A Survey on Developments in Face Recognition Techniques

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I. Abstract

Biometric systems consist of automatic real-time identification of an individual's physiological or behavioral characteristics (ex. like face features, fingerprint-scans, geometry of finger and hand, hand veins, palm, iris-scan, retinal-scan, voice, ear gait, signature, keystroke dynamics, etc.)[1]. Out of these stated traits face-recognition is one amongst popular cram areas in the field of computer vision, image processing, pattern recognition and neural network. Face recognition has received important attention due of its various applications in security, access control, computer entertainment, surveillance, law enforcement and Internet communication. Besides its popularity, face recognition still faces issues on its accuracy. This paper provides an overview of different pioneering developments in face recognition techniques and related important aspects.

II. Introduction

Unlike other biometric identification systems based on physiological characteristics, face recognition is a passive, non-intrusive system for verifying personal identity in a user-friendly way without having to interrupt user activity. This paper reviews major efforts and advances in face recognition techniques focusing on all types of variations in facial images. Techniques related to various challenges of face recognition are covered. Visual face recognition systems have demonstrated high performance under constrained conditions, such as frontal mug shot images and consistent lighting conditions. Performance of visual face recognition often degrades under uncontrolled illumination conditions as in outdoor surveillance applications. Face recognition has difficulties in detecting disguised faces, which can be critical in high end security applications. Each technique has its own advantages and disadvantages. Face recognition performance can be enhanced by the fusion of information obtained from different techniques.

Face biometrics offer following several advantages over others: For almost all the biometrics, user has to perform some voluntary action like putting hand over resting stand for capture of fingerprints or detecting hand geometry and has to rest in some particular position ahead of scanner for retina/iris scan. Face recognition does not require any explicit action or any cooperation from user because image of faces can be captured by a camera from a distance. This is favorable for safety and surveillance. Trait characteristic capturing via some biometric machines (using fingerprints and hand) can be ineffective when the epidermis tissue of skin is scratched (i.e., bruised/cracked). Retina and iris scanners are much more expensive and are very sensitive to body motion. Speech recognition is receptive to backdrop noises and acoustic fluctuations in the phone lines. Signatures can be forged or modified. Facial images may be acquired using inexpensive fixed cameras. Superior face recognition algorithms and preprocessing approaches may compensate some of the variations in pose, illumination and scale. Biometrics that requires users to utilize the same equipments to capture biometric data has the chances of exposing users to the conduction of microbes from other users. Conversely, in contrast face image capturing is non-intrusive and doesn't pose any type of such health threat.

A face recognition system most commonly consists of four modules as pictured in figure 1: viz. detection, alignment/preprocessing, feature removal, and matching. Face localization with normalization (face area detection, its alignment, noise removal and image resizing) are some processing steps followed prior to face recognition (face features extractions with matching) are carried out. The face recognition problem can be stated as: Given an input face image, determine or verify the identity of a person after comparing it with the face images from the database of known individuals.

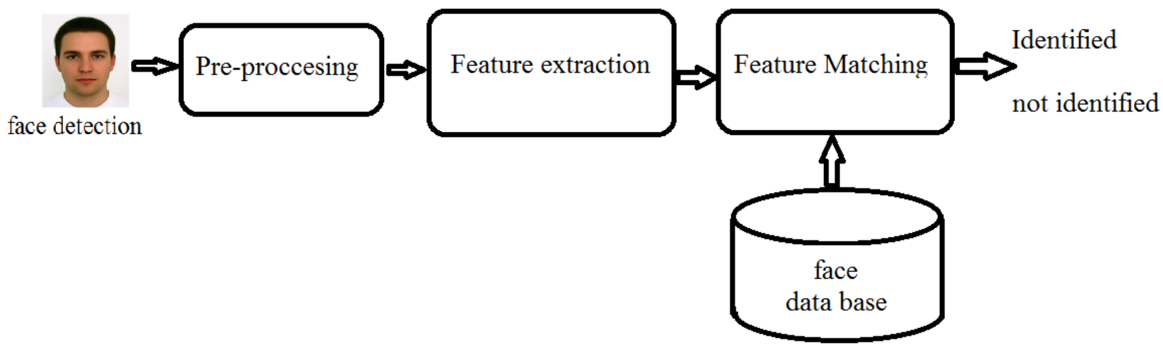

Figure 1: Face recognition system

III. Literature Review

Various techniques have been developed for solving the problem of face recognition and they are mainly categorized as a feature based, holistic and hybrid approaches.

In featured-based approach, unique facial features such as nose, eyes, maw, etc., or even some other present fiducial marks like moles or scratches are extracted, and then geometrical relations among those extracted facial feature points are computed. This condenses the input face image to a vector of geometrical features. These features are then used to perform comparison of face images using customary statistical pattern recognition algorithms. There is one well-known geometrical neighboring feature based method known as the Elastic Bunch Graph Matching (EBGM) method described by [2]. Untainted geometry, hidden Markov model and dynamic link architecture methods also belong to the same group.

Holistic approaches endeavor to classify face images using global entire images instead of local neighboring face features. Examples of holistic techniques are eigenfaces, fisherfaces, probabilistic eigenfaces, independent component analysis, support vector machines, and nearest feature lines (NFL) approaches. These are all types of principal component analysis (PCA) approaches that are used to simplify or convert a large dataset image features into a minor dimension while preserving the important characteristics of the dataset image features [3]. There exists hybrid approaches such as modular eigenfaces, hybrid local features, component based and shape normalized techniques.

In spite of the surfeit of techniques, and the noble efforts of most of the concerned researchers, efficient face recognition remains unsolved and in general difficult problem. Despite the fact that each of the above techniques performs well for the definite variation under study, their performance disgrace quickly with other types of variations presented. For occasion, the techniques designed to be invariant to illumination works better as long as facial expression or pose remains invariable, but suffers to be invariant when expression or pose is altered. This isn't a trouble for certain applications, like control of access to a secured room, because the training and probe images both can be captured with same surroundings. On the other hand for common unconstrained recognition, neither of these methods are sufficiently robust.
Two observations by [4] states that:

1. There doesn't seem to be any feature, set of options, or topological space that's at the same time invariant to any or several variations which a face image might exhibit.
2. When there are large numbers of training images, nearly any algorithm can ideally perform better.

There are many common face recognition algorithms proposed so far in recent few decades. Nevertheless, three of them have a great impact upon the face recognition research community and they have stimulated innumerable studies. These are Eigenfaces [5], Fisherfaces [3], and Bayesian face recognition [4]. Modern face recognition techniques can generally be categorized into two mentioned in brief in following paragraphs, viz. a. Holistic matching techniques and b. Local matching techniques.

a) Holistic matching techniques:

Making use of the entire face region as an input to a face recognition system, are comprehensively studied after the introduction of Eigenfaces by [3] and [5]. The theory behind holistic techniques is to create a subspace with either the principal component analysis techniques or linear discriminant analysis [3, 6, 7], or using independent component analysis (ICA) [8]. The probe face images are then projected and matched up to in a low-dimensional subspace thereby avoiding the nuisance of dimensionality. Careful comparative study with diverse options in the holistic recognition methods is reported [9, 10]. The Discriminative Common Vector technique which is based on the variation of Fishers Linear Discriminant Analysis for small sample size problems is given in [11]. The 2-stage LDA technique, namely LDA/QR that intends to overcome the singularity problems of the classical LDA, while accomplishing efficiency and scalability concurrently is proposed in [12]. Holistic methods use global representations i.e. whole face region instead of just local features to identify face images. These schemes are further divided into 2 categories: statistical approach and AI approach. Brief overview of these methods is given below:

1. Statistical: In the statistical approach, the image features are represented as a two dimensional array of intensity values and classification or matching is carried out by direct correlation matching among the asserted face image and entire face images in the stored gallery. These approaches suffer from usual drawbacks of correlation methods like sensitivity to face pose, size and illumination variation and background noise [9]. Additionally, these methods are computationally very costly as they perform categorization in very elevated dimensional spaces. To overcome this drawback of curse of dimensionality, several dimensionality reduction schemes are employed which retain the most useful feature dimensions to perform recognition. Some of them are discussed below:

Sirovich and Kirby [13, 14] were first to use PCA [3, 5] to represent face images economically. It is demonstrated that any of the face image could be rebuilt approximately with the use of few number of eigenfaces and their respective weights. These eigenfaces are actually the eigenvectors of covariance matrix computed for all the trained face images. Supporting with the findings of Sirovich and Kirby [13], the same PCA technique has been used by Turk and Pentland [5] for detection and identification of face images. They experimented the system on a database of 2500 face images of sixteen individuals considering every mixture of 3 head orientations, 3 head sizes and 3 lighting situations. The accuracy of recognition achieved was 96%, 85% and 64% for brightness, pose and scale variation. Though the system seems robust for variations in illumination, its performance degrades with changes in scale. Pentland et al. [15] extended the capabilities of this system in several ways and tested it on a database of 7562 face images of 3000 persons. They proposed a "multiple observers" method which deals with large pose variations: For N persons, with M views, the recognition can be performed either in universal eigenspace found using combination of set of M separate eigenspaces or a NM images (parametric approach) can be built, 1 for every of the N views (the view-based approach). The view-based technique demonstrates better result over parametric one. A modular eigenfeatures technique is anticipated to tackle with local changes in the facial appearance that has low resolution of face image is improved by superior resolution details. This system reported better performance as compared to eigenfaces approach. PCA performs better when a single image per person is available, however if there are multiple images per individual, then Belhumeur [3] argued that as Eigenfaces technique, that uses PCA for dimensionality reduction, gives projection directions such that the total scatter across entire images of all faces is maximized, it preserves unwanted changes because of facial expressions and lighting. As mentioned by Y. Cheng [16], "the dissimilarity between the images of a same face because of illumination and lighting direction are approximately always bigger than image deviation because of alteration in face identity". PCA projections can be most favorable for reconstruction from small dimensional basis; however they cannot be most favorable for discrimination. They proposed fisherfaces [3] method, which maximizes the between-class scatter while minimizing the within-class scatter in a projected space. This results in better classification. Fisherfaces method uses subspace projection before application of LDA projection so that it prevents the within-class scatter matrix from becoming worsen. They conducted experiments on 330 images of 5 people and reported that their "fisherfaces" method handles variations in illumination and expressions better. Swets et al. [17] reported 90% accuracy on the face database of 1316 face images from 504 different classes using same procedure.

Some work [6] showed that with small number of training images per class, PCA outperforms LDA. When the number of training images per class are large, there is larger probability of LDA outperforming PCA. Authors performed comparative analysis of PCA and LDA using standard Yale face database. For implementation, 10 different individuals were randomly selected and a subset of eighty images of ten different subjects is employed. Prior to the recognition process, each of the face image was cropped and resized with 50 x 50 pixels. It is normally alleged that the algorithms based on LDA techniques are superior to those that rely on PCA techniques. Experiments performed on small and large datasets showed that this isn't constantly true and concluded that with the small training data size, PCA can be better than LDA. It has been observed that LDA outperforms PCA when a representative and more training data set are used.

Standard eigenfaces and fisherfaces method assume that ideally the projection should be such that the projection of the images should be non-overlapping in the condensed subspace when each region belongs to distinct subject. On the other hand, in reality the images of dissimilar persons can map to similar regions in a face space, consequently the area corresponding to dissimilar persons cannot be all the time different.

2. AI Approaches: AI methods exploit tools such as machine learning techniques or neural networks and to recognize face image. The thought of hybrid techniques arrive from how the human vision mechanism interprets both local and whole face.

Lawrence et al. [18] used AT&T database and depicted recognition rate of 96.2% using hybrid neural network which merges local image sampling; a self organizing map and the convolutional neural network. Eleyan and Demirel [19] extracted features using PCA method and latter classified them with feed forward neural network. Experiments on ORL face database showed better performance as compared to eigenfaces method, which used nearest neighbor classifier.

Li and Yin [20] decomposed face image into 3 levels using a wavelet transform. Then Fisherfaces method is employed on every of the 3 low-frequency sub-images. Neural network is used for fusion of these three individual classifiers. This system is tested on FERET database which showed improvement in the performance over the separate classifiers and fisherfaces technique.Melin [21] sectioned face image into 3 regions, i.e. eyes, maw and nose, and asserted each section to module of neural network. concluding decision is made by combining the yields of the three modules using fuzzy Sugeno integral. This modular network showed enhanced results over monolithic one on a small database of 20 persons.

One amongst effective techniques for pattern recognition is Support Vector Machine (SVM) [22]. (a) Two class recognition: The given two sets of samples are projected to high dimensional feature space. SVM then finds a hyperplane which break up the prevalent possible samples of the same class category along the same side of the hyperplane and increases a distance from each category to a hyperplane. Such hyperplane reduces the misclassification of both the samples from training set and also unseen samples from probe-test set. (b) Multi-class recognition: Multi-class pattern recognition can be performed by merging 2-class SVMs. Classification is done by constructing bottom-up binary tree. Fig 2.1 shows decision tree for a training set of 8 classes where numbers 1-8 represents the classes. A winner is chosen from a current pair. The winners from lower stage of binary tree appear on upper stage for next round of tests. Lastly single class will appear upon the peak of the tree.

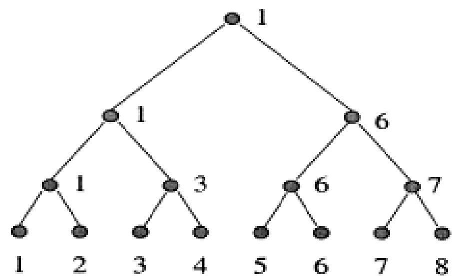

Figure 2.2.1: The binary tree structure for 8 classes face recognition

Hidden Markov models (HMM) also has been used for the reason of recognition of faces. Samaria and Harter [23] used 1- dimensional HMM on AT&T database and obtained accuracy of 87%. They upgraded the system to a pseudo 2-dimensional HMM [24] and reported accuracy of 95% on the AT&T database. They used 50% of the images for training purpose and remaining 50% for testing purpose.

The major benefit of the holistic techniques is that they can't eradicate any information in face images by focusing not only on interested region. However, this identical property becomes their biggest drawback. Because the majority of these holistic techniques are based on the basic guess that all pixels are of equal importance. These approaches are computationally expensive and also require high degree of association between training and testing images. Therefore they may not perform well for huge variations in illumination, expressions and pose. However, as mentioned earlier, numerous of these techniques have been customized to recompense for these discrepancy, and dimensionality diminution techniques have been employed. Seeing that the holistic techniques perform enhanced than the feature-based approaches.

b) Local matching techniques:

Local matching techniques has shown hopeful outcome in face recognition recently [24,25]. These approaches are also used in further visual recognition applications. The universal suggestion of local matching methods is to primary locate numerous facial features, and next classify face images by comparing and merging the respective local components. Owing to growing interest, in current surveys stand-alone fragments were purposely dedicated to local matching methods [26,27]. The improvement of face recognition in excess of the past few years consent to 3 types of recognition algorithms, viz view tolerant, frontal profile, based on sort of images and the recognition techniques. Whereas frontal recognition definitely is the classical method, view-tolerant techniques generally execute recognition with extra refined way.

These techniques extract local features such as the nose, maw, and eyes, with their locations and local statistics are providing to a structural classifier. In the early years of work on face recognition was mainly based on these techniques. Kanade et al. [28,29] used straightforward image processing techniques and extracted a vector of sixteen facial factors like areas and angles, ratios of distances, (to recompense for the unstable size of the images). The authors utilized Euclidean distance classifier and attained performance of 75% on a database of 20 persons with two images per subject where 1 is used in training and other used in testing.

Brunelli and Poggio [53] further used face database of 47 persons having four images per subject and extracted vector of 35 features and reported recognition rate of 90%. Cox et al. [31] reported accuracy of 95% on database of 685 persons with one image per person using physically extorted distances. Subsequently it is realistic to suppose that the result would contain lower performances if computerized feature extraction technique is used. Another well known feature-based technique, proposed by Wiskott et al. [2], the Elastic Bunch Graph Matching (EBGM) method is based on Dynamic Link Architecture (DLA) [32]. Here, a graph of each face is produced consisting of the sets of fiducial points on face image selected. Every tip is a node of a entirely linked graph, along with the label with the response of the Gabor filter useful to a windowpane just about the fiducial point. Every curve is labeled by distance linking the corresponding fiducial points. The concerned sets of graphs are the merged into stack-like configuration, which is referred as face bunch graph. After the system has the face bunch graph, then graphs for fresh face images are produced routinely using Elastic Bunch Graph technique. To recognize the face image, its image graph is matched with all of the stored image graphs furthermore the one with maximum resemblance is selected as a match. With this method, performance reported is 98% using training set of 250 persons. The system is enhanced to tackle dissimilar poses [2] however the performance remains the same for face images with similar orientation.

Although this technique was one of the greatest performing [33,34], it has a drawback that it requires graph assignment for the 1st seventy faces be done physically prior to elastic graph matching turn into sufficiently reliable. Campadelli [35] removed the requirement to do the graph placement physically with the use of parametric models which are dependent upon the deformable templates which situates fiducial points automatically. The recent variations in this substitute the Gabor features by the graph matching technique [36] and histograms of oriented gradients [37]. Substantial works have been done to recognize face images from their respective profiles [38] wherein feature removal turn out to be simpler 1- dimensional difficulty [39]. Using face profiles, Kaufman and Breeding [40] used database of only 10 persons and reported recognition rate of 90%.

The major advantage obtainable with feature-based technique is their robustness to variation within pose because the removal of feature points precede comparison of test image to the trained image. Other advantage is their trimness of depiction of the face images and high rapidity comparison. The drawback of feature-based technique is the complexity of automatic feature detection. The user has to decide arbitrarily regarding what features are imperative. In any case, when the feature set is deficient in distinguish power, then no technique can recompense with that scarcity.

An overview of major research on face recognition approaches based on different variations in face images is given in the following sections.

3.1 Related work in pose variation:

Considering the portion of pose invariance, face recognition techniques can be categorized into 2 groups:1) Global methods and 2) Component-based methods. Within the global methods, a single feature vector which represents complete face image is employed in the input to the system classifier. Numerous types of classifiers are anticipated in the survey e.g. least amount distance classification in the Eigenspace [5], Fishers discriminant analysis [3], and neural networks [18, 21]. Global methods work well for categorizing frontal views of face images. Conversely, they aren't robust against variations in pose since global features are extremely susceptible to rotation and translation of the face image. In order to get rid of this challenge an alignment stage can be added ahead of classifying the face image. It is essential to compute the correspondence amongst the two face images in order to align the input face image with the reference. The correspondence can be typically determined for a little number of prominent points within the face image as like the nostrils, the centre of the eyes, or the edges of the mouth. Depending on these correspondences, the probe test input face image can be perverted to a reference face image. The use of Active shape models is done by [41] to make the alignment of input faces with the model faces. Face recognition was performed with the help of independently matching the templates of 3 facial regions viz. nose, eyes and mouth in [30]. The arrangement of the components during categorization was unconstrained because a system didn't include the geometrical model of a face image.

3.2 Related work in expression variation:

Recent developments in pattern recognition and image analysis brought in a scope of automatic detection and classification of emotional and informal facial features. Automating countenance analysis might bring facial expressions into man-machine interaction as a replacement modality and create the interaction tighter and more economical. These systems might additionally create classification of facial expressions widly reachable as a tool for analysis in behavioural science and medication. Daugman in [42] observed many essential problems concerned in a good face recognition system, whereas the foremost recent and comprehensive survey from that of Zhao [27], wherever several of the newest techniques are reviewed. One among the basic problems concerning the facial expression analysis is that the illustration of the visual data that an examined face may reveal. Many experimentation advices that the visual properties of the faces could be made apparent by recitation the movements of points that belongs to the specific facial features viz. eyebrows, mouth, and eyes and after that by analyzing the relations amongst these movements, concerning the information about the presented facial expression. This motivated the researchers for vision-based facial gesture analysis to make diverse efforts to describe point-based visual properties of facial expressions.

Different investigative face representations give way, in that the face is modeled as a set of facial points or as a set of templates fixed to the facial features like the eyes and the mouth. In other methods to face representation using holistic methods, the face is represented as an entire unit. The three dimensional wireframe with a mapped surface [43] and the spatial-temporal model of facial image motions [44] are classic examples of the holistic methods for the face representation. The face image could also be modeled employing the hybrid method that characterizes a mixture of analytical and holistic methods for the face representation. In this method the group of facial points are typically used for deciding the initial position of the template which models the face image [45]. Irrespective of the sort of the face model applied, endeavors can be made for model then latter extract desired information about presented facial expression without loss of the information. Numerous factors make such assignment multifaceted. The first amongst possible ones is the presence of sun-glasses, beard or facial hairs, which can cause unintelligible facial features. One more challenge is changes in orientation and the size of input face images. These immobilize a search for fixed patterns within face images. Lastly, occlusion noise and can always be present to a little extent in the face images.

3.3 Related work in occlusion:

During the past few decades, canonical subspace projection methods like PCA, FLD and ICA has been extensively studied in the face recognition research [5, 8]. These methods represent the face as the linear combination of short rank basis images. These employs features vector that consists of coefficients which are obtained with simple projection of facial images onto their basis face images. In turn for the subspace projection based technique to be robust enough for the local distortions and partial occlusions, its basis face images must be effectively realized with the part based local representation. Local representation offers robustness for local distortions and partial occlusions since victorious face recognition is achieved by representing a few important facial parts which corresponds to the feature regions such as eye brows, nose, eyes and lips. This recognition by parts exemplar has been trendy in the object recognition research since the method may be successfully useful to challenges of object recognitions with occlusions. Recent work [46] used the Singular Value Decomposition and argued stating that the foremost base images, which correspond to huge singular values, are susceptible to the facial changes and also can dominate the composition of the face image.

3.4 Related work in age variation:

Facial aging is a multifarious process which influences both the texture and shape of a face. This aging phenomenon also appears in the different manifestations in diverse age groups. Although facial aging are frequently represented by facial expansion in the younger age groups, it is typically represented with moderately large texture variations and minor shape variations in the older age groups. Consequently, an age correction system needs to be able to recompense for both kinds of aging phenomenon. In a real passport photo verification task Ling [47] demonstrated how age differences influence the face recognition performance. Their results show that depending on the application of the system the aging process doesn't increase the recognition complexity, although it doesn't surpass the consequences of expression or illumination. Research on face recognition for age progression [48] have revealed that:

- Replication of texture and shape changes caused by aging is a demanding task due to factors like environment and lifestyle as well put in to facial changes in adding up to biological factors.
- The aging consequences can be better implicit by using three dimensional scrutinization of human head.
- The obtainable face image databases to learn facial aging are not only tiny but also enclose uncontrolled internal and external variations.

Because of these reasons the consequences of aging on facial recognition hasn't been as broadly examined like other factors which lead to the intraclass changes within facial image appearance. Such reviews have revealed that the cardioidal sprain is a foremost important factor in the aging of facial images. Many of these results also have been used in psychological research, ex. by introducing aging as caricatures generated by controlling three dimensional model structure [49].

3.5 Related work in illumination variation:

Illumination compensation is the significant subject in face recognition. The most widespread method is to use the illumination insensitive features, like local binary pattern features and Gabor features. Nevertheless, lighting insensitive features are inadequate to overcome large lighting variations which is pointed out by Adini in [50] and also provoked by the efforts of Belhumeur and Kriegman in [3].

IV. Comparative summary of few techniques:

Comparative summary of few techniques related to the face recognition has been given below in Table 1:

Table 1: Summary of face recognition techniques

Year	Author	Attributes		
		Challenge	**Feature extraction**	**Matching**
1991	Turk [5]	Expression, pose	PCA based Eigenfaces	Euclidean distance (ED)
1993	Brunelli [30]	Illumination, Pose	Geometrical Features	Template matching
1997	Wiskott et. al.[2]	One image per person	Gabor based labeled graphs	Graph similarity measure
1997	Belhumeur et. al. [3]	Lighting direction, expression	Class Specific Linear Projection	ED
2000	K. Jonsson et. al. [55]	Illumination	PCA+LDA	Support Vector Machines(SVM)
2000	Zhao et. al. [56]	Illumination	Symmetric Shape-from-Shading	Image difference, gradient measure
2001	Georghiades et. al. [53]	Pose, Illumination	Generative model	ED
2001	Shashua et. al.[51]	Illumination	Quotient Image	correlation
2002	Meng Joo et. al.[57]	Small training sets of high dimension	PCA+LDA	RBF NN
2002	Chengjun Liu, et. al.[52]	Illumination, Expression	Gabor features+ EFM	Gabor Fisher Classifier (GFC)
2003	Juwei Lu, et. al. [58]	Small sample size (SSS)	D-LDA, DF-LDA	ED
2005	Ruiz-del-Solar et. al. [59]	Expression, Pose	Eigenspace based features	ED
2005	Meng Joo, et. al. [60]	Illumination	DCT+FLD	RBF NN
2005	K.Chih Lee et. al. [61]	Illumination	Images rendered from a 3D model	NN
2006	Chen et. al. [54]	Illumination	DCT Log Domain	ED
2007	Jie Zou et. al. [10]	Illumination, Occlusion, Expression	Gabor features	Local regions +Borda count classifier
2008	Jun Liu et. al.[46]	Illumination, Expression, Occlusion	FSVDR	ED
2008	D.V. Jadhav et. al. [62]	Pose, Illumination	Radon+DCT	NN
2009	D.V. Jadhav et. al. [63]	Pose, Illumination	Radon + Wavelet	NN
2010	D.V. Jadhav et. al. [64]	Pose, Illumination	Radon+DCT +KFLD	NN
2010	SungWon Park	Pose, Illumination	Multifactor Discriminant	ED

	et. al. [65]		Analysis(MDA)+ Multilinear PCA (MPCA)	
2011	Yousra Ben Jemaa et. al. [66]	Expressions, Pose,	2DPCA	Genetic algorithm(GA)
2012	Kolhandai Yesu et. al. [67]	Pose, Illumination	PCA +DCT	General Feed Forward ANN (GFF ANN).
2012	K.C.Jondhale [68]	Expressions, Pose, Illumination	FSVD	RBF NN
2013	Gayathri Mahalingam et. al. [69]	Expressions, Pose, Illumination, Occlusions	three-patch LBP	Euclidean distance
2014	Jing Lu, et. al. [70]	Pose, Illumination, Occlusions	bi-directional two dimensional PCA (B2DPCA)	Two dimensional NN with random weights (2D- NNRW)
2014	Chuan-Xian Ren et. al. [71]	Pose, Illumination	Band-Reweighed Gabor Kernel Embedding	Mahalanobis distance
2015	S. M.M. Rahman et. al. [72]	Occlusion, Expression, Pose, Resolution	two-dimensional Gaussian-Hermite moments	Naive-Bayes
2015	Kankan Dai et. al. [73]	Expressions, Pose, Illumination, Occlusions	negative correlation learning (NCL)	Two dimensional neural network with random weights (2D-NNRW)
2016	Shanshan Guo et. al. [74]	Expressions, Pose, Illumination	CNN	SVM
2017	Xinfang Cui et. al. [75]	Expressions, Pose, Illumination	Local dominant orientation feature histogram (LDOFH).	Euclidean distance
2017	Amin Jalali, et. al. [76]	Blur	CNN	Convolutional Neural Networks (CNN)
2018	Changxing Ding et. al. [77]	Pose, Occlusion,	Trunk-Branch Ensemble	CNN
2018	Duc My Vo et. al. [78]	Illumination, noise	Hierarchical collaborative representation-based classification (HCRC)	Deep convolutional neural network (DCNN)

V. Conclusion

Face recognition has been a dynamic research field because of its potential application in the extensive diversity of law enforcement and commercial applications including security monitoring, video surveillance and access control. Different from other biometric recognition systems dependent on physiological characteristics, the face recognition is non-intrusive, passive system for the verification of personal identity in a user-friendly way without requiring interrupting user's activities. This chapter evaluates foremost advances and efforts in face recognition techniques that attempts to exploit all types of variations in facial images. Techniques related to various challenges of face recognition are covered. A visual face recognition system has verified high performance with constrained conditions like in frontal mug shot images and regular lighting variations circumstances. However the performance of the visual face recognition repeatedly deteriorates with uncontrolled illumination variations in outdoor surveillance use. Face recognition pose challenges in detecting concealed faces that are critical in high end security applications. Each of the available techniques has its own pros and cons. Face recognition performance may be further improved by fusing most important features obtained from diverse techniques. We aim to solve the problems in existing techniques through this work.

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