class scatter matrices as follows:

$$S_w^{(V)} = \sum_{i=1}^L \Pr(C_i) \Sigma_i,$$

$$S_b^{(V)} = \sum_{i=1}^L \Pr(C_i) (\mu - \mu_i)(\mu - \mu_i)^T.$$

C. Support Vector Machine

The Support Vector Machine is based on VC theory of statistical learning. It is implement structural risk minimization [19]. Basically, it was introduced as per a binary classifier. It estimates the support vectors through concluding a hyperplane. Support Vectors increase the distance or margin between the hyperplane and the closest points.

Suppose a set of N points and $X_i \in \mathbb{R}^n, i=1, 2, 3, \dots, N$. Each point belongs to one of the two classes i.e. $Y_i \in \{-1, 1\}$.

$$f(x) = \sum_{i=1}^L \alpha_i Y_i X_i \cdot X + b.$$

This quadratic equation $f(x)$ decides the Classification of a new point data in the above equation.

D. Independent Component Analysis

Generalization View of the PCA is known as ICA. Use for increases the second order and higher order dependencies in the input and determines a set of statistically independent variables or basis vectors.

Here we are using architecture which finds statistically independent basis images [2].

Follow the basic steps for ICA[9]:

- Collect X_i of n dimensional data set $X, i = 1, 2, 3, \dots, M$.
- Mean correct all the points: calculate mean M_x and subtract it from each data point, $X_i - M_x$
- Calculate the covariance matrix: $C = (X_i - M_x)(X_i - M_x)^T$
- The ICA of X factorizes the covariance matrix into the following form: $C = F \Delta F^T$ where Δ is a diagonal real positive matrix. F converts into the original data X into Z .

E. Singular Valued Decomposition

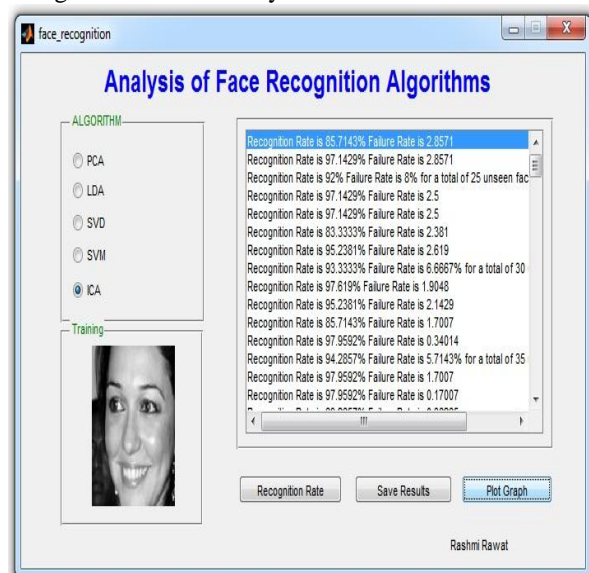
Basic steps for SVD as below:

- Obtain a training set S with N face images of known individuals.
- Compute the mean face f of S
- Forms a matrix A with the computed f .
- Calculate the SVD of A
- For each known individual, compute the coordinate vector X_i .
- For a new input image f to be identified, calculate its coordinate vector x ,
- Apply the Max-MIN Normalization to Bound the value obtained

III. EXPERIMENTAL RESULT

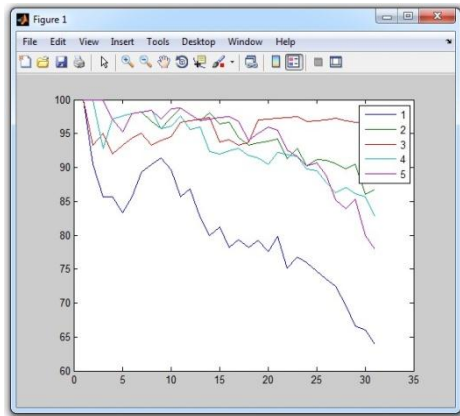
We have implemented "Analysis of Face Recognition Algorithms System" which was used to find out performance of various algorithms. Using this system selection of the algorithms was made one by one and then the recognition rate, failure rate, training time and recognition time information was generated for all the algorithms separately.

This information was used to plot the graphs comparing the above mentioned rate and time performances of the five algorithms under study.

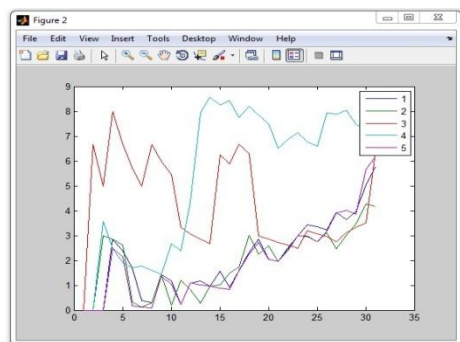


The graph shown below displays the recognition rates of the following five algorithms when applied on both the databases:

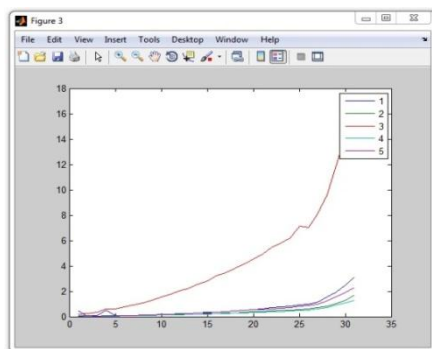
1.PCA 2.LDA 3.SVD 4.SVM 5. ICA



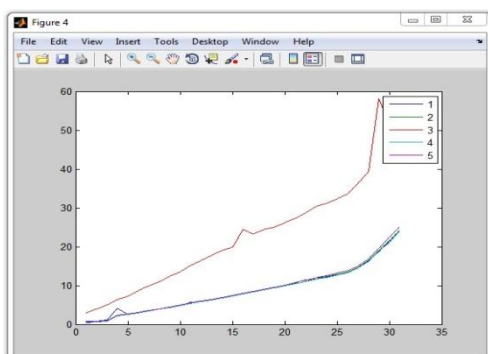
Following graph shows below comparison of failure rate when five algorithm applied on both database:



Following graph shows the comparison of training rate when the five algorithms were applied on both the databases:



Following graph shows the comparison of recognition time of the five algorithm when applied on both the databases:



IV. DISCUSSION

Following results were achieved after experimental analysis of the performance of above five algorithms.

- 1) According to comparison of recognition rate employed on five algorithms. The highest accuracy rate is 97.5% (SVD) and lowest is PCA accuracy rate is 93.7% but performance of LDA & SVM was same at 95.3%. ICA performed with an average recognition rate of 80%.
- 2) The second graph shows failure rate of algorithms when number of images were added to database. We analyzed that PCA performed very well on less number of images but with increased number of images failure rate grew. ICA performed opposite to PCA. SVD and LDA varied in terms of performance but resultant is fixed. Most of the fluctuation appeared in SVM when images were added on database, failure rate increases but after that decreased slowly. Comparing all of them SVD and LDA's performance was very good in terms of failure rate.
- 3) Comparison of algorithms on the basis of training time, we observed that SVD performance was best and SVM's lowest. PCA, LDA and ICA training time was average as comparison of SVD and SVM.
- 4) For the last one i.e. recognition time it was observed that time consumed by SVD was more than four times than that of other algorithms.

V. CONCLUSION

We have developed a system to compare the performance of five algorithms PCA, LDA, ICA, SVM and SVD on the basis of the recognition rate, failure rate, training time and recognition time. In order to compare the performance of some face recognition algorithms on faces we have prepared as well as presented a database and tested it. SVD recognition rate is highest 97.5% as well as training time. SVD consumes more recognition time on comparison to PCA, LDA, ICA and SVM.

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