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The Role of Similarity Measures in Face Recognition

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Abstract- **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 preprocessing and feature extraction. Surprisingly, however, it has not been made clear whether the similarity measures play an important role in the recognition of faces. Here, we report experimental results which suggest that for face recognition the similarity measures are influential. These results may have important implications for our understanding of the mechanisms of face recognition for the development of face-recognition systems.**

Keywords- ***Biometric; Face Recognition; Principal Component Analysis; 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.

In the PCA based face recognition system Euclidean Distance is used for calculating the similarity measure of the features.

This paper employed for finding the role of similarity measure in face recognition. In section 2 the PCA based face recognition system is discussed. The different similarity measures discussed in section 3 and experimental results are listed in section 4. Finally, sections 5 conclude and suggest the future scope.

II. PCA BASED RECOGNITION SYSTEM

Principal component analysis (PCA) was also called as *Eigenface [6]*. The following steps summarize the process of face recognition based on PCA:

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 $\{X_1, X_2, X_3 \ldots X_N\}$. The average face of the set

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

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

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

3. The Eigenvectors and corresponding eigenvalues are computed by using

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

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

4. Sort the eigenvector $V_i \in V$ according to their corresponding eigenvalues $\lambda_i \in \lambda 1.$ from high to low.
5. Each of the mean centered image project into

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

6. In the testing phase each test image should be mean centered, 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 (Euclidean Distance). The training image that is closest to the test image will be matched and used to identify.

III. SIMILARITY MEASURES

A. Euclidean Distance

The Euclidean distance also called as L_2 distance. L_2 is computed from the sum of square of the edge distances

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

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.

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

C. Minkowski Distance

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

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

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

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

E. Correlation Distance

The Correlation distance is computed by

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

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

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. Results and Discussion

Principal Component Analysis (PCA) has been proven to be an effective approach for the face recognition [5]-[11]. Therefore for experiments we used PCA as a feature extraction algorithm. The experiments has been done on the two face databases (ORL & Yale Face database), five similarity measures (i.e. Euclidean, Cityblock, Minkowski, Cosine, Correlation) has been consider with different number of training images (five, six, seven, eight, ten). ORL face database used for the first set of experiment, the results shown in the TABLE I and represented graphically in Fig. 3. The second set of experiment has been performed on Yale face database, the results shown in the TABLE II and represented graphically in Fig. 4. From TABLE I,II and Fig 3,4 it seems that the change in similarity measure affects on the recognition rate for the same number of training images and feature extraction algorithm.

TABLE I RECOGNITION RESULTS FOR ORL FACE DATABASE

Number of Training Images	Euclidean	CityBlock	Minkowski	Cosine	Correlation
Five	80.50	92.25	80.50	80.25	80.25
Six	83.00	89.50	83.00	81.50	82.00
Seven	82.75	92.00	82.75	81.75	81.75
Eight	85. 75	94.00	85.75	82.75	83.50
Nine	85.25	94.50	85.25	83.75	83.50
Ten	87.00	96.25	87.00	86.00	85.00

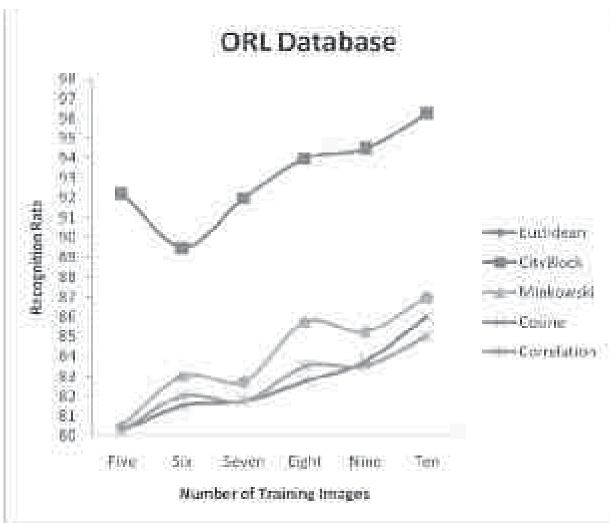


Fig. 3. Graphical representation of Table I

TABLE II RECOGNITION RESULTS FOR YALE FACE DATABASE

Number of Training Images	Euclidean	CityBlock	Minkowski	Cosine	Correlation
Five	51.52	73.33	43.03	56.36	55.15
Six	55.76	72.73	49.09	58.79	60
Seven	63.64	68.48	53.33	61.82	63.64
Eight	65.45	73.94	58.18	66.67	70.91
Nine	66.67	73.94	64.85	70.3	69.09
Ten	66.67	74.55	66.67	73.33	72.73

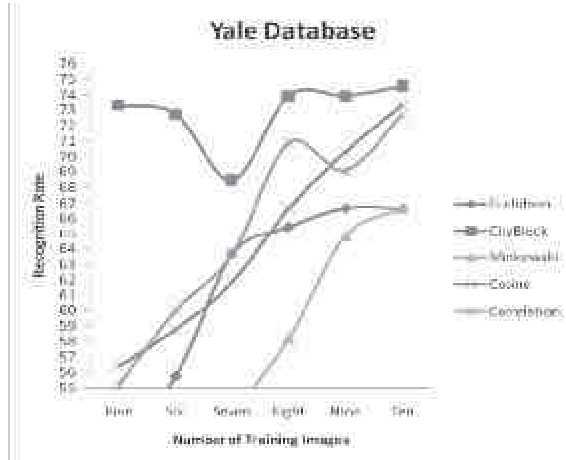


Fig. 4. Graphical representation of Table II

V. CONCLUSION

On the basis of various set of experiments and the predicted results, we come to conclude that the in addition to the feature extraction and preprocessing, a similarity measure should be considered for the improvement of the recognition rate. In the similarity measure Cityblock distance gives the improved recognition rate. In future this work can be extended for the other distance measures by integrating the PCA with other approaches like ICA, LDA, and Neural Network etc.

REFERENCES

[1] W. Zhao, R. Chellappa, A. Rosenfeld, and P. J. Phillips. "Face recognition: a literature survey" ACM Computing Surveys, Vol. 35, No. 4, December 2003, pp. 399–458.

[2] A. S. Tolba, A.H. El-Baz, and A.A. El-Harby "Face Recognition: A Literature Review", International Journal Of Signal Processing Volume 2 Number 2 2005 ISSN 1304-4494.

[3] R. Chellappa, C.L. Wilson and C. Sirohey, "Human and machine recognition of faces: A survey", Proc. IEEE, vol. 83, no. 5, pp. 705-740, may 1995.

[4] F Ming-Hsuan Yang, David J. Kriegman, and Narendra Ahuja, "Detecting Faces in Images: A Survey" IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 24, No. 1, January 2002.

[5] M. Turk, "A Random Walk Through Eigenface", IEICE Trans. INF. & SYST., Vol. E84-D, No. 12, Dec. 2001.

[6] M. Turk and A. Pentland, "Eigenfaces for recognition", J. of Cognitive Neuroscience, Vol. 3, No. 1, pp. 71-86, 1991.

[7] M. Turk and A. Pentland, "Face recognition using eigenfaces", Proceedings of IEEE, CVPR, pp. 586-591, Hawaii, June, 1991.

[8] I. Craw, N. Costen, T. Kato, and S. Akamatsu, "How Should We Represent Faces for Automatic Recognition?" IEEE Trans. on PAMI, Vol. 21, No.8, pp. 725-736, August 1999.

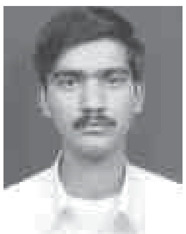
[9] A. Pentland, B. Moghaddam, T. Starner, "View-based and modular eigenspaces for face recognition", Proceedings of IEEE, CVPR, 1994.

[10] B. Moghaddam and A. Pentland, "Face Recognition using View-Based and Modular Eigenspace", Automatic Systems for the Identification and Inspection of Humans, 2277, 1994.

[11] P. Hall, D. Marshall, and R. Martin, "Merging and Splitting Eigenspace Models", IEEE Trans. on PAMI, Vol. 22, No. 9, pp. 1042-1049, 2002.

[12] Sirovich, L. & Kirby, M. "A low-dimensional procedure for the characterization of human face", Journal of the Optical Society of

America A, Vol. 4, No. 3, pp.519-524 1987.
[13] Kirby, M. And Sirovich, L. “Application of the Karhunen-Loeve procedure for the characterization of human faces”, IEEE Trans. Patt. Anal. Mach. Intell. Vol. 12, No. 1, pp. 103-107 1990.
[14] The ORL Database of Faces, Available: http://www.uk.research.att.com/facedatabase.html
[15] P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman. “Eigenfaces vs. fisherfaces: recognition using class specific linear projection”, IEEE Transactions on Pattern Analysis and Machine Intelligence, 19(7):711–720, July 1997.
[16] The Yale database, Available: http://cvc.yale.edu/
[17] F. Samaria and A. Harter. “Parameterisation of a stochastic model for human face identification”, In 2nd IEEE Workshop on Applications of Computer Vision, Sarasota, FL, 1994.



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