Face Recognition Based Principal Component Analysis And Wavelet Sub bands

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Abstract

Face recognition is important in human identification. The biological recognition technique acts as a good method and broad applications in security areas. This work presents a method to improve the face recognition accuracy using a combination of Principal Component Analysis (PCA), and Wavelet Transform. Wavelet Transform is used to decompose the input image with different levels and rearrangement of subband of wavelet in a way that extract a good information from the image; PCA is used as data redundancy and take the better representation of input data. We apply the proposed method on standard face recognition dataset, the ORL data and dataset from our environment to make the proposed method be practical. The comparison for different levels of wavelet show that the third level has better recognition accuracy with respect to other levels .Finally the performance of the proposed method is compared with other methods and gives better recognition accuracy.

Keywords—**Face recognition, wavelet transform, PCA**

تمييز الوجه باستعمال تحليل المركبات الأصلية للصورة مع تحويل المويجة

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الخلاصة:

يعتبر التعرف على الوجه من الأمور المهمة في تحديد الهوية البشرية و تعد تقنية التعرف البيولوجي بمثابة طريقة جيدة و ذات تطبيقات واسعة في المجالات الأمنية. يقدم هذا العمل طريقة لتحسين دقة التعرف على الوجوه باستخدام مزيج من المركبات الأصلية، وتحويل المويجات. يستخدم تحويل المويجات لتحليل الصورة المدخلة مع مستويات مختلفة، وإعادة ترتيب مركباته من المويجات بطريقة انتزاع معلومات جيدة من الصورة، كما يتم استخدام تحليل المركبات الاصلية لتقليل واتخاذ أفضل تمثيل من إدخال البيانات. طبقنا الطريقة المقترحة لبيانات قياسية، مجموعة البيانات ORL ومن بيئتنا لجعل الطريقة المقترحة أكثر عملية. ومقارنة لمستويات مختلفة من تحويل المويجات . كان المستوى الثالث لديه أفضل دقة التعرف فيما يتعلق بمستويات أخرى. وأخيرا تتم مقارنة أداء الطريقة المقترحة مع أساليب أخرى وأعطت نتائج أدق.

1. Introduction

The user authentication is increasingly important over the past few years, because the security is required everywhere.. Recently, biological authentication technologies across fingerprint, iris, palm print, and face, etc are playing a crucial role and attracting intensive interests for many researchers. Among them, face recognition is a friendly 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 [1].

Face recognition can be applied for a wide assortment of problems like image and film processing, human-computer interaction, criminal identification etc. A face image has high dimension. The Eigen faces algorithm has been a mainstay in the field of face recognition due to the high dimensionality of face images. While providing minimal reconstruction error, the Eigen face-based transform space de-emphasizes high-frequency information, effectively reducing the information available for classification.

The process of dimensionality reduction is an essential stage in face recognition tasks where the data have an intrinsically high dimensionality. Principal Component Analysis (PCA) is used to reduce the dimensionality of image space. Recognition is performed by projecting a new image into the subspace spanned by the Eigen faces ('face space') and then classifying the face by comparing its position in the face space with the positions of the known individuals. While trying to reduce the dimensionality of image space it can remove the information required to discriminate objects within that space [2].

In practice, there are several limitations accompanying PCA-based methods. Basically, PCA representations encode second-order dependencies of patterns. For face recognition, the pixel wise covariance among the pixels may not be sufficient for recognition. PCA usually gives high similarities indiscriminately for two images from two different persons or from a single person. It is well known that wavelet based image representation has many advantages and there is strong evidence that the human visual system processes images in a multiscale way according to psycho visual research. Converging evidence in psychology is consistent with the notion that the visual system analyses input at several spatial resolution scales. An image is represented as a weighted combination of basic functions by spatial frequency analysis, in which high frequencies carry finely, detailed information and low frequencies carry approximation information. Recently, there have been revived interests in applying wavelet techniques to solve many real world problems and computer vision in particular. Examples include image database retrieval and face recognition. An appropriate wavelet transform can result in robust representations of capturing substantial facial features while keeping computational complexity low [3].

In recent years, a number of approaches seem to offer promising, solutions to be practical tools for face recognition. One of the appeals of these approaches is their ability to take nonlinear or high-order statistical features into account while tackling the dimensionality-reduction problem efficiently. Examples of previous works include: 1) wavelet transform is used to decompose an image into different frequency subbands, and a lowland wavelet is used for PCA representation [4], the recognition result was 86%, 2) combining the wavelet subband representations and kernel associative memories [3] which satisfy the recognition result 98%. , 3) A technique for face recognition based on discrete cosine transform together with PCA [5], The recognition result was 96.5% and 4) connection of two stages – Feature extraction using principle component analysis and recognition using the feed forward back propagation Neural Network [6] with recognition 97%.Complementing the previously mentioned, we propose a method than can take all the bands of wavelet transform as feature extraction for face representation with PCA.

The paper is organized as follows. In the next section, we briefly describe the principle of PCA .Section 3 explains the eigenfaces. Section 4 describes wavelet transform and the lowest sub band image representation. Section 5 presents our proposed method, experiment results are summarized in Section 6 followed by discussions and conclusions in Section 7.

2. Principle Component Analysis (PCA)

PCA is one of the most successful methods that have been used in pattern recognition. The purpose of PCA is to reduce the large dimensionality of the data space for describing the data efficiently.

It is mathematically defined as an orthogonal linear transformation that transforms the data to a new coordinate system such that the largest variance by any projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on. PCA is theoretically the optimum transform for given data in least square terms. It can be used for dimensionality reduction in a data set by retaining those characteristics of the data set that contribute most to its variance, by keeping lower-order principal components and ignoring higher-order ones. Such low-order components often contain the "most important" aspects of the data [5]. This method can be described as follows:

Suppose $A= [a_{ij}]$ rxc is a face image, where *r* and *c* are the number of rows and column of the image, respectively; a_{ij} is the grey value of the pixel in the i^{th} row and j^{th} column. This matrix can be arranged into a column vector:

$$X = [a_{11}\ a_{21} \ldots a_{r1}\ a_{12}\ a_{22} \ldots a_{r2} \ldots.\ a_{1c}\ a_{2c} \ldots a_{rc}]^T \quad (1)$$

Where X is a D = rxc dimension vector.

One face image can be considered as statistical sample. Thus, giving a group of face M image samples in the training database.

$$G =\{ X_0, X_1, \ldots, X_{M-1} \} \quad (2)$$

and the covariance matrix can be calculated as

$$S = \frac{1}{M}\sum_{i=0}^{M-1} A_i . A_i^T \qquad (3)$$

$$A_j = \left(G_{ij} - m_j\right) \qquad (4)$$

where i=1,2,…,r.c , m is the average vector of the training samples and M is the number of images in the training sample set.

Let λ_1 , λ_2 ,…, λ_d and v_1 , v_2 ,…, v_d be eigenvalues and corresponding eigenvector obtain from the covariance of S respectively. The eigenvalues can be arranged in a descending order ($\lambda_1 \geq \lambda_2 \geq \ldots \lambda_d \geq 0$) with the highest eigenvalues corresponding to the eigenvectors dimensions that has the strongest correlation to the original image .

The eigenvalues that are very small, whose corresponding eigenvectors give not important contribution to represent the face image samples are ignored. The eigenvectors with the highest eigenvalues are projected into space and are known are eigenfaces since these images are like faces. This projection results in a vector represented by fewer dimensions (d<D) containing coefficients [a_1, …a_d][4]**.**

3. Eigenfaces

Basically, eigenface is the eigenvector obtained from PCA. In face recognition, each training image is transformed into a vector by row concatenation. The covariance matrix is constructed by a set of training images. Turk and Pent land [7] developed a face recognition system using PCA. The eigenface space is obtained by applying the eigenface method to the training images. Later, the training images are projected into the eigenface space. Next, the test image is projected into this new space and the distance of the projected test image to the training images is used to classify the test image [8].**Figure. (1)** shows the eigenface of training images.

Fig.(1) . Eigenface of training images

4. Discrete Wavelet Transform

Wavelet Transform has been a popular tool for multi resolution image analysis for the past years . An image, which is a 2D signal, is decomposed using the 2D wavelet tree decomposition algorithm . The original image is process along the x and y direction by H0[k] and H1[k] filter bank which, is the row representation of the original image. It is decomposed row-wise for every row using 1D decomposition algorithm to produce 2 levels of Low (L) and High (H) components approximation. The term L and H refer to whether the processing filter is low pass or high pass. Because of the down sampling operation that is perform on the L and H image the resultant matrices are rectangular of size (N x N/2). These matrices are then transposed and decomposed row-wise again to obtain four N/2 x N/2 square matrices. The down sampling that is then performs on these matrices will generate LL, LH, HH, HL components. Each of these images corresponds to four different wavelet sub band . The LL component (the approximation function component) decomposed to obtain further details of the image; the other wavelet component (LH, HH, HL) can also be decomposed further. Figure (1) shows two wavelet decomposition to one of training images [5].

Fig.(2) . Level 2 Wavelet Decomposition [5]

5. Proposed Method

A multi feature wavelet transform with PCA method is developed to overcome the limitation of the wavelet transform; we have utilized Euclidian distance in order to carry out the classification of faces. The proposed method is illustrated in Figure 3, 4.The proposed method consists of two stages, training stage in which the feature extraction, have been performed and the recognition stage to identify the unknown face image. The training step includes the feature extraction of training images. The extracting feature from the image identifies the representational basis for images in the domain of interest. Subsequently, the recognition step translates the unknown face according to the representational basis, identified in the training step.

Now suppose we have M images in the training set have size rxc.It need to build data base from these images, this building shown in the following steps:

1. Obtain M training images $P_1, P_2 \ldots, P_M$.
2. Apply wavelet transform (1 level) for each image to get $W_1, W_2 \ldots W_M$,which have four sub bands LL, LH, HL and HH.
3. Produce a new matrix called Yi that

$$Yi = [\ LL\ \ LH\ \ HL\ \ HH]. \tag{5}$$

4. Apply Esq.'s(1-4) on each matrices $Y_1, Y_2 \ldots, Y_M$ to get matrix S.

The Covariance matrix S has simply been made by putting one modified image vector obtained in one column each. Also note that S is a(r.c)x(r.c) matrix and A is a$(r.c)^2$xM matrix[9].

We now need to calculate the Eigenvectors ui of S , However note that S is a $(r.c)^2$x$(r.c)^2$ matrix and it would return $(r.c)^2$ Eigenvectors each being $(r.c)^2$ dimensional. For an image this number is huge. The computations required would easily make the system run out of memory. Instead of the Matrix AA^T consider the matrix A^TA. Remember A is a $(r.c)^2$xM matrix, thus A^TA is a MxM matrix. If we find the Eigenvectors of this matrix, it would return M Eigenvectors, each of Dimension Mx1, let's call these Eigenvectors v_i . The Eigenvectors of A^TA is u_i:

$$u_i = A.\ v_i \tag{6}$$

We have found out v_i earlier. This implies that using v_i we can calculate the M largest Eigenvectors of AA^T. M $\ll$ $(r.c)^2$ as M is simply the number of training images [7].

The Eigenvectors found at the end of the previous section, u_i .Now each face in the training set, can be represented as a linear combination of these Eigenvectors u_i, These Eigenfaces can be calculated as

$$\Omega_j = u_j^T A_i \tag{7}$$

Each normalized training image is represented in this basis as a vector.

$$\Omega^T = [\Omega_1 \quad \Omega_2 \quad \ldots \quad \Omega_M] \tag{8}$$

The weight form a vector Ω^T that describes the contribution of each eignface in representing the input face image treating the eigenfaces as a basis for face images [7] .Finally the data base of training faces is built as shown in **Figure.(3).**

Now suppose that we are given an unknown face and it is required classifying to nearest face. The simplest method for determining which face class provides the best description of an input face image is to find the face class k that minimizes the Euclidian distance

$$\varepsilon_k = \|\mu - \Omega_k\| \tag{9}$$

where Ω_k is a vector describing the kth face class. A face is classified as belonging to class k when minim ε_k .For distance measures the most commonly used measure is the Euclidean Distance The Euclidean Distance is probably the most widely used distance metric. It is a special case of a general class of norms.

Now consider we have found out the Eigenfaces for the training images, their associated weights after selecting a set of most relevant Eigenfaces and have stored these vectors corresponding to each training image. If an unknown probe face F is to be recognized the recognition stage is applied as shown in **Figure.(4)** and have the following steps::

1. Apply wavelet transform (1 level) for the image to get W, which have four subbands LL, LH, HL, and HH.
2. Produce a new matrix called Y that

$$Y= [\ LL\ \ LH\ \ HL\ \ HH]. \tag{10}$$

3. The incoming face Y is normalized as Z=Y-m .Where m is the average vector of the training faces.
4. Project this normalized face onto the eigenfaces to find μ.

$$\mu = u_j^T Z \tag{11}$$

5. Find ε_k in Eq(9) .if the ε_i is minimum distance the input face associated with class vector i.

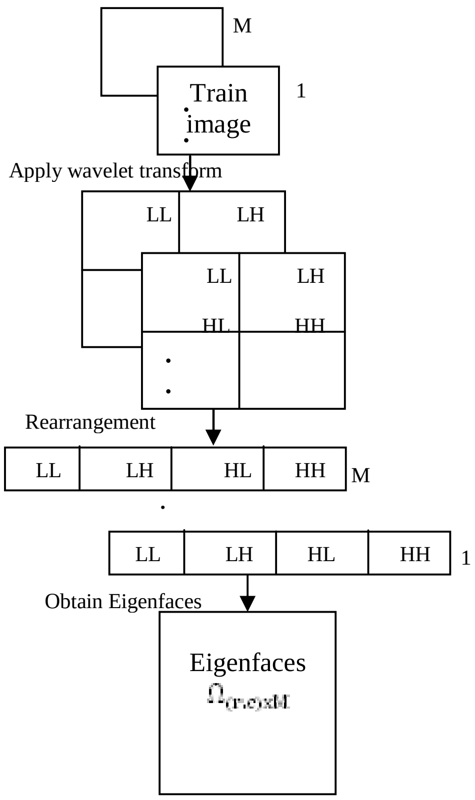

Fig.(3). Block diagram of training stage

6. Experimental Result

The software for face recognition was built using MATLAB. This environment was chosen because it easily supports image processing, image visualization, and linear algebra.

The proposed method was tested against different databases to determine the performance of the method. There are two face database used in the simulation. The first data set is from the Olivetti Oracle Research Lab ORL [10]. The ORL database (Fig.5) consists of 400 frontal faces (males and females); 10 tightly cropped images of 40 individuals with variations in pose, illumination, facial expressions and accessories. The size of each image is 92×112. The method was trained by T (number of training images) images for each person; the remaining images were used for testing.

The second data set is taken from our environment to show that, the proposed method can be applied practically in our live.Fig.6 shows these images. The result (listed in Table 1) shows that recognition accuracy of combination of wavelet with PCA and the proposed method for our data base with varying the number of the training images. From this table it can be noted that, increasing number of the training image improves the recognition accuracy.

In Table 2, the recognition results are illustrated for the ORL face dataset by comparing levels of wavelet decomposition, which show that three levels of decomposition yields better recognition accuracy as shown in **Figure.(7).** To show the quality of the proposed method the result is compared with the other techniques which are 1. Low band wavelet [4], 2. Wavelet with Kernel Associative Memory (WT-KAM) [3], 3. DCT Blocks with PCA [5], 4. PCA with neural network [6].

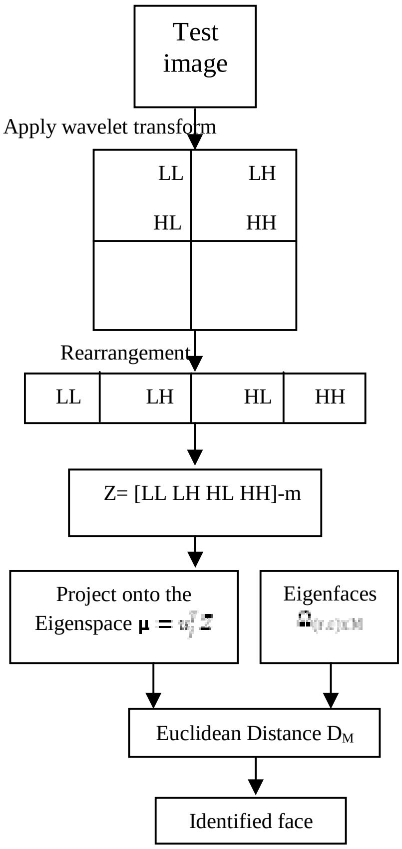

Fig.(4). Block diagram of recognition stage

Table 1. Effect of varying the number of training images for our data

Number of training images (T)	Recognition accuracy of proposed method (%)
2	70
3	100

Table 2. Comparison of the result

method	Recognition accuracy (%)
Low band wavelet	86
WT-KAM	98
DCT - PCA	96.5
PCA -NN	97

Fig.(5) .Example of ORL data base [9]

Fig.(6) .Example of our data base

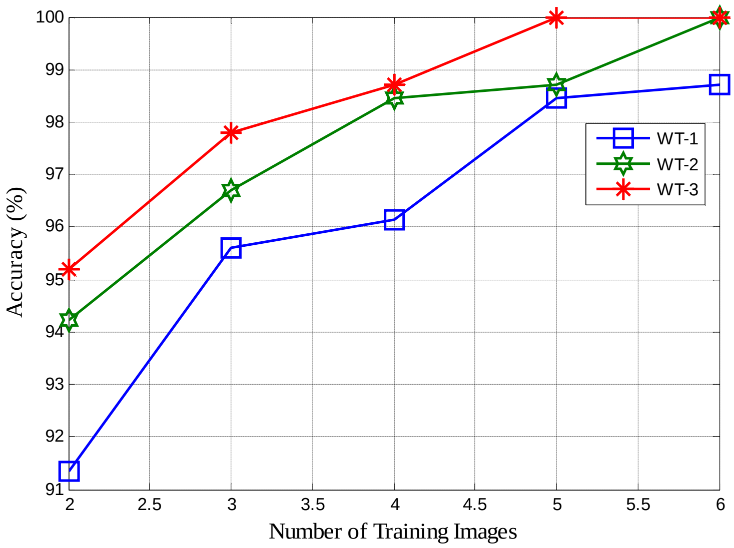

Fig.(7) comparison of the accuracy for different level of the wavelet transforms for ORL data.

7. Conclusion

A method for face recognition is presented in this paper by combining PCA with wavelet transform. Wavelet Transform is used to decompose the input image into several sub bands, each with a different frequency component which has import information. PCA is then applied on these sub bands to reconstruct the image into vector representation. This combination gives good recognition accuracy when applying the proposed method for our live images and standard faces images. From the results it can be concluded that, increase the number of images in training stages improves the efficiency of recognition as it is clear in tables and figures, also third level of wavelet is the best performance compared with other levels.

The proposed method is compared with other method as shown in result and it gives a better recognition rate. It can conclude that, the proposed method can be applied in practical recognition.

References

1. **M. Mazloom nd S. Kasaei," Face Recognition using Wavelet, PCA, and Neural Networks",Proceeding of the First International Conference on Modeling, Simulation and Applied Optimization, Sharjah, U.A.E. ICMSA0/05-6 ,2005.**
2. **D. Murugan1, S. Arumugam, K. Rajalakshmi and T .Manish ,"Performance Evolution of Face Recognition Using Gabor Filter, Log Gabor Filter and Discrete Wavelet Transform", international journal of computer science & information technology (IJCST) Vol.2, No.1 ,pp:125-133, 2010.**
3. **B.L. Zhang, H. Zhang, and S. S. Ge," Face Recognition by Applying Wavelet Subband Representation and Kernel Associative Memory",IEEE Trans. on Neural Networks, Vol. 15, No. 1, pp:166-177, 2004.(IVSL)**
4. **M. Sharkas," Application of DCT Blocks with Principal Component Analysis for Face Recognition ",Proceedings of the 5th WSEAS Int. Conf. on Signal, Speech and Image processing, Corfu, Greece, pp:107-111,2005 .**
5. **O. O. Khalifa, M. Yusuf and S. Gagula," Face Recognition Using PCA Wavelet Decomposition", International Archives of Photogrammetry Remote Sensing and Spatial Information Sciences, Vol. 35; Part 3, pp:780-783,2004.**
6. **M. Agarwal, N. Jain,M. Kumar and H. Agrawal,"Face Recognition Using Eigen Faces and Artificial Neural Network",International Journal of Computer Theory and Engineering, Vol. 2, No. 4, pp:1793-8201 ,2010.**
7. **M. Turk and A. Pentland," Eigenfaces for recognition ", Journal of Cognitive Neuroscience, Vol. 3,No.1, pp:71-86., 1991.**
8. **T. Verma, V. Verma and V. Sahu," Performance Evaluation of Principal Component Analysis Based Face Recognition System and Classifiers", International Journal of Advanced Research in Electronics and Communication Engineering ,Vol. 2, No. 1 ,pp: 94-97 ,2013**
9. **Shubhendu Trivedi ,"Face Recognition using Eigenfaces and Distance Classifiers", A Tutorial, February 11, 2009 online: http://onionesquereality.wordpress.com/author/shubhendu09/**
10. **AT&T Laboratories, Cambridge, U.K.,"The ORL Face Database ", Available at: http://www.cl.cam.ac.uk/research/dtg/attarchive/facedatabase.html**