Component Analysis based Hybrid Face Recognition System using Artificial Neural Network

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Abstract

Digital Face Recognition is a problem in Computer Vision, Computer Human Interface and especially in Biometrics for identifying and verifying the identity of persons. This paper presents a novel Hybrid Face Recognition System (FRS) basing on and modifying the existing component analysis based FRS. The proposed design is a hybrid system as it combines both the global feature based and local feature based face recognition techniques. To this end, the proposed system employs feed forward Artificial Neural Network (ANN) to dynamically learn and enhance the Correct Recognition Rate (CRR). The features extracted are robust to the variations in orientation and lighting in the images. This ensures better performance of the system as compared to the widely accepted techniques of Principal Component Analysis (PCA) and Modular PCA (MPCA) which show decline in correct recognition in the presence of light variation and orientation.

Keywords: Artificial Neural Network (ANN), Central Moment, Eigen Vectors, Hybrid Face Recognition System, Principal Component Analysis (PCA).

1. Introduction

The advancement of image processing techniques has seen an increased interest in digital face recognition. The interest is primarily due to the challenges inherent in simulating human person's ability to learn to recognize and identify the large number of persons one meets during one's life span. The task is challenging as human faces are very complex. The interest is also due to the increased security concerns in various fields. Face, a unique characteristic or feature of a person along with his other unique characteristics, plays a remarkable role in biometrics.

The challenge of enhancing the robustness of the Face Recognition Systems by improving the correct recognition rate and decreasing the time taken for the system to recognize, identify and distinguishing between faces has led to researchers coming up with varied algorithms. Along this line, this paper tries to carry forward the well known PCA and MPCA algorithms used in face recognition. The work offers a new technique to increase the performance of a FRS even in the presence of different facial expressions, variation in light directions of imaging and variety in face orientation and angle.

2. Literature Survey

There has been a remarkable increase in the interest shown by researchers in face detection, recognition and verification techniques. For the most part of 1970's, the technique of pattern classification was employed to solve the problem of computer face recognition. This technique, which can be termed as *analytic method*, used as features the distances between the vital and distinct points of the face like the distance between the pupils of the two eyes [1]. In the 1990's due to the increased need of surveillance and its related applications, researchers showed a significant interest in FRT. This witnessed the shift from pattern classification to appearance based method in FRT. In this new technique, images were represented by vectors in dimensional space [2]. This new space was of the same size of the original image. Thus the dimensional spaces remained as large as the faces. This consumed more time for face recognition while reducing the robustness of face recognition. This disadvantage was overcome by the advent of the techniques that reduced dimensionality using linear methods [3]. FRT based on Principal Component Analysis [4], Linear Discriminant Analysis [5] and Locality Preserving Projections [6] are examples of dimensionality reduction techniques. These techniques, commonly known as Holistic FRTs, work well only with frontal view of faces reducing the correct recognition for variations in pose, expression and light conditions. A solution was proposed using the view-based Eigen space method [7].

Improvements on FRT using modified techniques of Component Analysis have been presented in [8, 9]. Of these, one of the most significant innovations has been in the Modular Principal Component Analysis (MPCA) which partitions the face into smaller regions prior to applying PCA for these regions. MPCA has been reported to be more efficient especially when there are variations in pose and lighting conditions [10]. This however has the disadvantage of not reducing the dimensionality as effectively as PCA and also takes higher computational time. Artificial Neural Network (ANN) based FRT was proposed as an alternative to linear methods (PCA, LDA etc.). This method was reported to work efficiently in conditions of variation in pose and lighting conditions while at the same time reducing the dimensionality of the image [11]. A hybrid FRT with global features and other analytic features as the ANN decision variables was proposed in [12]. This paper carries forward the work of [12] to compare the efficiency of hybrid FRT systems as compared to other analytic and holistic techniques.

3. Problem Formulation

Face recognition system is a complex biometric tool with the objectives of:

- Recognizing and classifying a given human face relative to a collection of face of different individuals
- Correctly recognizing a face with minimum possible computational time and reduced dimensionality
- The system must make a decision that different images of the same person with different facial expressions are of the same person.

4. Basic Theory

The proposed FRS is a hybrid features based technique of face recognition. Therefore, the features extracted take both the global features i.e., the features from the whole face and also the local features by segmenting the face into many segmentations. The extracted features are used to train a General Feed Forward Artificial Neural Network. To reduce the dimensionality of the images the features resulting from the mathematical application of Principal Component Analysis, Central Moment and Covariance are extracted. These same features are extracted both for whole face and the segmented facial areas.

4.1. *Principal Component Analysis*

Principal Component Analysis is a mathematical procedure that reduces the dimensions of the given data set by linear combination. Each of these linear combinations is at once uncorrelated and indicates the greater variance in the data set. In face recognition, PCA is used to map the given set of faces onto a subspace that represents this set of faces with feature vectors of reduced dimension. In other words, the given images are transformed by linear transformation to map the k-dimensional data to n-dimensional orthonormal sub-space where n<k. Each k-dimensional face is represented by n-dimensional vector.

The principal components extracted from these vectors contain the maximum variations among the given set of images. Besides, these components show the directions of data with the succeeding component showing less direction and increased noise. The mathematical procedure for finding the principal components is given in Algorithm 1.

Algorithm 1: Extracting the Principal Components using PCA
Input: A set of N training images Output: A set of P Principal Components Step 1: Calculate the average/mean of all N images, $A = \frac{1}{N}\sum_{i=1}^{N}(x_i)$ Step 2: Normalize each image of the training set by subtracting it from the mean image, $Y_i = I_i - A \; \forall i$ Step 3: Compute the Covariance Matrix from the normalized images, $C = \frac{1}{N}\sum_{i=1}^{N} Y_i . Y_i^T$ Step 4: Compute the eigenvectors of C that are associated with the P largest Eigen values

4.2. *Modular Principal Component Analysis*

In this method, each image of vector size L^2 in the training set is segmented into N smaller images. The size of each sub-image will be L^2/N. The principal components are computed for each segmented sub image using Algorithm 1. Mathematically, the sub image is given by:

$$Iij(m,n) = Ii\left(\frac{L}{\sqrt{N}}(j-1) + m, \frac{L}{\sqrt{N}}(j-1) + n\right) \forall i, j \quad (1)$$

4.3. *Central Moment*

The PCA technique is inefficient for skewed images i.e., images where the face is tilted by a certain angle. This can be overcome by computing central moments. Central moment is a specific weighted average of the image pixels' intensities used in recognizing shape features. By using moments, the properties like area, total intensity, centroid and orientation of the image are easily computed. Mathematically, central moments can be expressed as:

$$\mu_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}(x-\bar{x})^p \,(y-\bar{y})^q f(x,y)dxdy \quad (2)$$

$\bar{x} = \frac{M_{10}}{M_{00}}$, $\bar{y} = \frac{M_{01}}{M_{00}}$, $\bar{x}$ and $\bar{y}$ are the components of the centroid.

$M_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}(x)^p \,(y)^q f(x,y)dxdy$ of a density distribution function *f(x, y)*. If $f(x,y)$ is a digital image, then the equation (2) becomes $\sum_x \sum_y (x-\bar{x})^p \,(y-\bar{y})^q f(x,y)$ (3)

In face recognition, the orientation in the image is computed with the second order central moments, μ'_{20}, μ'_{02} and μ'_{11}.

5. Algorithm

In this work, both the global and local features are used for recognizing faces. For the global features, the principal components corresponding to the highest twenty Eigen values along with the central moment of second order and the diagonal elements of the covariance of the image are used. For the local features too the same features are extracted with the difference that these features are extracted for all the segmentations of a face image. These features are then fed to a Back Propagation Feed Forward Artificial Neural Network. The ANN makes a dynamic decision and indicates the recognized face by a binary output.

Algorithm 2: Procedure of the Proposed Hybrid Face Recognition System

Input: Collection of face images
Output: Unique Binary Vectors generated by Back Propagation Feed Forward ANN
Begin:
For all images in the database $X_1, X_2, X_3 \ldots X_n$ do
Step 1: Pre-processing of the images of database
Resize the images $X_1, X_2, X_3 \ldots X_n$ to [50 50]
Perform illumination normalization by spreading the light intensity of the images
Step 2: Compute $\bar{X} = \frac{1}{N}\sum_{i=1}^{N}(x_i)$, where $\bar{X}$ is the average or mean face of the database faces
Step 3: Compute $Y_i = I_i - A\ \forall i$, where Y_i is the shifted/normalized image of the individual image i
Step 4: Compute the Covariance of Y_i of Step 4
Step 5: Extract twenty principal components for each image in the database corresponding to the highest twenty Eigen values. Store these principal components of each face image in different column vectors
Step 6: Compute the Central Moments of second order for all images of the database. Append the extracted moments of the face images to the corresponding principal components stored in column vectors of Step 5
Step 7: Extract the diagonal elements of the Covariance of face images computed in Step 4 and append these to the corresponding column vectors of Step 5
Step 8: Segment each face image of the database images into the required number of segmentations
Step 9: For all segmentations of each face image of the database,
Perform steps 2–7 and append the features of the sub images of the respective face image to the corresponding column vectors
Step 10: Train the designed network with the column vectors of step 8 as input data with unique binary vectors as corresponding targets.
End

6. Performance Analysis

The designed Hybrid FRS is tested on *Yale Database* which has 10 face images of 15 different individuals with different facial expressions and light conditions. 14 persons of this database are males while only one is a female. A sample of the *Yale Database* (after size normalization) is shown in Figure 1. The different facial expressions with different light intensity are shown in Figure 2.

Figure 1: Sample of the Face Images of *Yale Database*

Figure 2: Images with variations in lighting and expression

To make the system perform efficiently even in the presence of variation in light conditions, the design employs illumination normalization in the preprocessing stage. A sample of the image with unequal spread of light intensity and its equivalent after illumination normalization is shown in Figure 3. The average/mean image of all the images of the database and the shifted image resulting from the subtracting individual face images from the average/mean image is as shown in Figure 4. To extract the local features, the face images are segmented into sub images. A sample of a face image segmented into four sub images is given in Figure 5.

The Eigen faces obtained from further processing of the image is shown in Figure 6. The figure shows the Eigen faces corresponding to the highest thirty Eigen values. In this work, only the principal components corresponding to the highest twenty Eigen values are chosen as the components associated with the lower Eigen values show less direction and variation in the data and more of noise or redundant information.

Ill-illuminated Image

Image after Illumination Normalization

Figure 3: Sample of Illumination Normalization on Image

Mean Image Individual Image Shifted Image

The Subtraction of the Individual Image from the Mean Image results in the Shifted Image

Figure 4: Samples of Mean Image and Shifted Image

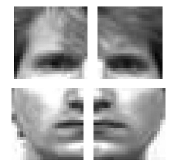

Figure 5: Segmented Face

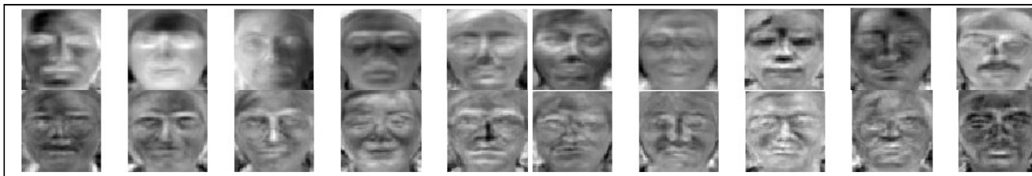

Figure 6: Eigen Faces Corresponding to the Twenty Highest Eigen Values

The length of the global and local features extracted from the component analysis and moments of the second order are as tabulated in Table 1. The original image had 50x50 features while the extracted features have highly reduced dimension. Table 2 presents the CRR of the proposed Hybrid Face Recognition System in comparison with PCA and MPCA techniques. It is observed that the designed system offers a CRR that is higher than PCA and MPCA techniques. The CRR reaches its highest of 89.18% for 7 images of each person in the training set. A comparison of the CRR of MPCA and the designed systems for 5 images in the training set is graphically represented in Figure 7.

Table 1: Length of the Extracted Features

Features Extracted	Global Features	Local Features for Different Segmentations		
		4 Segments	*9 Segments*	*16 Segments*
Principal Components corresponding to Highest Eigen Values	20	10 x 4	10 x 9	10 x 16
Moment of Second Order	50	25 x 4	16 x 9	12 x 16
Diagonal elements of the Covariance	50	25 x 4	16 x 9	12 x 16
Total Length of the Features	**120**	**240**	**378**	**544**

Table 2: Correct Recognition Rate (in Percentage)

Training Images	PCA	*Face Segmentation*	MPCA	Hybrid System
03	71.42	04	73.92	77.27
		09	76.75	79.39
		16	74.28	81.21
05	75.18	04	74.44	82.28
		09	77.00	85.17
		16	73.12	86.78
07	75.78	04	73.81	87.21
		09	76.78	88.27
		16	75.78	89.18

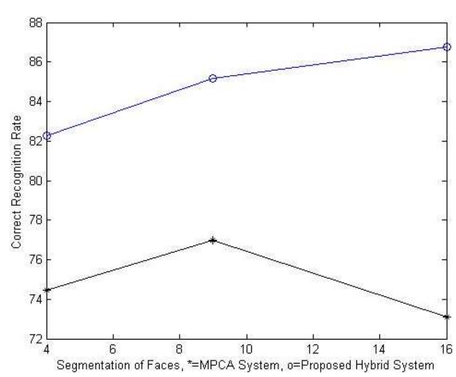

Figure 7: CRR of MPCA and Hybrid Systems

Table 3 presents a comparison of the computational of the three systems. The proposed hybrid system has a reduced computational time. A graphical representation of the same for a training set of 5 images is shown graphically in Figure 8.

Table 3: Computational Time (in Seconds)

Training Set Images	PCA	*Face Segmentation*	MPCA	Hybrid System
03	1.843	04	0.972	0.735
		09	1.206	0.925
		16	1.658	1.130
05	2.632	04	1.504	1.030
		09	1.716	1.341
		16	2.168	1.628
07	3.767	04	1.972	1.524
		09	2.376	1.837
		16	3.82	2.316

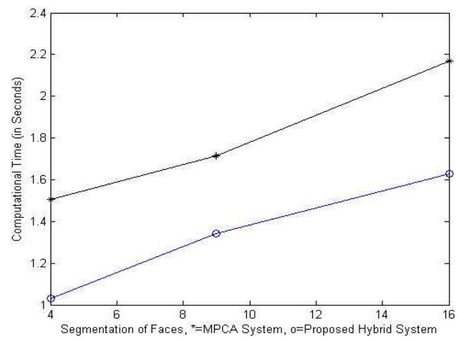

Figure 8: Comparison of the Computational Time of MPCA and Hybrid Systems in Seconds

7. Conclusion

A component analysis based FRS is proposed. The system uses both local and global features of the given face images. These features represent a high dimensional face in a low dimensional space. These features are used to train the system with Back Propagation Feed Forward ANN algorithm. The proposed system offers a higher CRR as compared to the existing PCA and MPCA FRS in the presence of variation in illumination and facial expression. The system reduces the computational time. However, the system has not been tested with face images bearing variation in orientation which is a greater challenge in digital face recognition.

References

[1] Bledsoe, Woody.: The Model Method in Facial Recognition in *Technical Report PRI 15*, (1964).
[2] Murase, H. and Nayar S. K.: Visual Learning and Recognition of 3-D Objects from Appearance in *Journal of Computer Vision*, vol. 14, pp. 5–24, (January 1995).
[3] Martinez, Aleix M and Kak, A. C.: PCA versus LDA in *Pattern Analysis and Machine Intelligence, IEEE Transactions*, vol. 23, no.2, pp.228-233, (February 2001).
[4] Turk, M.A and Pentland, A. P.: Face Recognition using Eigenfaces in *Computer Vision and Pattern Recognition, Proceedings CVPR '91, IEEE Computer Society Conference*, pp. 586-591, (June 1991).
[5] Belhumeur Peter N., Hespanha, Joao P. and Kriegman D. J.: Eigenfaces vs. Fisherfaces: Recognition Using Class Specific Linear Projection in *Computer Vision ECCV '*96, vol. 1064, pp. 43-58. Springer Heidelberg (1996).
[6] Niyogi P. and M. Belkin M.: Laplacian Eigenmaps and Spectral Techniques for Embedding and Clustering in T. G. Diettrich, S. Becker, and Z. Ghahramani (eds.) *Advances in Neural Information Processing Systems 14*, (2002).
[7] Pentland, A., Moghaddam, B., Starner, T.: View-based and Modular Eigenspaces for Face Recognition in *IEEE Computer Society Conference on Computer Vision and Pattern Recognition* , pp.84-91, (June 1994).
[8] Bartlett, M. S., Movellan, Javier R and Sejnowski, T. J.: Face recognition by Independent Component Analysis in *IEEE Transactions on Neural Networks and Learning System*, vol. 13, no. 6, pp.1450-1464, (November 2002).
[9] Yang, M. H.: Kernel Eigenfaces vs. Kernel Fisherfaces: Face Recognition using Kernel Methods in *International Conference on Automatic Face and Gesture Recognition*, pp. 205–211, (2002).
[10] Gottmukkal R. and Asari, V. K.: An Improved Face Recognition Technique Based on Modular PCA Approach in *Pattern Recognition Letters*, vol. 25, pp. 429–436, (March 2004).
[11] Weng, J., Ahuja, N. and Huang, T. S.: Learning Recognition and Segmentation of 3D Objects from 2D Objects in *Proceedings of International Conference on Computer Vision*, pp. 121-128, (1993).
[12] Yesu, K., Chakravorty, H. J., Bhuyan, P., Hussain, R. and Bhattacharyya, K.: Hybrid Features based Face Recognition Method using Artificial Neural Network in *2nd National Conference on Emerging Trends and Applications in Computer Science*, vol., no. 2, pp. 40-46, (March 2012).