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Keywords (separated by '-')	ICA - Architecture-I - Architecture-II - Performance evaluation - Analysis

Analysis and Performance Evaluation of ICA-based Architectures for Face Recognition

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1 Introduction

In image analysis and understanding, face recognition have been a challenging and quite attractive key area of research. It is usually used in security systems and can be compared to other biometrics such as eye iris recognitions or fingerprint. The recognition task has been done by selecting proper subspace projection to get facial features followed by classification in the space of compressed features. There are varieties of techniques employed for selecting subspace projection which projects consider face images as the points in high-dimensional spaces and reduce the dimension to find a more meaningful description. The central issue is how to determine and define image appearance in a high-dimensional image space to a low-dimensional subspace. The most noticeable method in this category is Principle Component Analysis (PCA) [14], which is concerned only second-order dependencies between variables. For past one and half decades, a generalized method of PCA, Independent Component Analysis (ICA) has received spacious notice. ICA technique is a relatively new invention which has been mainly used to Blind Signal Separation (BSS), though it has been successfully applied to the face recognition problem too [5]. ICA is concerned with high-order dependencies between variables in addition to the

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second order. PCA makes the data uncorrelated while ICA makes the data uncorrelated as well as unit variance i.e. as independent as possible. There are at least two benefits for face recognition using ICA: first, the high order dependencies among data may contain more information that is useful for face recognition than the second-order statistic representations. Secondly, ICA finds the directions such that the projection of the data into those directions has maximally "non-Gaussian" distributions.

2 Literature Review

The literature review of ICA on the subject is very contradictory. Bartlett et al. [1] were among the first to apply ICA to face identification task. They have used the Infomax algorithm [9] to employ ICA and recommended two ICA based architectures. Both architectures were evaluated on a subset of the FERET database along with PCA, and claims that the two ICA based architectures were equally powerful and both outperformed the PCA. Liu and Wechsler [11] also used FERET database to study the comparative assessment of ICA performance through Comon [4] ICA algorithm, and claims ICA outperform PCA. Guo et al. [8] also present the process of facial expression recognition based on ICA model. Their experimental results have shown that ICA is a more effective facial expression recognition method than that based on PCA and 2DPCA. Kishor et al. [10] proposed a new face recognition technique based on Independent Component Analysis of GaborJet (GaborJet-ICA). They transformed this GaborJet feature vector into the basis space of PCA, and prove that the difference in performance is insignificant between GaborJet-ICA and GaborJet-PCA. While other researchers reported differently. Socolinsky et al. [15] has reported that ICA performs better in case of visible images, and PCA performs better in case of infrared images. Draper et al. [6] again tested ICA architectures and PCA on the FERET database to come out from these conflicting results. The analysis has shown that ICA architecture-II provides the best results, followed by PCA with L1 or Mahalanobis distance metrics. Recommends the FastICA algorithm for ICA architecture-II, although the difference between FastICA and Infomax is not large. In recognizing facial actions, the recommendation is reversed: found the best result using Infomax to implement ICA architecture-I. Jian Yang et al. [18] also re-evaluated ICA architectures and PCA on the FERET, ORL, AR face databases, and claims as similar to Drapper et al. [6]. They construct two PCA baseline algorithms to re-evaluate ICA-based architectures, but observed no significant performance difference between ICA-I (II) and PCA-I (II).

The performance analyses of the two ICA architectures depended on the property of "intra feature correlation" and "inter feature correlation" of the feature vector of face images. The term "intra feature correlation" refers to the relationship of a feature vector with itself, and the term "inter feature correlation" refers to the relationship of a feature vector with other feature vectors. The relationship within the intra feature vectors should be very strong i.e. variance is one, and the relationship between the inter feature vectors should be poor i.e.

uncorrelated. The poor inter feature relationship decreases the correlation value making it more independent (as a contribution part) which gives better accuracy rate in classification of face images in a small dataset. From the several literature reviews, it has also been observed that many authors evaluated ICA according to some criteria, for example image pre-processing, ICA pre-processing steps, effect of different ICA algorithms, distance metrics, different types of images, and so on. As a consequence, it has been complicated to predict the best ICA architectures for a particular domain. So an analysis is carried out on feature vectors based on the correlation coefficient property, and it is found that Architecture-II is more potential than Architecture-I for performance analysis of face feature vectors.

3 Independent Component Analysis (ICA) and Its Two Architectures

Basically ICA is a method for extracting statistically independent components from a mixture of them [3]. The performance of ICA varies on the databases, the number of images, and the number of subspace dimensions reduced. Typically, the performance depends even more on the two ICA-based architectures of face representations namely Architecture-I and Architecture-II.

3.1 Architecture-I: Statistically Independent Basis Faces

In this architecture, ICA can be represented to treat face images as random variables and pixels are trials for the variables [2]. The approach illustrated in Fig. 1. Organizes each face image in the database as a lengthy vector with size of dimensions in the image, into a matrix X where each row vector is a different image. It makes sense to talk about independence of images. The ICA algorithms learn the weight matrix W, which is then projected onto the input images X to produce the independent basis images in the rows of S.

To illustrate the mathematical basis for Architecture-I, the following steps have been described. In the first step, form an image data matrix $X_{N\times M} = [x_1, x_2, ..., x_N]^T$ of a given set of N training samples $x_1, x_2, ..., x_N$ in R^M. Then center the data matrix X in a trail space R^M by subtracting the mean vector μ^I from each trail, and get the centered matrix $\bar{X}_{N\times M}$. In step 3, whiten the centered data matrix using PCA elements $U_{m\times m}$ and $V_{N\times m}$, and obtain the whitening matrix as

$$H_{N\times m} = VU^{-\frac{1}{2}} \tag{1}$$

Where U is the diagonal matrix of m largest positive eigenvalues, and V is a matrix of orthonormal eigenvectors of corresponding m largest positive eigenvalues. PCA enhances the performance of ICA by throwing away small-negative eigenvalues before whitening, and reduce computational complexity by minimizing pair-wise dependencies. So the data matrix $\bar{X}$ can be whitened using the transformation

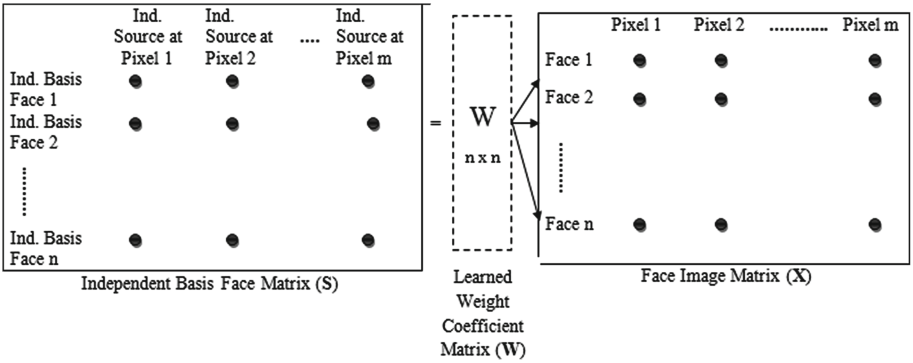


Fig. 1. Block diagram of finding statistically independent basis images.

$$\tilde{X}_{m\times M} = H^T\bar{X} \quad (2)$$

The main purpose of whitening is to make its components as uncorrelated and unit variances, such that $E\{\tilde{X}\tilde{X}^T\} = I$ [9]. Fourth, process the ICA on $\tilde{X}$ whitened matrix to generate a square learned weight matrix $W^I_{m\times m}$ by a given ICA algorithm. As a fifth step, produce the space S^I with m independent basis images in its rows by projecting weight matrix onto the centered whitened matrix as

$$S^I_{m\times M} = W^I\tilde{X} \quad (3)$$

At last, the compressed representation of images i.e. feature vectors space X^f of face image matrix X is given by

$$X^f_{N\times m} = \bar{X}(S^I)^T \quad (4)$$

Each row of X^f that represents the feature vectors, is used to represent the image matrix X for recognition purposes.

3.2 Architecture-II: Statistically Independent Coefficients

According to ICA definition, the coefficient matrix should be orthogonal. But in practice, it might be non-orthogonal. Apart from FastICA, many ICA algorithms such as Infomax, Comons give results in a non-orthogonal coefficient matrix [19]. So the basis images obtained in Architecture-I are statistically independent, but the coefficient matrix that represents input face images in the subspace defined by the basis face images is not statistically independent. Conversely, in Architecture-II, ICA is used to find a set of statistically independent coefficients to represent a face image and the resulting basis images may be statistically dependent. So the input face data matrix X is transposed from Architecture-I i.e. the pixels are variables and the images are trails [2], as shown in Fig. 2.

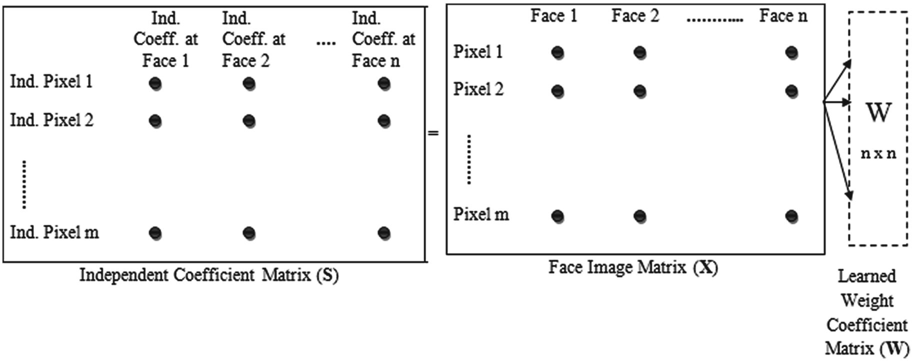


Fig. 2. Block diagram of finding statistically independent coefficients.

Now, each row of the learned weight coefficient matrix W is the basis images, and the statistically independent coefficients that comprise the input images are recovered in the columns of S. It makes sense to talk about independence of pixels.

The illustration of the mathematical basis for Architecture-II is roughly analogous to Architecture-I except (i) starting image data matrix will be in the form of transpose of $X_{N\times M}$, say $Y_{M\times N} = [y_1, y_2, ..., y_N]$, (ii) Architecture-I centering the data matrix by removing the mean of each image, and Architecture-II centering the data matrix by removing the mean image of all image samples. In this architecture, the independent coefficients are recovered in the columns of S^{II} as

$$S^{II}_{m\times M} = W^{II} H^T \tag{5}$$

Each column of Y^f that represents the feature vectors is given by

$$Y^{f}_{m\times N} = S^{II} \bar{Y} \tag{6}$$

4 System Overview

Figure 3 shows a block diagram of a generic human face analysis model for ICA. In image pre-processing stage, the database face images are manually cropped, resized, and finally the histogram equalization for image enhancement is processed. In the second stage, the two most important pre-processing steps that are centering and whitening to simplify and minimize the complexity of the problem for the actual ICA algorithms are carried out. While PCA is used to reduce the dimensions. Then the ICA algorithms for maximizing non-gaussianity as a measure of statistical independence are applied. In the fourth stage, the feature vectors of all the database images are extracted by projecting onto independent source outputs of ICA algorithms. At last, classification of the extracted features has been done using support vector machines, and the accuracy estimated.

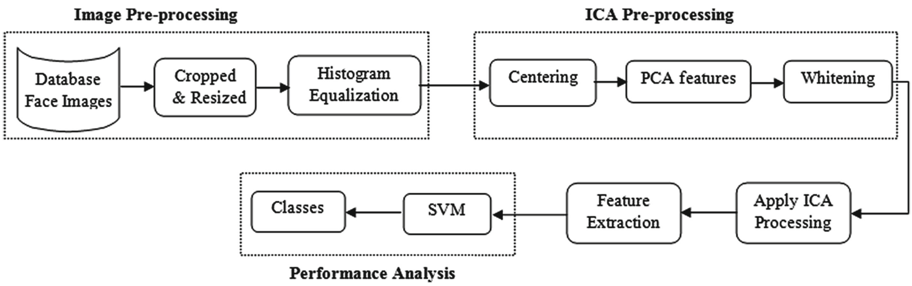


Fig. 3. Block diagram of ICA based feature extraction and classification.

5 Analysis

The analysis has been done in two steps. First, a statistical estimation has been carried out on the feature vectors, and secondly, a performance evaluation over the several databases has been conceded against different factors.

5.1 Numerical Analysis of Feature Vectors of Both Architectures

Table 1 represents some column feature vectors (FV 1 to FV 4) of dimension 15×1 taken from both architectures. In the case of intra feature vector analysis, it has been observed that the variations between the values of the feature vector (say, FV 1 column vector itself) of Architecture-I are very large than the variations of Architecture-II. Similarly it is tough to measure the correlation property of the intra feature vector analysis. Therefore, in Table 2, the values of correlation coefficient of intra and inter feature vectors are reported. In Table 2, rows 1, 5, 8, 10 show the correlation coefficient values of intra feature vectors from both architectures which give us the variance values of 1 indicating a very strong relationships. In the case of inter feature vector analysis, it has also been observed the similar variations (like values within the intra feature vectors) between the values of the feature vectors (FV1-FV2, FV1-FV3, FV1-FV4, FV2-FV3, FV2-FV4, FV3-FV4) from both architectures. For example, the data have been plotted between the feature vector of 1 and 4 in Fig. 4. Although the values between the feature vectors of Architecture-I contain large variation which is shown in Fig. 4a indicating that the points are scattered along the regression line and closer except one single point which indicates a stronger correlation. In Fig. 4b, some points are close enough towards regression line while rest of data points scattered in a wider band from regression line. The correlation coefficient value of 0.010 in Fig. 4b is showing a very weaker positive correlations in Architecture-II, where value of 0.074 in Fig. 4a is showing a comparably stronger positive relationship in case of Architecture-I. Other comparative inter correlation coefficient results between the feature vectors listed in Table 2. From rows 2, 3, 4, 6, 7, 9 it has been noticed that the correlation coefficient values of Architecture-II are less than Architecture-I. In case of Architecture-II, some coefficient values (row

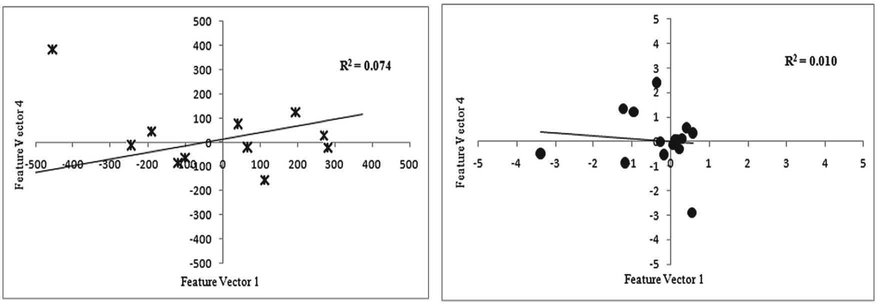
Table 1. Some (*feature vectors*) from both architectures. FV indicates Feature Vectors.

Architecture-I				Architecture-II			
FV 1	FV 2	FV 3	FV 4	FV 1	FV 2	FV 3	FV 4
373.926	313.148	855.538	827.955	0.297	0.119	0.340	0.121
280.486	−14.316	253.632	−19.910	0.174	−0.521	−0.133	0.088
38.602	55.394	6.900	75.637	0.0687	−0.145	−0.0202	−0.151
−246.216	−301.438	250.502	−12.590	−1.180	−0.919	0.173	−0.885
−119.288	−50.0679	−96.324	−81.723	−1.224	−0.813	0.714	1.332
−568.983	−471.674	−332.363	−355.828	−0.950	−0.780	1.177	1.211
269.229	397.313	147.475	33.0255	0.116	−0.350	0.945	0.0500
−456.105	−440.801	361.348	386.277	−3.387	−4.0462	0.1225	−0.506
−192.065	−43.943	−184.124	47.544	0.424	−0.140	0.219	0.558
194.332	134.580	7.094	128.992	−0.173	0.0621	−0.980	−0.550
110.288	51.262	−39.467	−152.434	0.551	−0.438	−1.160	−2.915
−100.337	−130.741	017.498	−59.829	0.571	−0.594	0.676	0.350
−600.982	−727.88	−262.249	−245.191	−0.358	0.370	1.860	2.397
243.287	32.925	−405.614	−536.619	−0.274	0.654	0.350	−0.0311
66.1689	10.324	−14.044	−20.276	0.232	−0.264	−0.892	−0.300

Table 2. Comparisons of the one feature vector with other feature vectors corresponding to Table 1

Sl. No.	FV	FV	Correlation type	Correlation coefficient value (R^2) of Architecture-I	Correlation coefficient value (R^2) of Architecture-II
1	FV 1	FV 1	intra	1	1
2	FV 1	FV 2	inter	0.908	0.684
3	FV 1	FV 3	inter	0.101	0.035
4	FV 1	FV 4	inter	0.074	0.010
5	FV 2	FV 2	intra	1	1
6	FV 2	FV 3	inter	0.113	0.002
7	FV 2	FV 4	inter	0.111	0.031
8	FV 3	FV 3	intra	1	1
9	FV 3	FV 4	inter	0.865	0.673
10	FV 4	FV 4	intra	1	1

4 and 6) of inter feature vectors are close to zero (0.010 and 0.002 respectively). Therefore, it has been found that Architecture-II has a better independedness property through correlation coefficient than Architecture-I which may lead better classification performance.



(a) (b)

Fig. 4. Correlation between two feature vectors [1 and 4] from (a) Architecture-I, (b) Architecture-II.

5.2 Performance Analysis of ICA Architectures

In this section, the experiments of ICA based two architectures are performed using four face databases: the FERET, ORL, CVL, and YALE databases. From these databases, experiments have done in frontal faces with different expressions, and illuminations.

Database Organization: The FERET [13] has total five probe sets of frontal (pose angle of zero degree) images namely fa, fb, ba, bj, bk. The number of subjects of "f" series does not match with the subjects of "b"series. So, for experiment analysis only "b"series has been taken where each of the 200 subjects has 3 images belonging to probe sets ba, bj, bk respectively. Probe set ba consists of 200 images of 200 subjects, and also set bj, bk consists of 200 images of 200 subjects each. The ORL database [17] consists of 10 different images of each of 40 distinct subjects. For experiments, only 3 frontal position images have been taken from each of the 40 subjects of varying lighting and facial expressions, and these 3 images are put to the manual sets namely set 1, set 2, set 3 backed by the idea to keep same number of images of each subject and same number of sets from several databases for the comparative study. Another face database called FRI CVL [16] consists of 7 different images of 114 number of unique people consists of 108 male and 6 female. The images were taken at different conditions: profile left/right, 45 degrees left/right, frontal, frontal smile, and frontal smile with teeth. As for comparative study, 3 frontal images are taken to the manual sets: set 1 consists of frontal smile images, set 2 consists of frontal smile with teeth, and set 3 consists of only frontal images. In the same way, the Yale database [7] is also prepared.

The purpose of the experiments is to compare the performance of two ICA based architectures for face recognition. To observe the recognition performance, 3 training sample set has been prepared and the recognition rate of each samples averaged. All these training samples are shows in Table 3. In training sample 1,

Table 3. Image sets used for training and testing.

Training sample	Condition		Description of sets	
	Training set	Testing set		
Sample 1	Set 1 and Set 2	Set 3	Set 1	Frontal regular facial expression. In FERET database, set 1 is indicated by ba
Sample 2	Set 2 and Set 3	Set 1	Set 2	Alternative facial expression to set 1. In FERET database, set 2 is indicated by bj
Sample 3	Set 3 and Set 1	Set 2	Set 3	This also contains frontal image taken under different lighting. In FERET database, set 3 is indicated by bj

the set 1/ba and set 2/bj are used for training purpose, and set 3/bk has been used for testing purpose. Similarly in training sample 2, the set 2/bj and set 3/bk are used for training purpose, and set 1/ba has been used for testing purpose. In training sample 3, the set 3/bk and set 1/ba are used for training purpose, and set 2/bj has been used for testing purpose.

Experiments: In the experiments, the face portion of each original image is manually cropped and resized to an image of 60 × 70 resolutions using bilinear interpolation. The resulting image is then pre-processed using histogram equalization method. Figure 5 shows some sample images after pre-processing.

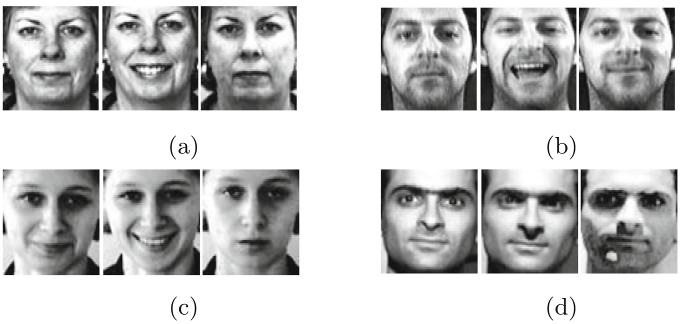
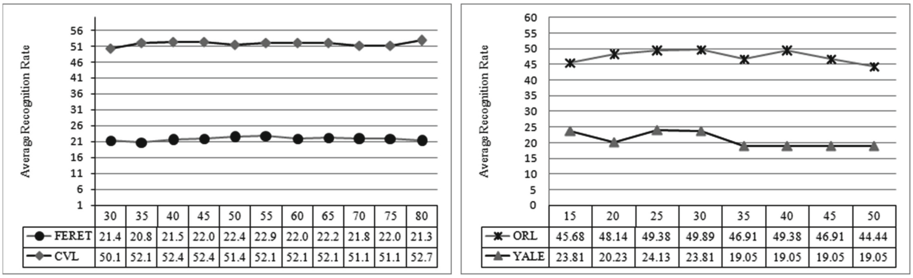


Fig. 5. Sample images of one subject from the (a) FERET (b) ORL (c) CVL (d) YALE databases.

Based on the first investigation, the assumption is that Architecture-II will produce better result than Architecture-I. In this correspondence, there are three



(a) (b)

Fig. 6. Recognition rate (*Average*) of architecture I against number of (*Principle Components (PCs)*) over (*(a) FERET, CVL (b) ORL, YALE*) databases.

experimental analyses have been done. Experiment 1 concerned on keeping same number of subjects and same number of independent components for each database, where experiment 2 is involved in keeping different number of subjects and same number of independent components. Liu [12] has shown that the selection of number of principle components has a significant effect on the performance of ICA based face recognition. In this regards, the third experiment has been drawn which is based on keeping different number of subjects along with different number of independent components (or principle components) for each database. So an analysis has conceded to find a number of independent components (ICs) for each database which maximizes the performances of ICA architectures. In selection of ICs approach, the numbers of principle components (PCs) vary from 30 to 80 with an interval of 5 in case of FERET and CVL database, and from 15 to 50 with an interval of 5 for ORL and YALE database. Hold the different ranges of PCs for the databases because number of subjects is not equal for all databases. Figure 6 shows the average recognition rates of Architecture-I versus the variation of the PCs. Finally an optimal number of PCs 55, 80, 30, 25 for FERET, CVL, ORL, and YALE databases respectively is chosen. These optimal PCs have been carried out in case of Architecture-II also.

The estimation of a weight matrix is prepared through the FastICA algorithm with the contrast function $G(u) = -\exp(\frac{u^2}{2})$. After feature extraction, SVM multi-classification strategy has been taken. For training support vector machines, polynomial kernel with degree 1 is used and 10-fold cross validation has been done to select proper parameters for kernel function.

Analysis and Observation

1. *Experiment 1: Same number of subjects and same number of ICs:* In this experiment, numbers of 20 subjects are taken from each database i.e. FERET, ORL, CVL, and YALE. From these 20 subjects, a total of 60 face images has been collected for each database. So, each set of training samples consists of 40 training images and 20 testing images. For each face images 15

features are extracted for recognition task. Table 4 lists the recognition rate of each training sample sets and two architectures over four databases. Average recognition rate of two architectures is also listed in this table. Table 4 shows us that Architecture-II significantly outperforms the Architecture-I in all three training samples no matter what database is used by Architecture-I. Also, in terms of the average recognition rate holding the same situation, but in CVL database the performance of Architecture-I is slightly better than other databases although less than Architecture-II with difference of accuracy between two architectures is 20 %. FERET and ORL giving us almost similar results with difference of accuracy between two architectures are 38.33 % and 35 % where YALE database with highest difference of 40 %. All these results are giving contradictory verdict with Bartlett et al. [1] where they had concluded that two ICA representations were equally powerful for face recognition. This analysis is consistent with Draper et al. [6] where concluded that Architecture-II is better than Architecture-I. At this instant, a question is: what are the causes that make notable distinction between the architectures performance? First reason is the architectural representation where Architecture-I centering the data matrix by removing the mean of each image, and Architecture-II centering the data matrix by removing the mean image of all training samples. Secondly, nature of the feature vectors of both architectures i.e. compactness of the feature values such that low compact features will enhance result than high compact features. It is clearly observed that for all four databases Architecture-II perform better than Architecture-I, no matter which databases are used.

Table 4. Keeping same number of subjects and same number of independent components from several databases.

Databases	FERET		ORL		CVL		YALE	
Methods	ICA I	ICA II	ICA I	ICA II	ICA I	ICA II	ICA I	ICA II
Training sample 1	50	75	40	75	55	80	50	45
Training sample 2	35	80	35	65	55	80	30	85
Training sample 3	45	90	50	90	55	65	20	90
Average	**43.33**	**81.66**	**41.66**	**76.66**	**55**	**75**	**33.33**	**73.33**

2. *Experiment 2: Different number of subjects and same number of ICs:* To verify whether the conclusion of experiment 1 depends on the varying number of subjects, the tested two architectures by taking different number of subjects for each database. In this experiment, numbers of 180 subjects and total of 540 face images are taken from FERET database, 103 subjects and total of 309 face images from CVL database, 28 subjects and total of 84 face images from YALE database, 27 subjects and total of 81 face images from ORL database are taken respectively. So, each set of training samples consists of 360, 206, 56, and 54 training images respectively for FERET, CVL,

YALE, ORL databases and 180, 103, 28, 27 testing images respectively for FERET, CVL, YALE, ORL databases. Like experiment 1, 15 features for each face images from all the databases are extracted. Table 5 lists the recognition rate and average recognition rate of each training sample set and two architectures over four databases. As similar with experiment 1, Table 5 also shows us that Architecture-II notably outperforms the Architecture-I in all three training samples no issue of how many images are intended for the experiment. But the recognition rate is become somehow lesser as compare to first experiment which has been more highlighting in FERET database. The explanation behind this the number of features is fewer as compared to the number of images. In terms of the average recognition rate, ORL and CVL database giving almost similar recognition rate with difference of accuracy between two architectures are 22.22 % and 23.31 %. The YALE database giving good recognition rate in case of Architecture-II but highest difference of accuracy along with Architecture-I, is 45.23 %. It seems that the performance varying when different number of subjects is considered, but it does not affect performance of the Architecture-II against Architecture-I.

Table 5. Keeping different number of subjects and same number of independent components from several databases.

Databases	FERET		ORL		CVL		YALE	
Methods	ICA I	ICA II	ICA I	ICA II	ICA I	ICA II	ICA I	ICA II
Training sample 1	14.44	41.67	48.15	70.37	41.75	67.96	39.29	39.29
Training sample 2	21.11	49.44	40.74	59.26	48.54	77.67	21.43	85.71
Training sample 3	17.78	43.33	48.15	74.07	47.57	62.14	10.71	82.14
Average	**17.78**	**44.81**	**45.68**	**67.9**	**45.95**	**69.26**	**23.81**	**69.04**

3. *Experiment 3: Different number of subjects and different number of ICs:* The choice of an optimum number of principle components has a significant effect on the recognition rate of ICA architectures. The number of ICs which maximizes the performances of ICA architectures is 55, 80, 30, and 25 for database FERET, CVL, ORL, and YALE respectively as shows in Fig. 6. So, this experiment is basically based on the different number of ICs along with different number of subjects for each database. The collection of number of subjects is analogous to previous analysis i.e. experiment 2. Table 6 lists the recognition rate and average recognition rate of each training sample set and two architectures over four databases. Although optimum number of PCs effects the recognition rate of ICA architectures as compared to previous experiment, this experiment also notify that the Architecture-II superior than the Architecture-I. The average recognition performances of experiment 2 and 3 are somehow reduced as compared to first experiment except few cases. So the number of subjects or images could also effect in the performances.

Table 6. Keeping different number of subjects and different number of independent components from several databases.

Databases	FERET		ORL		CVL		YALE	
Methods	ICA I	ICA II	ICA I	ICA II	ICA I	ICA II	ICA I	ICA II
Training sample 1	26.67	56.11	44.44	77.78	54.37	79.61	39.29	50
Training sample 2	17.22	72.78	44.44	66.67	51.46	85.71	21.43	85.71
Training sample 3	25.00	66.11	59.26	88.89	52.43	78.57	10.71	78.57
Average	**22.96**	**65**	**49.38**	**77.78**	**52.75**	**81.30**	**23.81**	**71.42**

In a word, the strong and weakly compact correlations between feature vectors of two architectures clearly define which architecture is better than the other. There is no effect of different databases, number of subjects, and number of principle components in the performances of both architectures against one another.

6 Conclusion

Evaluation between ICA architectures is difficult since there are lot of considerations must be taken into account such as differences in representation of architectures, database complication, optimum parameters selection for ICA processing and classification etc. This paper is to investigate the relationship of the feature vectors, and experiments based on several factors. As a conclusion, it has been seen that Architecture-II is outperforms than Architecture-I. In this process, it has been possible to verify the results of similar claims with few researchers and diverse views in case of other researchers.

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