International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:8, No:9, 2014

Quantitative Analysis of PCA, ICA, LDA and SVM in Face Recognition

Liton Jude Rozario, Mohammad Reduanul Haque, Md. Ziarul Islam, Mohammad Shorif Uddin

***Abstract*—**Face recognition is a technique to automatically identify or verify individuals. It receives great attention in identification, authentication, security and many more applications. Diverse methods had been proposed for this purpose and also a lot of comparative studies were performed. However, researchers could not reach unified conclusion. In this paper, we are reporting an extensive quantitative accuracy analysis of four most widely used face recognition algorithms: Principal Component Analysis (PCA), Independent Component Analysis (ICA), Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM) using AT&T, Sheffield and Bangladeshi people face databases under diverse situations such as illumination, alignment and pose variations.

***Keywords*—**PCA, ICA, LDA, SVM, face recognition, noise.

I. Introduction

IDENTIFICATION of human from face images is very necessary as it is very easy to convey identity and emotion. Still human identification is not completely perfect in various situations such as scale, orientation, illumination, emotion, and noise variations [1]. A good number of methods had been proposed for this purpose and also a lot of comparative studies were performed by the researchers to evaluate the best algorithm for recognition [2]-[8]. But it is interesting that there are often contradictory and confusing claims being made in these comparisons. For example, Bartlett et al [9] and Liu et al. [10] state that Independent Component Analysis **(**ICA) outperforms Principal Component Analysis (PCA), while Baek et al. [11] state that PCA is better. But Moghaddam [12] states that there is no significant difference. Beveridge et al. [13] states that Linear Discriminant Analysis (LDA) performed worse than PCA, Martinez [14] states that LDA is better for some tasks, Belhumeur et al. [15] and Navarrete et al. [8] state that LDA outperforms PCA. Becker et al [16] states that Support Vector Machine (SVM) performs well compared to above-mentioned algorithms. All these conclusions hold a good degree of truth, but different factors surrounding each conclusion i.e. the actual task statement, the subspace distance metrics, dimensionality retention and the non-standardized database choices etc. Hence these produced too much debate and confusion over the years, particularly for an individual who is new in the field of face or object recognition and who seeks a good comparative understanding of the available techniques. This paper tries to remove these contradictions through an extensive experimentation. Four most widely used methods such as PCA, ICA, LDA, SVM are taken into consideration.

The remainder of the paper is organized as follows. The recognition methodologies are described in Section II. Section III contains the experimental results and discussions. Finally conclusions are drawn in Section IV.

Liton Jude Rozario, Mohammad Reduanul Haque, Md. Ziarul Islam and Mohammad Shorif Uddin are with the Department of Computer Science and Engineering, Jahangirnagar University, Dhaka, Bangladesh (e-mail: litonjrozario@yahoo.com, reduanulhaque@gmail.com, zia08cse@gmail.com, shorifuddin@gmail.com).

II. Recognition Methods

A generic schematic flow diagram of a face recognition algorithm is shown in Fig. 1.

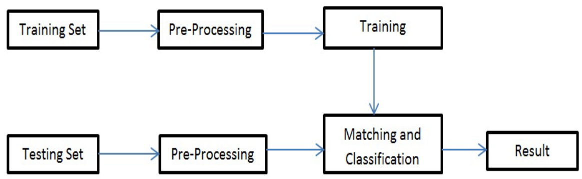


Fig. 1 Schematic diagram of face recognition

A brief explanation of the investigated face recognition algorithms is given below.

A. Principal Component Analysis (PCA)

PCA [8] is one of the oldest face recognition methods. It finds t-dimensional subspace from an n-dimensional vector of each face in a training set of M images, where t < n. The dimensionality reduction is based on the basis vectors correspond to the maximum variance direction in the original image space. All the images of known (training) faces are projected onto the face space to find a set of weights that describes the contribution of each vector. To identify an unknown (test) face, it is projected onto the face space to obtain its set of weights. By comparing set of weights for the unknown face to set of weights of known face, the face is identified. The PCA basis vectors are defined as eigenvectors of the scatter matrix S_T defined as:

$$S_T = \sum_{k=0}^{M} (x_i - \mu)(x_i - \mu)^T \quad (1)$$

where μ is the mean of all faces of the training set and x_i is the *i*-th face.

B. Independent Component Analysis (ICA)

Independent component analysis [9] is a technique to find a linear transform for the input data using a basis as statistically independent as possible. Hence, ICA can be considered as a special case of PCA.

C. Linear Discriminant Analysis (LDA)

LDA [17], [18] is a method that works on the basis of Fisher criterion. It finds the vectors that best discriminate among classes. For all samples and classes, let S_B is the between class scatter matrix and S_W is the within class scatter matrix. The goal is to maximize S_B while minimizing S_W, in other words, maximize the ratio $\det|S_B|/\det|S_W|$.

D. Support Vector Machine (SVM)

SVM [19] is mainly a linear machine terms as discriminative classifier consisting of two separated classes. However, it can be extended to multiclass separation. In this paper, we are using a multiclass SVM that works on the basis of total face. Given a group of labeled training data the algorithm outputs an optimal hyperplane, which categorizes new examples.

III. Experimental Results and Discussions

For our experiment, we used three databases; the Sheffield Face Database [20], AT&T Database [21] and a face database (developed by us) including 20 different Bangladeshi people under various illuminations, poses and alignments.

The Sheffield (previously UMIST) Face Database consists of 564 images of 20 individuals (with multiple images of each person under different races, appearances, illuminations and alignments). The images are of size 220 × 220 pixels. AT&T database consists of 400 images of 40 individuals with 10 images of each person under distinct subjects. For some subjects, the images were taken at multiple times, varying the lighting, facial expressions (open / closed eyes, smiling / not smiling) and facial details (glasses / no glasses). All the images were taken against a dark homogeneous background with an upright frontal position.

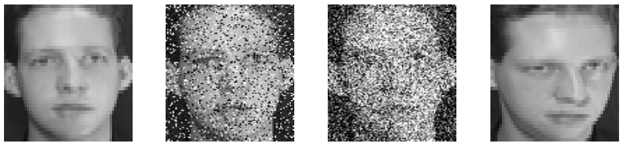
In Bangladeshi people face database, there are 200 different images of 20 distinct people with 10 images of each person under varying illumination, alignment and pose. These images are manually cropped and preprocessed.

Figs. 2-4 are the images of a person from different database.

Fig. 2 Images of a person under different illumination, alignment and pose from the AT&T database

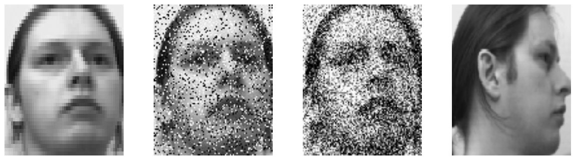
Fig. 3 Images of a person under different illumination, alignment and pose from the Sheffield database

Fig. 4 Images of a person under different illumination, alignment and pose from the Bangladeshi people face database



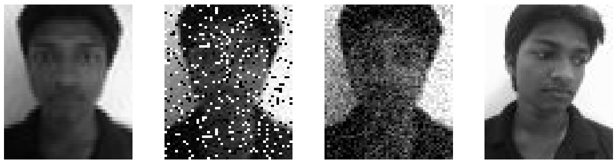
(a) (b) (c) (d)

Fig. 5 Face images under diverse situations in AT&T database: (a) original face image; (b) corrupted face image by Salt & Pepper noise with density, d = 0.2; (c) corrupted face image by Gaussian noise with mean = 0 and variance, v = 0.1; (d) Face image with 30° rotation



(a) (b) (c) (d)

Fig. 6 Face images under diverse situations in Sheffield database: (a) original face image; (b) corrupted face image by Salt & Pepper noise with density, v = 0.2; (c) corrupted face image by Gaussian noise with mean = 0 and variance, v = 0.1; (d) face image with 90° rotation



(a) (b) (c) (d)

Fig. 7 Face images under diverse situations in Bangladeshi people database: (a) original face image; (b) corrupted face image by Salt & Pepper noise with density, d = 0.2; (c) corrupted face image by Gaussian noise with mean = 0 and variance, v = 0.01; (d) face image with 45° rotation

It is observed that recognition rate of the Sheffield database is higher as compared to AT&T and Bangladeshi people database.

Table I shows the comparative performance of PCA, ICA, LDA and SVM methods for rotated (both clockwise and anti-clockwise) images. This comparative result confirms that SVM matches for more degrees than PCA, ICA and LDA.

TABLE I
RECOGNITION UNDER DIFFERENT ROTATIONAL SITUATIONS

Database	**Recognized for maximum rotation by**			
	PCA	***ICA***	***LDA***	***SVM***
AT&T, Sheffield, Bangladeshi People	1°	1°	5°	25°

Table II presents the comparative performance of PCA, ICA, LDA and SVM methods for images with Salt and Pepper noise. This comparative result confirms that LDA and SVM performs better (on the basis of noise density) than PCA and ICA. Table III shows the similar result for Gaussian noise and it confirms that LDA performs better (on the basis of noise variance) than PCA and ICA. However, SVM exhibits the best performance.

TABLE II
RECOGNITION UNDER NOISY SITUATIONS (FOR SALT AND PEPPER NOISE WITH DENSITY, d)

Database	**Recognized by**			
	PCA	***ICA***	***LDA***	***SVM***
AT&T, Sheffield, Bangladeshi People	$d < 0.01$	$d < 0.01$	$d < 0.6$	$d < 0.6$

TABLE III
RECOGNITION UNDER NOISY SITUATIONS (FOR GAUSSIAN NOISE WITH MEAN=0 AND VARIANCE, v)

Database	**Recognized by**			
	PCA	***ICA***	***LDA***	***SVM***
AT&T, Sheffield, Bangladeshi People	$v < 0.01$	$v < 0.01$	$v < 0.3$	$v < 0.4$

TABLE IV
RECOGNITION (WITHOUT ANY CONTRAST STRETCHING) UNDER DIFFERENT ILLUMINATIONS

Database	**Recognized by**			
	PCA	***ICA***	***LDA***	***SVM***
AT&T, Sheffield, Bangladeshi People	Average intensity $I_{avg} > 140$		Average intensity $I_{avg} > 65$	

Table IV shows the recognition result under different illuminations. LDA and SVM perform better compared to PCA and ICA for darker images. Table V presents the overall recognition accuracy for different methods. In finding the overall recognition accuracy, illumination variation is compensated using selective histogram equalization (for average intensity values mentioned in Table IV) approach. It confirms that SVM outperforms PCA, ICA and LDA. Some visual data are shown in Figs. 8 and 9.

The methods have been implemented with Matlab (R2009a) using an Intel Core i5 processor with 4 GB RAM in Windows 8.1 platform. Processing time depends on number of images (along with image resolution) in the database and recognition accuracy depends on image quality and variations of illumination, alignment, noise and pose.

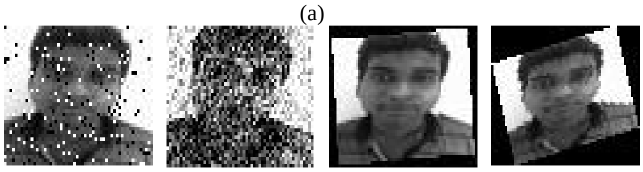
IV. CONCLUSION

In this paper a quantitative analysis of PCA, ICA, LDA and SVM is performed. From the experimental results, we have found that this analysis is significant for developing new robust algorithms for face recognition. The experimental results show that SVM gives better accuracy (i.e. most robust) in comparison with other face recognition algorithms in terms of diverse illumination, alignment, noise and pose situations.

TABLE V
RECOGNITION ACCURACY USING DIFFERENT DATABASES

Database	**PCA**	**ICA**	**LDA**	**SVM**
AT&T	90.33 %	91.12 %	95.43 %	98.55 %
Sheffield	92.43 %	92.88 %	96.87 %	99.02 %
Bangladeshi People	91.03 %	91.33 %	96.24 %	98.89 %

(a)



(b) (c) (d) (e)
*Images are taken from Bangladeshi people face database

Fig. 8 Images of a person under different noise levels and rotational variations: (a) original image; (b) corrupted image by Salt & Pepper noise with density, d = 0.1 (SVM and LDA recognized this face correctly, but PCA and ICA failed.); (c) corrupted image by Gaussian noise with mean = 0 and variance, v = 0.1 (SVM and LDA recognized this face correctly, but PCA and ICA failed.); (d) image with 4° rotation (SVM and LDA recognized this face correctly, but PCA an ICA failed.); (h) image with 15° rotation (SVM recognized this face correctly, but PCA, ICA and LDA failed.)

(a) (b) (c)
*Images are taken from AT&T face database

Fig. 9 Images of a person under varying pose: (a) original image; (b) test image (SVM and LDA recognized this face correctly, but PCA and ICA failed as facial expression is close to the original image.); (c) test image (none of PCA, ICA, LDA and SVM recognized this face as facial expression is too different from the original image.)

REFERENCES

[1] Toygar Onsen and Acan Adnan (2003): Face recognition using PCA, LDA and ICA approaches on colored images, Journal of electrical and Electronics Engineering vol. 3, No. 1, 735 – 743. J. Clerk Maxwell, A Treatise on Electricity and Magnetism, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp. 68-73.

[2] Belhumeur P. N., Hespanha J. P. and Kriegman D. J (1997): Eigenfaces vs. Fisherfaces: Recognition Using Class Specific Linear Projection," in IEEE TPAMI. vol. 19, pp. 711-720.K.

[3] Becker B.C. and Ortiz E.G. (2008): Evaluation of Face Recognition Techniques for Application Facebook, in Proceedings of the 8th IEEE International Automatic Face and Gesture, 14 (2008), Carnegie Mellon Univ., Pittsburgh, PA, pp. 1-6.

[4] Delac K., Grgic M., Grgic S. (2002): Independent Comparative Study of PCA, ICA, and LDA on the FERET Data Set, International Journal of Imaging.

[5] Martinez A.M., Kak A.C. (2001): PCA versus LDA, IEEE Trans. Patt. Anal. Mach. Intell. 23 (2) 228–233.6. Mazanec Jan and et al. (2008): Support Vector Machines, PCA and LDA in face recognition, Journal of Electrical engineering, vol. 59, No. 4, pp. 203–209.

[6] Mazanec Jan and et al. (2008): Support Vector Machines, PCA and LDA in face recognition, Journal of Electrical engineering , vol. 59, No. 4, pp. 203–209.

[7] Turk M. A. and Pentland A. P. (1991): Face Recognition Using Eigenfaces, IEEE CVPR 1991, pp. 586-591.

[8] Turk M., Pentland A. (1991): Eigenfaces for Recognition, Journal of Cognitive Neuroscience, Vol. 3, No. 1, 1991, pp. 71-86.

[9] Bartlett M.S., Movellan J.R., and Sejnowski T.J. (2002): Face Recognition by Independent Component Analysis, IEEE Trans. on Neural Networks, Vol. 13, pp. 1450-1464.
[10] Liu C. and Wechsler H. (1999): Comparative Assessment of Independent Component Analysis (ICA) for Face Recognition, Second International Conference on Audio and Videobased Biometric Person Authentication, AVBPA'99,Washington D. C., USA, March 22-24.
[11] Baek K., Draper B., Beveridge J.R. and She K. (2002): PCA vs. ICA: A Comparison on the FERET Data Set, Proc. of the Fourth International Conference on Computer Vision, Pattern Recognition and Image Processing, pp. 824-827.
[12] Moghaddam B. (2002): Principal Manifolds and Probabilistic Subspaces for Visual Recognition, IEEE Trans. on Pattern Analysis and Machine Intelligence, Vol. 24, pp. 780-788,.
[13] Beveridge J.R., She K., Draper B., and Givens G.H. (2001): A Nonparametric Statistical Comparison of PrincipalComponent and Linear Discriminant Subspaces for Face Recognition, Proceeding of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 535-542.
[14] Martinez A.M. and Kak A.C (2001): PCA versus LDA, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 23, pp. 228-233.
[15] Belhumeur V., Hespanha J., and Kriegman D. (1997): Eigenfaces vs. Fisherfaces: Recognition using class specific linear projection, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 19, pp. 711-720.
[16] Navarrete P. and Ruiz-del-Solar J. (2002): Analysis and Comparison of Eigenspace-Based Face Recognition Approaches, International Journal of Pattern Recognition and Artificial Intelligence, Vol. 16, pp. 817-830.
[17] Belhumeur P., Hespanha J., Kriegman D. (1996): Eigenfaces vs. Fisherfaces: Recognition Using Class Specific Linear Projection, Proc. of the Fourth European Conference on Computer Vision, Vol. 1, 14-18 April 1996, Cambridge, UK, pp. 45-58.
[18] Zhao W., Chellappa R., Krishnaswamy A. (1998): Discriminant Analysis of Principal Components for Face Recognition, Proc. of the 3rd IEEE International Conference on Automatic Face and Gesture Recognition, 14-16 April 1998, Nara, Japan, pp. 336-341.
[19] Cortes C. and Vapnik V. (1995): Support-vector networks, Machine Learning, Vol. 20, No. 3, pp. 273.
[20] Sheffield Face Database, available online: http://www.sheffield.ac.uk/eee/research/iel/research/face
[21] AT&T Face Database, available online: http://www.cl.cam.ac.uk/Research/DTG/attarchive:pub/data/att_faces.zp