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A Survey of Face Recognition Methods

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Abstract

Face recognition presents a challenging problem in the field of image analysis and computer vision, and as such has received a great deal of attention over the last few years because of its many applications in various domains. Face recognition techniques can be broadly divided into three categories based on the face data acquisition methodology: methods that operate on intensity images; those that deal with video sequences; and those that require other sensory data such as 3D information or infra-red imagery. In this paper, an overview of some of the well-known methods in each of these categories is provided and some of the benefits and drawbacks of the schemes mentioned therein are examined. This paper also mentions some of the most recent algorithms developed for this purpose and attempts to give an idea of the state of the art of face recognition technology.

Keywords: *Face Recognition, Person Identification, Biometrics*

I. INTRODUCTION

Biometric-based techniques **(Jain et.al.1999)** have emerged as the most promising option for recognizing individuals in recent years since, instead of authenticating people and granting them access to physical and virtual domains based on passwords, PINs, smart cards, plastic cards, tokens, keys and so forth, these methods examine an individual's physiological and/or behavioral characteristics in order to determine and/or ascertain his identity. Passwords and PINs are hard to remember and can be stolen or guessed; cards, tokens, keys and the like can be misplaced, forgotten, purloined or duplicated; magnetic cards can become corrupted and unreadable. However, an individual's biological individuality cannot be misplaced, forgotten, stolen or forged. Biometric-based technologies include identification based on physiological characteristics (such as face, fingerprints, finger geometry, hand geometry, hand veins, palm, iris, retina, ear and voice) and behavioral traits such as gait, signature and keystroke dynamics.

Face recognition appears to offer several advantages over other biometric methods, a few of which are outlined here: Almost all these technologies require some voluntary action by the user, i.e., the user needs to place his hand on a hand-rest for fingerprinting or hand geometry detection and has to stand in a fixed position in front of a camera for iris or retina identification. However, face recognition can be done passively without any explicit action or participation on the part of the user since face images can be acquired from a distance by a camera. This is particularly beneficial for security and surveillance purposes. Furthermore, data acquisition in general is weighed down with problems for other biometrics: techniques that rely on hands and fingers can be rendered useless if the epidermis tissue is damaged in some way i.e., bruised or cracked. Iris and retina identification require expensive equipment and are much too sensitive to any body motion. Voice recognition is susceptible to background noises in public places and auditory fluctuations on a phone line or tape recording. Signatures can

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be modified or forged. However, facial images can be easily obtained with a couple of inexpensive fixed cameras. Good face recognition algorithms and appropriate preprocessing of the images can compensate for noise and slight variations in orientation, scale and illumination. Finally, technologies that require multiple individuals to use the same equipment to capture their biological characteristics potentially expose the user to the transmission of germs and impurities from other users. However, face recognition is totally non-intrusive and does not carry any such health risks.

Generally speaking, there are two categories of methods in face recognition **(Kim et.al,2)**. One approach is based on facial feature. Firstly, the features such as eyes, nose and mouth first are located and then various feature extraction methods can be adopted to construct feature vectors of these facial features. Finally, traditional pattern recognition methods like a neural network can be used to recognize the feature vectors. The other approach takes a holistic view of the recognition problem. It extracts the statistical characterization by the statistical method directly out of the entire training sample images instead of extracting the feature of the nose, mouth, or the eyes separately.

Table 1. Applications of Biometrics

Areas	Specific applications
Entertainment	Video game, virtual reality, training programs
	Human-robot-interaction, human-computer-interaction
Smart cards	Drivers' licenses, entitlement programs
	Immigration, national ID, passports, voter registration
	Welfare fraud
Information security	TV Parental control, personal device logon, desktop logon
	Application security, database security, file encryption
	Intranet security, internet access, medical records
	Secure trading terminals
Law enforcement	Advanced video surveillance, CCTV control and surveillance
	Portal control, post event analysis
	Shoplifting, suspect tracking and investigation

II. REVIEW OF FACE RECOGNITION METHODS

2.1. Appearance-based face recognition

Appearance-based face recognition can be divided into linear analysis methods such as PCA, ICA and LDA and non-linear analysis methods, such as KPCA.

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Classical linear appearance-based analyses are PCA, ICA and LDA and each of them has its own basis vectors of a high dimensional face image space. The face vectors can be projected to the basis vectors by using those linear analysis methods.

Dimensionality of original input image space can be reduced through the projecting from a higher dimensional input image space to a lower dimensional space. The matching score between the test face image and training images can be achieved by calculation the differences between their projection vectors. The higher the score, the more similar between these two face images.

2.1.1) Principal Component Analysis

Principal component analysis is used to calculate the vectors which best represent this small region of image space. It is also known as Karhunen-Loève expansion, eigenpicture, eigenvector, and principal Component [3-5].

The main idea of the principal component analysis is to find the vectors which best describe the distribution of face images within the entire image space. Its principle can be illustrated by Figure1. PCA is performed by projecting a new image into the subspace called face space spanned by the eigenfaces and then classifying the face by comparing its position in face space with the positions of known individuals.PCA aims to extract a subspace where the variance is maximized

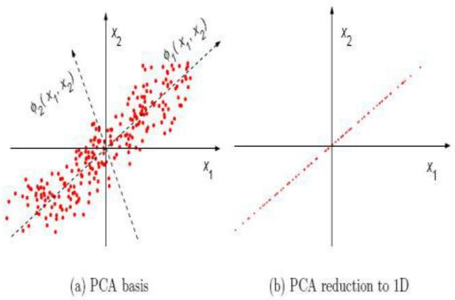

Fig.1. The principle of PCA

2.1.2) Linear Discriminant Analysis

Similar images projections are close together, different images projections locate far away when using PCA, but the projection from different classes of images are mixed together.

LDA is also called Fisher Discriminant Analysis. LDA is able to maximize the ratio of between-class distribution to that of within-class distribution [7, 8]. The principle of LDA can be illustrated in Figure3.

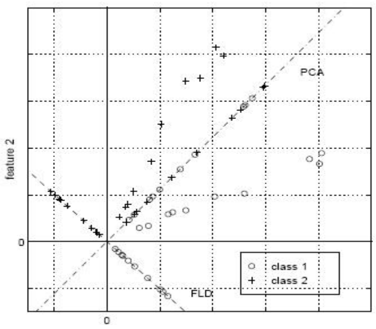

Fig.2. The principle of PCA

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2.1.3) Nonlinear analysis

Linear discriminant methods are insensitive to the relationship among multiple pixels in the images. Some nonlinear relations may exist in a face image, especially under a complicated variation in viewpoint, illumination and facial expression which is highly nonlinear.

To extract nonlinear features of images, linear analysis method was extended to nonlinear analysis such as Kernel PCA, Kernel ICA and Kernel FLD etc [9, 10].

By using nonlinear analysis approaches the original input image space is projected nonlinearly onto a high dimensional feature space. In this high dimensional space,the distribution of image vectors could be simplified to linear pattern. Comparison of PCA and KPCA can be demonstrated in Figure3.

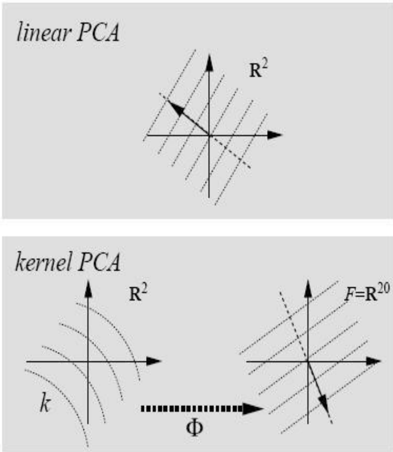

Fig.3. Comparison of PCA and KPCA

2.1.4) Independent Component Analysis

PCA derives only the most expressive features which are unrelated to actual face recognition, and in order to improve performance additional discriminant analysis is needed. However, ICA provides a more powerful data representation than PCA as its aim is to provide an independent rather than uncorrelated image decomposition and representation. ICA is a generalization of PCA [6]. The principle of ICA can be described in Figure2.

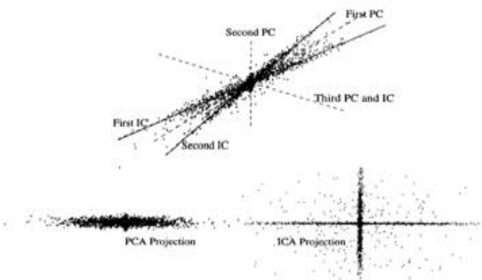

Fig.4. The principle of ICA

2.2. Featured-based

Feature-based approaches first process the input image to identify and extract (and measure) distinctive facial features such as the eyes, mouth, nose, etc., as well as other fiducial marks, and then compute the geometric relationships among those facial points, thus reducing the input facial image to a vector of geometric features. Standard statistical pattern recognition techniques are then employed to match faces using these measurements.

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Early work carried out on automated face recognition was mostly based on these techniques. One of the earliest such attempts was by Kanade [15], who employed simple image processing methods to extract a vector of 16 facial parameters - which were ratios of distances, areas and

angles (to compensate for the varying size of the pictures) - and used a simple Euclidean distance measure for matching to achieve a peak performance of 75% on a database of 20 different people using 2 images per person (one for reference and one for testing).

Brunelli and Poggio [16], building upon Kanade's approach, computed a vector of 35 geometric features from a database of 47 people (4 images per person) and reported a 90% recognition rate. However, they also reported 100% recognition accuracy for the same database using a simple template-matching approach.

Furthermore, a certain tolerance must be given to the models since they can never perfectly fit the structures in the image. However, the use of a large tolerance value tends to destroy the precision required to recognize individuals on the basis of the model's final best-fit parameters and makes these techniques insensitive to the minute variations needed for recognition [15]

Cox et al. [16] reported a recognition performance of 95% on a database of 685 images (a single image for each individual) using a 30-dimensional feature vector derived from 35 facial features . However, the facial features were manually extracted, so it is reasonable to assume that the recognition performance would have been much lower if an automated, and hence less precise, feature extraction method had been adopted. In general, current algorithms for automatic feature extraction do not provide a high degree of accuracy and require considerable computational capacity

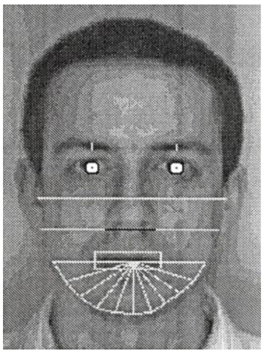

Fig.5. Geometrical features (white) used in the face recognition experiments [46].

Another well-known feature-based approach is the elastic bunch graph matching method proposed by Wiskott et al. [17] . This technique is based on Dynamic Link Structures [18]. A graph for an individual face is generated as follows: a set of fiducial points on the face are chosen. Each fiducial point is a node of a full connected graph, and is labeled with the Gabor filters' responses applied to a window around the fiducial point. Each arch is labeled with the distance between the correspondent fiducial points. A representative set of such graphs is combined into a stack-like structure, called a *face bunch graph*.

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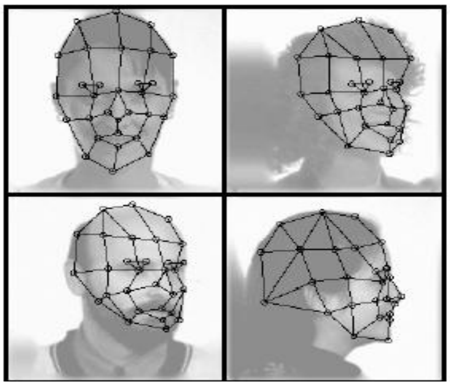

Fig. 6. Grids for face recognition [2].

III. NEURAL NETWORKS

The attractiveness of using neural networks could be due to its non linearity in the network. Hence, the feature extraction step may be more efficient than the linear Karhunen-Loève methods. One of the first artificial neural networks (ANN) techniques used for face recognition is a single layer adaptive network called WISARD which contains a separate network for each stored individual [19]. The way in constructing a neural network structure is crucial for successful recognition. It is very much dependent on the intended application. For face detection, multilayer perception [21] and convolutional neural network [21] have been applied. Reference [21] proposed a hybrid neural network which combines local image sampling, a self-organizing map (SOM) neural network, and a convolutional neural network. The SOM provides a quantization of the image samples into a topological space where inputs that are nearby in the original space are also nearby in the output space, thereby providing dimension reduction and invariance to minor changes in the image sample. A simple neural network is described in Fig.7.

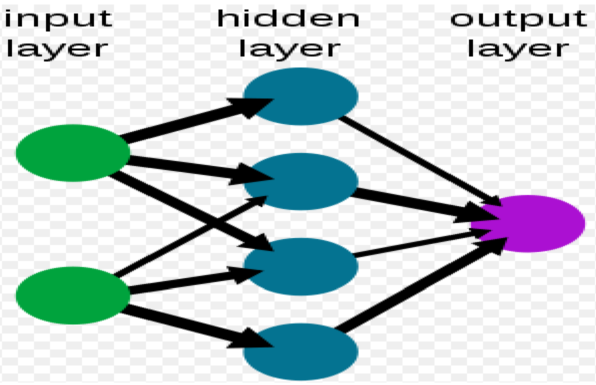

Fig.7..A simple neural network

IV. HIDDEN MARKOV MODELS (HMMS)

Stochastic modeling of nonstationary vector time series based on (HMM) has been very successful for speech applications. Reference [22] applied this method to human face recognition. Faces were intuitively divided into regions such as the eyes, nose, mouth, etc., which can be associated with the states of a hidden Markov model. Since HMMs require a one-dimensional observation sequence and images are two-dimensional, the images should be converted into either 1D temporal sequences or 1D spatial sequences.

V. SUPPORT VECTOR MACHINE (SVM)

Applying SVM to computer vision problem has been proposed in recent years. Osuna et al [24] train a SVM for face detection, where the discrimination is between two classes: face and non-face, each with thousands of examples.

For a two-class classification problem, the goal is to separate the two classes by a function which is induced from available examples.SVM is a learning technique that is considered an effective method for general purpose pattern recognition because of its high generalization performance without the need to add other knowledge [25].

Intuitively, given a set of points belonging to two classes, a SVM finds the hyperplane that separates the largest possible fraction of points of the same class on the same side, while maximizing the distance from either class to the hyperplane. According to [25], this hyperplane is called Optimal Separating Hyperplane (OSH) which minimizes the risk of misclassifying not only the examples in the training set but also the unseen example of the test set.

VI. CONCLUSIONS

Face recognition is a challenging problem in the field of image analysis and computer vision that has received a great deal of attention over the last few years because of its many applications in various domains. Research has been conducted vigorously in this area for the past four decades or so, and though huge progress has been made, encouraging results have been obtained and current face recognition systems have reached a certain degree of maturity when operating under constrained conditions; however, they are far from achieving the ideal of being able to perform adequately in all the various situations that are commonly encountered by applications utilizing these techniques in practical life. The ultimate goal of researchers in this area is to enable computers to emulate the human vision system

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