Analysis of Principal Component Analysis (PCA) Face Recognition: Effects of Similarity Measure

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***Abstract*— In this paper, the effects of similarity measure to the performance of PCA based face recognition are presented. A fundamental challenge in face recognition lies in determining which steps are important in the recognition of faces. Several studies have indicated the significance of certain steps in this regard, particularly pre-processing and feature extraction. Surprisingly, however, it has not been made clear whether the similarity measures play an important role in the recognition of faces. Twelve similarity measures have been used for the classification. Extensive experiments have been conducted on ORL and Yale face databases. The experimental results show the importance of using appropriate similarity measure.**

***Keywords*— Security, Biometrics, Face Recognition, Principal Component Analysis, Eigenspace, Similarity Measure**

I. Introduction

Face recognition has been studied extensively for more than 40 years. Now it is one of the most imperative sub-topics in the domain of face research [1]-[4]. Face recognition is a technology which recognize the human by his/her face image. Face recognition can be divided into two core approaches namely, content-based and appearance based [1].

Content-based recognition is based on the relationship between facial features like eyes, mouth & nose etc.

In appearance based recognition the face is treated as a two dimensional pattern of intensity variation. The face matching is done through its underlying statistical regularities.

Principal Component Analysis (PCA) has been proven to be an effective approach for the face recognition [5]-[11]. Sirovich and Kirby (1987 & 1990) used the eigenfaces for efficiently representing the face images using principal component analysis [12], [13]. In 1991 Turk and Penland developed a face recognition system using PCA [7], [6]. Then onwards the PCA has been widely used in face recognition and is considered as one of the most successful algorithm. It reduces the dimension effectively without losing the primary information.

Using PCA we find the eigenvectors (Principal Component or Principal Direction) in a set of training faces. Then we project faces in to this eigenvectors and get feature vectors. Matching is performed by calculating the similarity between these vectors. Usually comparison of face images is performed by Euclidean distance between feature vectors. Some times the angle based distance also used. Although there are many more other similarity measures, we were able to find only few attempts to compare and use other similarity measures in order to achieve better recognition.

This paper employed for finding effects of similarity measure in face recognition. In section II the PCA based face recognition system is discussed. The different similarity measures discussed in section III and experimental results are listed in section IV. Finally, sections V conclude and suggest the future scope.

II. PCA

Principal component analysis (PCA) was also called as Eigenface [6]. The following steps summarize the process:

1. Let a face image X(x, y) be a two dimensional mXn array (8-bit Gray Scale) of intensity values. An image may also be considering the vector of dimension mn, so that a typical image of size 112x92 becomes a vector of dimension 10304. Let the training set of images {X1, X2, X3… XN}. The average face of the set is defined by

$$\overline{X} = \frac{1}{N}\sum_{i=1}^{N} Xi \qquad (1)$$

2. Calculate the covariance matrix to represent the scatter degree of all feature vectors related to the average vector. The covariance matrix C is defined by

$$C = \frac{1}{N}\sum_{i=1}^{N}(Xi-\overline{X})(Xi-\overline{X})^T \qquad (2)$$

3. The Eigenvectors and corresponding eigenvalues are computed by using

$$CV = \lambda V \qquad (3)$$

Where V is the set of eigenvectors associated with its eigenvalue λ.

4. Sort the eigenvector according to their corresponding eigenvalues from high to low
5. Each of the mean centred image project into eigenspace using

$$W_i = V_i^T (X_i - \overline{X}) \qquad (4)$$

6. In the testing phase each test image should be mean centred, now project the test image into the same eigenspace as defined during the training phase.
7. This projected image is now compared with projected training image in eigenspace. Images are compared with similarity measures. The training image that is closet to the test image will be matched and used to identify.

III. Similarity Measures

Let x, y be the feature vectors of length n. then we can calculate the following distances between these feature vectors [6]

A. Euclidean Distance:

The Euclidean distance also called as L2 distance. L2 is computed from the sum of square of the edge distances

$$\delta(x,y) = \|x-y\|_2 = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \qquad (5)$$

B. City Block Distance:

This distance metric is variously named as block distance, L1 distance or city block distance. The L1 or block distance is calculated from summing the edge distances.

$$\delta(x,y) = \|x-y\|_1 = \sqrt{\sum_{i=1}^{n}|x_i - y_i|} \qquad (6)$$

C. Minkowski Distance:

Minkowski distance (L_m) is computed from the sum of m^{th} power of the edge distance.

$$\delta(x,y) = \|x-y\|_m = \sqrt[m]{\sum_{i=1}^{n}(x_i - y_i)^m} \qquad (7)$$

for special case of m=1, the Minkowski distance gives the City Block distance, and for m=2, the Minkowski distance gives the Euclidean distance.

D. Cosine Distance:

The Cosine distance is computed by

$$\delta(x,y) = 1 - \left(\sum_{i=1}^{n} x_i y_i \Big/ \sqrt{\sum_{i=1}^{n} x_i^2 \sum_{i=1}^{n} y_i^2} \right) \qquad (8)$$

E. Correlation Distance:

The Correlation distance is computed by

$$\delta(x,y) = 1 - \left(\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y}) \Big/ \sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2 \sum_{i=1}^{n} (y_i - \bar{y})^2} \right) \qquad (9)$$

Where $\bar{x} = \sum_{i=1}^{n} x_i$ & $\bar{y} = \sum_{i=1}^{n} y_i$

F. Bhattacharyya Distance:

$$\delta(x,y) = \sum_{i=1}^{n} \sqrt{x_i y_i} \qquad (10)$$

G. Squared Euclidean Distance (SSE):

$$\delta(x,y) = \|x-y\|^2 = \sum_{i=1}^{n}(x_i - y_i)^2 \qquad (11)$$

H. Mean Squar Distance (MSE):

$$\delta(x,y) = \frac{1}{n}\|x-y\|^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2 \qquad (12)$$

I. Chi Squar Distance (CSD):

$$\delta(x,y) = \sum_{i=1}^{n} \frac{(x_i - y_i)^2}{x_i + y_i} \qquad (13)$$

J. Canberra Distance (CD):

$$\delta(x,y) = \sum_{i=1}^{n} \frac{|x_i - y_i|}{|x_i| + |y_i|} \qquad (14)$$

K. Modified Manhattan Distance (MMD):

$$\delta(x,y) = \frac{\sum_{i=1}^{n} |x_i - y_i|}{\sum_{i=1}^{n} |x_i| \sum_{i=1}^{n} |y_i|} \qquad (15)$$

L. Modified SSE-based Distance (MSSE):

$$\delta(x,y) = \frac{\sum_{i=1}^{n} (x_i - y_i)^2}{\sum_{i=1}^{n} x_i^2 \sum_{i=1}^{n} y_i^2} \qquad (16)$$

IV. Experiments

A. Databases

The Olivetti Research Lab (ORL) Database [14] of face images provided by the AT&T Laboratories from Cambridge University has been used for the experiment. It was collected between 1992 and 1994 [15]. It contains slight variations in illumination, facial expression (open/closed eyes, smiling/not smiling) and facial details (glasses/no glasses). It is of 400 images, corresponding to 40 subjects (namely, 10 images for each class). Each image has the size of 112 x 92 pixels with 256 gray levels. Some face images from the ORL database are as follows:

Fig. 1. Some Face images from ORL Database

The Yale Face database [16] [17] contains 11 frontal face images of 15 subjects, giving a total of 165 images. Each image has the size of 320 × 243 pixels with 256 gray levels. Lighting variations include left-light, center-light, and right-light. Spectacle variations include with-glasses and without-glasses. Facial expression variations include normal, happy, sad, sleepy, surprised, and wink. Some face images from the Yale face database are as follows:

Fig. 2. Some Face images from Yale Database

B. *Experimental Setup*

The experiment has been done on two face databases ORL face database and Yale face database, with different number of training images i.e. five, six, seven, eight, nine, and ten. For testing all the images in the database has been considered. The PCA developed in MATLAB 7.0. In all the experiments the feature vectors has been calculated using PCA, only change the similarity measure between the feature vectors. For the comparison the Receiver Operating Characteristic (ROC)-based measures i.e. Equal Error Rate (EER) and Receiver Operating Characteristic Area (ROCA).

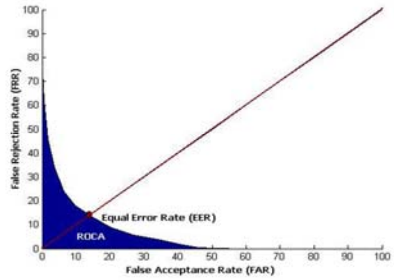

Fig. 3. Receiver Operating Characteristic.

C. *Results and Discussion*

The experimental results are summarized in Tables I and II. Table I summarizes the results on the ORL face database and Table II summarizes the results on the Yale face database. From these tables we can how different similarity measures affect performance of the face recognition system. For measuring the overall goodness of the similarity measure with respect to the verification accuracy, we use area below the receiver operating characteristic curve.

The graphical representations of the results are shown in the figures 4-7. The smaller values of the EER and ROCA means better the results.

TABLE I
RECOGNITION RESULTS FOR ORL DATABASE

	Number of Training Images											
Similarity Measures	**5**		**6**		**7**		**8**		**9**		**10**	
	EER	**ROCA**	**EER**	**ROCA**	**EER**	**ROCA**	**EER**	**ROCA**	**EER**	**ROCA**	**EER**	**ROCA**
Bhattacharyya	23	1835.511	26	2153.641	26	2031.488	24	1900.683	24	1981.992	24	1970.95
Euclidean	5	131.1162	5	168.2139	5	140.6074	5	128.7885	5	116.6571	6	117.1026
City Block	3	67.1883	3	98.90064	3	64.3766	3	56.7492	3	52.53045	3	50.65064
Minkowski	6	180.0577	6	216.1667	6	191.6691	6	183.4014	6	167.7845	6	158.5497
Cosine	8	276.6258	8	333.7997	8	289.867	8	288.7228	8	265.9239	8	251.3373
Correlation	8	286.6675	8	343.0738	8	289.0213	8	289.0438	8	289.0438	8	257.5375
Squared Euclidean Distance (SSE)	7	131.2893	7	168.4551	7	139.0425	7	128.2796	7	119.3894	7	115.6394
Mean Square Distance (MSE)	7	131.2893	7	168.4551	7	139.0425	7	128.2796	7	119.3894	7	115.6394
Chi Square Distance (CSD)	52	974.9736	54	5205.252	54	584.2861	48	4619.686	52	801.8277	48	3948.569
Canberra Distance (CD)	6	92.50401	6	137.5441	6	101.6803	6	145.2372	6	99.03686	5	63.04968
Modified Manhattan Distance (MMD)	50	4974.728	50	4985.926	50	4944.496	50	5035.529	50	4648.726	62	2075.22
Modified SSE-based Distance (MSSE)	18	1151.593	25	2022.585	18	1492.184	18	1495.616	17	1386.52	17	1316.344

TABLE II
RECOGNITION RESULTS FOR YALE DATABASE

Similarity Measures	Number of Training Images											
	5		6		7		8		9		10	
	EER	ROCA	EER	ROCA	EER	ROCA	EER	ROCA	EER	ROCA	EER	ROCA
Bhattacharyya	41	3833.701	40	3740.338	32	3021.553	31	3057.851	31	2899.593	29	2869.146
Euclidean	23	1780.716	21	1503.096	20	1547.265	18	1429.516	16	1376.676	16	1337.505
City Block	18	1108.684	16	1074.131	16	1151.948	16	1133.583	16	1121.514	15	1152.105
Minkowski	30	2113.617	24	1765.407	20	1696.511	20	1569.487	16	1534.724	16	1428.139
Cosine	22	1350.295	20	1219.494	20	1196.012	19	1144.969	18	1098.649	18	1091.801
Correlation	23	1362.101	20	1200.14	20	1215.46	18	1129.856	18	1087.833	18	1082.802
Squared Euclidean Distance (SSE)	24	1914.155	22	1728.939	20	1801.955	19	1770.077	18	1750.859	18	1773.921
Mean Square Distance (MSE)	24	1914.155	22	1728.939	20	1801.955	18	1770.077	18	1750.859	18	1773.921
Chi Square Distance (CSD)	40	3569.789	50	4982.172	50	1444.877	50	4809.944	46	4565.67	50	4844.641
Canberra Distance (CD)	10	547.173	10	590.791	7	323.7702	7	330.3949	10	415.1778	10	456.3951
Modified Manhattan Distance (MMD)	50	4639.549	54	3372.374	50	5661.938	56	4815.748	50	4929.481	50	5068.918
Modified SSE-based Distance (MSSE)	44	3947.533	40	3556.27	30	2520.31	30	2313.225	30	2361.145	28	2197.861

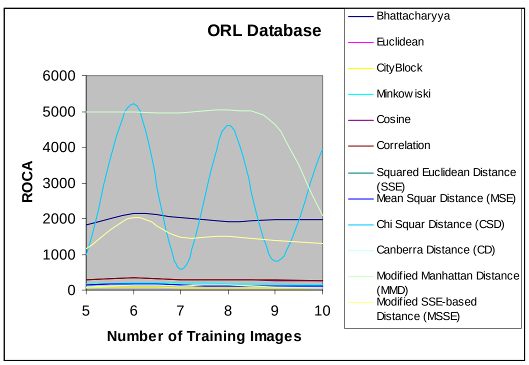

Fig. 4. Comparison of Similarity Measures with respect to equal error rate and Number of training images

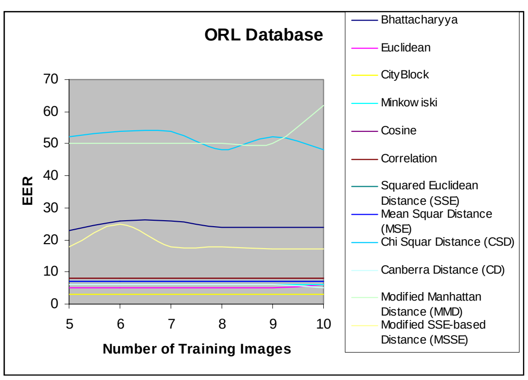

Fig.5. Comparison of Similarity Measures with respect to equal error rate and Number of training images

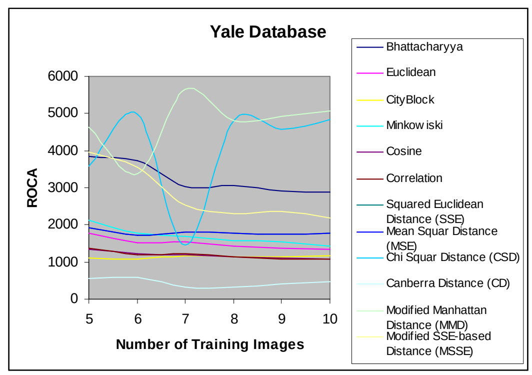

Fig. 6. Comparison of Similarity Measures with respect to equal error rate and Number of training images

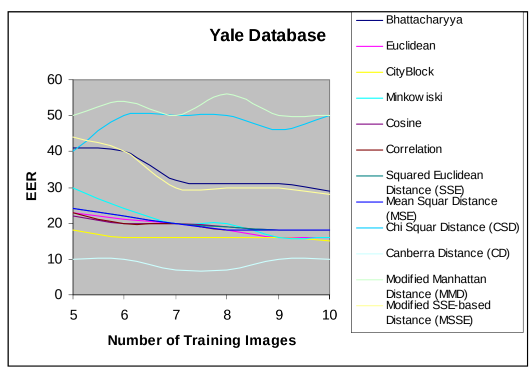

Fig. 7. Comparison of Similarity Measures with respect to equal error rate and Number of training images

V. Conclusions

In this paper we compared twelve (12) similarity measures for the principal component analysis based face recognition. The experiments were performed on the ORL and Yale Face databases. The experiments show that the City block and Canberra are the first two best measures with respect to EER and ROCA of the face recognition system. We also showed that similarity measure has to be also considered as an important step in the face recognition system.

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