Available online at www.elixirpublishers.com (Elixir International Journal)

Electrical Engineering

Elixir Elec. Engg. 77 (2014) 29249-29251

ISSN: 2229-712X

Intelligent human face recognition using wavelet transform

Leila Jahanpanah
Department of Electrical Engineering, Dezful Branch, Islamic Azad University, Dezful, Iran.

ARTICLE INFO

Article history:
Received: 25 May 2014;
Received in revised form:
5 December 2014;
Accepted: 16 December 2014;

Keywords
Gabor Wavelet Transform,
PCA,
Radial Basis Function Network.

ABSTRACT

Face recognition recently plays an important role in many application areas such as: commercel, politic, and security. That’s why recognition and high recognition rates of them is very important. features extraction ,decrease of extracted features dimentions and classify are three major and important in the face recognition systems, in the project, we apply third level of gabor wavelet transform for compress and features extraction, also, we apply principle component analyse(PCA)for dimention decrease of extracted features at extremity, we use radial basis function network(RBFN)for classify and recognition this proposal system performs on the ORL face database. This system results average correct recognition percent 97.75% on ORL database.

Introduction

Face detection is one of the examples of mind which can show how much human being have got powerful abilities and it is one the commonest reactions that it can be seen in human's transactions regardless of changes of location, age and people changes and whatever causes human faces to change and easily not being recognized by other people whom have got accustomed to. In fact, in order to identify people various ways can be used like fingerprints, signature verification and voice recognition but face detection is one of the most outstanding to be used among them and in comparison to other ways face detection is also one of the most easiest way to do. The face recognition technology has got numerous business and legitimate applications. These applications include its constant comparisons of photos amended such as passports, credit cards, ID photos, driver's license and the hands and face photos with the real video imaginary.

It appears that human being can easily recognize the images if they are classified. In this case, the blurred images, photos and other images which are not crystal clear will be recognized more accurately. Using machines and other applications by human to understand and detect the people's faces is another challenge for psychologists and neuroscientists nowadays and for this reason, in addition to recognize other aspects of human being facial recognition has become one of the important issues right now.

Description of the Presented Approach for Face Recognition

Our approach consists of several phases. The algorithm uses a database of face images for training and recognition. The test images are acquired by the system via camera .In the first phase of facial system designing which can be done with the help of recent techniques in facial detection and recognition, the current face should be done algorithmically and then normalized. It is appropriate to mention here that since ORL database has been used in this system the recognition and facial detection does not seem to be necessary and if in this these steps were crucial to proceed for normalizing the input images the pro-processing techniques can be used. To apply this system in this project Gabor Wavelet was used to compress the images, PCA was used to reduce the dimension of matrix and at the end RBF neural network was used to classify and recognize those images.

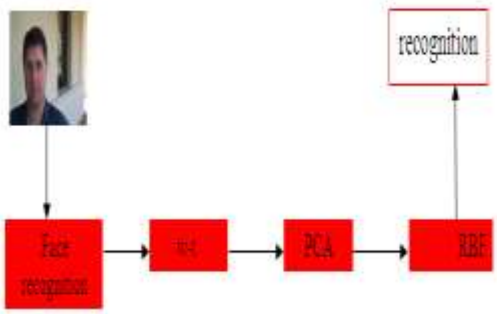

Figure 1. shematic of the system

Level 3 Wavelet Packet Decomposition

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 sub images are reduced. In turn, the computational complexity will be reduced dramatically by operating on a lower a resolution image.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. In our approach we size 32x32 and the subbands 8,9,10 are of size 64x64. use wavelet packet decomposition on the extracted face image. During wavelet packet decomposition the original image is decomposed into 4 sets of wavelet coefficients that represent approximation and details. At each step the previous 4 sub-images of wavelet coefficients are further decomposed into 4 new sub-images: approximation and details:

For the purpose of face recognition we use the third-level approximations of the faces, In the first level of Wavelet

Tele:
E-mail addresses: Jahanpanah.leila@yahoo.com

decomposition, the original image will be decomposed in an approximation image and three detailed images. And in order to obtain the three stage Gabor's system, the mentioned Wavelet's system should be applied to the image for three times. In the second phase of Wavelet's decomposition, the approximated image itself is divided into a second phased approximation and details. And the detailed image will be divided as appropriately as the approximations [4].

In this project in order to make the size of the images very small and to get more valuable information we have used the Wavelet's decomposition in the third phase. In the first place the database image sizes were 128 x 128 and then by applying the Wavelet's third phase the sizes reduced to 16 x 16 consequently.An image is decomposed into four subbands as shown in Figure 2. The band LL is a coarser approximation to the original image. The 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 Figure 4. if the resolution of an image is 128x128 the subbands1,2,3,4 are of size 16x16, the subbands 5,6,7 are of size 32x32 and the subbands 8.9.10 are of size 64x64[1,9,12].

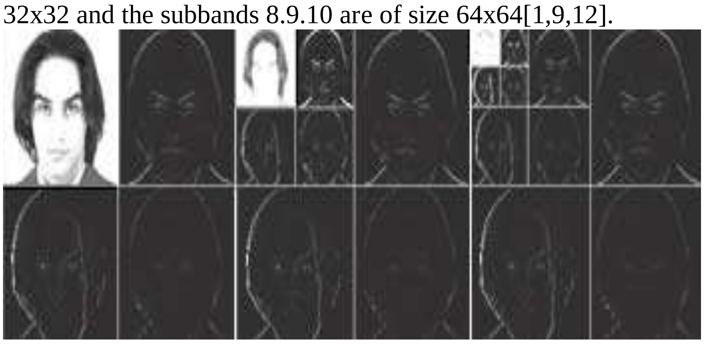

Figure 2.Waveletdecompositio decomposition

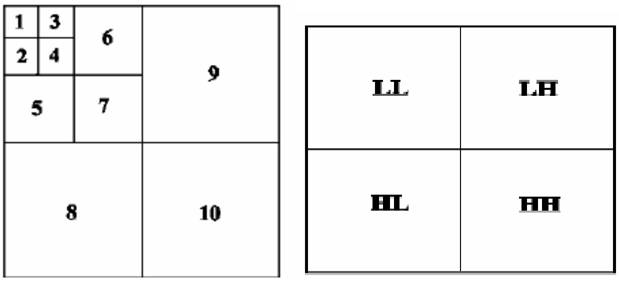

Figure 3. Face image with one- level two level and three level

Principal Component Analysis For Face Recognition

PCA is used to find a low dimensional representation of data. Some important details of PCA are highlighted as follows [20].

Let X = {x_n ,n =1,...,N}∈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.

$$E(x)=\frac{1}{N}\sum_{n=1}^{N} Xn \quad (1)$$

After subtracting the average from each element of X, we get a modified ensemble of vectors $\bar{X}$= { $\bar{X}_n$,n=1,…..N } with

$$\bar{X}_n = X_n - E(X) \quad (2)$$

The auto-covariance matrix M for the ensemble X is defined by

$$M = \mathrm{cov}(\bar{X}) = E(\bar{X} \otimes \bar{X}) \quad (3)$$

Where M is d^2 x d^2matrix, with elements

$$M(i,j) = \frac{1}{N}\sum \bar{X}_n(i)\bar{X}_n(j), \quad 1 \le i. \quad j \le d^2 \quad (4)$$

It is well known from matrix theory that the matrix M is positively definite (or semi-definite) and has only real nonnegative 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^2 x d^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-Ltransform. 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 d^2 x d^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,….., $a_{d'}$.

RBF Neural Network

After applying the PCA techniques and extracting the features of facial images, the vectors of features of the mentioned facial images –which are the same Eigen vector or Eigen face – are applied to the RBF neural network in order to have an appropriate classification.

The number of neurons in the input layer is equal to the size of the input feature vector and the number of neurons in the output layer is equal to the number of image classes which refers to the different people's number in database. And the network parameters are the neurons of the middle layer and the values of the weights between the second and the third layers and this is not possible to determine their network parameters unless we do it through training and educating.

Experimental Results

In our approach we have used the ORL face database found at www.ORL.com. This database consists of a total of 400 images (15 persons (males and females),with 11 images for each person). These images are of various illumination and facial expression, as well as of wearing glasses. All of these images have a resolution of 112x92 in this project we have used 5 image for training and 5 image for test.

For the first test on the ORL database, five images of a person were randomly used in order to train the system. As the result, 200 images were used for training and 200 images for testing in this experiment. The numbers of inner layer and outer layer are equal to the numbers of basic vectors (the principle component) and the numbers of different classes of output which are the same as the current people in the database and the numbers of neurons of the middle layer are obtained by trial and error.

The experimental results obtained by vector 30 (Eigen Face) is the optimal number of the basis vectors. The optimal numbers of middle layer is 45 which we could get by using trial and error. Therefore, the optimal network structure is an RBF network with topology of 30- 40- 50. This system shows the average percentage of correct recognition on ORL database with %97.75.

Table 1. The varying number of basis vectors used in this system and the average percentage obtained for their detection.

The number of basis vectors)Principle Component(	The structure of neural network	The maximum of correct detection percentage (in 10 tests)	Average percent detection
5	5-45-40	88.34%	87.63%
10	10-45-40	89.21%	89.1%
20	20-45-40	96.24%	89.1%
30	30-45-40	98.33%	97.75%

Table 2. Performance comparision of this system with other systems

Feature extraction method	Classifier	Percentage of correct diagnosis on ORL
Wavelet transform	MLP neural network	94.25%
PCA	MLP neural network	90.00%
DCT	MLP neural network	97.45%
LDA	MLP neural network	93.90%
PCA+wavelet transform (present method)	RBF neural network	97.75%

References

[1] A. Averbuch, D. Lazar, and M. Israeli, “Image Compression Using Wavelet Transform and Multiresolution Decomposition” IEEE Trans. Image Processing, vol. 5, no. 1, Jan. 1996.

[2] P.N. Belhumeur, J.P. Hespanha, and D.J. Kriegman, “Eigenfaces versus Fisherfaces: Recognition Using Class Specific Linear Projection” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 19, no. 7, pp. 711-720, July 1997.

[3] R. Brunelli and T. Poggio, “Face Recognition: Features versus Templates” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 15, no. 10, pp. 1042-1052, Oct. 1993.

[4] T. Chang and C.-C.J. Kuo, “Texture Analysis and Classification with Tree-Structured Wavelet Transform” IEEE Trans. Image Processing, vol. 2, no. 4, pp. 429-441, Oct. 1993.

[5] Y. Cheng, K. Liu, J. Yang, Y. Zhuang, and N. Gu, “Human Face Recognition Method Based on the Statistical Model of Small Sample Size,” SPIE Proc. Intelligent Robots and Computer Vision X: Algorithms and Technology, pp. 85-95, 1991.

[6] T.M. Cover and P.E. Hart, “Nearest Neighbor Pattern Classification,” IEEE Trans. Information Theory, vol. 13, pp. 21-27, Jan. 1967.

[7] K. Etemad and R. Chellappa, “Face Recognition Using Discriminant Eigenvectors,” Proc. IEEE Int’l Conf. Acoustic, Speech, and Signal Processing, pp. 2148-2151, 1996.

[8] R.A. Fisher, “The Statistical Utilization of Multiple Measurements,” Annals of Eugenics, vol. 8, pp. 376-386, 1938.

9] R. Foltyniewicz, “Automatic Face Recognition via Wavelets and Mathematical Morphology,” Proc. Int’l Conf. Pattern Recognition, pp. 13-17, 1996.

[10] K. Fukunaga, Introduction to Statistical Pattern Recognition. New York: Academic Press, 1990.

[11] A.J. Goldstein, L.D. Harmon, and A.B. Lesk, “Identification of Human Faces,” Proc. IEEE, vol. 59, no. 5, pp. 748-760, May 1971.

[12] A.Z. Kouzani, F. He, and K. Sammut, “Wavelet Packet Face Representation and Recognition,” Proc. IEEE Conf. Systems, Man, and Cybernetics, pp. 1614-1619, 1997.

[13] S.Z. Li and J. Lu, “Face Recognition Using the Nearest Feature Line Method,” IEEE Trans. Neural Networks, vol. 10, no. 2, pp. 439-443, Mar. 1999.

[14] S.H. Lin, S.Y. Kung, and L.J. Lin, “Face Recognition/Detection by Probabilistic Decision-Based Neural Network,” IEEE Trans. Neural Networks, vol. 8, no. 1, pp. 114-132, Jan. 1997.

[15] C. Liu and H. Wechsler, “Learning the Face Space—Representation and Recognition,” Proc. Int’l Conf. Pattern Recognition, vol. 1, pp. 249-256, 2000.

[16] C. Liu and H. Wechsler, “A Shape- and Texture-Based Enhanced Fisher Classifier for Face Recognition,” IEEE Trans. Image Processing, vol. 10, no. 4, pp. 598-608, Apr. 2001.

[17] M.J. Lyons, J. Budynek, and S. Akamatsu, “Automatic Classification of Single Facial Images,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 21, no. 12, pp. 1357-1362, 1999.

[18] A.V. Nefian and M.H. Hayes III, “Hidden Markov Models for Face Recognition,” Proc. IEEE Int’l Conf. Acoustic, Speech and Signal Processing, pp. 2721-2724, 1998.

[19] R.M. Rao and A.S. Bopardikar, Wavelet Transforms—Introduction to Theory and Applications. Addison Wesley Longman, 1998.

[20] D.L. Swets and J. Weng, “Using Discriminant Eigenfeatures for Image Retrieval,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 18, no. 8, pp. 831-836, Aug. 1996.

[21] M.A. Turk and A.P. Pentland, “Face Recognition Using Eigenfaces,” Proc. IEEE Conf. Computer Vision and Pattern Recognition, pp. 586-591, 1991.

[22] J. Zhang, Y. Yan, and M. Lades, “Face Recognition: Eigenface, Elastic Matching, and Neural Nets,” Proc. IEEE, vol. 85, no. 9, pp. 1423-1435, Sept.