Face Recognition using Locality Preserving Projection on Wavelet Subband and Artificial Neural Network

Qiang Hua[a], YiGong Liu[a], LiLi Sun[b], Jasmy Faddel Miazonzama[a]

[a] *Key Lab. of Machine Learning and Computational Intelligence,*
College of Mathematics and Information Science, Hebei University, Baoding, China, P.R.
[b] *Hebei Education Examinations Authority, Shijiazhuang, China P.R.*

Abstract: *In past recent years, Locality preserving Projection (LPP) has proved to be an alternative to Principal Component Analysis in Face Recognition. Despite the fact that LPP is better than PCA, it has some limits. In order to overcome that limits, many new methods still emerging. In this paper we propose a method using Locality preserving Projection on Wavelet Subband for features extraction and Artificial Neural Network for recognition. A comparative study has been done between the new method, the Locality Preserving Projection, the Principal Component Analysis and the Principal Component Analysis on Wavelet Subband by considering execution time, recognition rate and dimension reduction power. Experiments have been done on two face data bases: ORL and Yale data bases. Results show that the new method improve a little bit the execution time.*

Keywords: Neural Network (NN), Locality Preserving Projection (LPP), Principal Component Analysis, Wavelet Subband

1. INTRODUCTION

The goal of face recognition is to identify a person from an input face image and a database of face images of known individuals. However, when using face recognition, the dimensional space is too large to allow robust and fast recognition. A common way to attempt to resolve this problem is to use dimensionality reduction techniques [1]. The main issue is how to properly define and determine a low-dimensional subspace of face appearance in a high-dimensional image space.

Thereby In 1988, Kirby and Sirivich [2] have proposed Principal Component Analysis (PCA) for dimension reduction. In 1997, Belhumeur and al. have introduced linear Discriminant Analysis (LDA) [3]. PCA and LDA have been widely used for face recognition. Recently, a number of research efforts have shown that in many real-world classification problems, the local manifold structure is more important than the global Euclidean structure. However, PCA see only the global structure of the image space. In order to overcome that problem, Xiaofei He and al., in 2003, have proposed Locality Preserving Projection (LPP) [4] which aims to preserve the local structure of the image space.

Though LPP have been applied in many domains, it has some limits to solve recognition problem. In order to improve the discriminating power of LPP, Xiaofei et al. have introduced Orthogonal Locality Preserving Projection (OLPP) [5]. In 2005, Weiwei et al. have proposed Discriminant Locality Preserving Projection (DLPP) [6] to achieve better face recognition performance than LPP. In 2009, Jie GUI Et Al. have introduced Locality Preserving Discriminant Projection (LPDP) [7] to find a subspace which have more discriminant power than LPP.

In other hand, in 2000, G. C. Feng have proposed a methodology based on PCA on Wavelet subband [8]. The goal was to overcome poor discriminatory power of PCA. Since, many other works have shown that applying PCA on Wavelet can really overcome the traditional PCA [9], [10]. In this paper, we are going to apply LPP on Wavelet subband and use Back Propagation Neural Network for classification. After that, a comparative study will be done between the new method, the Locality Preserving Projection, the Principal Component Analysis and the Principal Component Analysis on Wavelet Subband Three kind of performance will be considered: Execution time, Recognition rate and Dimension reduction power.

2. LOCALITY PRESERVING PROJECTION

Locality Preserving Projection (LPP) was introduced by He Xiaofei and Partha Niyogi to overcome some limits in face recognition area. It maps the face data onto a low-dimensional face feature subspace called "Laplacianfaces" [11], which aims to preserve the local structure of the image space. It is a linear dimensionality reduction algorithm.

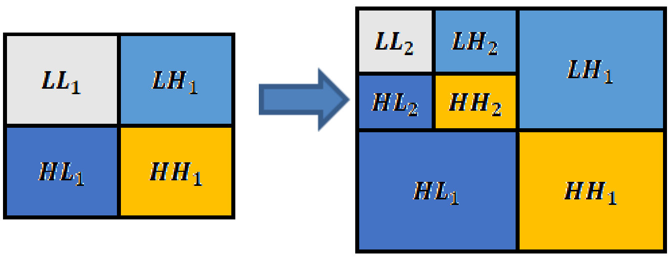

Figure 1: 1 and 2-level Wavelet decomposition

The algorithm used for Locality Preserving Projection has for steps ([4]):

1) The image set is first projected into a PCA subspace by throwing away the smallest principal components.
2) Constructing the nearest-neighbor Graph
3) Setting the weight between neighbors
4) Solving the Eigen problem

The main objective of LPP is to preserve the local structure computing the eigenvectors a and eigenvalues λ for the generalized eigenvector problem:

$$XLX^t a = \lambda XDX^t a \quad (1)$$

Where D is a diagonal matrix whose entries are columns sums of W, $D_{ii} = \sum_j W_{ij}$ and $L = D - S$ is the Laplacian matrix. Let the column vectors $a_1, a_2, \dots, a_l$ be the solution of eq. (6), ordered according to their eigenvalues $\lambda_1 < \lambda_2 < \cdots < \lambda_l$. Thus the projection matrix is $A = (a_1, a_2, \dots, a_l)$, and the embedding is as follows:

$$x_i \rightarrow y_i = A^t x_i \quad (2)$$

Where x_i is an n-dimensional vector, y_j is an l-dimensional vector, and A is an $n \times l$ matrix.
The justification and demonstration of eq. (1) is done in [4].

3. WAVELET TRANSFORM

Wavelet Transform (WT) was borne out of a need for further developments from Fourier transforms. It has recently become a very popular when it comes to analysis, de-noising and compression of signals and images. It is a feature extraction method. The main reasons for Wavelet transforms popularity lie in the low computational complexity. In practical application, Wavelet transforms have shown better recognition accuracy and discriminatory power. They reduce the computational load significantly when the image database is large, with more than 256 training images. There are two big classes of wavelet transforms - continuous and discrete.
Discrete Wavelet Transform (DWT) is generally preferred to Continuous Wavelet Transform (CWT) because CWT provides redundant information and requires a lot of computations. Wavelet Transform divides information of an image into approximation and detail subsignal. The approximation subsignal shows general trend of pixel values and three detail subsignals on the horizontal, vertical and diagonal details. The band LL is the approximation to the original image. The bands LH and HL record the edges along the horizontal and vertical directions respectively. The HH band records the diagonal edges present in the image. This is the first level decomposition. Further decomposition can be conducted on the LL subband [9] [10]. The figure below shows the first and the second level Wavelet decomposition.

Considering the fact that Daubechies wavelet D4 is better than other wavelets [8], therefore, Daubechies wavelet D4 is adopted for image decomposition in our system. In our case, we are using image of 64x64 pixels. So we will have only 2-level decomposition to get 16x16 pixels images. Them, we are going to apply LPP on LL_2 subband.

4. ARTIFICIAL NEURAL NETWORK AND BACK PROPAGATION ALGORITHM

Artificial Neural Networks can be grouped into two groups: *feed-forward* and *recurrent (feed-back)* Networks. Among the *feed-forward* networks the "Back-Projection" algorithm is the best and most widely used learning algorithm [12] [13]. Back-Propagation is a multi-layer feed-forward, supervised learning network based on "*gradient descendent*" learning rule (or *delta rule*). It was proposed by Rumelhart and McClelland in 1986. It has since become a famous learning algorithm among ANNs, and has been successfully applied in diverse application, such as pattern recognition.

The idea of the back propagation is to reduce the error (difference between actual and expected results), until the ANN learns the training data. The training begins with random weights, and the goal is to adjust them so that the error will be minimal. The artificial neural network may have one or more intermediate hidden layers. Here, we use only one hidden layer.
The activation function is used for limiting amplitude of the output of the neuron. There are a variety of activation functions. Concerning the back propagation algorithm, since this method requires computation of the gradient of the error function at each iteration step, we must guarantee the continuity and differentiability of the error function. So, the "*sigmoid*" function is commonly used in multilayer networks that are trained using the back propagation algorithm.

Now, the goal of the training process is to obtain a desired output when certain inputs are given. Since the error is the difference between the actual and the desired output, the error depends on the weights, and we need to adjust the weights in order to minimize the error. We can define the error function for the output of each neuron

$$E = \frac{1}{2}\sum_j (d_i - y_i)^2 \quad (3)$$

We can adjust the network's weights using the *delta rule* defined by:

$$\Delta\omega_{ji} = -\mu \frac{\partial E}{\partial \omega_{ji}} \quad (4)$$

According to the correction $\Delta\omega_{ji}$ applied to ω_{ji}, the new weights can be defined by the following equation:

$$\omega_{ji}(new) = \omega_{ji}(old) + \Delta\omega_{ji} \quad (5)$$

The updated process of the weights is repeated until the error reaches a minimum value.

5. EXPERIMENT AND RESULTS

5.1 Image database

For our experimentation, we are using face images (64x64 pixels) of ORL and Yale databases. ORL data base contains 400 grayscale images of 40 distinct subjects, 10 different images of each. Yale data base Contains 165 grayscale images of 15 individuals. There are 11 images per subject.

Figure 2 : Sample cropped face images of three individuals from ORL database.

Figure 3 : Sample cropped face images of three individuals from Yale database.

5.2 Extraction of local feature and neural network training

To extract the local feature of the images, we first applied Wavelet Subband on each face images of both databases. After applying the 1-level Wavelet decomposition, we got images of 32x32 pixels. Then, we applied the 2-level wavelet decomposition to get 16x16 pixels images. Therefore, subbands HL_1, LH_1 and HH_1 are of size 32x32 pixels and subbands LL_2, HL_2, LH_2 and HH_2 are of size 16x16 pixels (fig. 1). The subband LL_2 is chosen for the continuation of the experiment.

The second step consists to apply LPP and PCA on that subband. 70% and 30% of images have been respectively taken for training and testing.

Finally, Back Propagation is used to achieve the recognition. To train the back propagation neural network, the choice of convenient parameters is very important. So, to get the best results the initial weights are set to a random number between -0.5 and 0.5. For hidden units, we take the half of Eigenvectors. Below is a table summarizing the other parameters used to train the network.

TABLE I
Parameters used to train the Back Propagation Neural Network

Learning rate	0.4
No. of epochs	300
Performance par.	10^{-5}
Activation function	Tansig
No. of epochs between displays	50

5.3 Results

After training the network, the recognition have been achieved. Afterwards, the reduced dimension, the recognition rate and the execution time of LPP, LPP+DWT, PCA and PCA+DWT have been noticed. Tables below show the results.

TABLE II
Dimensions reduction for ORL Database

Nb of imag.	Dimensions			
	LPP	**LPP+DWT**	**PCA**	**PCA+DWT**
100	9	9	34	20
200	19	19	56	28
300	29	29	72	33
400	39	39	85	36

TABLE III
Dimensions reduction for Yale Database

Nb of imag.	Dimensions			
	LPP	**LPP+DWT**	**PCA**	**PCA+DWT**
33	2	2	14	10
66	5	5	23	16
99	8	8	31	19
132	11	11	35	21
165	14	14	40	23

TABLE IV
Recognition rate for ORL Database

Nb of imag	Recognition rate (%)			
	LPP	**LPP+DWT**	**PCA**	**PCA+DWT**
100	99.8545	99.8121	97.8235	98.4416
200	99.8749	99.6468	96.3734	96.9291
300	99.7241	99.476	95.7641	96.6296
400	99.7761	99.0974	94.8826	95.4095

TABLE V
Recognition rate for Yale Database

Nb of imag	Recognition rate (%)			
	LPP	**LPP+DWT**	**PCA**	**PCA+DWT**
33	98.6874	98.8959	96.0716	98.4425
66	99.7491	99.6155	98.0148	98.2856
99	99.8330	99.7337	96.9461	97.9129
132	99.8464	99.7086	96.8244	96.7851
165	99.8534	99.5581	96.0758	96.1519

TABLE VI
Execution times for ORL Database

Nb of imag.	Execution times (sec.)			
	LPP	**LPP+DWT**	**PCA**	**PCA+DWT**
100	32	31	37	28
200	35	32	154	34
300	43	38	494	46
400	73	63	1153	58

TABLE VII
Execution times for Yale Database

Nb of imag.	Execution times (sec.)			
	LPP	**LPP+DWT**	**PCA**	**PCA+DWT**
33	36	30	26	26
66	34	33	29	28
99	34	34	37	30
132	34	33	40	27
165	35	33	56	31

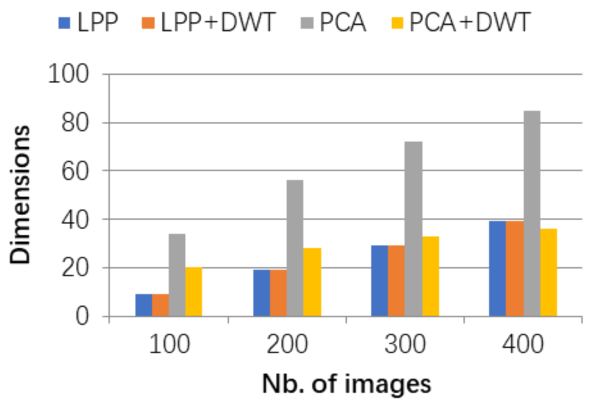

Figure 4: Dimension reduction power on ORL Database

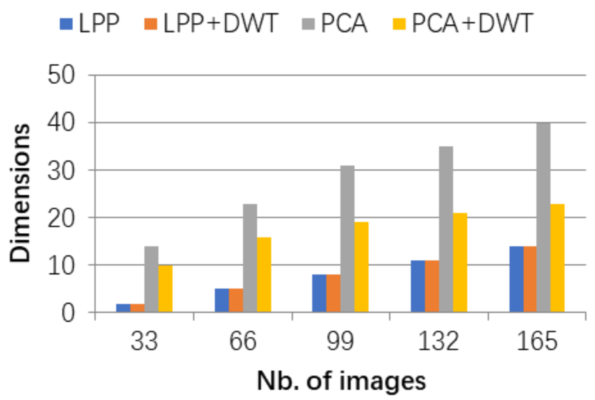

Figure 5: Dimension reduction power on Yale Database

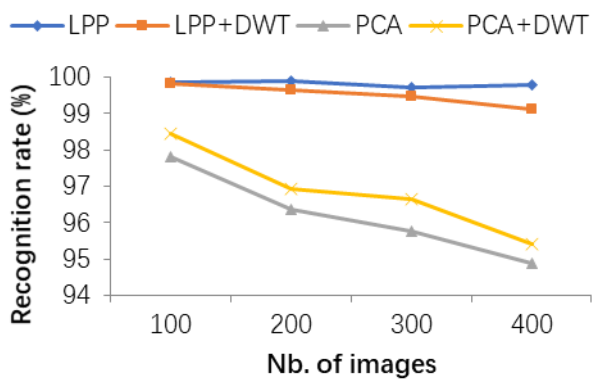

Figure 6: Recognition rate on ORL Database

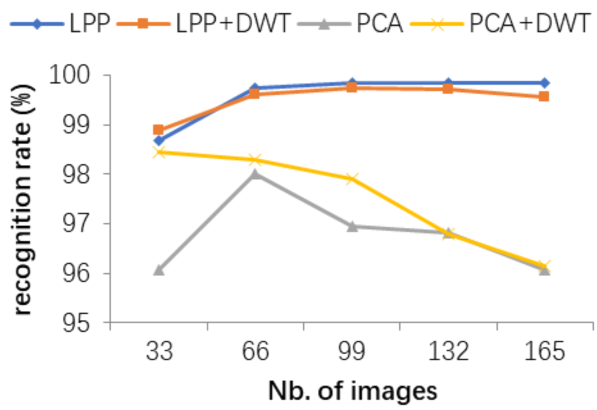

Figure 7: Recognition rate on Yale Database

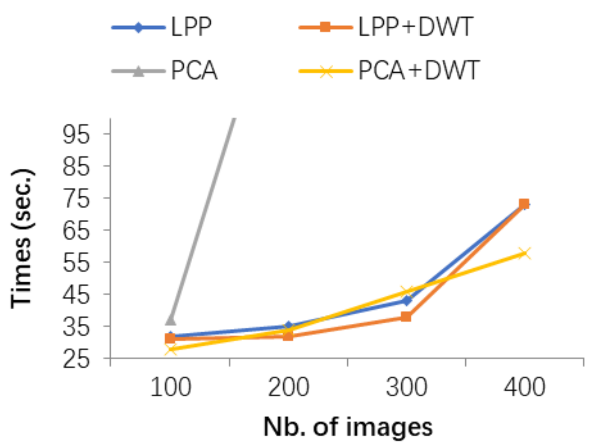

Figure 8: Execution time on ORL Database

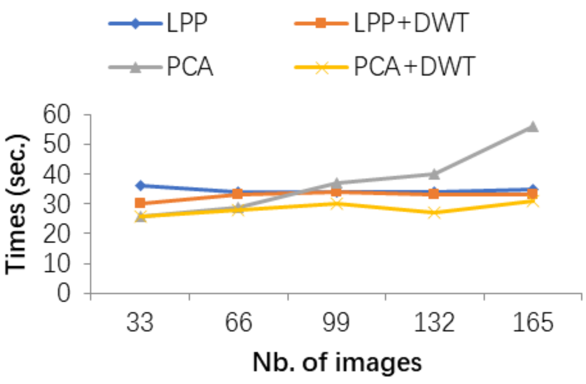

Figure 9: Execution time on Yale Database

5.4 Discussion

From TABLE III and IV, we can see that applying LPP on Wavelet Subband doesn't influence the Dimension Reduction Power. For PCA applied on Wavelet Subband, it is different. Applying PCA on Wavelet Subband really influence the Dimension Reduction Power. In the case of PCA+DWT, the Dimension Reduction Power is more effective when the number of data is important.

TABLE IV and V show that applying LPP on Wavelet Subband regresses a little bit the Recognition Rate while applying PCA on Wavelet Subband really increase the Recognition Rate.

Concerning the Execution Time, applying LPP on Wavelet Subband reduce a little bit the Execution Time. The difference is important when the number of data is more than 200. PCA on Wavelet shows an important reduction of Execution Time when data are more than 100.

From TABLE IV and V, we can see that LPP and LPP+DWT provide better Recognition rate than PCA+DWT. LPP and LPP+DWT have also better discriminatory power than PCA+DWT.

6. CONCLUSION

As we can see, applying LPP on Wavelet Subband reduce a little bit the execution time. It falls to improve The Dimension Reduction Power and the Recognition Rate. On the other side, applying PCA on Wavelet Subband really improved the Dimension Reduction Power, Recognition Rate and Execution Time. Despite the fact that PCA on Wavelet Subband is very advantageous, it is not able to overcome LPP. Therefore, till now, LPP seems to be an alternative to PCA and its improvements.

ACKNOWLEDGEMENTS : This research is supported by the Natural Science Foundation of Hebei Province (F2018201115, F2018201096), the Foundation of Research and Practice of Teaching Reform in Higher Education of Hebei province (2016GJJG012) and the Youth Scientific Research Foundation of Education Department of Hebei Province (QN2017019).

REFERENCES

[1] Sharath S S, Balasubramanya M K N, Natarajan S. Dimensionality Reduction Techniques for Face Recognition. Reviews, Refinements and New Ideas in Face Recognition. InTech, 2011.

[2] M. Kirby and L. Sirovich, Application of the karhunen-loeve procedure for the characterization of human faces, IEEE Pattern Analysis and Machine Intelligence, 12(1): 103-108, 1990

[3] Belhumeur, Peter N., João P. Hespanha, and David Kriegman. Eigenfaces vs. fisherfaces: Recognition using class specific linear projection. IEEE Transactions on Pattern Analysis and Machine Intelligence, 19(7): 711-720, 1997

[4] He X, Niyogi P. Locality preserving projections. Advances in Neural Information Processing Systems, 16(1):186-197, 2004

[5] Cai D, He X, Han J, et al. Orthogonal laplacianfaces for face recognition. IEEE Transactions on Image Processing, 15(11):3608-14, 2006

[6] Yu W, Teng X, Liu C. Face recognition using discriminant locality preserving projections. Image & Vision Computing, 24(3):239-248, 2006

[7] Shikkenawis G, Mitra S K. Locality Preserving Discriminant Projection. IEEE International Conference on Identity, Security and Behavior Analysis. IEEE,1-6, 2015

[8] Feng, G. C., Yuen, P. C., & Dai, D. Q. Human face recognition using PCA on wavelet subband. Journal of Electronic Imaging, 9(2): 226-233, 2000

[9] Satone, M., & Kharate, G. K. Face Recognition Based on PCA on Wavelet Subband of Average-Half-Face. Journal of Information Processing Systems, 8(3): 483- 495, 2012

[10] Satone, M., & Kharate, G. K. Selection of Eigenvectors for Face Recognition. International Journal of Advanced Computer Science and Applications, 4(3): 95-98, 2013

[11] Xiaofei He et al., Face Recognition Using Laplacianfaces. IEEE trans. Pattern Analysis and Machine Intelligence, 27(3): 328-340, 2005

[12] Rizon, Mohamed, et al., Face recognition using eigenfaces and neural networks. American Journal of Applied Sciences, 2(6): 1872-1875, 2006

[13] N. Revathy and T.Guhan, Face Recognition System Using Back Propagation Artificial Neural Networks. International Journal of Advanced Engineering Technology, 3(1): 321-324, 2012