Human Face Recognition Based on Improved D-LDA and Integrated BPNNs Algorithms

Wenkai Xu and Eung-Joo Lee

Department of Information & Communications Engineering,
Tongmyong University, Busan, Korea
xwk6298@hotmail.com, ejlee@tu.ac.kr

Abstract

In this paper, a combination methodology of Discrete Cosine Transform (DCT) and an improved D-LDA and Neural Networks was proposed. DCT can compress the information of original signal efficiently, so we reduce the dimension firstly and then extract features by improved D-LDA on the low dimension space to overcome the shortages of LDA maximally. After calculating the eigenvectors and a new Fisher's criterion using improved D-LDA algorithm we proposed, the projection vectors are calculated for the training set and then used to train the neural networks for human identity. The experimental results on ORL face database show that this combined method has well performance.

Keywords: *Human face recognition, DCT, improved D-LDA, BPNNs*

1. Introduction

During the past 30 years, many different face-recognition techniques have been proposed, motivated by the increased number of real-world applications requiring the recognition of human faces. PCA algorithm is known as Eigen face method; In PCA method the images are projected onto the facial value so called eigenspace [1] and [2]. PCA approach reduces the dimension of the data by means of basic data compression method [3] and reveals the most effective low dimensional structure of facial patterns [4]. LFA method of recognition is based on the analysis the face in terms of local features e.g. eye, nose etc. by what is referred LFA kernels. Recognition by Neural Network [5] and [6] are based on learning of the faces in an "Example Set" by the machine in the "Training Phase" and carrying out recognition in the "Generalization Phase". Support Vector Machines (SVM) technique is in fact one of the binary classification methods. The support vectors consist of a small subset of training data extracted by the algorithm given in [7]. Face recognition based on template matching represents a face in terms of a template consisting of several enclosing masks the projecting features e.g. the mouth, the eyes and the nose [8]. In [9], a face detection method based on half face-template is discussed.

In this paper, we presents a muti-algorithmic approach, where in a combination of three individual face recognition techniques for enhancing the performance and accuracy of biometric face recognition system. We reduce the dimension firstly using DCT, and then extract features by improved D-LDA on the low dimension space to overcome the shortages of LDA maximally. After calculating the eigenvectors and a new Fisher's criterion using improved D-LDA algorithm we proposed the projection vectors are calculated for the training set and then used to train the neural networks (NNs) for human identity.

2. Feature Extraction in DCT Domain

DCT own fast Fourier Transform algorithm (FFT), as great speed advantage than K-L transform. Based on the theory [10], we implement the original face image with DCT before the extraction of face feature. We only reserve the part of DCT coefficient on the top-left corner to reduce dimensions, it can concentrate the energy and overcome the shortcomings of missing useful information in S_w null space indirectly when wiping off S_b null space using LDA at next step.

3. Improved D-LDA Algorithm for Feature Extraction

There is a problem in D-LDA algorithm: its optimization criteria are not directly related to the classification accuracy, as well as traditional LDA algorithm. Because the edge class plays a leading role which decomposes to the characteristic, it leads to dimension reduction matrix emphases the class excessively which has been classed well, thereby to make the others classes overlapped. To this problem, we redefine the within-class scatter matrix and the between-class scatter matrix of the sample.

Firstly, for inhibiting the effect of edge class and strengthening the effect of the classes within short distance in original sample space, we redefine the between-class scatter matrix by weighting:

$$S_b^{\wedge} = \sum_{i=1}^{c} \Phi_i \Phi_i^T \tag{1}$$

$$\Phi_i = \left(\frac{N_i}{N}\right)^{1/2} \sum_{j=1}^{c} \left(\omega(d_{ij})\right)^{1/2} (z_i - z_j) \tag{2}$$

$$d_{ij} = \|z_i - z_j\| \tag{3}$$

d_{ij} is euclidean distance between the class z_i and z_j, $\omega(d_{ij})$ is a monotonic decreasing function about d_{ij}, its only limitation is that its rate of decline should be faster than Euclidean distance.

Secondly, there is a hypothesis in a general way while using LDA algorithm, i.e. different kinds of sample of classes are content with Homoscedastic Gaussian Model (HOG), namely, all of these samples' Probability Distribution Function (PDF) are subject to Gaussian distribution: different kinds of classes have different mean vector, but all of classes have the same covariance matrix. However, since the small number of sample and edge class, the estimation of mean vector and covariance matrix is not accuracy. So, we redefine the general within-class scatter matrix as below.

$$S_w^{\wedge} = \frac{1}{N} \sum_{i=1}^{c} N_i r_i S_{cwi} \tag{4}$$

$$r_i = \sum_{j \neq i} \frac{1}{L_{ij}} \tag{5}$$

$$L_{ij} = d_{ij} = \|z_i - z_j\| \tag{6}$$

r_i is the weighting value of Z_i class, for guaranteeing to decrease influence while calculating the general within-class scatter matrix , if Z_i is a edge class. L_{ij} is in a measurement for the separability between Z_i and Z_j class, we define L_{ij} as Euclidean distance d_{ij}. In addition, r_i is normalized for making its maximum value to be 1. Through the analysis above, the matrix of defining general divergence is:

$$S_t^{\wedge} = S_b^{\wedge} + S_w^{\wedge} \tag{7}$$

$$W_{opt} = \arg\max_{A} \frac{|AS_tA^T|}{|AS_wA^T|} \tag{8}$$

To take place (1) for solving the SSS problem, moreover the recognition rate is better than [11]. Combining with [12], we come up with a new Fisher's criterion function:

$$W_{opt} = \arg\max_{A} \frac{|AS_t^{\wedge}A^T|}{|AS_w^{\wedge}A^T|} \tag{9}$$

4. Integrated BPNNs Algorithm for Face Recognition

In this paper, we construct integrated BP neural networks to identify face. The core of integrated networks design is dividing K categories into 2-category problems. This construction can swift one complex problems into several easy questions and the modules in integrated networks are mutual parallel connection and each is in charge of one mode identify. According to this idea, we design a kind of integrated sorter composed by several BP networks. Namely, we integrate K multi-input and single-output BP networks and one BP networks is one sub networks charging one mode class in K categories.

We apply these eigenvectors and relative teacher signals to train integrated BP networks after extracting the characters of face image with improved D-LDA based on DCT. And BP sub networks is the standard 3 level BP networks , in addition, as to networks level selection, the reference [13] has proved that : one three-level BP networks can realize arbitrary precision and approximate arbitrary successive function.

We keep that Input level nerve number is I, implication level nerve number is H and output level number is J. Obviously, every BP sub networks J=1. If the dimension of extracted eigenvector is M, networks input level nerve number is M. Also implication level node number is one important parameter. While it is too little, the capability of networks getting information from face is bad and it cannot cover the law of sample; while it is too many, "excessive fusion" may happen and increase study time. Furthermore, nerve number in implication level is not clearly formulated and usually by experience or repeatedly test. Here, we first refer to hidden neural function (10)

$$(I + 1)H + (H + 1)J \leq KI \tag{10}$$

K is the number of training samples.

And we choose a certain number nerve and make comparison by test, and then the reasonable hidden neural number can be gained by further rectification. After each BP sub networks convergence and networks weighted value keeping, all integrated BP networks training finished. When face recognizing, we input extracted untrained face image eigenvector to the trained integrated nerve networks and observe the output of each integrated nerve networks. We set each sub networks output as $O_1, O_2, \ldots, O_j$, and then select the maximum of sub networks to match them with training sample. For example, the number j sub networks are in charge of number j class people. And when recognizing face image, the number j sub networks' output O_j comes maximum, then such face image belongs to number j class people.

5. Experimental Results

First of all, we research the relationship between the numbers of DCT coefficient and recognition rate. We randomly choose five images per person for training without any preprocessing, the other five for testing, and use Z-type for extraction of DCT coefficients, the experimental results show us as Figure 1. Based on these experiments, it is obvious to find that the recognition rate reach the pack when the numbers of coefficients selected about 55, namely, the more DCT coefficients do not means the better recognition results; oppositely, the optimum reconstruction or presentation cannot bring any benefit any more.

Then we build one BP sub networks for each class person in image library to differ others, in which face category number is named integrated sub networks. Although it increases networks number comparing with single networks, each sub networks output node number just comes to single networks 1/k and networks structure simplifies enormously. Therefore, the velocity of study becomes much faster and the convergence turns much easier. At the same time, system gains strong expansibility: when increasing or decreasing the recognition of one class of people, what we need to do is that add or delete one sub networks but destroy to system brought by single BP networks. The comparison of recognition rate by using different methods is shown as Figure 2.

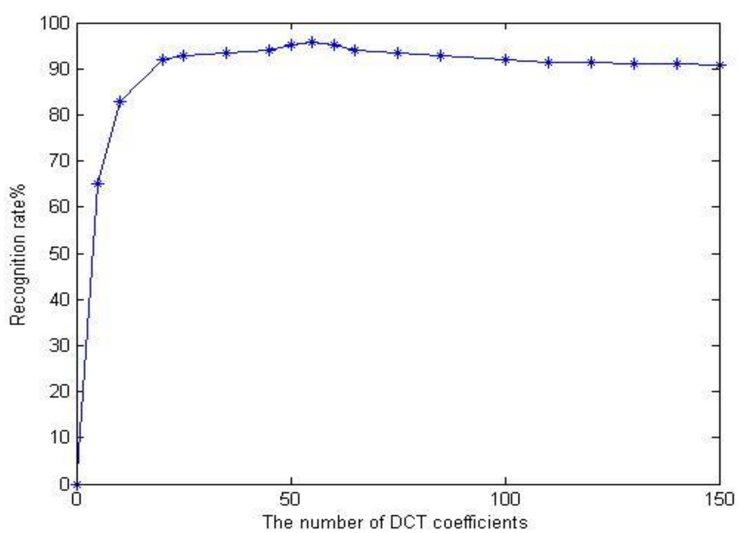

Figure 1. The Relationship between the Number of DCT Coefficients and Recognition Rate

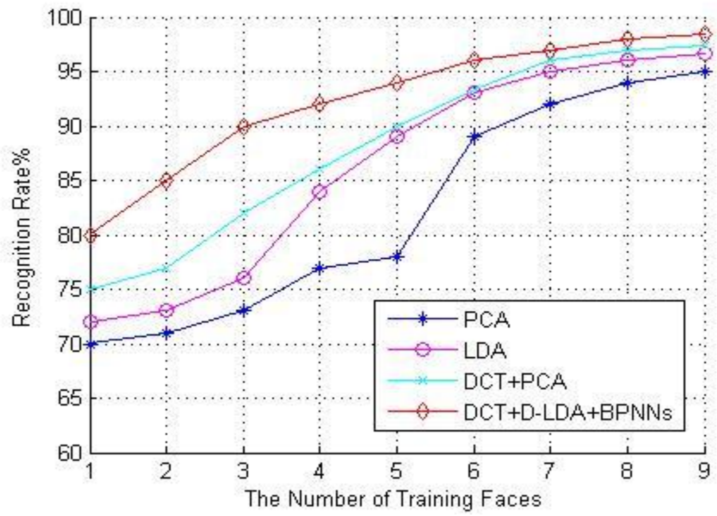

Figure 2. The Comparison of Different Methods

6. Conclusion

In this paper, a combination methodology of Discrete Cosine Transform (DCT) and an improved LDA and integrated BPNNs was proposed. The method based on DCT can compress the information of original signal efficiently; Furthermore, the improved D-LDA algorithm we proposed can withhold useful information and restrain the effect of edge class preferable through redefining the within-class scatter matrix and between-class scatter matrix, enhance the recognition rate by reducing dimension, and it can solve the small sample size problem without losing useful information. After that, the projection vectors are calculated for the training set and then used to train the neural networks for human identity.

Acknowledgements

This research was supported by the MKE (The Ministry of Knowledge Economy), Korea, under the IT/SW NHN Program supervised by the NIPA (National IT Industry Promotion Agency)" (NIPA-2011-C1820-1102-0010).

References

[1] M. Turk and A. Pentland, "Eigenfaces for Recognition", Journal of Cognitive Neuroscience, pp.71-86 **(1991)**.

[2] Tat-Jun Chin and D. Suter, "A Study of the Eigenface Approach for Face Recognition", In: Technical Report of Monash University, Dept.Elect & Comp.Sys Eng (MECSE 2004) Australia, pp.1-18 **(2004).**

[3] D. Blackburn, M. Bone and P. Phillips, "Facial Recognition Vendor Test 2000: Evaluation Report", National Institute of Science and Technology, Gaithersburg, USA **(2000).**

[4] P. J. Phillips, H. Moon, S.Rizvi and P. Rauss, "FERET Evaluation Methodology for Face Recognition Algorithms", IEEE transaction on pattern analysis and machine intelligence (PAMI 2000), Los Alamitos, USA, pp.1090-1103 **(2000).**

[5] D. Bryliuk and V. Starovoitov, "Access Control by Face Recognition using Neural Networks and Negative Examples", 2nd International Conference on Artificial Intelligence **(2002)**, Crimea, Ukraine, pp. 428-436.

[6] S. A. Nazeer, N. Omar and M. Khalid, "Face Recognition System using Artificial Neural Networks Approach", IEEE International Conference on Signal Processing, Communications and Networking, pp. 420-425 **(2007)**.

[7] Huang, X. Shao and H. Wechsler, "Face Pose Discrimination Using Support Vector Machines", Technical report of George Mason University and University of Minnesota, Minneapolis Minnesota, United States **(1998)**.

[8] R. Brunelli and T. Poggio, "Face Recognition: Features versus Templates", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 15, no.10, pp. 1042-1052 **(1993)**.

[9] W. Chen, T. Sun, X. Yang and L. Wang, "Face detection based on half face template", Proc. of the IEEE Conference on Electronic Measurement and Instrumentation, pp. 54-58 **(2009)**.

[10] W. Chen, M. Joo Er and S. Wu, "PCA and LDA in DCT domain", Pattern Recognition Letters, vol. 26, pp. 2474–2482 **(2005)**.

[11] H. Yu and J. Yang, "A direc LDA algorithm for high-dimension data with application to face recognition", Pattern Recognition, Vol. 34, pp. 2067-2070 **(2001)**.

[12] Wu Xiao-Jun, Josef K.,Yang Jing-Yu, "A New direct LDA (D-LDA) algorithm for feature extraction in face recognition", Proceedings of the 17th International Conference on Pattern Recognition **(2004)**, Cambridge, England, UK.

[13] R. H. N, Theory of the Back propagation Neural Network, Washington. DC., pp. 583-604 **(1989)**.

Authors

Wenkai Xu

Wenkai Xu received his B. S. at Dalian Polytechnic University in China (2006-2010). Currently, he is studying in Department of Information and Communications Engineering Tongmyong University, Korea for master degree. His main research areas are image processing, computer vision, biometrics and hand recognition.

Eung-Joo Lee

Eung-Joo Lee received his B. S., M. S. and Ph. D. in Electronic Engineering from Kyungpook National University, Korea, in 1990, 1992, and Aug. 1996, respectively. Since 1997 he has been with the Department of Information & Communications Engineering, Tongmyong University, Korea, where he is currently a professor. From 2000 to July 2002, he was a president of Digital Net Bank Inc. From 2005 to July 2006, he was a visiting professor in the Department of Computer and Information Engineering, Dalian Polytechnic University, China. His main research interests include biometrics, image processing, and computer vision.