A Comparative Study of Baseline Algorithms of Face Recognition

Zahid Mahmood[#1], Tauseef Ali[*2], Shahid Khattak[+3], Samee U. Khan[#4]

[#]*Department of Electrical & Computer Engineering, North Dakota State University, USA.*
[1]zahid.mahmood@ndsu.edu, [4]samee.khan@ndsu.edu

[*]*Faculty of Electrical Engineering, Mathematics, and Computer science, University of Twente, Netherlands.*
[2]t.ali@utwente.nl

[+]*Department of Electrical Engineering, COMSATS Institute of Information Technology, Pakistan.*
[3]skhattak@ciit.net.pk

***Abstract*—In this paper we present a comparative study of two well-known face recognition algorithms. The contribution of this work is to reveal the robustness of each FR algorithm with respect to various factors, such as variation in pose and low resolution of the images used for recognition. This evaluation is useful for practical applications where the types of the expected images are known. The two FR algorithms studied in this work are Principal Component Analysis (PCA) and AdaBoost with Linear Discriminant Analysis (LDA) as a weak learner. Images from multi-pie database are used for evaluation. Simulation results revealed that given one gallery (Training) face image and four different pose images as a probe (Testing), PCA based system is more accurate in recognizing pose, while AdaBoost was more robust on recognizing low resolution images.**

***Key Words*—AdaBoost, LDA, PCA.**

I. Introduction

FACE Recognition (FR) is a phenomenon that humans usually do unconsciously. FR is defined as given an input face image of unknown subject and a database containing face images of known subjects, task is to determine the identity of the subject in the input image. Two basic FR scenarios are: (a) Identification and, (b) Verification. In *Identification* (1:N matching), a probe image of an unknown individual is identified by comparing the image with an image gallery of known individuals [1]. In *Verification* (1:1 matching), two images are compared with each other to conclude whether they originate from the same person [2]. *Identification* and *Verification* depend on various factors, such as change in facial expressions, appearance, aging, surgery, facial hairs, and changes in hairstyle. Moreover, occlusion, changes in scales, rotating faces in plan, variations in lighting/camera, and change in channel characteristics effect FR accuracy significantly [8].

FR has remained a challenging problem in image processing and computer vision [3]. Due to abrupt increase in crimes and terrorism in recent times, FR systems demand more attention in terms of accuracy and robustness when used in various domains, such as forensic applications. In such applications, the robustness of the system plays an important role [4]. Figure 1 explains general face verification/recognition procedure. First features are calculated in gallery images. These features are then compared with the features of the probe image and a similarity score is computed for a given comparison. Larger the similarity scores, the more similar images are in the given pair of images [22].

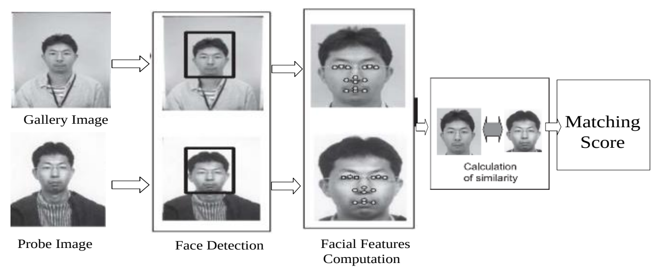


Figure. 1. Face verification procedure

The rest of the paper is organised as follows. Section II discusses the related work and highlights problem, this paper is focusing on. Section III briefly outlines the two face recognition algorithms that are compared. Simulation results are shown in Section IV. Finally, conclusions and future research directions are highlighted in Section V.

II. Related Work

During the past three decades much effort has been done to improve the accuracy and robustness of the current FR systems. Researchers of [5] addressed phenomenon of FR using information in edges as independent components. They used Laplacian of Gaussian (LoG) and canny edges along with Principal Component Analysis (PCA) and Independent Component Analysis (ICA). This system suffered badly with the slight change in pose. Accuracy of this system was found to be 76.5%. The authors in [6] discussed FR using feed forward neural networks along with principal components. Results reported had 90% accuracy. The system had a drawback of being complex having high execution time.

In [7], a component based technique along with global methods for FR was presented. Results were evaluated with respect to robustness and pose up to $\pm 40^0$. This system had a drawback that it was unable to deal with full range of poses from frontal to profile views. In [8], the authors tackled recognition problem by combining the strengths of robust illumination normalization with local texture based face representations along with distance transform based matching. Published results show an accuracy of 90%. The researchers were unable to cover full range of lighting conditions. The authors of [9] focused on the numerical implementation of a sparsity-based framework. Sparse representation was thought to recover human identities from high-dimensional facial images corrupted by disguise, illumination, and pose. Experiments were conducted to compare performance against several *L*-1-minimization solvers. Promising results were obtained in terms of accuracy up to 82%. Detailed surveys regarding FR can be seen in [10], [11].

Zhang *et al*. [12] compared three popular FR system performances. The systems were, PCA, LDA, and Elastic Bunch Graph Matching (EBGM). Recognition performance was evaluated on three different databases. **(1)** Facial Recognition Technology (FERET) database [13] **(2)** Yale Database [14], and **(3)** University of Essex database [15]. FR was evaluated in terms of accuracy, computational cost, and recognition tolerance. During experiments frontal facial images were analysed. EBGM outperformed PCA and LDA on FERET database in terms of FR accuracy at the cost of higher computation time. LDA performed well on Yale and University of Essex database by yielding higher accuracy in less execution time than PCA and EBGM. Authors concluded that EBGM and LDA performed better than PCA.

In the surveys mentioned above it is apparent that FR is still unresolved issue. The factors affecting any FR performance are: extreme lighting conditions, pose, low resolution, and occlusion. Therefore, any FR system is yet to be use reliably in real-life. Now, after 30 years of research is just beginning to yield useful technological solutions to identify individuals [16].

In this paper we have investigated the two well-known FR systems under different pose from completely frontal up to $\pm 45^0$ view and Low Resolution (LR) images. Given the one gallery (Training) image and four different pose images as probe (Testing), PCA based system was found to be more accurate in recognizing pose than AdaBoost based system. While, AdaBoost based system was found to be more robust in recognizing LR images as small as 5 x 5. In section III, we present brief overview of the two FR systems compared in this paper.

III. Face Recognition Systems

A. *AdaBoost with LDA as a weak learner*

This system is based on Adaptive Boosting (AdaBoost) [17], [18] algorithm with LDA as a weak learner for feature selection whereas Nearest Center Classifier (NCC) is used for classification. The task of learning can be formulated as:

Let a training set, $\mathcal{Z} = \{\mathcal{Z}_i\}_{i=1}^{C}$ containing C classes with each class $\mathcal{Z}_i = \{(\mathbf{z}_{ij}, y_{ij})\}_{j=1}^{Li}$ consisting of a number of samples $\mathbf{z}_{ij}$ and their corresponding class labels y_{ij}, a total of $N = \sum_{i=1}^{C} Li$ samples are available in the set. Let $\mathbb{Z}$ be the sample space: $\mathbf{z}_{ij} \in \mathbb{Z}$, and $\mathbb{Y} = \{1,., C\}$ be the label set: $y_{ij}\ (=i) \in \mathbb{Y}$. Now taking as input such a set $\mathcal{Z}$, the objective of learning is to estimate a function or classifier $h(z) : \mathbb{Z} \rightarrow \mathbb{Y}$, i.e. h will correctly classify unseen samples (z,y). Now Adaptive Boosting algorithm operates by repeatedly applying a given weak learner to a weighted version of the training set in a series of several rounds $t = 1, \ldots T$, and finally linearly combines weak classifiers $\{h_t\}_{t=1}^{T}$ constructed in each round into a single, accurate, robust, and strong classifier h_f. Equation (1) shows the final strong classifier.

$$h_f(\mathbf{z}) = \underset{y \in Y}{\arg\max} \sum_{t=1}^{t=T} (\log \frac{1}{\beta_t}) h_t(z,y) \qquad (1)$$

The efficiency of LDA based technique is further strengthened by combining with the boosting framework. The final classifier obtained is an ensemble of several LDA solutions with more than 90% accuracy. The pseudo code of AdaBoost-LDA based face recognition system is given in Table I. Further details of this recognition system can be found in [19], [23].

B. *PCA Based Face Recognition System*

In PCA based face recognition system, first of all face images are decomposed into small sets of featured images, that are actually the Principal Components or *Eigenfaces* of initial training set [19]. Then, all centred images are projected into face space by multiplying in Eigenface basis's. *Euclidean distance* between the projected test image and the projection of all cantered training images is calculated. Test image is supposed to have minimum distance with corresponding image in the training database. Figure 2 shows PCA based recognition system procedure.

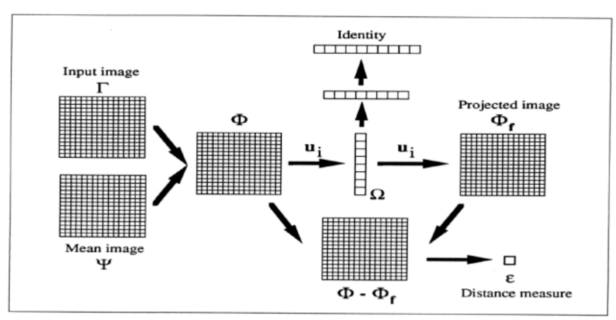


Figure. 2. PCA based face recognition procedure

TABLE I ADABOOST BASED FACE RECOGNITION SYSTEM

Input: A set of training images $Z = \{(\mathbf{z}_{ij}, y_{ij})\}_{j=1}^{L_i}$ with labels y_{ij} (=i) ϵ Y , where Y = {1,...., *C*}; a LDA-style learner; and the iteration number, *T*.
Let $B = \{(\mathbf{z}_{ij}, y): \mathbf{z}_{ij} \in Z, \mathbf{z}_{ij} \in R^{J}, y \in Y, y \neq y_{ij}\}$.

Initialize

$\gamma 1(zij, y) = \frac{1}{|B|} = \frac{1}{N(C-1)}$ the mislabel distribution over B.

(For simplicity, we denote the LDA-based feature extractor as a function ₤ (.), which has $(\psi_t, \{\bar{\mathbf{z}}_{i,t}\})_{i=1}^{C}$ = ₤ $(R_t, D^{\wedge}_t, A_t)$.

Do for $t = 1, \ldots.. T$:

1. Update the pseudo sample distribution: $D^{\wedge}_t(\gamma_t)$.
2. **If** $t = 1$ then
   randomly choose r samples per class to form a learning set $R_t \subset Z$.
   else choose r hardest samples per class based on $D^{\wedge}_t$ to form $R_t \subset Z$.
3. Train a LDA-style feature extractor with:
   ₤ $(R_t, D^{\wedge}_t, A_t)$ to obtain $(\psi_t, \{\mathbf{z}_{i,t}\})_{i=1}^{C}$).
4. Build a gClassifier $h_t = d(\psi_t, \{\bar{\mathbf{z}}_{i,t}\}_{i=1}^{C})$, apply it into the entire training set Z, and get back corresponding hypotheses,
   h_t: $R^{J} \times Y \rightarrow [0,1]$.
5. Calculate the pseudo-loss produced by h_t as: $\varepsilon^{\wedge}t = \sum_{(zij,y)\in B} \gamma_t(zij, y)\,(1 - h_t(zij, y) + h_t(zij, y))$
6. Set $ß_t = \epsilon^{\wedge}_t / (1 - \epsilon^{\wedge}_t)$. If $ß_t = 0$, then set $T = t - 1$ and abort loop.
7. Update the mislabel distribution: $\gamma_{t+1}(\mathbf{z}_{ij}, y) = \gamma_t(\mathbf{z}_{ij}, y) \,.\, ß_t^{(1+ht(zij,\, yij) - ht(zij,y))/2}$.
8. Normalize γ_{t+1} so that it is a distribution,
   $$\gamma_{t+1}(zij, y) \leftarrow \frac{\gamma_{t+1}(zij, y)}{\sum (zij, y) \in \beta)\gamma t + 1(zij, y)}$$

Output the final composite gClassifier,

$$h_f(\mathbf{z}) = \underset{y \in Y}{\operatorname{argmax}} \sum_{t=1}^{t=T} (\log \frac{1}{\beta_t}) h_t(z, y)$$

In PCA based system as the image is projected on to the face space, there are four possible options.

1) If input image is near face space and near face class, then the individual is recognized.
2) If input image is near face space, but not near known face class, then it is an unknown person.
3) If input image is distant from face space and near face class, then it is not a face image.
4) If input image is distant from face space and known face class, even then it is not a face image.

Table II summarizes the PCA based Face Recognition system.

One of the very distinguishing features of PCA based recognition system is its ability to learn and recognize new face images in unsupervised manner. More details about this system can be found in [20].

IV. Experimental Results

To perform the task of FR, AdaBoost based system uses *AdaBoost algorithm* with Linear Discriminant Analysis (LDA) for facial feature selection and Nearest Centre Classifier (NCC) for classification. The PCA based system uses *Principal Components* and *Eigen vectors* of covariance matrix of the set of the distributed faces treating each face image as vector in a high dimensional space and projecting face images on to a feature space spanning the Eigen vectors.

Both the systems are near real-time and fully capable of recognizing a person by comparing attributes of test face to known faces. Detailed experiments were performed to investigate the effect of pose and facial expression on each face recognition algorithm. Experiments were done in two phases. In phase I, *pose* was studied, while in phase II, *Low Resolution* (*LR*) images were analysed.

A. Pose Analysis

To analyse the pose, images from Pose Illumination Expression (PIE) database were utilised [21]. PIE database contains large variety of images of different subjects. Currently, PIE database has 750,000 facial images of 337 subjects collected up to four different poses in a span of 5 months. Key characteristics of PIE database is that subjects

TABLE II PCA BASED FACE RECOGNITION SYSTEM

1. Collect a set of characteristic face images of the known individuals. Set must have various number of face images of each person with variation in lighting and expressions. Let this set is M.
2. Calculate matrix of step 1, say it is L and find its eigenvectors and eigenvalues and choose M' eigenvectors with the highest associated eigenvalues.
3. Combine the normalized training set of images using equation
$$u\ell = \sum_{k=1}^{k=M} v lk \Phi k$$
This will produce eigenfaces $\mathbf{u}_k$.
4. For each known individual, calculate the class vector Ω_k by averaging the eigenface pattern vectors Ω using equation
$$\epsilon_k^2 = \|\Omega - \Omega_k\|^2$$
These are calculated from original set. Choose a threshold θ_ϵ which defines the maximum allowable distance from the eigenfaces according to equation
$$\epsilon^2 = \|\ \Phi - \Phi_f\|^2$$
5. To identify new face image, calculate its pattern vector Ω, the distance ϵ_i to each known class and the distance ϵ to the face space.
   If minimum distance $\epsilon_k < \theta_\epsilon$ and the distance $\epsilon < \theta_\epsilon$ classify the input face as the individual associated with the class vector Ω_k.
   else if minimum distance $\epsilon_k > \theta_\epsilon$ but distance $\epsilon < \theta_\epsilon$ then classify face as "unknown".
6. If the face is unknown, then image is added to original set of known faces and recalculate eigenfaces from step 1 to 4. It modifies face space and system knows more instances of known faces.

are imaged under 15 different view angles and 19 illumination conditions. Moreover, the database also contains frontal High Resolution (HR) images. Because of the large diversity in PIE database, we decided to use in our experiments. Figure 3 shows the four different facial pose images taken from PIE database. During experiments, size of the images was set to 200 x 200.

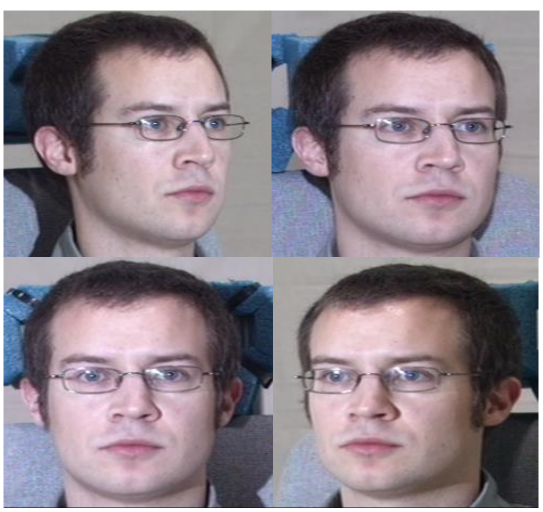


Figure. 3. Four different facial poses from PIE database

To start with recognition experiments 15 subjects, both males and females were chosen. Initially, 1 sample was used in gallery (Training), while four samples shown in Figure 3 were used as probe (Test). Table III gives classification results of 15 subjects of both genders from frontal up to $\pm 45^0$. In Table III, a tick (✓) shows correct classification/recognized face, while a cross (×) indicates an unrecognized face.

TABLE III
RECOGNITION RESULTS PCA VS ADABOOST

Subjects	Face Recognition System	Pose with Decision			
		Pose 1 ($+45^0$)	Pose 2 ($+30^0$)	Pose 3 (Frontal)	Pose 4 (-35^0)
1	PCA	✓	✓	✓	✓
	AdaBoost + LDA	×	×	✓	×
2	PCA	✓	✓	✓	✓
	AdaBoost + LDA	✓	×	✓	✓
3	PCA	✓	✓	✓	✓
	AdaBoost + LDA	✓	×	✓	×
4	PCA	✓	✓	✓	✓
	AdaBoost + LDA	×	×	✓	×
5	PCA	✓	✓	✓	✓
	AdaBoost + LDA	×	×	✓	✓
6	PCA	✓	✓	✓	✓
	AdaBoost + LDA	×	✓	✓	×
7	PCA	✓	✓	✓	✓
	AdaBoost + LDA	×	✓	✓	×
8	PCA	✓	✓	✓	✓
	AdaBoost + LDA	✓	×	✓	✓
9	PCA	✓	✓	✓	✓
	AdaBoost + LDA	×	×	✓	✓
10	PCA	✓	✓	✓	✓
	AdaBoost + LDA	×	×	✓	×
11	PCA	✓	✓	✓	✓
	AdaBoost + LDA	×	×	✓	×
12	PCA	✓	✓	✓	✓
	AdaBoost + LDA	×	×	✓	×
13	PCA	✓	✓	✓	✓
	AdaBoost + LDA	×	×	✓	×
14	PCA	✓	✓	✓	✓
	AdaBoost + LDA	×	×	✓	×
15	PCA	✓	✓	✓	✓
	AdaBoost + LDA	×	×	✓	×

Table IV summarizes the results to 760 subjects. Clearly, PCA based system outperforms AdaBoost in terms of pose variation, while both systems perform perfectly for frontal pose. The results obtained were verified up to image size of 200 x 200, 120 x 140, 80 x 80, 60 x 60, 50 x 50, and 30 x 30.

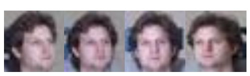
TABLE IV
SUMMARY OF RECOGNITION PCA VS ADABOOST

Subjects	Face Recognition System	Recognition Accuracy %			
		Pose 1 ($+45^0$)	Pose 2 ($+30^0$)	Pose 3 (Frontal)	Pose 4 (-35^0)
760	PCA	100	100	100	100
	AdaBoost + LDA	30	60	100	40

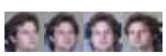
B. *Low Resolution* (*LR*) *Images Analysis*

In next phase of our experiments we focused on LR images to analyse the performance of each algorithm. During LR image analysis, we observed 100% FR accuracy on various image sizes, such as 40 x 40, 30 x 30, and 20 x 20 by PCA based FR system. The accuracy of AdaBoost based FR system varied according to Table IV. However, FR accuracy abruptly changed for PCA based FR system on face image size less than 20 x 20. Figure 4 shows LR face images of sizes 40 x 40, 30 x 30, 20 x 20, 10 x 10, and 5 x 5.

(a) Face images of size 40 x 40



(b) Face images of size 30 x 30



(c) Face images of size 20 x 20

(d) Face images of size 10 x 10

(e) Face images of size 5 x 5

Figure. 4. Low resolution facial images of various sizes

Figure 5 shows the recognition performance of four poses of both systems for face size of 10 x 10. As can be seen from Figure 5, that AdaBoost based FR system comprehensively outperforms the PCA based FR for a sample size of 10 x 10. Figure 6 depicts the recognition performance for said poses for extremely small face size, such as 5 x 5. Clearly, from Figure 5 and 6, one notable feature is that AdaBoost based recognition systems has 100% accuracy for frontal facial image of size of 10 x 10 and for a challenging face sample size of 5 x 5.

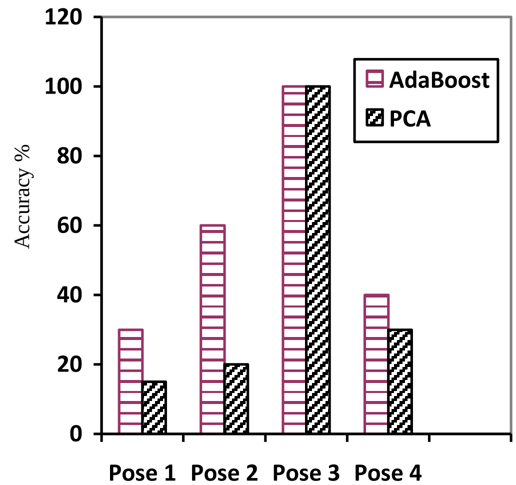


Figure. 5. Recognition Accuracy of Face Size 10 x 10

In normal circumstances, even a human eye is unable to recognize a small size as 5 x 5. Therefore, an interesting finding of our work is that AdaBoost based FR system surpasses PCA based system on LR images.

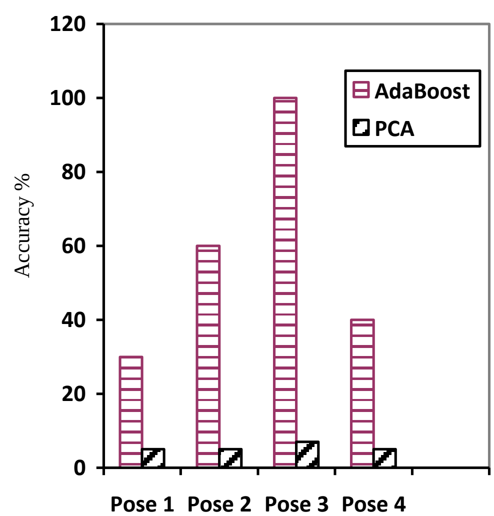


Figure. 6. Recognition Accuracy of Face Size 5 x 5

V. CONCLUSIONS

In this paper we presented a comparative study of two well-known face recognition algorithms. Face recognition algorithms studied in this work are Principal Component

Analysis (PCA) and AdaBoost with Linear Discriminant Analysis (LDA) as a weak learner. Main task of the work was to explore the robustness of each face recognition algorithm with respect to various factors, such as pose and low resolution of the images used for recognition. Images from PIE database were used for evaluation. For face size of 200 x 200 up to 30 x 30 PCA based system was found to be more accurate in classifying the four poses, while for low resolution images of size 10 x 10 and 5 x 5, AdaBoost based system surpassed the PCA. For frontal face, AdaBoost based system have 100% accuracy in classifying face image from non-face sample for size of 10 x 10 and 5 x 5. A huge number of potential applications need completely reliable FR system [22], [24], and [25]. Therefore, the FR technology has to mature more to be deployed more in common practice.

A general trend in the researchers is to focus on one aspect, such as occlusion or illumination and they try to optimize algorithm accordingly. This is in fact a useful strategy, as in most cases the complete scenario of the system is known. The ultimate target of researchers in FR area is to develop an automated FR system that can imitate the Human Vision System (HVS). To reach this objective, mutual, coordinated, and consistent efforts are required among the computer vision researchers, neuroscientists, and psychophysicists.

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