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Performance Evaluation of Optimised PCA and Projection Combined PCA methods in Facial Images

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Abstract

Several techniques have been developed for both identification and verification of faces. The most explored one is the eigen-based (Principal Component Analysis) method. Of all the variants of PCA considered, only the Projection Combined PCA used by Wu and Zhou, employed single training face per individual. In this experiment, an evaluation of Optimised PCA and Projection Combined PCA techniques was carried out based on following parameters, such as recognition accuracy, total training time, average recognition time. Overall results indicated that OPCA performed better than $(PC)^2A$.

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1 Introduction

Face recognition is an active area of research which has aroused interest of researchers from security, psychology, neuroscience and image processing to computer vision. It is one of the biometric techniques that identify people by “who they are” and not by “what they have” or “what they know”. Biometric systems are systems that identify people based on behavioural and physiological traits. These traits are unique to every individual; they include finger prints, palm patterns, face geometry, speech, gait, signature dynamics, iris etc. Among these traits, the physiological ones (face, fingerprints, iris) are more reliable and stable than the behavioural traits (signature dynamics, gait and speech). The reason being the non-alterable natures of the physiological features but the behavioural traits have the advantage of being non-intrusive [6]. Biometric systems have the advantages of both high accuracy and low intrusiveness [7]. They are not easy to forge and are therefore, more reliable because they use biological characteristics to identify people rather than physical (material) possessions [6,7].

It is useful in identity verification, security monitoring system, location tracking system and in access control.

2 Principal Component Analysis

PCA is a mathematical tool for achieving dimensionality reduction in image compression and recognition problems. It is also known as Eigenspace projection or Karhumen-Loeve transformation [11].

Kirby and Sirovich were among the first to apply PCA to face images, and found that it effectively and efficiently represents pictures of faces into its eigenface components. They also showed that PCA is an optimal compression scheme that minimizes the mean squared error between the original images and their reconstructions for any given level of compression [5].

Turk and Pentland popularized the use of PCA for face recognition and came up with a set of subspace basis vectors for a database of face images [11]. PCA projects images into a subspace such that the first orthogonal dimension of this subspace captures the greatest amount of variance among the images and the last dimension of this subspace captures the least amount of variance among the images. The main goal of PCA is the dimensionality reduction.

2.1 Optimized PCA (OPCA)

OPCA [7,8]. aims at reducing the dimension of the covariance matrix involved. It was based on a theorem in linear algebra that states that: Given a Matrix X, the eigenvalues of XX^T and X^TX are the same and that the eigenvectors of XX^T are the same as the eigenvectors of X^TX multiplied by the matrix X and normalized [2,4,12].

Using this theorem, the optimized PCA method was used to create the eigenspace from an MxM matrix rather than an NxN matrix where M<<N.

The following steps show the optimized PCA:

1. Center data as in standard PCA.
2. Create data matrix as in the standard PCA.
3. Create covariance matrix: the data matrix's transpose is multiplied by the data matrix to create a covariance matrix.

$$' \Omega \nu = A^T A$$

4. Compute the eigenvalues and eigenvectors of Ω': The eigenvalues and corresponding eigenvectors are computed for Ω'.

$$\Omega' \nu' = \square' \nu'$$

5. Compute the eigenvectors of AA^T: Multiply the data matrix by the eigenvectors. Then, divide the eigenvectors by their norm.
6. Order eigenvectors as in the standard PCA

2.2 Projection Combined- PCA $(PC)^2$ A

As stated by Jain *et. al* (2000)[3], the training phase in a statistical pattern recognition system can be divided into three successive stages, i.e the preprocessing stage, the feature extraction stage, and the learning stage. At present, most of the extensions of the eigenface technique focus on the feature extraction stage or the training stage. Projection Combined PCA was proposed as an extension of PCA by Wu and Zhou (2002)[13] to cater for the preprocessing stage. $(PC)^2$ A employs a special preprocessing mechanism specially designed face recognition purposes.

Analysis of $(PC)^2$A

Let P(x,y) be an intensity image of size $N_1 * N_2$, x[1, N1], y[1,N2], and P(x,y) [0,1].

The vertical and horizontal integral projections are defined respectively as:

$$\begin{aligned} V_p(x) &= \sum_{y=1}^{N_2} P(x,y) \\ H_p(y) &= \sum_{x=1}^{N_1} P(x,y) \end{aligned} \tag{2.1}$$

Now, the projection map Mp(x,y) of P(x,y) is defined as:

$$M_p(x,y) = \frac{V_p(x) H_p(y)}{N_1 N_2 \overline{P}} \tag{2.2}$$

Where $\overline{P}$ is at the average intensity of the image, i.e.

$$\overline{P} = \frac{\sum_{x=1}^{N_1}\sum_{y=1}^{N_2} P(x,y)}{N_1 N_2} \tag{2.3}$$

Then, the projection-combined version of P(x,y) as:

$$P_\alpha(x,y) = \frac{P(x,y) + \alpha M_p(x,y)}{1+\alpha} \tag{2.4}$$

Where α is the combination parameter.

In $(PC)^2A$, PCA is performed on the projection combined version of the image, i.e.

$P_\alpha(x,y)$, instead of on the original face image, i.e.P(x,y)

Properties of $(PC)^2A$

It is derived that P(x,y), and $P_\alpha(x,y)$ have the following properties.

(1) The average intensity of P(x,y) is equal to the average intensity of $M_P(x,y)$.

(2) So long as α is not equal to -1, the average intensity of P(x,y) is equal to the average intensity of $P_\alpha(x,y)$

(3) As α approaches 0, $P_\alpha(x,y)$ turns to be exactly P(x,Y).

(4) As α approaches infinity; $P_\alpha(x,y)$ approaches $M_p(x,y)$.

(5) The intrinsic dimensionality of $M_p(x,y)$ is much smaller than that of P(x,y).

2.3 Methodology

Face images of forty-two individuals were captured. This acquisition was done using digital camera. For each individual, eight images of different facial expressions and lightening conditions were captured while the best six frontal images were selected.

Face images were cropped out from the original captured images and were later resized from the original dimension of 480 x 640 pixels to 180 x 200 pixels.

The resized images of each individual were grouped into two folders. One folder contained training images while the other was used for testing the system. The folder containing the training images was sub-divided into four (4) folders with each containing different number of training images ranging from four to one image per person.

The colored images were cropped to sizes of 50x50, 60x60, 70x70, 80x80, 90x90 and 100x100 pixels from the centre of the image by the program in order to extract features like eyes, nose, eyelids and lips. The different pixel sizes indicate varying numbers of important facial features. The coloured cropped images in the database were converted into grayscale so as to make it suitable for the face recognition system. This was done because most of the present face recognition algorithms require two-dimensional arrays in their analysis.

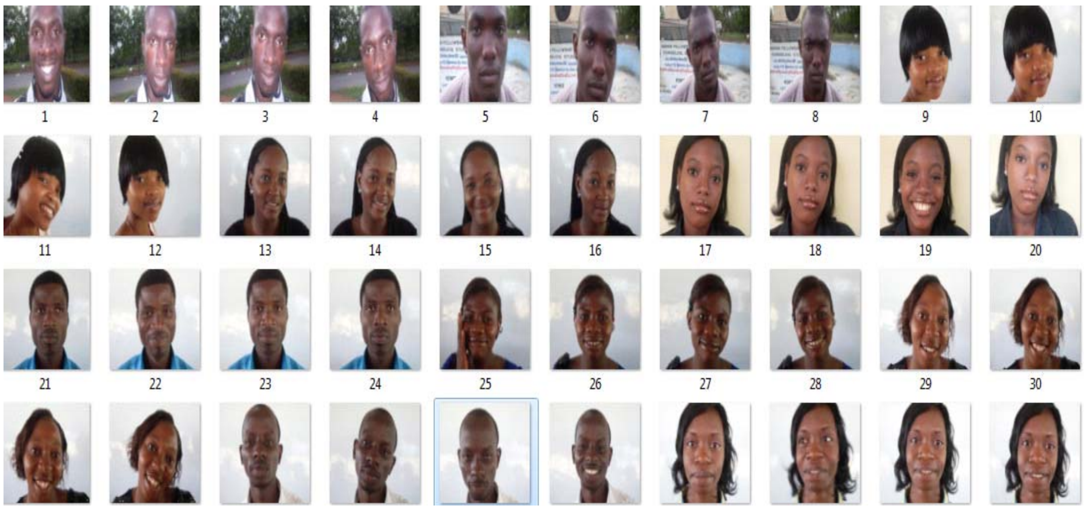

Figure 1: Some of the raw images used for training the database

The first set of experiments were performed in determining the Average recognition time, Total number of unidentified images, Total training time and Percentage recognition accuracy using different number of training images per individual for both OPCA and (PC^2A). The number of training images was varied from four down to one. Results of the experiments are as shown in Tables 1 to 4.

Second set of experiments were also performed using different image resolutions; cropped ace images of sizes between 50 x50 pixels to 100x100 pixels were used during the experiments in order to determine the effect of image resolution on the evaluation parameters. Results are also shown it Tables 1 to 4.

3 Results and Discussion

The MATLAB implementation of both algorithms was carried on a Pentium dual processor with 2.00GHz processor speed. The face recognition system was experimented with a total of 252 images, out of which 168 images were used in training the database and 84 images were used for testing the created database. This represents six images (four training and two testing) for 42 individuals.

OPCA and $(PC)^2A$ algorithms were experimented by implementing both with different facial expressions in the order of between 50x50 and 100x100 pixels resolutions. With both OPCA and $(PC)^2A$ algorithms, the following parameters were taking into consideration namely:

- The recognition accuracy
- Total training time
- Average recognition time
- Resolution of cropped face images

Table 1: Total number of unidentified images for different level of cropping of the original image for OPCA and $(PC)^2A$ with different training images per person

Image resolution (pixels)	Total number of unidentified images (using 4-image database)		Total number of unidentified images (using 3-image database)		Total number of unidentified images (using 2-image database)		Total number of unidentified images (using 1- image database)	
	OPCA	$(PC)^2A$	OPCA	$(PC)^2A$	OPCA	$(PC)^2A$	OPCA	$(PC)^2A$
50 * 50	11	13	15	17	26	25	30	33
60 * 60	8	9	12	15	23	21	28	32
70 * 70	6	7	10	12	22	20	27	29
80 * 80	5	5	8	10	19	19	28	27
90 * 90	3	5	6	7	17	18	25	28
100 * 100	3	4	5	6	16	15	23	28

Table 2: Percentage recognition Accuracy(%) for different level of cropping of the Original image for OPCA and $(PC)^2A$ with different training image per person

Image resolution (pixels)	Percentage Accuracy(%) (using 4- image database)		Percentage Accuracy(%) (using 3- image database)		Percentage Accuracy(%) (using 2- image database)		Percentage Accuracy(%) (using 1- image database)	
	OPCA	$(PC)^2A$	OPCA	$(PC)^2A$	OPCA	$(PC)^2A$	OPCA	$(PC)^2A$
50 *50	86.90	84.52	82.14	79.76	69.05	70.24	64.29	60.71
60 * 60	90.48	89.29	85.71	82.14	72.62	75.00	66.67	61.90
70 * 70	92.86	91.67	88.10	85.71	73.81	76.19	67.86	65.48
80 * 80	94.08	94.08	90.48	88.10	77.38	77.38	66.67	67.86
90 * 90	96.43	94.08	92.86	91.67	79.76	78.57	70.24	66.67
100 * 100	96.43	95.24	94.08	92.86	80.95	82.14	72.62	66.67

Table 3: Total training time(Sec) for different level of cropping of the original image for both OPCA and $(PC)^2A$ with different training image per person

Image resolution (pixels)	Total training time(sec) (using 4 image database)		Total training time(sec) (using 3 image database)		Total training time(sec) (using 2 image database)		Total training time(sec) (using 1 image database)	
	OPCA	$(PC)^2A$	OPCA	$(PC)^2A$	OPCA	$(PC)^2A$	OPCA	$(PC)^2A$
50 * 50	13.7687	4.8373	10.3779	4.6367	7.1994	4.2843	4.1262	3.8212
60 * 60	14.2408	5.4418	10.7325	5.3452	7.4769	4.9718	4.2851	4.1564
70 * 70	14.7591	7.8489	11.2863	7.4518	7.7609	6.542	4.4481	5.6972
80 * 80	15.8298	8.0418	11.9022	7.9897	8.2210	7.1289	4.6989	6.6614
90 * 90	16.2842	10.2759	12.4582	9.7685	9.0738	8.2654	4.8920	7.8533
100 * 100	17.5264	10.6341	13.1549	10.1647	8.9904	9.8724	5.2632	9.1498

Table 4: Average Recognition time(sec) for different level of cropping of the original image for both OPCA and $(PC)^2A$ with different training image per person

Image resolution (pixels)	Average Recognition time (sec) (using 4-image database)		Average Recognition time(sec) (using 3- image database)		Average Recognition time(sec) (using 2- image database)		Average Recognition time(sec) (using 1- image database)	
	OPCA	$(PC)^2A$	OPCA	$(PC)^2A$	OPCA	$(PC)^2A$	OPCA	$(PC)^2A$
50 * 50	0.2335	1.5022	0.2452	1.5042	0.2296	0.7854	0.2337	0.3437
60 * 60	0.2408	1.5035	0.2511	1.5063	0.2301	0.7956	0.2345	0.3440
70 * 70	0.2384	1.5043	0.2376	1.5136	0.2321	0.7978	0.2349	0.3452
80 * 80	0.2507	1.5068	0.2434	1.5197	0.2341	0.8068	0.2506	0.3454
90 * 90	0.4766	1.5098	0.2431	1.5237	0.2362	0.8353	0.2511	0.3485
100 * 100	0.5699	1.5121	0.5408	1.5259	0.2313	0.8414	0.2572	0.3514

The results of the research work (Table 1) showed that the number of unidentified images increased with reduction in both image resolution and number of training images per individual for both algorithms. This implies that the more the facial features that are included in the training images, the better the recognition performances. It also indicates that performance increases with increase in number of training image employed per person and that OPCA performed better than $(PC)^2A$.

In table 2, there was increase in percentage accuracy with increase in resolution of cropped images and increase in available number of training image of both algorithms. It should be noted that both algorithms performed well (recognition accuracy > 80%) when the training images are more than two except for 100*100 resolution in the two-image database. Their performances reduce with decrease in the size of cropped image and are worst when only one image was used with the algorithms. However, it was observed that OPCA gives a better accuracy in all situations considered.

Results in Table 3 revealed that the higher the resolution of cropped image, the more time it takes to train the database. Likewise, the total training time also increases with increase in the number of training images per person; this may be linked with increase in the sizes of the database as the number of training image increases. The results also showed that OPCA required more training time than $(PC)^2A$.

It took a longer time to recognize images with $(PC)^2A$ than OPCA (Table 4). Both techniques indicated that the average recognition time reduces with decrease in the number of training images per individual. Also, it can be deduced that average recognition time increases with increase in resolution of cropped images.

OPCA algorithm performs better than $(PC)^2A$ when all parameters considered are taken into consideration. The percentage recognition accuracies is greater than 80% [10] for all level of cropping when more than two training images are used and even for 100*100 with two training images. Likewise, the average recognition time was less than one minute with OPCA (average of 0.57 sec) for all images considered; this is another requirement of a standard face recognition system. These parameters are considered to be very critical and determinants of any robust face recognition system

It should be noted that the results got were basically limited by configuration of the computer system used, resolution of the digital camera, different environmental conditions like illumination and different distances between the camera and every face. Also, the face database under consideration was developed entirely from the scratch and the facilities for proper face alignment used were those at our disposal. Other errors encountered in recognition can be attributed to poor normalization, emphasizing the importance of strictly standardized databases.

4 Conclusion

An overview of two PCA-based face recognition algorithms has been presented in this research work. It was discovered that while $(PC)^2A$ modifies PCA by performing image projection before applying PCA on the image, OPCA aims at reducing the dimension of the covariance matrix involved in PCA.

The design of the face recognition system is based on eigen faces and has been separated into five major sections – face acquisition, pre-processing, feature extraction, training and recognition/testing. The results of evaluation between both algorithms based on black faces showed that OPCA and $(PC)^2A$ gave recognition accuracies of between 96% to 64% and between 95% to 60% respectively. However, when all other parameters were considered such as total training time, average recognition time, overall results indicated that OPCA performed better than $(PC)^2A$.

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