Face Recognition Techniques: A Review

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ABSTRACT
Face recognition has long been a goal of computer vision, but only in current years reliable automated face recognition has become a realistic target of biometrics research. A lot of work has been done, extensively on the most of details related to face recognition. There are two reasons for the trend the first is the wide range of commercial and law enforcement application and the second is the availability of feasible technologies. Recently in the society of network multimedia information access face recognition is attracting much attention. With the development of face recognition techniques it has not just become practically unfeasible for the hackers to steal one's "password", but also increases the user friendliness in human-computer interaction. Government agencies are investing a considerable amount of resources into improving security systems as result of recent terrorist events that dangerously exposed flaws and weaknesses in today's safety mechanisms. This paper presents an overview of a number of traditional face recognition technologies and a comprehensive discussion of the training requirements for various face recognition technologies and their advantages and limitations.

Keywords - **Face Recognition, Hidden Markov Model (HMM), Independent component analysis (ICA), Linear Discriminant Analysis (LDA), Principal Component Analysis (PCA).**

I. INTRODUCTION

Many recent actions, such as terrorist attacks, uncovered serious weakness in most sophisticated security systems. Due to which various government agencies are now more encouraged to improve security data systems based on body or behavioural characteristics, often called biometrics [1]. Basically, raw data is processed by the biometric systems in order to develop a template as it is easier to accumulate and process and it also contains most of the information needed. In general, it can be incorporated into any purpose requiring precautions, safety or admittance control and also effectively eradicate risks linked with less superior technologies, due to which it has been proved to be a very eye-catching technology.

Face recognition technology is one of the finest biometric technology and on the other hand slightest troubling too. It works with the most evident individual identifier– the human face. Initially the image of person face is captured from a digital camera and then its features are extracted which are examined by the face recognition-system. Based on the input image, the face recognition system measures on the whole face composition, together with distances between eyes, nose, mouth and chicks. Through the use of these unique features face recognition-system store face template into its database. Badge or password-based authentication procedures are too simple to hack. Biometrics represents a convincing substitute but then to they suffer from certain limitations. For example Iris or retina scanning is very unfailing or can say reliable but too invasive; fingerprints are widely accepted, but not appropriate for non-consentient people. In contrast, face recognition represents a better negotiation between what's publicly acceptable and what's trustworthy, even when functioning under inhibited environment.

These days a vital task in computer vision is of detecting human faces and facial features and it has got plentiful potential applications including video surveillance, human computer interaction, face tracking and face recognition. The objective of face detection is to determine whether or not there is any face in the image, and if any, then to specify the face location. The goal of facial feature localization is to detect the presence and location of features, based on the locations of faces which are extracted by any face detection method. There are several challenges associated with face and facial feature detection and recognition and can be attributed by the following factors [2].

a) Intensity: Basically intensity is divided into 3 types- binary, color, and gray.

b) Pose: Due to variation in pose relative to camera certain features specially eyes may appear partially or fully obstructed or closed.

c) Structural components: There are certain things or features like glasses, beards and moustaches which may or may not be always present.

d) Image rotation: Face images fluctuate or differ by various rotations.

e) Poor quality: Certain images which may contain noise or are blurred or distorted may result into a poor quality of face recognition.

f) Facial expression: The expressions of the faces may vary from person to person.

g) Unnatural intensity: Faces from three dimensional models such as rendered faces, animated movies and cartoon faces have unnatural intensity.

h) Occlusion: Things like scarf, hand and variation in pose may result into partially or fully occluded face.

i) Illumination: The location of light source may result into variation in face images.

The skill to identify human faces is a demonstration of unbelievable human intelligence. Over the last three decades researchers have been making attempts to study this outstanding visual perception of human beings in machine recognition of faces [3-4]. However, there are still substantial challenging problems such as intra class variations in 3D pose, make-up and illumination condition, facial appearance as well as occlusion and messed up background. To deal with these complications, various techniques have been projected.

This paper proceeds in IV sections Section II shows the related works. Section III provides an introduction of the various face recognition techniques with their benefits and limitations. Finally the conclusion and future scope of the paper is given in section IV**.**

II. RELATED WORKS

In the past few years a tremendous work has been done by the researchers in order to develop reliable face recognition techniques.

One of the commonly employed techniques involves representing the image by a vector in a dimensional space of size similar to the image [5]. However, the large dimensional space of the image reduces the speed and robustness of face recognition. This problem is overcome rather effectively by dimensionality reduction techniques such as the Principal Component Analysis (PCA) and the Linear Discriminant Analysis (LDA).

PCA is an eigenvector method designed to model linear variation in high-dimensional data. PCA performs dimensionality cutback by projecting an original x-dimensional data onto a y (<< x)-dimensional linear subspace spanned by the leading eigenvectors of the data’s covariance matrix [6].

LDA is a supervised learning algorithm. LDA features are obtained by computing the edge response values in all eight directions at each pixel position and generating a code from the relative strength magnitude. For face recognition process each face is represented as a compilation of LDP codes [7].

While PCA uses orthogonal linear space for encoding information, LDA encodes using linearly separable space in which bases are not necessarily orthogonal. Experiments carried out by researchers thus far points to the superiority of algorithms based on LDA over PCA.

Another face analysis technique is the Locality Preserving Projections (LPP). It consists in obtaining a face subspace and finding the local structure of the manifold. Basically it is obtained by finding the optimal linear approximations to the Eigen functions of the Laplace Betrami operator on the manifold. Therefore, it recovers important aspects of the intrinsic nonlinear manifold structure by preserving local structure though it is a linear technique [8].

Ramesha K and K B Raja, proposed Dual Transform based Feature Extraction for Face Recognition (DTBFEFR). Here Dual Tree Complex Wavelet Transform (DT-CWT) is employed to form the feature vector and Euclidean Distance (ED), Random Forest (RF) and Support Vector Machine (SVM) are used as the classifiers [9].

Weng and Huang presented a face recognition model based on hierarchical neural network which is grown automatically and not trained with gradient-descent.

Good results for discrimination of ten distinctive subjects are reported [10].

Delac et al. [11] presented an autonomous, relative study of three most accepted appearance-based face recognition projection methods (PCA, ICA, and LDA) in completely equal working conditions.

This paper proposes a review of various face recognition techniques such as DCT Based Face Recognition which include neural network and support vector machine for classification. Component Analysis (Statistical) Techniques which include PCA, LDA, and ICA. Hidden Markov Model Techniques. Embedded HMM Face Models.

III. FACE RECOGNITION ALGORITHMS

Face recognition systems are now replenishing the need for security to cope up with the current misdeeds. It is really influential with the market information that undoubtedly depicts the rising attractiveness of the face recognition system. In the present era, the threat of protecting the information or physical property is becoming more and more difficult and important. Now a day the crimes of computer hackings, credit card deception or security violation in a company or government building has noticed to be increased [12].

To a large extent our approaches has been decisive on determining methods of more accurate recognition result by combining the outputs of various face recognition techniques to produce a single recognition technique [13]. Thus in this section we review some of the known techniques for face recognition, discussing the relative advantages and disadvantages of each technique. There are numerous algorithms for face recognition reported in the literature discussed below. Initial approaches [14] were based on a simple comparison of distances between different characteristics of the face like forehead, eyes, nose, mouth.

3.1 Discrete Cosine Transformation (DCT) Based Face Recognition

The next generation of algorithms were based on the overall appearance of the face. They are usually based on projecting the face image into a face space and using classification algorithms in this face space for computing similarities between faces. One of these techniques is based on computing the DCT spectrum of the face image and then using the entire spectrum of just a part of it for classification. The classification algorithms can vary from simple distances between DCT coefficients vectors or more complex algorithms employing neural network techniques [15], or support vector machines [16,17]. The advantages of the tested algorithm are its simplicity and the straightforward implementation in hardware. The main disadvantage is the low accuracy when working with consumer images with a high degree of face variation.

3.2 Component Analysis (Statistical) Techniques

Another important group of algorithms are called sub-space methods. Examples include principal component analysis (PCA) or eigenface techniques [18], linear discriminate analysis (LDA) or fisherface techniques [19] and independent component analysis (ICA) [20]. The main disadvantage of these methods is that these components are data dependent so every time the collection of faces changes the basis vectors for projection should be recomputed which leads to significant workflow. The key difficulty is how to dynamically incorporate new data and refine the basis vectors without retraining the entire data set after each new image acquisition [13]. However an incremental PCA algorithm can be used for updating the PCA data without completely retraining the collection of images as suggested in [21], due to which it has been possible to make the use of PCA algorithm for in-camera face recognition and other applications with limited resources.

3.2.1 Principal Component Analysis

Principal component analysis (PCA) PCA is a statistical dimensionality reduction method, which produces the optimal linear least-square decomposition of a training set. Kirby and Sirovich [22] applied PCA for representing faces and Turk and Pentland [18] extended PCA for identifying faces. In applications such as image compression and face recognition a helpful statistical technique called PCA is utilized and is a widespread technique for determining patterns in data of large dimension. PCA commonly referred to as the use of Eigen faces [22]. With PCA, the probe and gallery images must be the same size and must first be normalized to line up the eyes and mouth of the subjects within the images. The PCA approach is then applied to reduce the dimension of the data by means of data compression, and reveals the most effective low dimensional structure of facial patterns. The advantage of this reduction in dimensions is that it removes information that is not useful and specifically decomposes the structure of face into components which are uncorrelated and are known as Eigen faces [6]. Each image of face may be stored in a 1D array which is the representation of the weighted sum (feature vector) of the Eigen faces. In case of this approach a complete front view of face is needed; or else the output of recognition will not be accurate. The major benefit of this method is that it can trim down the data required to recognize the entity to 1/1000th of the data existing.

The following steps summarize the process PCA. Let a face image $X(x, y)$ be a two dimensional m x n array of intensity values. An image may also be considering the vector of dimension mn, so that a typical image of size 112x92 becomes a vector of dimension 10304. Let the training set of images $\{X_1, X_2, X_3 \ldots X_N\}$. The average face of the set is defined by:

$$\bar{X} = \frac{1}{N}\sum_{i=1}^{N} X_i \qquad (1)$$

Calculate the estimate covariance matrix to represent the scatter degree of all feature vectors related to the average vector. The covariance matrix C is defined by [23]:

$$C = \frac{1}{N}\sum_{i=1}^{N}(\bar{X} - X_i)(\bar{X} - X_i)^{T} \qquad (2)$$

The Eigenvectors and corresponding Eigen-values are computed by using

$$CV = \lambda V \qquad (V \in R_n, V \neq 0) \qquad (3)$$

where V is the set of eigenvectors matrix C associated with its eigenvalue λ. Project all the training images of i^{th} person to corresponding eigen-subspace:

$$y_k^i = w^T(x_i) \qquad (i = 1,2,3 \ldots \ldots \ldots N) \qquad (4)$$

In the testing phase each test image should be mean centred, now project the test image into the same eigenspace as defined during the training phase. This projected image is now compared with projected training image in eigenspace. Images are compared with similarity measures. The training image that is the closest to the test image will be matched and used to identify. Calculate relative Euclidean distance between the testing image and the reconstructed image of i^{th} person.

3.2.2 Linear Discriminant Analysis (LDA)

LDA is a data separation technique. The objective of LDA is to find the directions that can well separate the different classes of the data once projected upon. The database of human faces is represented as a records matrix X, where each row indicates to a different human face. Each image X, represented by a (n, m) matrix of pixels, is represented by a high dimensional vector of n*m pixels. Turk and Pentland [24] were among the first who used this representation for face identification. Two dimensional principal component analysis (2dPCA) which unswervingly calculates the Eigenvectors of the covariance matrix without matrix to vector conversion was proposed [25]. Two dimensional LDA [26, 27] computes directly the directions which will separate the classes without matrix to vector conversion as well. Higher recognition rate was reported for both cases. The PCA/LDA-based face recognition systems suffer from the scalability difficulty. One of the solution of this difficulty is taking use of an incremental approach but the main problem in developing the incremental PCA/LDA is to calculate covariance matrix and to hold the inverse of the inside class scatter matrix. Online development of 2-d filters requires that the system perform while new sensory signals run inside. Both the calculation and storage complication cultivate significantly, if the dimension of the image is large. Thus, the proposal of using a real time method becomes very proficient consecutively to calculate the principal components for faces received successively. It should be noted that the incremental PCA-LDA has the following advantages:

a) Low memory demands: No need to store all the images (mainly due to the incremental structure of the PCA). All you need to store are the Eigenvectors. Given a new image or a new class, the Eigenvectors will be updated using only the stored Eigenvectors. From a practical point of view, there is no need to store any face database (store the unrecognized Eigenvectors) and some image data could not be presently available. It should be noted that 2dPCA, 2dLDA, and SVD work in batch mode.

b) Low computational complexity: The batch PCA-LDA needs to compute all the Eigenvectors of all the data then gets the first k Eigenvectors. The incremental PCA-LDA operates directly on the first k Eigenvectors (unwanted vectors do not need to be calculated). The processing of IPCA_LDA is restricted to only the specified number of k directions and not on all the directions.

c) Enhanced recognition accurateness and a smaller amount of implementation time.

d) Modifying the inverse of the inside class scatter matrix without computing its inverse.

3.2.3 Independent component analysis (ICA)

Marian S Bartlett used version of ICA [28] derived from the principle of optimal information transfer through sigmoidal neurons on face images from FERET database has proved that ICA representation gave the best performance on the frontal face images. Feature selection in the independent component subspace [29] which gives the benefits for face recognition with changes in illumination and facial expressions. Fusion of ICA features like Spatial, Temporal and Localized features [30] for Face Recognition are considered as optimization method. An independent Gabor features (IGFs) method and its application to face recognition using ICA is discussed by Kailash J.Karande & Sanjay N Talbar[31].

Independent component analysis (ICA) is a statistical and computational technique for revealing hidden factors that underlie sets of random variables. ICA defines a generative model to observe multivariate data which are typically given by a large dataset of samples. In the model, the data variables are assumed to be linear mixtures of some unknown latent variables, and the mixing system is also unknown. The latent variables are assumed non-gaussian and mutually independent and they are called the independent components of the observed data.

We can use a statistical "latent variables" model. Assume that we observe n linear mixtures x_1, x_2, x_3..., x_n of n independent components.

$$x_j = a_{j1} s_1 + a_{j2} s_2 + \dots + a_{jn} s_n \quad \text{for all 'j'} \quad (5)$$

We assume that each mixture x_j as well as each independent component s_k is a random variable, instead of a proper time signal.

We use vector-matrix notation instead of the sums like in (1). Let x denote the random vector whose elements are the mixtures x_1, x_2, x_3..., x_n. Likewise by s the random vector with elements s_1, s_2, s_3..., s_n. Let A be the matrix with elements a_{ij}. As we understand that, all vectors are column vectors; thus x^T is a row vector. Using this vector-matrix notation, we define:

$$\mathbf{x} = As \quad (6)$$

Or

$$\mathbf{x} = \sum_{i=1}^{n} a_i \, s_i \quad (7)$$

The statistical model in (2) is called independent component analysis or ICA model [32].The independent components are latent variables, meaning that they cannot be directly observed.
A very simple assumption that the components s_i is statistically independent is made. Also, the independent component must have non-gaussian distributions. For the sake of simplicity, we do not assume these distributions are known. We are also assuming that the unknown mixing matrix is a square matrix. After estimating the matrix A, compute its inverse, say W, and obtain the independent component by:

$$s = W\mathbf{x} \quad (8)$$

3.3 Hidden Markov Model Techniques
In simple words, HMM is defined as set of restricted states with coupled probability distributions. Hidden Markov model (HMM) is a promising method that works well for images with different face expressions, changes in pose and lighting and in different rotations. The temporal or space sequences need to be considered if images are to be processed using HMM. The name Hidden Markov Model is given because only the output is visible to the outside user and not the states [33].

Baum et al. [34-37] developed the theory of one-dimensional HMMs in the 1960s and has earned its popularity mainly due to the successful application in speech recognition. HMMs are a set of statistical models used to characterize the statistical properties of a signal. It consist of two interconnected procedures : a fundamental, unobservable Markov chain with a restricted number of states, a state transition probability matrix and an initial state probability distribution, and a set of observations, defined by the observation density functions associated with each state [34].

One probable substitute to embedded face recognition that we experienced is a 2D variant of Hidden Markov Models (HMMs) called embedded HMMs (EHMM). The main advantage of the HMMs is that the models for each person are build independently. So every time we want to add a new person to the collection we just have to add a new model without modifying the other models.

For frontal face images, the significant facial regions such as hair, forehead, eyes, nose, mouth and chin come in a natural order from top to bottom, even if the images undergo small rotations in the image plane and/or rotations in the plane perpendicular to the image plane. Each of these facial regions is assigned to a state in a left to right 1D continuous HMM.

3.4 Embedded HMM Face Model techniques

The embedded HMM was first introduced for character recognition by Kuo and Agazzi in [35] and has a large applicability in pattern recognition involving two dimensional data. The embedded HMM is a generalization of the classic HMM, where each state is the one dimensional HMM is itself an HMM. Thus, an embedded HMM consists of a set of super states along with a set of embedded states.Super states model the data in one direction (top-bottom). Embedded states model the data in another direction (left-right).Transition from one super state to another is not possible. Hence named Embedded HMM.

IV. CONCLUSION AND FUTURE SCOPE

In many fields of machine learning and pattern recognition, many algorithms are universal. But these algorithms should be improved when they are used in a certain application. Face recognition is a both challenging and important recognition technique. Among all the biometric techniques, face recognition approach possesses one great advantage, which is its user-friendliness (or non-intrusiveness). Several face recognition algorithms were introduced in recent years. The objective for researchers was to seek to implement recognition algorithms that are more accurate in terms of face identification.

In this paper a comparative study of various face recognition algorithms have been shown. All these algorithms have some advantages and some disadvantages as well. Component Analysis (Statistical) Techniques namely Principal component analysis (PCA), Linear Discriminant Analysis (LDA), Independent Component Analysis (ICA) are gaining attention as efficient techniques for face recognition. A major challenge faced by any face recognition system is its ability to identify images, which may be tampered or undetectable due to various reasons. Varying lighting conditions or face expressions reduces the recognition rate resulting in poor performance of the system. In order to avoid these difficulties different image enhancement methods can be employed.

In this paper, an introductory survey for the face recognition technology has been given and covered issues such as the generic framework for face recognition, factors that may affect the performance of the recognizer, and several state-of-the-art face recognition algorithms. The future work is to investigate effect weights of organ's features in face recognition. It means that which part of organs is more important in face recognition? What the proportion is of each part?

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