Combination of Wavelet and PCA for Face Recognition

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***ABSTRACT* — This work presents a method to increase the face recognition accuracy using a combination of Wavelet, PCA, and Neural Networks. Preprocessing, feature extraction and classification rules are three crucial issues for face recognition. This paper presents a hybrid approach to employ these issues. For preprocessing and feature extraction steps, we apply a combination of wavelet transform and PCA. During the classification stage, the Neural Network (MLP) is explored to achieve a robust decision in presence of wide facial variations. The computational load of the proposed method is greatly reduced as comparing with the original PCA based method on the Yale and ORL face databases. Moreover, the accuracy of the proposed method is improved**.

***Index Terms* — MLP Neural Network, Wavelet Transform, PCA, Face recognition.**

I. Introduction

Over the past few years, the user authentication is increasingly important because the security control is required everywhere. Traditionally, ID cards and passwords are popular for authentication although the security is not so reliable and convenient. Recently, biological authentication technologies across voice, iris, fingerprint, palm print, and face, etc are playing a crucial role and attracting intensive interests for many researchers. Among them, face recognition is an amicable alternative because the authentication can be completed in a hands-free way without stopping user activities. Also, the face recognition system is economic with the low-cost of cameras and computers.

It is extensively feasible to identity authentication, access control, and surveillance, etc. Over the past 20 years, extensive research works on various aspects of face recognition by human and machines [1, 2, 12, 19, 20,21 ,22,25] have been conducted by psychophysicists, neuroscientist and engineering scientists. Psychophysicists and neuroscientists have studied issues such as uniqueness of faces, how infants perceive faces and organization of memory of faces. While engineering scientist have designed and developed face recognition algorithms. This paper continues the work done by engineering scientist in face recognition by machine. Automatic face recognition by computer can be divided into two approaches [1, 2], namely, content-based and face-based. In content-based approach, recognition is based on the relationship between human facial features such as eyes, mouth, nose, profile silhouettes and face boundary [3, 4, 5, 6]. The success of this approach relies highly on the accurately is difficult. Every human face has similar facial features; a small derivation in the extraction may introduce a large classification error.

Face-based approach [7, 8, 5, 9] attempts to capture and define the face as a whole. The face is treated as a two-dimensional pattern of intensity variation. Under this approach, face is matched through identifying its underlying statistical regularities. Principal Component Analysis (PCA) [7, 8, 10, 20, 23] has been proven to be an effective face-based approach. Sirovich and Kirby [10] first proposed using Karhunen-Loeve (KL) transform to represent human faces. In their method, faces are represented by a linear combination of weighted eigenvector, known as eigenfaces. Turk and Pentland [8] developed a face recognition system using PCA.

However common PCA-based methods suffer from two limitations, namely, poor discriminatory power and large computational load. It is well known that PCA gives a very good representation of the faces. Given two images of the same person, the similarity measured under PCA representation is very high. Yet, given two images of different persons, the similarity measured is still high. That means PCA representation gets a poor discriminatory power. Swets and Weng [11] also observed this drawback of PCA approach and further improve the discriminability of PCA by adding Linear Discriminant Analysis (LDA). But, to get a precise result, a large number of samples for each class is required. On the other hand, O'Toole et al. [12] proposed different approach for selecting the eigenfaces. They pointed out that the eigenvectors with large eigenvalues are not the best for distinguishing face images. They also demonstrated that although the low dimensional representation is not optimal for recognizing a human face, gives good results in identifying physical categories of face, such as gender and race. However, O’Toole et al. have not addressed much on the selection criteria of eigenvectors for recognition.

The second problem in PCA-based method is the high computational load in finding the eigenvectors. The computational complexity of this is O(d^2) where d is the number of pixels in the training images which has a typical value of 128x128. The computational cost is beyond the power of most existing computers. Fortunately, from matrix theory, we know that if the number of training images, *N*, is smaller than the value of *d*, the computational complexity will be reduced to O(N^2). Yet still, if *N* increases, the computational load will be increased in cubic order.

In view of the limitations in existing PCA-based approach, we proposed a new approach in using PCA – applying PCA on wavelet subband for feature extraction. In the proposed method, an image is decomposed into a number of subbands with different frequency components using the wavelet transform. The result in [29] show that three level wavelet has a good performance in face recognition. The proposed method works on lower resolution, 16 x 16, instead of the original image resolution of 128 x 128. Therefore, the proposed method reduces the computational complexity significantly when the number of training image is larger than 16 x 16, which is expected to be the case for a number of real-world applications. Moreover, experimental results demonstrated that applying PCA on WT sub-image gives better recognition accuracy and discriminatory power than applying PCA on the whole original image. Then feature vectors classify by MLP Neural Network.

This paper is organized as follows. Section II reviews the background of PCA. Wavelet decomposition of an image reviews in section III. The proposed method is discussed in section IV. Experimental results are presented in section V and finally, section VI gives the conclusions.

II. REVIEW OF PCA

PCA is used to find a low dimensional representation of data. Some important details of PCA are highlighted as follows [13].

Let $X = \{X_n, n = 1,..., N\} \in R^{dxd}$ be an ensemble of vectors. In imaging applications, they are formed by row concatenation of the image data, with *dxd being* the product of the width and the height of an image. Let be the average vector in the ensemble.

$$E(X) = \frac{1}{N}\sum_{n=1}^{N} X_n$$

After subtracting the average from each element of X, we get a modified ensemble of vectors, $\overline{X} = \{\overline{X}_n, n = 1,..., N\}$ with $\overline{X}_n = X_n - E(X)$. The auto-covariance matrix *M* for the ensemble *X* is defined by $M = \mathrm{cov}(\overline{X}) = E(\overline{X} \otimes \overline{X})$ Where *M* is d^2xd^2 matrix, with elements $M(i, j) = \frac{1}{N}\sum \overline{X}_n(i)\overline{X}_n(j), 1 \le i.j \le d^2$

It is well known from matrix theory that the matrix *M* is positively definite (or semi-definite) and has only real non-negative eigenvalues [13]. The eigenvectors of the matrix *M* form an orthonormal basis for R^{dxd} . This basis is called the K-L basis. Since the auto-covariance matrix for the K-L eigenvectors are diagonal, it follows that the coordinates of the vectors in the sample space *X* with respect to the K-L basis are un-correlated random variables. Let $\{Y_n, n = 1,..., N\}$ denote the eigenvectors and let *K* be the d^2xd^2 matrix whose columns are the vectors $Y_1,..., Y_N$. The adjoint matrix of the matrix *K*, which maps the standard coordinates into K-L coordinates, is called the K-L transform.

In many applications, the eigenvectors in *K* are sorted according to the eigenvalues in a descending order. In determining the *dxd* eigenvalues from *M*, we have to solve a d^2xd^2 matrix. Usually, *d*=128 and therefore, we have to solve a 16x16 matrix to calculate the eigenvalues and eigenvectors. The computational and memory requirement of the computer systems are extremely high.

From matrix theory that if the number of training images *N* is much less than the dimension of *M*, i.e. $N < dxd$, the computational complexity is reduced to O (N). Also, the dimension of the matrix M in equation (4) needed to be solved is also reduced to *NxN*. Details of the mathematical derivation can be found in [7]. Since then, the implementation of PCA for characterization of face becomes flexible. In most of the existing works, the number of training images is small and is about 200. However, computational complexity increases dramatically when the number of images in the database is large, say 2,000.

The PCA of a vector y *related* to the ensemble *X* is obtained by projecting vector y *onto* the subspaces spanned by *d' eigenvectors* corresponding to the top *d' eigenvalues* of the autocorrelation matrix *M* in descending order, where d' *is* smaller than *d*. This projection results in a vector containing d' coefficients $a_1,..., a_{d'}$. The vector y is then represented by a linear combination of the eigenvectors with weights $a_1,..., a_{d'}$.

III. WAVELET DECOMPOSITION OF AN IMAGE

Wavelet Transform (WT) has been a very popular tool for image analysis in the past ten years. The mathematical background and the advantages of WT in signal processing have been discussed in many research articles. In the proposed system, WT is chosen to be used in image decomposition because:

- By decomposing an image using WT, the resolution of the subimages are reduced. In turn, the computational complexity will be reduced dramatically by operating on a lower a resolution image. Harmon [16] demonstrated that image with resolution 16x16 is sufficient for recognizing a human face. Comparing with the original image resolution of 128x128, size of the sub-image is reduced by 64 times, and the implies a 64 times reduction in recognition computational load.

- Under WT, images are decomposed into subbands, corresponding to different frequency ranges. These subbands meet readily with the input requirement for the next major step, and thus minimize the computational overhead in the proposed system.

- Wavelet decomposition provides the local information in both space domain and frequency domain, while the Fourier decomposition only supports global information in frequency domain.

Throughout this paper, we applied two well known mother wavelet Daubechies D4 [17, 18] and Haar [27]. We proposed method that uses by coefficients:

$$h_0 = 0.48296291314453$$
$$h_1 = 0.83651630373781$$
$$h_2 = 0.22414386804201$$
$$h_3 = 0.12940952255126$$

for daubechies mother wavelet and coefficients:

$$h_0 = 0.5, h_1 = 0.5$$

for haar mother wavelet .An image is decomposed into four subbands. The band LL is a coarser approximation to the original image. bands LH and HL record respectively the changes of the image along horizontal and vertical directions while the HH band shows the higher frequency component of the image. This is the first level decomposition. The decomposition can be further carried out for the LL subband. After applying a three-level Wavelet transform, an image is decomposed into subbands of different frequency as shown in Fig. 1.if the resolution of an image is 128x128 the subbands1, 2, 3, 4 are of size 16x16, the sub bands 5, 6, 7 are of size 32x32 and the subbands 8,9,10 are of size 64x64.

IV. PROPOSED METHOD

A wavelet-based PCA method is developed so as to overcome the limitation of the original PCA method; furthermore, we have utilized a neural network in order to carry out the classification of faces. We adopted a multilayer perceptron architecture which is fed by the reduced input units, feature vectors generated by combination of wavelet and PCA. We propose the usage of a particular frequency band of a face image for PCA to solve the first problem of PCA.

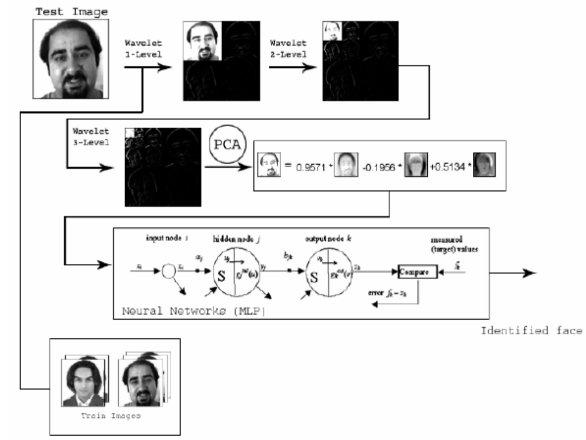

Fig. 1. Block diagram of the proposed face recognition system.

The second limitation can be dealt with by using a lower resolution image. The combination of new wavelet-based PCA and neural network is illustrated in Fig. 1. Our proposed system consists of two stages, namely training step in which the feature extraction, dimension reduction and adjusting the weight of MLP neural networks have been performed and the recognition step to identify the unknown face image. The training stage includes the feature extraction of reference images and the adjustment of neural network parameters. The extracting feature identifies the representational basis for images in the domain of interest. Subsequently, the recognition stage translates the input unknown image according to the representational basis, identified in the training stage.

There are three significant steps in the training stage. In the first step, wavelet transform (WT) is applied to decompose reference images; consequently, sub-images in the form of 16x16 pixels obtained by three level wavelet decomposition are selected. In the next step, Principal Component Analysis (PCA) is performed on the sub-images to obtain a set of representational basis by the selection of d' eigenvectors corresponding with the largest eigenvalues and sub-space projection.

Finally, the feature vectors of reference images obtained by previous steps are used so as to train neural networks using back propagation algorithm. Processing in the recognition stage is similar to the training stage, except that recognition stage also incorporates steps to match the input unknown images with those reference images in the database by neural network. When an unknown face-image is presented to the recognition stage, WT and PCA are applied to transform the unknown face-image into the representational basis identified in the recognition stage, and the classification is achieved by trained MLP neural networks [14, 15].

V. EXPERIMENTAL RESULT

To evaluate the performance of the proposed method, we used the face-image database of Yale University [26] and ORL face database [28]. All of the images in Yale database have a resolution of 160x121. But the dimension of these images is not the power of 2, so that the wavelet transform can not be applied effectively. For solving this problem, we crop these images to 91x91 and, then resize them into 128*128. All of the images in ORL database also resize into 128*128. In this work, the resolution of images is changed in from of 128x128 to 16x16 using the third level of wavelet decomposition. Table I and II show the result of suggested algorithm on Yale and ORL database using haar mother wavelet. Table III and IV show the result of suggested algorithm on Yale and ORL database using daubechies mother wavelet. According to the results, using of daubechies wavelet is better than haar wavelet.

TABLE I. Result of suggested algorithm on Yale database and haar mother wavelet.

	PCA on image	PCA on LL band of three level wavelet
Size of image	128*128	16*16
Recognition rate	81.78%	82.2%

TABLE II. Result of suggested algorithm on ORL database and haar mother wavelet.

	PCA on image	PCA on LL band of three level wavelet
Size of image	128*128	16*16
Recognition rate	90%	91.80%

TABLE III. Result of suggested algorithm on ORL database and Daubechies4 mother wavelet.

	PCA on image	PCA on LL band of three level wavelet
Size of image	128*128	16*16
Recognition rate	90%	97.68%

TABLE IV. Result of suggested algorithm on Yale database and Daubechies4 mother wavelet.

	PCA on image	PCA on LL band of three level wavelet
Size of image	128*128	16*16
Recognition rate	81.78%	90.35%

After choosing mother wavelet, the number of principal component indicating number of neuron in input layer in neural network has to be determined. Table V and VI show the recognition performance on test images of Yale and ORL database using the different number of principal components. In the next step, we have to specify the topology of our neural network. Table VII and VIII show the Recognition performance on test images of Yale and ORL database using MLP Neural networks regarding fixed size neuron in input layer extracted from previous step. Combination of wavelet and PCA outperforms PCA, DWT, and DCT. The results are demonstrated on table X.

TABLE V. Recognition performance on test images of Yale database using the number of principal components.

Number of principal components	Neural network structure	Recognition rate (per 10 attempts)	Average of recognition (per 10 attempts)
1-15	15:25:15	88.37%	86.56%
1-25	25:30:15	90.35%	89.23%
1-35	35:30:15	89.78%	87.24%
1-45	45:25:15	88.92%	87.68%
1-60	60:35:15	89.67%	88.23%
1-80	80:40:15	85.56%	83.78%
1-105	105:45:15	84.76%	83.67%

TABLE VI. Recognition performance on test images of ORL database using the number of principal components.

Number of principal components	Neural network structure	Recognition rate (per 15 attempts)	Average of recognition (per 15 attempts)
1-25	25:40:40	95.37%	94.14%
1-30	30:80:40	94.47%	93.15%
1-35	35:80:40	96.81%	95.45%
1-40	40:40:40	97.68%	96.56%
1-50	50:40:40	96.56%	95.24%
1-100	100:60:40	92.22%	91.72%

TABLE VII. Recognition performance on test images of Yale database using MLP Neural networks by 25 of principal components.

Number of principal components	Neural network structure	Recognition rate (per 10 attempts)	Recognition rate (per 10 attempts)
1-25	25:15:15	89.69%	87.56%
1-25	25:20:15	90.06%	89.45%
1-25	25:25:15	90.10%	89.25%
1-25	25:30:15	90.35%	89.23%
1-25	25:40:15	90.05%	87.45%
1-25	25:50:15	90.%	88.34%
1-25	25:60:15	89.86%	87.24%

TABLE VIII. Recognition performance on test images of ORL database using MLP Neural networks by 40 of principal components.

Number of principal components	Neural network structure	Recognition rate (per 15 attempts)	Recognition rate (per 15 attempts)
1-40	40:10:40	89.67%	87.64%
1-40	40:20:40	91.34%	90.78%
1-40	40:30:40	96.99%	94.67%
1-40	40:40:40	97.68%	96.58%
1-40	40:50:40	96.89%	95.24%
1-40	40:60:40	96.57%	95.67%
1-40	40:70:40	95.98%	94.67%

TABLE X. Performance comparison of recognition rate

Feature extraction method	Classification method	Recognition rate ORL	Yale
Wavelet transform	MLP	94.25%	89.45%
Principal component analysis	MLP	90.00%	81.27%
DCT	MLP	97.45%	-----
Wavelet transform	NFL[24]	95.40%	-----
LDA	MLP	93.90%	89.24%
Proposed method	MLP	97.68%	90.35%

VI. Conclusion

This paper presents a hybrid approach for face recognition by handling three issues put together. For preprocessing and feature extraction stages, we apply a combination of wavelet transform and PCA. During the classification phase, the Neural Network (MLP) is explored for robust decision in the presence of wide facial variations. The experiments that we have conducted on the Yale database and ORL database vindicated that the combination of Wavelet, PCA and MLP exhibits the most favorable performance, on account of the fact that it has the lowest overall training time, the lowest redundant data, and the highest recognition rates when compared to similar so-far-introduced methods.

Our proposed method in comparison with the present hybrid methods enjoys from a low computation load in both training and recognizing stages. As another illustration of the privileges of our introduced method, we can mention its great precision.

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