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Enhanced Face Recognition System Combining PCA, LDA, ICA with Wavelet Packets and Curvelets

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Abstract. Face recognition is one of the most frequently used biometrics both in commercial and law enforcement applications. The individuality of facial recognition from other biometric techniques is that it can be used for surveillance purposes; as in searching for wanted criminals, suspected terrorists, and missing children. The steps in a face recognition steps are preprocessing (image enhancement), feature extraction and finally recognition. This paper identifies techniques in each step of the recognition process to improve the overall performance of face recognition. The proposed face recognition model combines enhanced 2DPCA algorithm, LDA, ICA with wavelet packets and curvelets and experimental results proves that the combination of these techniques increases the efficiency of the recognition process and improves the existing systems.

Keywords: Face Recognition, Feature extraction, Curvelets, Wavelets ,Radial basis function

1 Introduction

Security through person identification and authentication has emerged as a key technology and the use of biometrics for this purpose is increasing steadily. Several state-of-the-art biometric techniques have been developed in recent years which use a variety of human characteristics for identification and recognition (Arvind, 2009). In the present scenario, most of the efforts in authentication systems tend to develop more secure environments, where it is harder to create a replication of the biometric properties that are used by the recognition system to discriminate between authorized and unauthorized individuals (Marino *et al.*, 2005). One biometric, which can satisfy the above requirements, is Face. Facial properties of a person are very accurate and are unique to an individual. They are very difficult to duplicate and the authentication systems based on face prove to produce very low false acceptance rate and false rejection rate (Zhanjie and Li, 2008).

Although facial patterns may be altered through factors like illumination conditions, scale variability, age variation, glasses and moustaches, the face recognition system is still considered as one of the most frequently used biometric authentication system. The reason behind such popularity is that other biometric systems, like fingerprint, iris and retina, are intrusive and their success highly depends on user cooperation, where the user has to sit directly before a scanner or fingerprint device. On the other hand, acquiring a face image for identification/authentication is non-intrusive and can be easily obtained through mobile, camera or video. It can be used either in an Overt (user aware) or covert (user unaware) applications.

Although a large number of approaches have been proposed in the literature which has been implemented successfully for real-world applications, robust face recognition is still a challenging subject. This paper aims to develop a person recognition and authentication system using face biometric that would operate efficiently on two constraints, namely high accuracy and high speed, simultaneously. For this purpose, two well-known techniques, namely, curvelets and wavelet packets are combined.

Any face recognition system consists of two steps, namely, feature extraction and face recognition. The main goal of feature extraction is to represent the face in a lower dimensional space computed using linear or non-linear transformation. Examples of such methods include Principle Component Analysis (PCA), Linear Discriminant Analysis (LDA), Independent Component Analysis (ICA). While all the three techniques work well for face recognition, the time complexity is high and their performance degrades when the dimensionality is high. This problem can be solved by combining them with transformation techniques like discrete wavelet transformation. In this paper, a face recognition model is designed which combines the three feature extraction techniques, PCA, LDA and ICA with two transformation based techniques, Discrete Wavelet Packet Transformation (DWPT) and Curvelet Transformation (CT). Both the transformation techniques used in the study enhances Discrete Wavelet Transformation. The rest of the paper is organized as follows: Section 2 presents a brief study on the existing face recognition systems. The proposed methodology is discussed in Section 3, while Section 4 presents the experimental results of performance evaluation. Section 5 concludes the work with future research directions.

2 Literature Study

The techniques published can be grouped into two categories, namely, Feature Based techniques (Analytic) and Global techniques (Holistic). Analytic techniques uses facial features (local features) during recognition, while holistic techniques uses information obtained from the whole face pattern. Hybrid techniques contain technique which combines both local and global methods for face recognition. A detailed survey of face recognition approaches is given by Chellappa *et al*. (1995) and Heisele *et al*. (2001).

Holistic techniques which are based on the global features of the face are more popular among researchers. Based on PCA, Kirby and Sirovich (1990) first developed the well-known Eigenface method for both face representation and recognition. PCA can achieve the optimal representation in the sense of maximizing the overall data variance. However, the difference between faces from the same person due to illumination and pose (within-class scatter) seems to be larger than that due to facial identity (between-class scatter). Based on this observation, LDA was applied for Fisher face methods (Belhumeur *et al*., 1997). LDA defines a projection that makes the within-class scatter small and the between class scatter large. This projection improved classification performance over PCA. However, LDA requires a large training sample set for good generalization, which is usually not available for face recognition applications. To address such Small Sample Size (SSS) problems, Zhao *et al*. (1998) perform PCA to reduce feature dimension before LDA projection. By using higher order statistical analysis, ICA was first adopted by Bartlett *et al*. (2002) for face recognition. The works showed that ICA outperformed PCA. However, Draper *et al*. (2003) observed that when the right distance metric is used, PCA significantly outperforms ICA on the FERET database.

Neural networks have also been used to classify global facial features. When face images are treated as 1D signals and wavelet analysis was used for face feature extraction (Liu, 2004), the Radial Basis Function (RBF) network was applied to the projection of face images to Fisherfaces for classification (Howell and Buxton, 1996). While PCA + LDA technique was first used to decrease the feature dimension of face patterns, sample information was adopted to determine the structure and initial parameters of the RBF network. Since SVM is a binary classifier, Phillips (1998) turned the face recognition problem into a two class problem by introducing the difference space. Two classes, the dissimilarities between faces of the same person and dissimilarities A single SVM was trained to classify the intra-person and inter-person difference classes. A binary tree system was adopted by Guo *et al*. (2000) where SVMs were used for the multi-class face recognition problem.

3 Proposed Methodology

This paper proposes techniques to enhance the task of person authentication using the face biometric. For this purpose, three holistic techniques and two transformation techniques are used. The two holistic techniques are PCA, LDA and ICA and the two transformation techniques used are DWPT and CT. The system uses a multiple projection method and consists of the steps outlined in Figure 1.

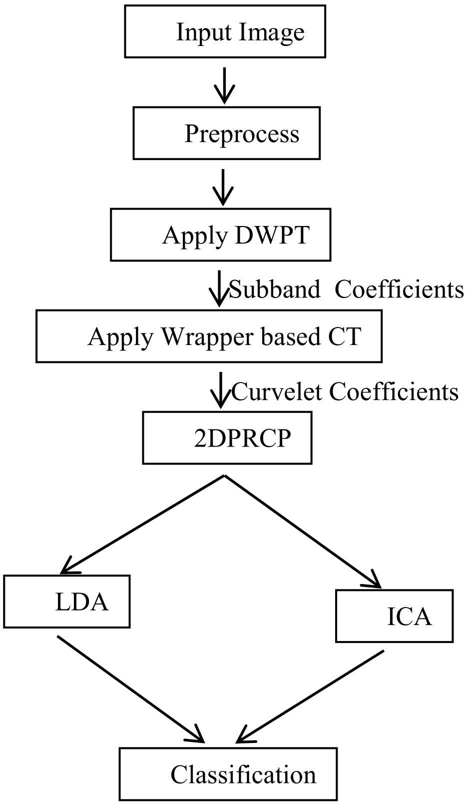

Figure 1 : Steps in Proposed Face Recognition Model

The first step performs preprocessing, where the face image is enhanced through noise removal and illumination variation correction. A face image is normally affected by Salt & Pepper noise, which is removed using a weighted median filter (Arce, 1998; Lukac *et al.*, 2004; Lukac, 2004). Similarly, the illumination and lighting variations are corrected using a brightness preserving dynamic histogram equalization (BPDHE) (Ibrahim and Kong, 2007) method.

The proposed feature selection method applies wavelet packet transform to the input face image to obtain the four wavelet subbands (LL, LH, HL, HH). As wavelets cannot capture curved edges, the wrapping based curvelet transform, which can capture the edge information more accurately, is used on each subband image (with scale-3 and angle-8). This results with curvelet coefficients for each subband, which forms the first level of projection. The main drawback here is the quantity of face data obtained. This is solved using the three algorithms, 2DPRCP, LDA and ICA algorithms. 2DPRCP is an enhanced version of 2DPCA algorithm and the process is given below.

The main objective of the proposed model is to enhance the use of PCA algorithm for improving face recognition process. The enhancement is brought in three manners. The first modification is made in the method of projection used to build the feature matrix of face image. In general, PCA uses an orthogonal projection using only the row of covariance matrix and thus, the resultant feature matrix always have only row-related features. The study enhances the 2DPCA (Yang *et al.*, 2004) algorithm to include column-related features also. The proposed model includes both row and projections and is termed as 2DPCA with Row and Column Projections (2DPRCP). The steps involved in 2DPRCP are given in Figure 2.

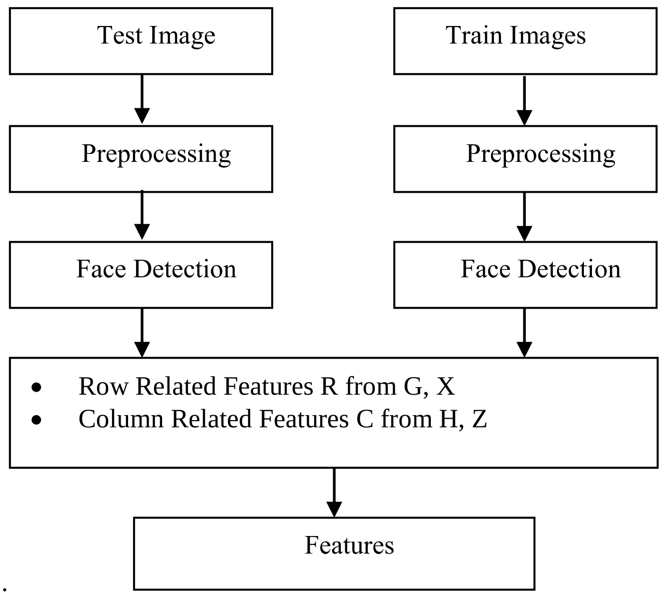

Figure 2 : 2DPRCP Method

The 2DPCA constructs a covariance matrix (G) of the training facial images and builds feature matrix by orthogonal projection of the image onto the p most significant eigenvectors of G. Here, the projections are performed using rows of A_i and the matrices B and B_i (training and testing feature vectors) becomes row-related feature matrices and the column-related features are ignored. As mentioned previously, this study considers both row and column related features during the building of PCA coefficients. The 2DPRCP algorithm works with both two covariance matrices and relates them to respective feature matrices. These feature matrices are then used to train and test a RBF neural network for recognition.

Given a set of M training face images A_i of size m × n, which contains K classes (individuals) {Ω_j, j = 1, …, K} of data, with each class having L = M/K images denoted by { $A_k^{(j)}$, k = 1,2, ,L}. The pair of covariance matrices {$G \in R^{n \times n}$, $H \in R^{m \times m}$ } of respective sizes n × n and m × m is defined using Equations (1) and (2).

$$G = \frac{1}{M}\sum_{i=1}^{M}(A_i - \overline{A})^T (A_i - \overline{A}) \qquad (1)$$

where $\overline{A}$ is the mean of the M training face images and is calculated as $\overline{A} = \frac{1}{M}\sum_{k=1}^{M} A_k$.

$$H = \frac{1}{M}\sum_{i=1}^{M}(A_i - \overline{A})^T (A_i - \overline{A}) \qquad (2)$$

Let {x_k, k = 1, ---, p} and {z_k, k = 1, …, p} be the p orthonorrmal eigenvectors of G and H that are associated with the first largest p eigenvalues respectively. Given a test (facial) image A, two feature matrices denoted by R and C are constructed by orthogonal projection of the rows of A onto {x_k } and columns of A onto {z_k}, respectively. This is represented using Equations (3) and (4).

$$R = A \,.\, X = [r_1\ r_2\ \ldots\ r_p] \qquad (3)$$

$$C = Z^T \,.\, A = [c_1\ c_2\ \ldots\ c_p]^T \qquad (4)$$

where $X = [x_1\ x_2\ \ldots\ x_p]$ and $Z = [z_1\ z_2\ \ldots\ z_p]$ are the optimal projection matrices of size n× p and m× p respectively. Here, $R \in R^{m \times p}$ is the same feature matrix as that used by Yang *et al.* (2004), while $C \in R_{pxn}$ gathers column-related features of the image. Similarly, for each class Ω_j in the training set, a pair of class-average feature matrices { $\overline{R}_j, \overline{C}_j$ } are defined as the arithmetic means over the row-related and column-related feature matrices of the images in that class respectively (Equations 5 and 6).

$$\overline{R}_j = \frac{1}{L}\sum_{k=1}^{L} R_k^{(j)} = \left[\frac{1}{L}\sum_{k=1}^{L} A_k^{(j)}\right] X = \overline{A}_j X \qquad (5)$$

$$\overline{C}_j = \frac{1}{L}\sum_{k=1}^{L} C_k^{(j)} = Z^T\left[\frac{1}{L}\sum_{k=1}^{L} A_k^{(j)}\right] = Z^T\overline{A}_j \qquad (6)$$

where $\overline{A}_j$ is the arithmetic mean of the images in class Ω_j (Equation 7).

$$\overline{A}_j = \frac{\left(\sum_{k=1}^{L} A_k^{(j)}\right)}{L} \qquad (7)$$

The second modification is made by combining the 2DPRCP features with LDA (Fukunaga, 1990) and ICA (Bartlett and Sejnowski, 1997) features. The third modification in PCA is brought by combining 2DPRCP with two transformation algorithms, namely, Discrete Wavelet Packet Transformation (DWPT) and Curvelet Transformation (CT). In this step, the advantages of both DWPT and CT are combined. The combined model is termed as WPC (Wavelet Packet with Curvelets) model. Thus, this paper proposes the following two models.

(i) 2DPRCP + LDA with WPC referred as WPCPL model

(ii) 2DPRCP + ICA with WPC referred as WPCPI model

After computation of the matrix of eigenfaces, it uses the images of wavelet-coefficients for input and projects them onto the low-dimensional subspace using the eigenface transformation matrix. Projection of feature selection algorithm on the transformation coefficients reduced feature subspace. To further improve the recognition process, the Projection of 2DPRCP algorithm is further used in the realization of LDA or ICA algorithms.

4. Experimental Results

To analyze the performance of the proposed models, experiments were conducted with two standard datasets, namely, YALE face database (Yale Database, 1997) and FERET face database (FERET Database, 2004). The Yale database contains 5760 single light source images of 10 subjects each seen under 576 viewing conditions (9 poses x 64 illumination conditions). FERET (Face Recognition Technology) database is the de-facto standard in facial recognition system evaluation. The systems were evaluated in terms of False Acceptance Rate (FAR), False Rejection Rate (FRR), Accuracy and Execution Time. Table I shows the results of FAR, FRR and accuracy of WPCPL and WPCPI models. The results are compared with 2DPRCP, DWPT and CT models.

Table 1 : Performance of the Face Recognition Models

Model	Metric	2DPRCP	DWPT	Curvelets	WPCPL	WPCPI
YALE	FAR	4.97	4.43	3.56	2.03	2.31
	FRR	11.06	12.90	10.71	7.68	8.33
	Accuracy	93.47	94.15	97.17	99.04	98.72
FERET	FAR	5.03	4.99	3.72	2.82	2.92
	FRR	11.37	11.35	10.33	8.45	8.63
	Accuracy	93.52	95.91	96.98	99.63	99.56

From the results, it is evident that the performance of the proposed WPCPL model WPCPI models has improved the face recognition results in terms of FAR, FRR and Accuracy. Comparison of WPCPL and WPCPI shows that WPCPL model that combining 2DPRCP, LDA with Wavelet Packets and Curvelets is efficient than WPCPI model combining 2DPRCP, ICA with Wavelet Packets and Curvelets.

Figure 3 shows the average speed of the recognition process while using the two databases.

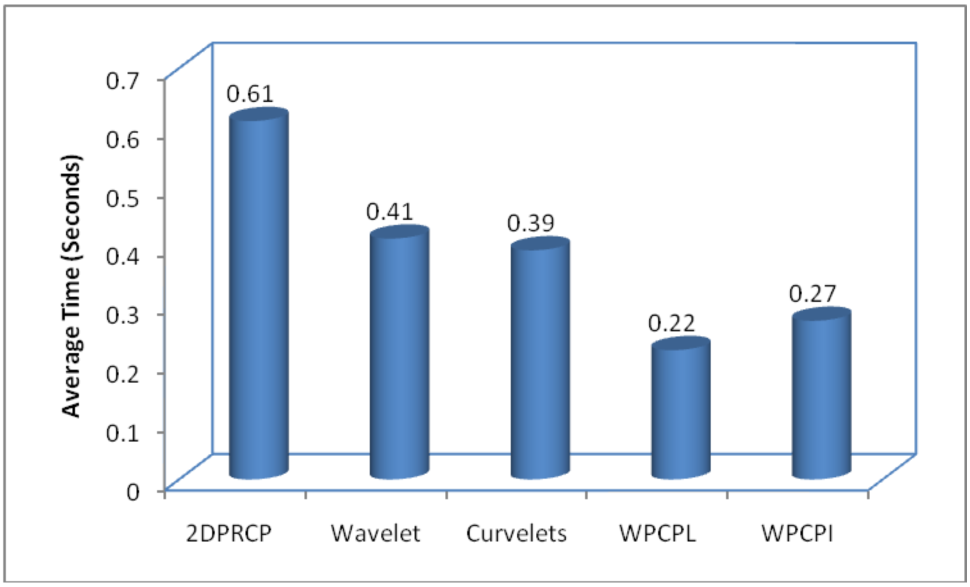

Figure 3 : Speed of the Face Recognition Models

From the results pertaining to speed, again the WPCPL model is the fastest when compared with 2DPRCP, wavelet, curvelets and WPCPI model. The increased time efficiency obtained by both the proposed algorithms prove that the dimensionality reduction algorithms are efficient.

5. Conclusion

Demand for high security using non-intrusive biometrics has increased worldwide and the number of places using human face for this purpose has increased steadily in the past few decades because of its discriminating features which are difficult to reproduce. This study focuses on recognizing the input face image for authentication. For this three subspace reduction algorithms namely, Enhanced 2-Dimensional Principal Component Analysis with row and column projections (2DPRCP), Linear Discriminant Analysis (LDA), Independent Component Analysis (ICA) along with two transformation techniques, wavelet packet and curvelets via wrapping transformation are considered and combined. The proposed method first combines the advantages of wavelet packets and curvelets, followed by the application of multiple projection algorithms that combines 2DPRCP with LDA and ICA to retrieve the reduced feature set. A RBF network classifier is used to recognize the faces. The experimental results prove that the proposed amalgamation of techniques have improved the recognition results. Future research is planned in the usage of these models for occluded face recognition.

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