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Face Recognition Techniques: A Review

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Abstract *- In recent years face recognition has received significant attention from both research communities and society of network multimedia information access. Major progress and immense range of biometric applications in banking, national identity, law enforcement, immigration, and logical access control have projected face recognition technology into the spotlight. Though earlier, simple geometric models were used for face recognition but now the recognition process has graduated into a science of much more sharp and mature mathematical representations and matching processes. This paper reviews the existing approaches of face recognition techniques and offers some insights into the studies of machine recognition of faces. A number of typical appearance and feature based approaches are discussed. Furthermore, some efforts have been put to outline the motive for using face recognition, applications and some of the difficulties disturbing current systems with regard to this task.*
Keywords *- Biometrics, Face Recognition Techniques, Appearance-based Approaches, Feature-based Approaches, Problems, Applications.*

I. INTRODUCTION

Face recognition basically relates to the task of identifying an already detected face as a known or unknown face. We generally assume face detection and face recognition as similar terms but they are technically different in meaning.
Face detection is to identify an object as a 'face' and locate it in the input image while face recognition is to decide if this 'face' is someone known or unknown depending on the database of faces it uses to validate this input image.
As given in figure input image is first detected as a face and then the recognition of the face is done by extracting the features and matching them with the database images.

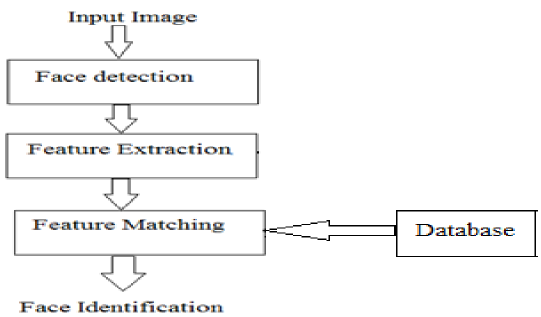

Fig.1: Face Recognition System

Face recognition system generally falls into two categories: verification and identification.
Face verification is considered as 1:1 match that compares a face image against a template face image whose identity is being claimed.
Face identification is a 1: N problem that compares a query or input face image against all image templates in a face database.
Face recognition is quite a relevant subject in pattern recognition [1], neural networks [2], computer graphics, psychology [3] and image processing. The primitive works on this subject were made in the 1950's in psychology. Face recognition is a non-intrusive biometric method and is considered as a better biometric method than iris recognition, gait recognition, finger print recognition, etc.

Many well known face recognition techniques have been developed over the last few decades. Research in automatic face recognition started in 1960's with the innovative work of Bledsoe [4]. In 1960s, the first semi-automated system for face recognition was proposed wherein the administrator had to first locate features such as nose, mouth, eyes and ears on the photographs and then calculate the distances and ratios to a common reference point. This distance and ratios were then compared to reference data in the database. Goldstein, Harmon, and Lesk [5] in 1970s introduced the use of 21 specific subjective markers such as hair colour, eye lobes, lip thickness, etc. to perform the recognition. But the problem with both these solutions was the manual computation of the measurements and locations. The implementation of first fully functional automated face recognition system was produced after Kanade's paper [6] in 1977.But the major milestone in face recognition came in 1988, when Kirby and Sirovich [7] applied a standard linear algebra technique called principle component analysis. This technique showed that less than one hundred values are capable to accurately code a suitably aligned and normalized face image. Since many approaches have been proposed, there have also been extensive surveys [3] written over the last thirty years.

II. FACE RECOGNITION TECHNIQUES

There are mainly three approaches for face recognition:

Appearance based (or holistic matching) methods use the whole face region as the raw input to a recognition system. The face recognition problem is firstly transformed to a face space analysis problem and then a number of well known statistical methods are applied to it. They are quite prone to the limitations caused by facial variations such as illumination, 3D pose and expressions.

Feature based matching methods first extract the local features such as the nose, eyes and mouth. Their locations and local statistics (geometric and/or appearance) are then fed into a structural classifier.

Hybrid methods use both the appearance and feature based method i.e. it uses both local features and the whole face region to recognize a face.

A. Appearance Based Approaches

1) The Eigenface Method

Kirby and Sirvoich first used eigenfaces for recognition. Inspired by their work, Turk and Pentland [8] proposed eigenfaces method based on Principal Component Analysis (PCA) for face recognition. The main procedure in PCA is based on Karhumen-Loeve transformation. PCA is a well-known linear dimensionality reduction technique which finds a set of mutually orthogonal basis functions and uses the leading eigenvectors of the sample covariance matrix to characterize the lower dimensional space as shown in figure 2.

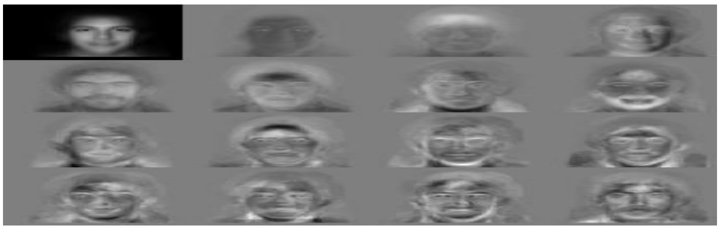

Fig.2: Standard Eigenfaces: Feature vectors are derived using eigenfaces [9]

Another Bayesian PCA method was suggested by Moghaddam et al [10] . By this system, the Eigenface Method based on simple subspace-restricted norms is extended to use a probabilistic measure of similarity. Chung et al. [11] suggested the combined use of PCA and Gabor Filters. Their method consists of two parts. First, use Gabor Filters to extract facial features from the original image on predefined fiducial points and then use PCA to classify the facial features optimally.

Examples of some recent PCA-based algorithms include:

Kernel PCA methods [12] provides generalisations which take higher order correlations into account, handles non linearity in face recognition and achieve lower error rates.

Symmetrical PCA [13] in which PCA is combined with even-odd decomposition principle. This method uses the different energy ratios and sensitivities of even/odd symmetrical principal components for feature selection.

Two-dimensional PCA [14] involves framing of a 2-dimensional matrix instead of 1 D vector. Adaptively weighted subpattern PCA [15] involves the division of the original whole image pattern into sub patterns and then the features are extracted from them. The classification is done by adaptively computing the contributions of each part.

Weighted modular PCA [16] methods involves partitioning the whole face into different modules or sub-regions such as mouth , nose, eyes and forehead and then the weighted sum of errors of all these regions is found to get the final decision.

2) The Fisherface Method

Belhumeur, 1997 [17] proposed this Fisherface method, a derivative of Fisher's Linear Discriminant (FLD) which includes linear discriminant analysis (LDA) to extract the most discriminant features. Also, it is a dimensionality reduction technique. Fisherface method uses both PCA and LDA to produce a subspace projection matrix, analogous to that used in the eigenface method. LDA tries to find a set of projection vectors which form the maximum between-class scatter and minimum within-class scatter matrix simultaneously (Chen et al [18]) and provides lower error rates than eigenface method. Figure 3 shows the example of six different classes using LDA with large variances between classes, but little variance within classes.

Fig.3: Example of Six Classes Using LDA [9]

Kernel FLD [19] is able to extract the most discriminant features in the feature space, which is equivalent to extracting the most discriminant nonlinear features in the original input space and provides better results than the conventional fisherface which is based on second order statistics of image-set and does not take into account the higher order statistical dependencies such as relationships among three or more pixels.
Some of the recent LDA-based algorithms include [20]:
Direct LDA [21] which forms the image scatter matrix from a normal 2-d image and has the capability to solve small sample size problem.
Further, Dual-space LDA [22] makes use of full discriminative information of face space and tries to overcome the same problem.
Direct-weighted LDA [23] merges the privileges of both direct LDA and weighted pairwise Fisher criteria.
Block LDA [24] partitions the whole image into blocks and represents each block as a row vector. These row vectors for each block form 2D matrices and represent the image and then LDA is applied to these matrices.
A methodology to fuse the LDA and PCA [25] representations using two approaches: the K-Nearest Neighbour approach (KNN) and the Nearest Mean approach (NM) was done on the AT&T and the Yale datasets.

3) Frequency Domain Analysis Method

Frequency domain analysis methods have been widely acquired in face recognition which transform the image signals from spatial domain to frequency domain and analyze the features in frequency domain. Only limited low-frequency components having high energy are selected to represent the image. Different from PCA and LDA, frequency domain analysis methods are independent of data and do not require training images [26]. Moreover, smart and fast algorithms are available which provides easy implementations and have high computation efficiency.

(i) Discrete Fourier Transform
Fourier Transform is a frequency domain analytical method. For an $1\times N$ input signal, $f(n)$. Discrete Fourier Transform is defined as

$$F(k) = \int_{n=1}^{N} f(n) e^{-j2\pi(k-1)\left(\frac{n-1}{N}\right)} dt$$

$1 \le k \le N$

The 2D face image is first converted to 1D vector, $f\ (n)$ by cascading each column together and transforming them into frequency domain. Only few low frequency coefficients are chosen since they contain most of the signal's energy.

(ii) Discrete Cosine Transform
Ahmed, Natarajan, and Rao [27] were the first ones to introduce the discrete cosine transform (DCT) in the early seventies. The DCT [28] is basically computed for a cropped version of an input image. This cropped input image contains a face and a small subset of the coefficients which is maintained as a feature vector.The DCT performs the transformation of spatial information to decoupled frequency information in the form of DCT coefficients. The DCT for an N × N image can be defined as :

$$C(u,v) = \alpha(u)\alpha(v) \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} Z(x,y) cos \frac{\pi(2x+1)u}{2N} cos \frac{\pi(2y+1)v}{2N}$$

u,v= 0,1,2,….,N-1

$$\propto (u) = \begin{cases} \sqrt{1/_N} & u = 0 \\ \sqrt{2/_N} & u \ne 0 \end{cases}$$

The matrix coefficients for an N × N image cover the whole frequency space of image components. The upper left of the matrix contains the DCT coefficients with higher values. As a feature extraction method, DCT changes the face images with high dimension to a subspace with low dimension. The most important features of face such as the lines belonging to hairs and face, the position of eyes, nose and mouth remains in the DCT coefficients.

(iii). Discrete Wavelet Transform
Discrete Wavelet Transform (DWT) [29] represents a signal in terms of wavelets using dilation and translation which are successfully used in image processing. The wavelet families Haar, Symelt are used. It can capture localized time-frequency information of image and thus motivate its use for feature extraction. The data is decomposed into different frequency ranges and then the frequency components introduced by intrinsic deformations due to expression or extrinsic factors (like illumination) are isolated into certain sub bands. Wavelet-based methods trim away these variable sub bands, and just consider the sub bands that contain the most relevant information to represent the data. As compared to DFT, the DWT is preferred or applied as it possesses a better space frequency localization.

4) Independent Component Analysis

ICA can be considered as generalization of PCA and is argued to have more representative power than PCA. ICA finds a linear transformation to express a set of random variables as linear combinations of statistically independent source variables. It was argued that for face recognition more important information is present in high order statistics therefore; ICA was used to extract the features. ICA encodes face images with statistically independent variables. These variables are not necessarily associated with the orthogonal axes and looks for direction that are most independent from each other. ICA decorrelates the high-order moments of the input in addition to the second-order moments and its possible use for face recognition has been shown by Bartlett and Sejnowski [30].

5) Support Vector Machines

To improve the classification performance of the PCA and LDA subspace features, more sophisticated classifiers, support vector machines (SVM) are used [31]. SVM are the classifiers which are generally trained through supervised learning. SVM uses a training set of images to compute the Optimal Separating Hyperplane (OSH), minimising the risk of mis-classification between two classes of image in some feature space. Guo et al [32] applied this method to face recognition. He used a binary tree classification technique in which a face image is iteratively classified as belonging to one of two classes. A binary tree structure is propagated up until the two classes denote individual subjects and a final classification decision can be made. SVM has been employed for face recognition by several other researchers and has been shown to yield good results.

6) The Laplacianfaces approach

Different from PCA and LDA which effectively see only the Euclidean structure of face space and if the face images lie on a nonlinear sub manifold hidden in the image space, then they fail to discover the underlying structure. The manifold structure is modeled by a nearest- neighbor graph which preserves the local structure of the image space. Locality Preserving Projections (LPP) obtains a face subspace that best detects the essential face manifold structure [33]. Each face image in the image space is mapped to a low dimensional face subspace characterized by a set of feature images. These feature images are called as *Laplacianfaces.*

LPP suffers from a limitation that it does not encode discriminant information, which is very important for recognition tasks. Recently, several modified LPP algorithms have been proposed to make use of the label information. Yu et al. [34] presented a discriminant locality preserving projections (DLPP) algorithm to improve the classification performance of LPP and applied it to recognize faces. Null space discriminant locality preserving projections (NDLPP) [35] was proposed to avoid the small sample size problem of DLPP by solving an eigenvalue problem in null space. L. Zhu and S.N. Zhu [36] introduced an orthogonal discriminant locality preserving projections (ODLPP) method based on OLPP. Cai et al.[37] proposed a locality sensitive discriminant analysis (LSDA) method where the data points are mapped into a subspace in which the nearby points with the same label are close to each other while the nearby points with different labels are far apart.

7) Probabilistic Decision Based Neural Network (PDBNN)

Probabilistic Decision Based Neural Network (PDBNN) face recognition system proposed by Lin et al [38] consists of three different modules (a face detector, an eyes localizer and a face recognizer).In this method only the facial regions of upper face i.e. eyes, eyebrows and nose are considered. The mouth is not considered to avoid the extreme facial variations due to the motion of the mouth. The segmented upper facial region images are first processed to produce two features at a reduced resolution and normalized intensity features and edge features, both in the range [0, 1] which are then fed into two PDBNNs and the final recognition result is the fusion of the outputs of these two PDBNNs.

B. Feature Based Approaches

1) Face Recognition through geometric features

In this method, a set of fiducial points are detected first in every face and the geometric features like distances between these points are explored and the image closest to the query face is selected. Some of the earliest works in this direction was done by Kanade [6] who used the Euclidean distance for matching between 16 extracted feature vectors based on a database of 20 different people with 2 images per person and got a performance rate of 75% .Carrying forward his work, Brunelli and Poggio [39] used 35 geometric features from database of 47 different people with 4 images per person as shown in the figure 4 and achieved a performance rate of 95% . Most recently, Cox et al. [40] derived 35 facial features from a database of 685 images and reported a recognition performance of 95% on a database of 685 images with a single image for each individual.

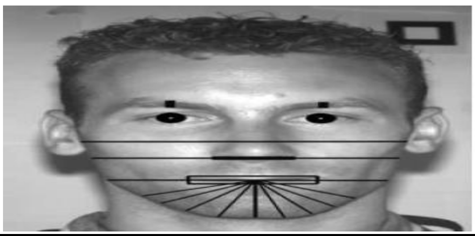

Fig.4: Geometrical features used by Brunelli and Poggio[39]

2) Elastic Bunch Graph Matching (EBGM)

All human faces possess a similar topological structure. The real face images have many non- linear characteristics such as variations in illumination, pose and expression and show differences in appearance in various scenarios. These variations cannot be addressed by the linear analysis. So, Wiskott et al [41] presented a face recognition method using ‘elastic bunch graphs’.

In this basically, faces are represented as graphs with nodes positioned at fiducial points (Eyes, nose...). The edges are labeled with 2D distance vectors with each node containing a set of 40 complex Gabor wavelet coefficients at different scales and orientations (phase, amplitude). They are called "jets" and the recognition is based on labeled graphs.

Elastic bunch graph matching (EBGM) uses model graph to represent a human face and encodes local appearance using 'wavelet jets'. A Gabor wavelet transform creates a dynamic link architecture that projects the face onto an elastic grid. The Gabor jet is basically a node on the elastic grid, denoted by circles on the given image as shown in the figure 5. These nodes describe the behaviour of image around a given pixel and also represents the frequencies at a given image pixel. When the image is convolved with a Gabor filter, the result obtained can be used for shape detection and to extract features using image processing. A convolution blends the functions together and expresses the amount of overlap from functions. Similarity of the Gabor filter response at each Gabor node is the basis of recognition.

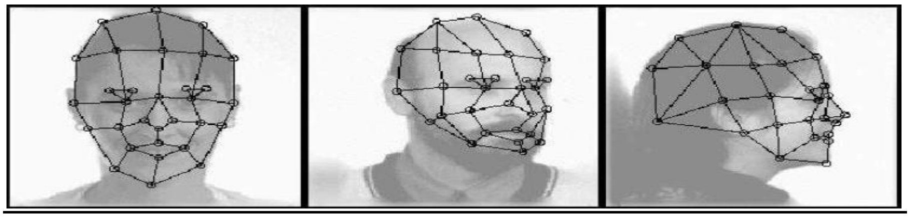

Fig.5: Multiview faces overlaid with labeled graphs [41]

3) Hidden Markov Model (HMM)

The first efforts to use HMM were introduced by Samaira and Young [42] . HMM works effectively for images with variations in lighting, facial expression, and orientation and thus has an advantage over the holistic approaches. For processing images using HMM, the temporal or space sequences are considered. HMM can basically be defined as a set of finite states with associated probability distributions. The reason why it is named Hidden Markov Model is that the states are not visible and only the result is visible to the external user.

The HMM based methods use strips of pixels that cover the forehead, eye, nose, mouth, and chin without finding the exact locations of facial features. The face structure is viewed as a sequence of discrete parts. The order of this sequence should be conserved for e.g., it should run from top to bottom from forehead, eyes, nose, mouth, and chin as shown in figure 6. Each of these facial regions is assigned to a state from left to right 1D continuous HMM.

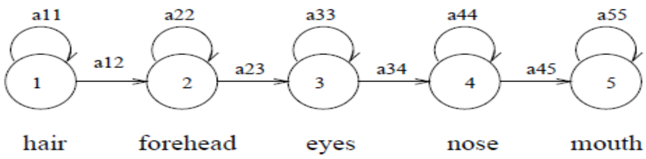

Fig.6: Left to Right HMM for face recognition

4) *Convolution Neural Networks*

The neural network approaches use a training set of face images in order to create a neural network based classifier. Kohonen was the first to demonstrate that a neural network could be used to recognize aligned and normalized faces. Since then a number of methods have been proposed. Intrator et. Al [43] proposed a hybrid or semi supervised method in which they combined unsupervised methods for extracting features and supervised methods for finding features able to reduce classification error. For classification purpose, they used feed-forward neural networks (FFNN).

Lawrence et. al [44] describes a neural network approach for identification and verification of facial images. It used self-organizing map neural network and Convolutional networks. An unsupervised learning method based on Self-organizing maps (SOM) is used to project the data in a lower dimensional space and a Convolutional Neural Network (CNN) for partial translation and deformation invariance. But overall, FFNN and CNN classification methods are not optimal in terms of computational time and complexity.

5) Active Appearance Model (AAM)-2D Morphable Method

Faces are highly variable and deformable objects. Depending on pose, lighting, expression, faces can have different appearances in images. Cootes, Taylor, and Edwards [45] proposed Active Appearance Model which is capable of 'explaining' the appearance of a face in terms of a compact set of model parameters.

AAM is an integrated statistical model. This method involves combining a model of shape variation with a model of the appearance variations in a shape normalized frame. AAM is constructed on the basis of a training set having labeled images. The landmark points are marked on each example face at key positions to highlight the main features as shown in figure 7. Model parameters are found to perform matching with the image which minimizes the difference between the image and a synthesized model example projected into the image.

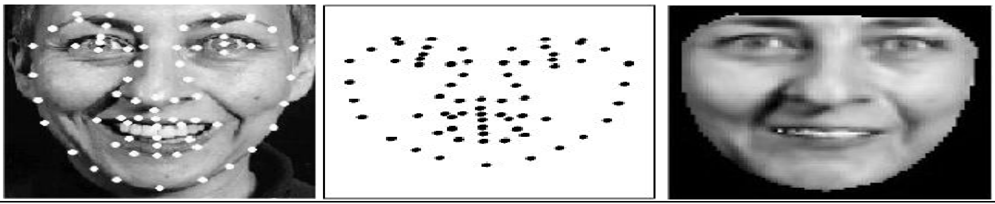

Fig.7: The training image is split into shape and shape normalized texture [45]

6) 3D Morphable Model

To handle the facial variations such as pose, illumination etc. it is better to represent the face using the 3 D models. 3D morphable model is a strong, effective and versatile representation for human faces. To make a model, high quality frontal and half profile pictures are taken first of each subject under ambient lighting conditions. These images are then used as input to the analysis by synthesis loop which yields a face model.

Blanz et al. [46] proposed this method based on a 3D morphable face model in which he tries to find an algorithm to recover the parameters like shape and texture from the single image of a face and encodes them in terms of model parameters. The 3D morphable model provides the full 3D correspondence information which allows for automatic extraction of facial components and facial regions

C. HYBRID METHODS

These methods use both the holistic and feature-based methods to recognize the face and show better results. Some of the hybrid methods include Modular Eigenfaces and Eigenmodules proposed by Pentland et al. [47], which uses both global eigenfaces and local Eigenfeatures and shows much better results than the holistic eigenfaces. Penev and Atick [48], gave a method called Hybrid LFA (Local Feature Analysis). Shape-normalized Flexible appearance models by Lanitis et al. [49] and Component-based Face region and components by Huang et al. [50] which combines component based recognition and 3D morphable models for face recognition. The first step is to generate 3D face models using 3D morphable model from the three input images of each person in the training. These images are rendered under varying pose and illumination conditions to build a large set of synthetic images which are used to train a component-based face recognition system [50]. A Support Vector Machine (SVM) based recognition system is used which decomposes the face into a set of components that are interconnected by a flexible geometrical model so that it can account for the changes in the head pose leading to changes in the position of the facial components.

However, the major drawback of the component-based system was the need of a large number of training images taken from different viewpoints and under different lighting conditions which is not available in many real world applications. So, to eliminate this drawback 3D morphable models were incorporated.

III. APPLICATIONS OF FACE RECOGNITION

Face recognition provides numerous applications of image analysis. For example, Automated crowd surveillance which was used at the Super Bowl 2001 game at Tampa, Florida ; access control; mugshot identification; Witness faces reconstruction; Designing of human computer interface (HCI) . In Multimedia communication, it can be used for the generation of synthetic faces. In video indexing it can be used to label faces in video; for gender classification; recognizing expressions and tracking and facial feature recognition. It has widespread use in “Smart Card” applications and content-based image database management. In the field of biometrics, human face recognition is currently an active research area with the motive to perform robust and reliable biometric identification and shows better results and advantages over other biometrics modalities such as iris, fingerprint, speech, gait and ear recognition. Besides being nonintrusive and natural, the biggest advantage of face is that it can be captured at a distance and in a convert manner. Also, a large number of commercial, security, and forensic applications are using the face recognition technologies. Recently, a number of commercial face recognition systems have been implemented, such as Cognitec [51] and Identix [52]. Moreover, the automobile companies are trying to develop sleep detectors to increase safety.

IV. CHALLENGES IN FACE RECOGNITION

Even though current machine recognition systems have reached a certain level of perfection but still there are many real application conditions which limits their good performance.

1). 3D head pose changes are some unavoidable problems which appear in the variety of practical applications, since the people are not always frontal to the camera. The difference between the same person under the varied poses is larger than the difference between the distinct persons under the same pose. Therefore, it is difficult for the computer to do the face identification when the poses of the probe are different.

2). Illumination (including indoor / outdoor) variations due to skin reflectance properties and the internal camera control. Face recognition systems encounter difficulties in extreme illumination conditions where significant parts of the face sometimes become invisible. Furthermore, it becomes more difficult when illumination is coupled with pose variation.

3). Facial expression: Faces undergo large deformations under extreme facial expressions and present problems for the algorithms.

4). Occlusion: Due to other objects or accessories (e.g., sunglasses, scarf, etc.) performance of face recognition algorithms gets affected.

5).Time Delay: Human face changes over time. There are changes in makeup, presence or absence of facial hair, muscle tension, hair style, appearance of the skin, facial jewellery, glasses and aging effects.

V. DATABASES FOR FACE RECOGNITION

When benchmarking an algorithm it is recommendable to use a standard test data set for researchers to be able to directly compare the results. A number of databases are in use currently and the choice of an appropriate database to be used is made based on the task given (aging, expressions, lighting etc). Some face data sets frequently used by researchers [53]:

Table I:

Database	No. of subjects	conditions	Image resolution	No. of images
AR Database [54] (http://rvl1.ecn.purdue.edu/˜aleix/aleix face DB.html)	116 (63 men and 53 women)	Facial expressions Illumination Occlusion Time	768×576	3288
FERET(The Facial Recognition Technology) [55] (http://www.nist.gov/humanid/feret/)	1199	Facial expressions Illumination Pose Time	256×384	1451
MIT Database (ftp://whitechapel.media.mit.edu/pub/images/)[8]	16	Head orientation Illumination Scale	120×128	433
Yale Face Database [56] (http://cvc.yale.edu/projects/yalefaces/yalefaces.html)	15	W/ and w/o glasses Illumination Facial expressions	320×243	165

Also,there are other well known databases like *Face Recognition Vendor Test* (FRVT) (Phillips et al.[3]) and *Face Recognition Grand Challenge* (FRGC) (Phillips et al.,2005) which have served to better simulate the practical real-world operational scenarios of face recognition.

VI. CONCLUSION

Face recognition has recently become a very active and interesting research area. Vigorous research has been conducted in this area for the past four decades and huge progress with encouraging results has been obtained. The goal of this paper is to provide a survey of recent holistic and feature based approaches that complement previous surveys. Current face recognition systems have already reached a certain level of maturity when operating under constrained conditions. However, we are still far from achieving the ideal and adequate results in all the various situations. Still more advances need to be done in the technology regarding the sensitivity of the face images to environmental conditions like illumination, occlusion, time-delays, pose orientations, facial expressions. Furthermore, research work on 3 D face recognition and face recognition in videos is also pacing parallel. However, the error rates of current face recognition systems are still too high for many of the applications. So, the researchers still need to go far to get accurate face recognitions.

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