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Vertical and Horizontal Diagonal Feature Extraction Techniques for Content Based Image Retrieval

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Abstract—In this paper, a novel dimensionality reduction method is called hybrid principal component analysis (hi-PCA) is proposed for face content based image retrieval. In contrast to feature extraction of standard hybrid PCA (vertical and horizontal diagonal PCA) represented as the optimal projective vectors from vertical and horizontal diagonal face images without image-to-vector transformation. Distance measure techniques are Euclidean, SSE, MSE, Manhattan etc. Experiments show that hi-PCA is much more accurate than both PCA and 2DPCA. Furthermore, it is shown that the accuracy can be further improved by combining hi-PCA with 2DPCA.

***Index Terms*—Vertical Diagonal PCA, Horizontal Diagonal PCA, Eigen Valué. Eigen Vector, Manhattan Distance, Euclidean Distance.**

I. INTRODUCTION

Content based image retrieval system has been the subject of recognition. In which challenges are recognize the content from a general point under different types such as color, shape, texture. Applications of content based image retrieval are video surveillance either online or offline such as medical, military, digital libraries, shopping, advertising and entertainment.Humans are able to recognize faces effortlessly under all kinds of adverse conditions, but this simple task has been difficult for computer systems even under fairly constrained conditions. Successful face recognition entails the ability to identify. The same person under different circumstances while distinguishing between individuals. Variations in scale, position, illumination, orientation, and facial expression make it difficult to distinguish the intrinsic differences between two different faces while ignoring differences caused by the environment. Even when acceptable recognition has been accomplished with a computer, the actual implementation has typically required long run times on high performance workstations or the use of expensive supercomputers. The goal of this work is to develop an efficient, real-time face recognition system that would be able to recognize a person in a matter of a few seconds. Face recognition has been the focus of computer vision researchers for many years. There are two basic approaches to face recognition, (i) parameter-based and (ii) template-based. In parameter-based recognition, the facial image is analyzed and reduced to a small number of parameters describing important facial features such as the eye shape, nose location, and cheek bone curvature. These few extracted facial parameters are subsequently compared to database of known faces. Parameter-based recognition schemes attempt to develop an efficient representation of salient features of an individual. While the database search and comparison for parameter-based recognition may not be computationally intensive, the image processing required to extract the appropriate parameters is quite computationally expensive and requires careful selection of facial parameters which will unambiguously describe an individual's face.

2DPCA

Principal Component Analysis (PCA)[8][12] is one of the most popular technique which is used for reduction of the dimensionality. Feature classification is easily implemented using PCA compared to other methods. Image features are divided into two approaches. One is global approach and another one is local approach. Global feature analysis is easy to implement. But, sometimes it gives false results. In that case local feature is more useful. Finally some mathematical distance techniques are used to retrieve the relevant faces from the database based on minimum distance. Distance measures are angle based, Euclidean, mahalanobis, sum square error based distance, and their modifications. However, the projective vectors of2DPCA only reflect variations between rows of images, while the omitted variations between columns of images are usually also useful for recognition.

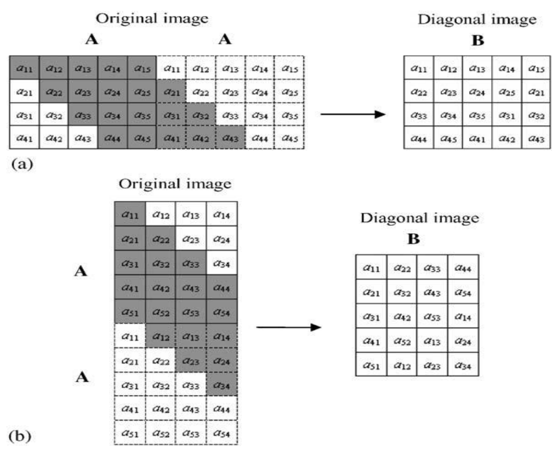

Fig 1. Illustration Ofthe Ways for Deriving the Diagonal Face Images.

In that case, 2DPCA can hardly obtain improved accuracy. In this paper, a novel method called diagonal principal component analysis (DiaPCA) is proposed. In contrast to 2DPCA, DiaPCA seeks the optimal projective vectors from

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diagonal face images and therefore the correlations between variations of rows and those of columns of images can be kept. Experimental results on a subset of FERET database show that DiaPCA is much more accurate than both PCA and 2DPCA. Furthermore, it is shown that the accuracy can be further improved by combining DiaPCA and 2DPCA together.

II. PROPOSED ALGORITHM

Block diagram for the proposed method is shown below:

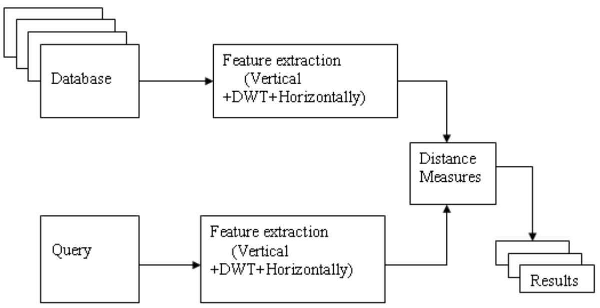

Fig 2. Block Diagram for the Proposed Method

Detailed algorithm is presented below:

1. Each image is represented as vertical and horizontal diagonal using PCA.
2. Each diagonal matrix image is used for further processing.
3. Convert the each image into column data matrix. Each of them can be expressed in the order of a D-by-N.
4. Calculate mean value for each sub image.
5. Subtract the mean value from column data matrix of each sub image then obtain vertically centered column data matrix C_{vi}
6. Rearrange the elements to get square matrix.
7. Collect Eigen values, Eigen vectors, and diagonal values of the square matrix $P_{Vi} = \{P_{i1} + P_{i2} + P_{i3} + \ldots\ldots + P_{iL}\}$ with i = 1, 2….S. here L is the feature of the sub image. Then obtain training data base matrix $G_{vi} = P_{Vi}^{T} C_{vi} = \{G_{i1} + G_{i2} + \ldots\ldots + G_{iN}\} = 1, 2\ldots K$.
8. Repeat the same procedure for row data matrix.
9. Reduce the feature size as per the requirement. $G_{Vj} = (G_{1j}^{T}, G_{2J}^{T}, \ldots\ldots G_{Sj}^{T})^{T}$, j = 1,2,..N. This is denoted as feature 1.
10. Above steps are repeated for the whole image without PCA to generate the feature 2.
11. Feature 1 and 2 are combined to get the global feature.
12. Minkowski distance is used to retrieve the relevant images.
13. Minkowski distance is concentrated on Euclidean [19] space, which can be considered as a generalization of both Euclidean and Manhattan distance for getting more recognition efficiency. Minkowski distance is based on factor p.

$$p = (x_1, x_2, \ldots\ldots x_n)$$

Minkowski distance is typically used with p being 1 or 2. In the limiting case of p reaching infinity we obtain the chebyshev distance.

$$d(Y,Z) = L_p(Y,Z) = (\sum_{i=1}^{n} | x_i - y_i |^p)^{i/p}$$

Minkowski distance is often used when variables are measured on ration scales with absolute zero value.

III. EXPERIMENTAL RESULTS

The proposed methods are tested using a subset of the FERET face database [5,4]. It comprises 400 gray-level frontal view face images from 200 persons, each of which is cropped with the size of 60×60. There are 71 females and 129 males; each person has two images (**fa** and **fb**) with different facial expressions. The **fa** images are used as gallery for training while the **fb** images as probes for test. PCA (eigenfaces), 2DPCA and the proposed DiaPCA and DiaPCA+2DPCA methods are used for feature extraction, Recognition performance in terms of average recognition rate and recognition time of the proposed face recognition system is tested by conducting experiments on Yale data base

Feature selection

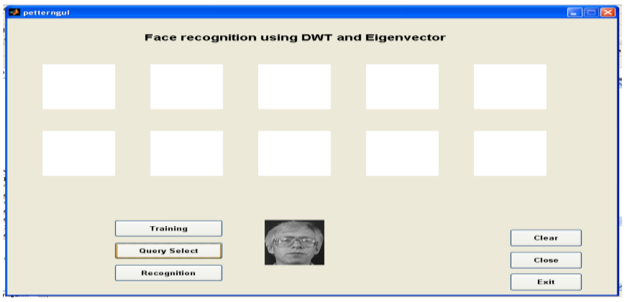

Fig 3. Sample Image from Face Database.

From the query image feature is taken based on the proposed method. In this paper 64×1 vector is generated for all images of the particular image(S=16). For each sub-pattern four positive eigenvectors (largest eigenvector) of the sub-part is considered. By considering query image results are shown in figure.

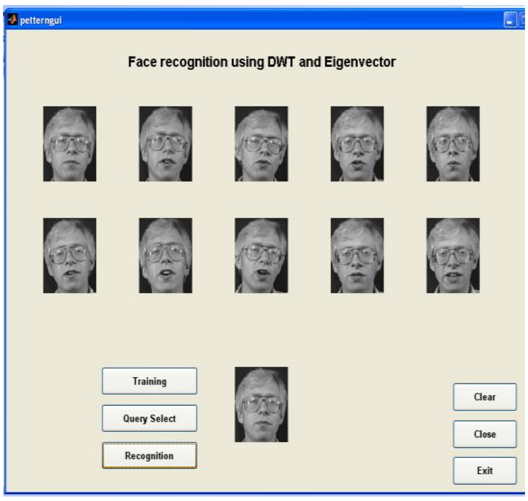

Fig 4. Recognized Images.

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Methods	Number of top matches 1	3	5	7	10
Mean value	100	77.5	71	65	58
Variance	100	58.5	50.5	44.2	36.25
Diagonal (SVD)	100	60	54.5	48.2	42.25
2DPCA (Vertical & horizontal) (Proposed)	**100**	**91**	**87**	**81.35**	**71.5**

IV. CONCLUSION

A novel face recognition method called diagonal principal component analysis (DiaPCA) is proposed in this paper. The essential idea of the proposed method is to generate the diagonal face images from the original training images, from which the optimal projective vectors are sought; therefore the correlations between variations of rows and those of columns of images can be reserved. Experimental results on a subset of FERET database show that DiaPCA is much more accurate than both PCA and 2DPCA. It is shown that the accuracy can be further improved by combining DiaPCA and 2DPCA together.

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REFERENCES

[1] Graham, D.B., Allinson, G.N.M., 1998. Characterizing virtual Eigen signatures for general purpose face recognition. Face recognition: From theory to applications. NATO ASI Series F, computer and Systems Sciences 163, 446–456.

[2] Swets, D.L., Pathak, Y., Weng, J.J., 1998. An image database system with support for traditional alphanumeric queries and content-based queries by example. Multimedia Tools Appl. (7), 181–212.

[3] D.Q. Zhang, S.C. Chen, J. Liu, Representing image matrices: eigenimages vs. eigenvectors, in: Proceedings of the Second International Symposium on Neural Networks (ISNN'05), Lecture Notes in Computer Science, vol. 3497, Chongqing, China, 2005, pp. 659–664.

[4] Paul Computer and Ahmad, Afandi and Amira, Abbes, optimal discrete wavelet transform (dwt) features for face recognition Nicholl, (2010), Malaysia J. 2000.

[5] Vytautas Perlibakas "distance measure for PCA-based face recognition. Pattern Recognition Letters 25 (2004) 711–724P

[6] Gupta Navarre, P., Ruiz-del-Solar, J., 2001. Eigen space-based recognition of faces: Comparisons and a new approach. In: international Conference on Image Analysis and Processing ICIAP2001. pp. 42–47

[7] Yang J and Zhang D. Two-dimensional pca:a new approach to appearance-based face representation and recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 26(1):131–137, 2004.

[8] K.Tan and S.Chen. Adaptively weighted sub-pattern pca for face recognition. Neurocomputing, 64:505–511, 2005.

[9] S.Chen and Y.Zhu. Subpattern-based principle component analysis. Pattern Recognition, 37:1081–1083, 2005.

[10] M.Safayani, M.T.Manzuri Shalmani, and M.Khademi. Extended two-dimensional pca for efficient face presentation and recognition. ICCP, pages 295–298, Aug 2008.

[11] Zhu, J., Vai, M.I., Mak, P.U., 2003. Face Recognition Using 2D DCT with PCA. The 4th Chinese Conference on Biometric Recognition (Sino biometrics 03), Beijing, PR china.

[12] C minh N Do and martin vettrli. The Contour let Transform: An Efficient Directional multiresolution Image Representation. IEEE Transactions on Image Processing, Vol. 14, No. 12, December

[13] M. N. Do and M. Vetterli. Pyramidal Directional Filter banks and curvelets. IEEE Conference on Image Processing, Thessaloniki, Greece, October 2001.

[14] KHiremath.P.S, Shivashankar. S. Wavelet based features for texture classification, GVIP Journal, Vol. 6, Issue 3, pp 55-58, December 2006.

[15] P.j burt and E.H adelson.laplacian pyramid as a compact image code.IEEE transaction on a communications.vol.COM-31.No.4pp.532-540.

[16] Belhumeur, P.N., Hespanha, J.P., Kriegman, D.J., 1997. Eigenfaces versus fisher faces: recognition using class specific linear projection. IEEE Trans. Pattern Anal. Mach. Intell. 19 (7), 711–720.

[17] Beveridge, R., Bolme, D., Teixerira, M., Draper, B., 2003. The CSU Face Identification Evaluation System User s Guide: Version 5.0. Colorado State University. Chen, L.-F., Liao, Ko, M.-T., Lin, J.-C., Yu, G.-J., 2000.

[18] A new LDA-based face recognition system which can solve the small sample size problem. Pattern Recognit. 33, 1713–1726.

[19] Fukunaga, K., 1990. Introduction to Statistical Pattern Recognition, second ed. Academic Press. Gonzalez, R.C., Woods, R.E., 1992.

[20] Digital Image Processing. Addison-Wesley. Hafed, Z.M., Levine, M.D., 2001.

[21] Face recognition using the discrete cosine transform. Int. J. Comput. Vis. 43 (3), 167– 188.