International Journal of Research in Advent Technology (IJRAT) Special Issue
E-ISSN: 2321-9637
Available online at www.ijrat.org
*International Conference "*INTELINC 18*", 12th & 13th October 2018*

Wavelet and PCA Based Face Descriptor for Image Retrieval Using K-Nearest Neigbour Alogrithm

[1]Dinesh Arumugam , [2]Kulothungan.S
Assistant professor, Department of Electronics and communication Engineering, Government College of Engineering Sengipatti,Tamil Nadu, dineshcolours@gmail.com
Assistant professor, Department of Electronics and communication Engineering, Government College of Engineering Sengipatti,Tamil Nadu, kulothungann@gmail.com

Abstract— Face recognition is one of the challenging applications of image processing. This has become an important issue in many applications such as security systems, credit card verification and criminal identification etc. Robust face recognition algorithm should posses the ability to recognize identity despite many variations in pose, illumination , texture and appearance. Principal Component Analysis (PCA) has been frequently used as the potential algorithm for dimension reduction. However, it has its limitations like poor discriminatory power and large computational load. In view of these limitations, the proposed work combines PCA and different types of wavelet for a better feature representation. In this method, wavelet transform is used to decompose an image into different frequency sub bands as a pre processing step followed by PCA to reduce the dimensionality of the image matrix into feature matrix. K-nearest neighbour method is used for classification. The proposed method gives better recognition rate and discriminatory power. Further, the proposed method reduces the computational load significantly even when the image database is large. This paper details the design and implementation of the proposed method, and presents encouraging experimental results with standard face AT&T database. The effectiveness of the proposed work is justified by Recognition rate & FAR (False Acceptance Rate), FRR (False Rejection Rate) and Significant improvements in terms of both FRR and FAR are observed. When compared with conventional methods.

Keywords--- Human face recognition, Principal Component Analysis, Sub band, Wavelet transforms.

I. INTRODUCTION

In an image processing, the pattern recognition and computer vision, Human face detection is an active area of research spanning several disciplines such as with wide range of applications such as personal identity verification, video-surveillance, facial expression extraction, advanced human and computer interaction. The wide-range variations of human faces due to pose, illumination, and expression, results in highly complex distribution and deteriorate the recognition performance. Hence, there is a need to develop robust face recognition algorithm. Block diagram of a typical face recognition system is shown in Fig. 1. In preprocessing, the frontal face images are resized, normalized or gray converted in order to prepare the image to a standard format for further processing. Classification is usually one of standard methods like minimum distance classifier, artificial neural networks, etc. Feature extraction is the area that tends to differ. This paper addresses the feature extraction by applying PCA on sub band images.

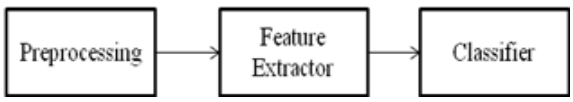

Fig. 1 Block diagram of a typical face recognition system.

A good survey of face recognition system is found in [1]. The methods for face recognition can be divided into two different classes: geometrical features matching and template matching. In the first class, some geometrical measures about distinctive facial features such as eyes, mouth, nose and chin are extracted. In the second class, the face image is represented as a two-dimensional array of intensity values and this is compared to a single or several templates representing a whole face. This method is also called as image based system.

Image based approach the most relevant information that best describes a face is derived from the entire face image. Based on the Karhunen-Loeve expansion in pattern recognition, M. Kirby and L. Sirovich [6, 7] have shown that any particular face could be economically represented in terms of a best coordinate system that they termed "eigen faces". These are the eigen functions of the averaged covariance of the ensemble of faces. Later, M. Turk and A. Pentland [16] have proposed a face recognition method based on the eigen faces approach.

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.

In view of the limitations existing in PCA-based approach, in this paper, a new approach based on PCA – applying PCA on wavelet sub band is addressed. In the proposed method, an image is decomposed into a number

of sub bands with different frequency components using the wavelet transform (WT). The sub band image with reduced dimension is selected to compute the representational bases. Also the proposed work takes the face images with changes in illumination and pose. The proposed method works on lower resolution, instead of the original image resolution of 92x112. Therefore, the proposed method reduces the computational complexity significantly when the number of training image is larger, which is expected to be the case for a number of real-world applications.

The paper organized in the following manner: section 2 review the background of wavelets. Section 3 details about PCA and eigen faces. The proposed method is reported in section 4. Experimental results drawn from the research is gives in section 5 and finally conclusions are given in section 6.

II. WAVELET

Wavelets lead to a multi resolution analysis of signals. Wavelet algorithm looks at the data at different scales and resolution. Wavelets are used for compression and it can be achieved by transforming the data, projecting it on a basis of functions, and then encoding the resulted coefficients. It is a tool for carving up functions, operators, or data into components of different frequencies, allowing one to study each component separately. The wavelet transform of a signal f(t) is the function of scale (or frequency) and time. Thus, wavelets provide a tool for time-frequency localization. The wavelet transform cuts up the image into a set of sub images with different resolutions corresponding to different frequency bands. One encoding approach is based on quantizing the coefficients using vector quantization

The main characteristic of wavelets is the possibility to provide a multi- resolution analysis of the image in the form of coefficient matrices. Strong arguments for the use of multi resolution decomposition can be found in psycho visual research, which offers evidence that the human visual system processes the images in a multi-scale way. Moreover, wavelets provide a spatial and a frequential decomposition of the image at the same time.

In the proposed system, It Decompose the image into wavelet domain then Alter the wavelet coefficients, according to our applications such as denoising, compression, edge enhancement and finally reconstruct the image with the altered wavelet coefficients

1. By decomposing an image using WT, the resolutions of the sub band images are reduced.

2. Wavelet decomposition provides local information in both space domain and frequency domain.

In 2-D case, the wavelet transform is usually performed by applying a filter bank to the image. Typically, a low pass filter and a band pass filter are used. The convolution with the low pass filter results in an approximation images and the convolutions with the band pass filter in specific directions result in detail images. In practice the usual choice for a two-dimensional scaling function or wavelet is a product of two one-dimensional functions.Wavelet coefficients are organized into wavelet blocks as shown in Fig.2 and 3, where h, v, and d correspond to horizontal, vertical, and diagonal sub images.

The energy of the original image concentrates within the approximation image. Images showing the most significant components in using four stages of decomposition using wavelets are shown in Fig. 2 and 3.

Fig. 2 Original image and 2 level decomposed image.

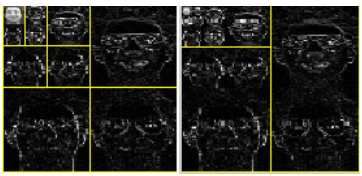

Fig.3 Decomposition at third and fourth level.

Here, select the approximation components because it produces the better recognition rate compare to the other components. In the feature extraction method uses the approximation component of the wavelet coefficients in the principal component analysis

III. PRINCIPLE COMPONENT ANALYSIS

The main idea of the principal component analysis is to find the vectors to describe the distribution of face images within the entire image space.Face space is comprised of Eigen faces, which are the eigenvectors of the set faces. .PCA is an orthogonal transformation of the coordinate system in which the pixels are described. The new coordinate values are principal component PCA is performed by projecting a new image into the subspace called face space spanned by the Eigen faces and then classifying the face by comparing its position in face space with the positions of known individuals.

It can transform each original image of the training set into a corresponding Eigen face. The relevant information in a face image is extracted and encoded as efficiently as possible, and then compared with a database of models encoded similarly. Objects are represented as a cloud of n points in a multidimensional space with an axis for each of the p variables and the centroid of the points is defined by the mean of each variable the variance of each variable is the average squared deviation of its n values around the mean of that variable. Degree to which the variables are linearly correlated is represented by their covariance

Project faces onto a lower dimensional sub-space with no distinction between inter- and intra-class variabilities.It is optimal for representation but not for discrimination The training face images and new face images can be represented as linear combination of the Eigen faces.

Each Eigen face deviates from uniform gray where some facial feature differs among the set of training faces. Eigen faces can be viewed as a sort of map of the variations between faces.. The best M Eigen faces span in an M-dimensional subspace which is called as the face space with all possible images.

So, in order to reconstruct the original image from the Eigen faces, building a kind of weighted sum of all Eigen faces is required. The face images can be reconstructed by weighted sum of a small collection of characteristic features or Eigen pictures. Therefore, each individual is characterized by a small set of feature or Eigen picture weights (eigenvectors) needed to describe and reconstruct them.

A. Mathematics of PCA

A 2-D facial image can be represented as 1-D vector by concatenating each row (or column) into a long thin vector.

To assume the training set of face images be Γ_1 , Γ_2 ……. Γ_M, with each image I(x,y) where (x,y) is the size of the image.

1. Convert each image into set of vectors and new full-size matrix (M * p) , where M is the number of training images and p is x * y the size of the image.

2. Then the average of the set is defined by

$$\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n \quad (8)$$

3. Calculate the each face differs from the average by the vector

$$\Phi_i = \Gamma_i - \Psi \quad (9)$$

i = 1, 2, 3….M. and a set of matrix is obtained with A = [Φ_1, Φ_2 … Φ_M] is the mean-subtracted matrix with its size A_{M*p}.

4. By implementing the matrix transformations, the vector matrix is reduced by:

$$C = \frac{1}{M}\sum_{n=1}^{M}(\Phi_n\Phi_n^T) \quad (10)$$

Where C is covariance matrix

5. Find the eigen vectors V_{mm} and eigen values λ_m from the C matrix and ordered the eigen vectors by highest eigen values.

6. These vectors determine linear combinations of the M training set face images to form the eigen faces u_l.

$$u_l = \sum_{k=1}^{M} v_{lk}\Phi_k \quad (11)$$

7. With this analysis, the calculations are greatly reduced, from the order of the number of pixels in the images x*y to the order of the number of images in the training set (M). In practice, this forms the Eigen space of size (M << N2), and the calculations become quite manageable.

8. The weights form a feature vector,

$$\Omega_T = [w_1, w_2, w_3 \dots \dots w_{M'}] \quad (13)$$

9. The unknown face is taken as input for the recognition stage and the normalized form is obtained by

$$\Phi = \Gamma - \Psi \quad (14)$$

10. The normalized face is projected on the Eigen space to reconstruct the face image using

$$\Phi_j = \sum_{j=1}^{M} w_j u_j \quad (15)$$

11. Representing Φ_j as

$$\Omega_T = [w_1, w_2, w_3 \dots \dots w_k] \quad (16)$$

12. A measure of similarity is done with Euclidean distance measure with the weights of the test image and the weights from the library.

13. The index of distance with minimum weight represents the face from the library that closely matches with the test image

IV. PROPOSED WORK

The sample images are taken from AT&T database. This database has 40 different classes, with 10 images for each class totaling 400 face images. The image size is 92 x 112. A random index selector is in the proposed work. From this random index selector, images were grouped into train and test set. The system has two phases namely the training and testing phase. Fig.4 shows the block diagram of the proposed face recognition system. In training stage, wavelet (Haar, Daubechies, Coiflet & Symlet filters) is used in the preprocessing stage. Using different wavelets lets the face image being splitted into various subbands. This preprocessing results a face recognition system which robust to changes in illumination, pose, and compress the image size. According to the filter, image size will change and it gives the four different values (approximation, vertical, horizontal & diagonal values).

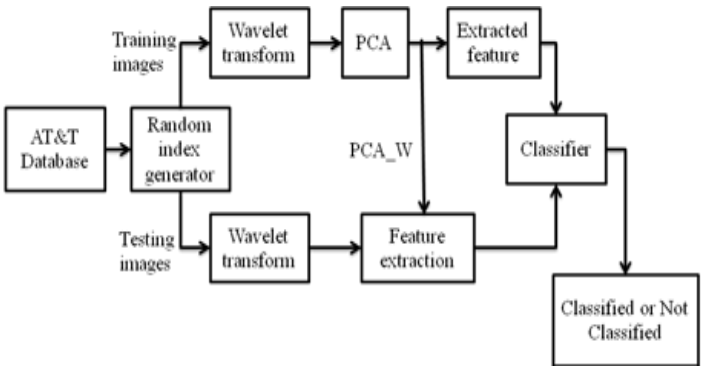

Fig. 4 Block diagram of the proposed work

The approximation co-efficient is taken as the input to the next stage. This stage uses the PCA for reducing the dimension of the image space into feature space and extracts

the principle features. Here the eigenvectors were calculated, sorted and the top Eigen vectors are used for representation of principle features.

In the recognition stage, the test samples were taken and the initial preprocessing is done as done for the training frontal images. The classification stage uses The classification stage uses k-Nearest Neighbour algorithm (k-NN) is a method for classifying objects based on closest training examples in the feature space.

STEPS FOR K-NEAREST NEIGBOUR ALGORITHM

All training data are simply stored, with their class labels.

- Given a point x to be classified,
- Select the K - nearest neighbors of x.
- Assign to x the majority label of these K neighbors.
- Usually, K is odd.
- Ties can still occur: e.g. 3 classes, and K= 3
- This is not optimal classifier, but given "enough" training data, P (error $_{KNN}$) $\leq$ 2 P (error Bayes)
- Notion of "nearness": Distance metric important.

V RESULTS

The implementation and results of wavelet (Haar, Daubechis, Coiflet), PCA based face recognition system with K- Nearest neighbour algorithm A naïve Nearest Neighbor classifier is usually employed in the approaches that adopt a dimensionality reduction technique and are employ for classification purpose and respective results were given in this section.. The system is tested with the AT&T database.

Database	**Performance comparison**		
AT&T	**Methods**		**Recognition Rate in (%)**
	Wavelet + PCA+K		97.5
	PCA		83.2
	Wavelet	**Db**	93.5
		Coiflet	94
	Wavelet + PCA	**Db**	94.5
		Coiflet	96.17

TABLE 1 PERFORMANCE COMPARISON OF WAVELET & PCA BASED SYSTEM

Threshold value	**PCA**	**Wavelet (Coiflet)**	**Wavelet (Coiflet) +**		**PCA**	
	FAR in (%)	**FRR in (%)**	**FAR in (%)**	**FRR in (%)**	**FAR in (%)**	**FRR in (%)**
0.3	24.397	2.5	44.602	0	34.589	0
0.35	12.538	7.5	31.384	0	20.897	3.5
0.4	4.487	12.5	21.153	2.5	11.474	3.5
0.45	1.282	30	12.564	7.5	4.679	10
0.5	0.713	45	5.961	12.5	1.154	24.5
0.55	0.124	65	1.866	21	0.128	35
0.6	0	90	0.124	35	0	54.5
0.65	0	97.5	0	54.5	0	78

TABLE 2 FALSE **ACCEPTANCE RATE** AND FALSE REJECTION RATE FOR PCA &WAVELET BASED STSTEM

Methods	**Threshold**	**FAR in (%)**	**FRR in (%)**
PCA + K	0.3768	8.5	8.5
Wavelet + K	0.7623	11.641	11
Wavelet + PCA +K	0.422	8.5	8.5

TABLE 3 **COMPARISON OF WAVELET & PCA BASED SYSTEM WITH K-NN**

VI CONCLUSION

Human memory for faces is characterized by robust generalization to new viewing conditions for faces that are familiar to us. There are a lot of ongoing researches in this area for finding out suitable models for this kind of generalized approaches. This project investigates a hybrid approach for face recognition; using WAVELET & PCA based feature parameter with K-NN algorithm. K-NN Is highly effective inductive inference method for noisy training data and complex target functions Final results shows K-NN is better classifier used in the face recognition system and time consuming .K-Nearest Neighbour algorithm with WAVELET &PCA methods shows Genuine False recognition rate and false acceptance rate. It gives high recognition rate when it compares other face recognition methods

REFERENCES

[1] F.Galton, “Personal identification and description 1, 1 Nature, pp.173-177, 21 June1988.

[2] Sir Francis Galton, Personal identification and description-II”, Nature 201- 203, 28 June 1988.

[3] Goldstein, A. J., Harmon, L. D., and Lesk, A. B., Identification of human faces", Proc. IEEE 59, pp. 748-760, (1971).

[4] Kanade, T., "Picture processing system by computer complex and recognition of human faces", Dept. of Information Science, Kyoto University, (1973).

[5] 5. Duda O. R; Hart E. P. & Stork G. D. (2001). *Pattern Classification*, Wiley-Interscience, ISBN: 0-471-05669-3, United States of America.

[6] Kirby, M., and Sirovich, L., “Application of the Karhunen-Loeve procedure for the characterization of human faces”, IEEE PAMI, Vol. 12, pp. 103-108, (1990).

[7] Turk, M., and Pentland, A., “Eigenfaces for recognition”, Journal of Cognitive Neuroscience, Vol. 3, pp. 71-86, (1991).

[8] Dakshina Ranjan Kiskul, Phalguni Gupta2, Jamuna Kanta Sing Department of Computer Science and Engineering, Asanol Engineering College.

[9] Terzopoulos, D., and Waters, K., “Analysis of facial images using physical and anatomical models”, Proc. 3rd Int. Conf. on Computer Vision, pp. 727-732, (1990).

[10] Nabeel Younus Khan Computer Science Department Otago University Dunedin, New Zealand Email: nabeel@cs.otago.ac.

[11] Vladimir C. & Filip M. (1998). *Learning From Data: Concepts, Theory, and Methods*, Wiley Inter-Science, ISBN: 0-471-15493-8, USA

[12] H. Yu, J. Yang, "A direct LDA algorithm for high-dimensional data - with application of face recognition", *Pattern Recognition*, vol. 34, no. 10, pp. 2067-2070, 2001.

[13] W. S. Lee, H. J. Lee, J. H. Chung, "Wavelet-based FLD for face recognition", *Circuits and Systems Proc. 43rd*, vol. 2, pp. 734-737, 2000.

[14] C. Xiang, X. A. Fan, T. H. Lee, "Face recognition using recursive Fisher linear discriminant with Gabor wavelet coding", *Proc. IEEE conf. on Image Processing*, vol. 1, pp. 79-82, 2004.

[15] R. Gottumukkal, V. K. Asari, "Real time face detection from color video stream based on PCA method", *Applied Imagery Pattern Recognition Workshop Proc. 32nd*, pp. 146-150, 2003.

[16] T. Morris, V. Chauhan, "Facial feature tracking for cursor control", *Journal of Network and Computer Applications*, vol. 29, no. 1, pp. 62-80, 2006.

[17] P. Ballard, G. C. Stockman, "Computer operation via face orientation", *Proc. IEEE conf. on Pattern Recognition*, vol. 1, pp. 407-410, 1992.