IET Computer Vision

Review Article

ISSN 1751-9632
Received on 7th April 2014
Accepted on 23rd October 2014
doi: 10.1049/iet-cvi.2014.0084
www.ietdl.org

Face recognition: challenges, achievements and future directions

M. Hassaballah[1] ✉, *Saleh Aly*[2]

[1]*Department of Mathematics, Faculty of Science, South Valley University, Qena 83523, Egypt*
[2]*Department of Electrical Engineering, Faculty of Engineering, Aswan University, Aswan, Egypt*
✉ *E-mail: m.hassaballah@svu.edu.eg*

Abstract: Face recognition has received significant attention because of its numerous applications in access control, law enforcement, security, surveillance, Internet communication and computer entertainment. Although significant progress has been made, the state-of-the-art face recognition systems yield satisfactory performance only under controlled scenarios and they degrade significantly when confronted with real-world scenarios. The real-world scenarios have unconstrained conditions such as illumination and pose variations, occlusion and expressions. Thus, there remain plenty of challenges and opportunities ahead. Latterly, some researchers have begun to examine face recognition under unconstrained conditions. Instead of providing a detailed experimental evaluation, which has been already presented in the referenced works, this study serves more as a guide for readers. Thus, the goal of this study is to discuss the significant challenges involved in the adaptation of existing face recognition algorithms to build successful systems that can be employed in the real world. Then, it discusses what has been achieved so far, focusing specifically on the most successful algorithms, and overviews the successes and failures of these algorithms to the subject. It also proposes several possible future directions for face recognition. Thus, it will be a good starting point for research projects on face recognition as useful techniques can be isolated and past errors can be avoided.

1 Introduction

In recent years, biometric-based techniques have emerged as the most promising option for recognising individuals. These techniques examine an individual's physiological and behavioural characteristics in order to determine and ascertain their identity instead of authenticating people and granting them access to physical domains by using passwords, PINs, smart cards, plastic cards, tokens or keys. Passwords and PINs are hard to remember and can be stolen or guessed easily; 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 traits cannot be misplaced, forgotten, stolen or forged [1]. Face recognition is one of the least intrusive and fastest biometrics compared with other techniques such as fingerprint and iris recognition. For example, in surveillance systems, instead of requiring people to place their hands on a reader (fingerprinting) or precisely position their eyes in front of a scanner (iris recognition), face recognition systems unobtrusively take pictures of people's faces as they enter a defined area. There is no intrusion or capture delay, and in most cases, the subjects are entirely unaware of the process. People do not necessarily feel under surveillance or their privacy being invaded [2, 3].

Owing to its use in several applications, face recognition has received substantial attention from both research communities and the market, and there has been an emerging demand for robust face recognition algorithms that are able to deal with real-world facial images [4, 5]. To validate the hypothesis about growth in face recognition publications, a simple exercise is conducted using Google Scholar. We searched for published articles and patents containing the words 'face recognition' and 'face recognition patents' within each year from 2000 to 2012. Fig. 1*a* shows the number of published papers, and the registered face recognition patents during this period are shown in Fig. 1*b*. It is necessary to note that citations of 2013 are not yet completed which explains why we do not include the year of 2013 in this exercise. Moreover, the names of some companies that produce systems or technologies of face recognition are listed in Table 1.

A general statement of the automatic face recognition problem is simply formulated as follows: given still or video images of a scene, identify or verify one or more persons in the scene using a stored database of faces [6]. In other words, the face recognition system generally operates under one of two scenarios: verification (one-to-one) or identification (one-to-many), where in the verification scenario, the similarity between two face images is measured and a determination of either match or non-match is made. Although, in the identification scenario, the similarity between a given face image (i.e. probe) and all the face images in a large database (i.e. gallery) is computed; in this case the top (rank-1) match is returned as the hypothesised identity of the subject [7]. In some cases, probe images may be of any other modality (i.e. near-infrared, thermal or sketches) [8], thus heterogeneous face recognition (HFR) will be of interest for the case. HFR involves matching two face images from alternate imaging modalities, such as an infrared image to a photograph or a sketch to a photograph [9, 10].

Solving this problem can be divided into three major tasks: face detection from a scene, feature extraction and representation of the face region and face matching/classification. Face detection may include face edge detection, segmentation and localisation; namely obtaining a preprocessed intensity face image from an input scene, either simple or cluttered, locating its position and segmenting the image out of the background. Using the detected face patches directly for face recognition has some disadvantages; first, each patch usually contains over 1000 pixels, which are too large to build a robust recognition system. Second, face patches may be taken from different camera alignments, with different face expressions, illuminations and may suffer from occlusion and clutter. To overcome these drawbacks, feature extractions are performed to do information packing, dimension reduction, salience extraction and noise cleaning. After this step, the face patch is usually transformed into a vector with fixed dimension or a set of fiducial points and their corresponding locations or

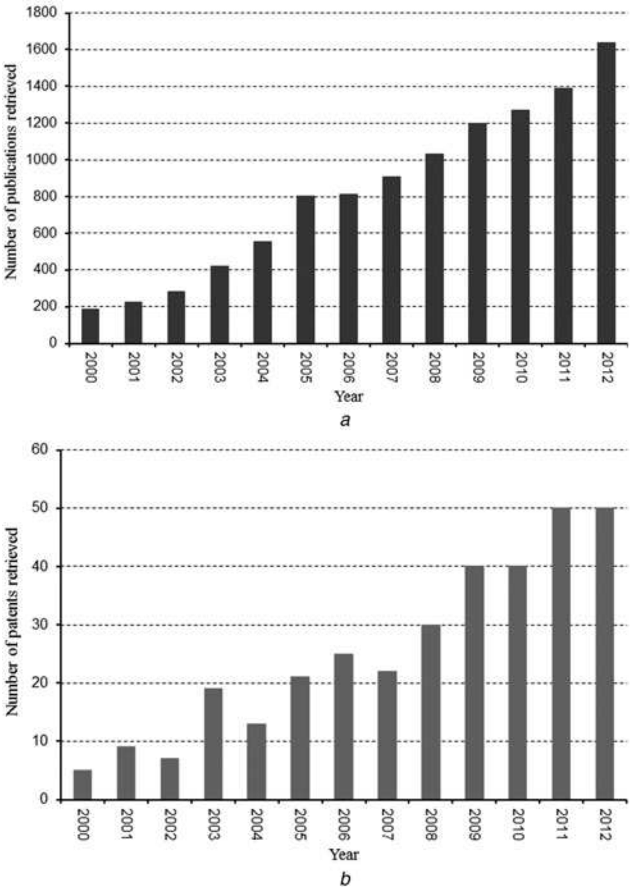

Fig. 1 *Trends in publications containing words face recognition and face recognition patents*

a Face recognition articles
b Face recognition patents

applying feature extraction techniques. Feature extraction may denote the acquirement of the image features from the image such as visual features, statistical pixel features, transform coefficient features and algebraic features, with emphasis on the algebraic features, which represent the intrinsic attributes of an image. Face recognition may perform the classification of the above image features in terms of a certain criterion. The main components of a general face recognition system are illustrated in Fig. 2.

For certain real applications, some researchers consider face recognition as a multiclass classification problem with uncertain

Table 1 Some companies that produce face recognition technologies

Company name	Place of company	Web address
FaceKey Corporation	TX, USA	http://www.facekey.com/
Luxand Inc.	Alexandria, USA	http://www.luxand.com/
Digital Signal Corporation	USA	http://www.digitalsignalcorp.com/
Ayonix Inc.	Tokyo, Japan	http://www.ayonix.com/
OMRON Corporation	Tokyo, Japan	http://www.omron.com/okao/
Toshiba Corporation	Tokyo, Japan	http://www.toshiba.co.jp/
Cybula Ltd.	York, UK	http://www.cybula.com/
Panvista Limited	Sunderland, UK	http://www.panvista.co.uk
Aurora	UK and Middle East	http://www.facerec.com/
Avalon Biometrics	UK, Spain	http://www.avalonbiometrics.com/
Cognitec Systems	Dresden, Germany	http://www.cognitec-systems.de/
Speed Identity AB	Mediavägen, Sweden	http://www.speed-identity.com
XID Technology Ltd.	Singapore	http://www.xidtech.com
Neurotechnology	Lithuania	http://www.neurotechnology.com/
Suprema Inc.	Republic of Korea	http://www.supremainc.com/
Morpho Company	Paris, France	http://www.morpho.com/

class number [11, 12]. For instance, in a face identification system, the number of face classes equals to the number of registered subjects. When a subject is added, the number of classes is changed. This is a characteristic of face recognition different from the general object recognition problems, where the number of classes is usually fixed. The face recognition algorithms are required to adapt to the variation of class numbers. Therefore, classification mechanisms successfully applied to general object recognition may not be applicable to face recognition. However, others formulate the face recognition problem as a groupwise registration and feature matching problem [13].

Although there are a large number of automatic face recognition methods or even electronic devices available now, none of them can cope with all kinds of image variability encountered in the real world [14]. Even in relatively constrained conditions, performance is far from perfect and current accuracy levels would translate to thousands of errors in any large-scale system [15, 16]. This is without ignoring that there are few methods that are proposed for dealing to some extent with some real-world face recognition problems [17, 18]. Besides, several performance evaluation studies have demonstrated that face recognition algorithms that operate well in controlled environments tend to suffer in the real world [19–22]. Since in the real world, as is explained in Section 3, the face images are usually affected by different imaging conditions such as occlusions and illuminations, expressions, poses and the difference of face images from the same person could be larger than those from different ones. Furthermore, the faces in Internet videos (e.g.

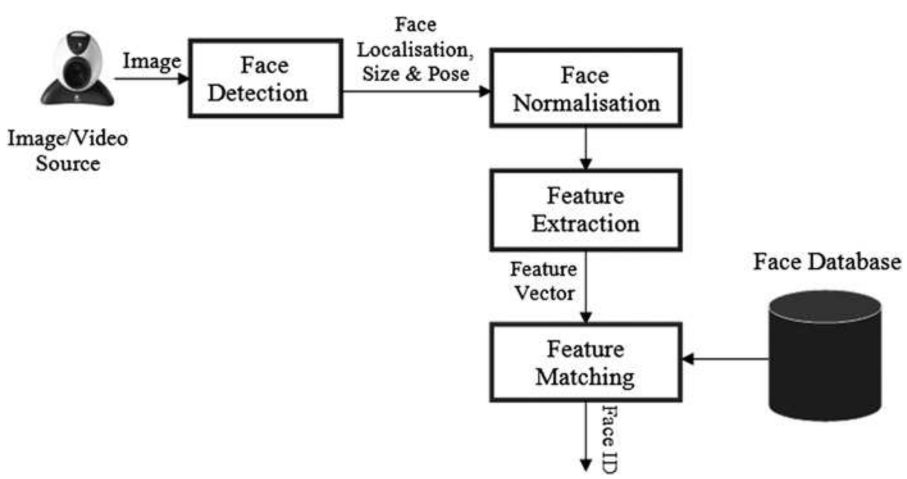

Fig. 2 *Block diagram of a general face recognition system*

YouTube videos) or surveillance are commonly with low-resolution (LR) and may be even blurred, which in turn brings additional challenges for real-world face recognition systems [23].

In this respect, claims that face recognition is a solved problem are overly bold and optimistic. On the other hand, claims that face recognition in real-world scenarios is next to impossible are simply too pessimistic, given the success of the aforementioned commercial face recognition systems. We hope this paper on face recognition will serve as a reference point for better addressing the challenges of face recognition in the real-world scenarios and towards an objective evaluation of the recent community's progress on face recognition research field.

2 Applications of face recognition

Many published works mention numerous applications in which face recognition technology is already utilised including entry and egress to secured high-risk spaces such as border crossings, military bases and nuclear power plants, as well as access to restricted resources like computers, networks, personal devices, banking transactions, trading terminals and medical records [1, 6, 24]. On the other hand, there are other application areas in which face recognition has not yet been used; furthermore, the current commercial markets have so far only scratched the surface of the potential. The potential application areas of face recognition technology can be outlined as follows:

- Automated surveillance, where the objective is to recognise and track people who are on a watchlist. In this open world application, the system is tasked to recognise a small set of people while rejecting everyone else as being one of the wanted people [25].
- Monitoring closed circuit television (CCTV), the facial recognition capability can be embedded into existing CCTV networks, to look for known criminals or drug offenders, then, authorities can be notified when one is located. In other words, if the face recognition system is employed, it can alert authorities to the presence of known or suspected terrorists or criminals whose images are already enrolled in a gallery. Moreover, it can be used for tracking down lost children or other missing persons.
- Image database investigations, searching image databases of licensed drivers, benefit recipients, immigrants and police bookings, and finding people in large news photograph and video collections [26, 27], as well as searching in the Facebook social networking web site [28].
- Multimedia environments with adaptive human computer interfaces (part of ubiquitous or context aware systems, behaviour monitoring at childcare or centres for old people, recognising customers and assessing their needs) [22].
- Airplane-boarding gate, the face recognition may be used in places of random checks merely to screen passengers for further investigation. Similarly, in casinos, where strategic design of betting floors that incorporates cameras at face height with good lighting, could be used not only to scan faces for identification purposes, but possibly to afford the capture of images to build a comprehensive gallery for future watchlist, identification and authentication tasks [29].
- Sketch-based face reconstruction, where law enforcement agencies in the world rely on practical methods to help crime witnesses reconstruct likenesses of faces [30]. These methods range from sketch artistry to proprietary computerised composite systems [31–33].
- Forensic applications, where a forensic artist is often used to work with the eyewitness in order to draw a sketch that depicts the facial appearance of the culprit according to his/her verbal description. This forensic sketch is used later for matching large facial image databases to identify the criminals [34, 35]. Yet, there is no existing face recognition system that can be used for identification or verification in crime investigation such as comparison of images taken by CCTV with available database of mugshots. Thus, utilising face recognition technology in the forensic applications is a must as discussed in [7, 36].
- Face spoofing and anti-spoofing, where a photo or video of an authorised person's face could be used to gain access to facilities or services. Hence, the spoofing attack consists in the use of forged biometric traits to gain illegitimate access to secured resources protected by a biometric authentication system [37, 38]. It is a direct attack to the sensory input of a biometric system and the attacker does not need previous knowledge about the recognition algorithm. Research on face spoof detection has recently attracted an increasing attention [39], introducing few number of face spoof detection techniques [40–42]. Thus, developing a mature anti-spoofing algorithm is still in its infancy and further research is needed for face spoofing applications [43, 44].

3 Challenges facing face recognition

3.1 Image acquisition and imaging conditions

Generally, in consumer digital imaging, face recognition must contend with uncontrolled lighting conditions, large pose variations, facial expressions, makeup, changes in facial hair, ageing and partial occlusions without forgetting that the human face is not a unique rigid object. Similarly, in scenarios such as visual surveillance, videos are often acquired in uncontrolled situations or from moving cameras [24]. In fact, there are several challenges and key factors that can significantly impact face recognition performance as well as other factors that can impact matching scores. Some of these challenges are illustrated in Fig. 3, which can be classified into five categories as follows:

- *Illumination variations:* When the image is formed, factors such as lighting (spectra, source distribution and intensity) and camera characteristics (sensor response and lenses) affect to some degree the appearance of the human face. Illumination variations can also do this because of skin reflectance properties and because of the internal camera control [45, 46]. In building a robust and efficient face recognition system, the problem of lighting/illumination variation is considered to be one of the main technical challenges facing system designers, where the face of a person can appear dramatically different [47, 48] (see Fig. 4). Several two-dimensional (2D) methods do well in recognition tasks only under moderate illumination variation, whereas the performance notably drops when severe illumination occurs [49, 50]. Most of the existing approaches for illumination variations make strong assumptions that are very hard to meet in practice [51]. Model-based approaches, for example, require several images per person recorded at different lighting conditions [52, 53]. Experimental results on invariant feature extraction approaches (i.e. 2D Gabor, edge map, …) indicate that image representations are insufficient to overcome severe illumination variation [54, 55]. To handle variations in lighting conditions or pose, an image relighting technique based on pose-robust albedo estimation can be used to generate multiple frontal images of the same person with variable lighting [56]. One limitation of the albedo estimation is that they require the images to be aligned as well as sensitivity to facial expressions. Even though image preprocessing techniques are simple and fast, they ignore the effect of lighting direction changes which produce large changes in the local features [57, 58].
- *Pose/viewpoint:* The images of a face vary because of the relative camera face pose (frontal, 45°, profile, upside down) [18], and some facial features such as the eyes or nose may become partially or wholly occluded [59]. In fact, pose changes affect the recognition process because of introducing projective deformations and self-occlusion. Thus, pose-tolerance becomes even more critical for face recognition systems that rely on a single view of a subject [60]. Blanz *et al.* [61] categorised viewpoint face recognition methods into two alternate paradigms; namely viewpoint-transformed and coefficient-based. Viewpoint transformed approaches essentially act in a preprocessing manner to transform/warp the probe image, based on estimated pose parameters, to match the gallery image in pose. Although

Fig. 3 *Examples of some challenges that may be existing in a human face*

a Challenges because of illumination variations
b Challenges because of pose/viewpoint variations
c Challenges because of ageing variations
d Challenges because of facial expression/facial style
e Challenges because of occlusion

Fig. 4 *Same face seen under varying light conditions can appear dramatically different*

coefficient-based recognition attempts to estimate the light field of the face (i.e. the face under all viewpoints or at least the face under the gallery and probe viewpoints) based on a single image [62]; this is done for both the gallery and probe images. A notable example of viewpoint transformed recognition, with the transform/warp being applied to the histogram of texture extracted from the face image rather than the face image itself, can be found in [63]. On the other hand, for face recognition across pose, local patches are considered more robust than the whole face, and several patch-based methods have been proposed [64, 65]. A generative model for generating the observation space from the identity space using an affine mapping and pose information is proposed by Prince *et al.* [66]. Solving the problem of pose is also investigated via the combination of 2D and 3D data in [67, 68].

- *Ageing and wrinkles:* Ageing can be natural (because of age progression) and artificial (using makeup tools). In both cases, ageing and wrinkles can severely affect the performance of face recognition methods [69]. In general, the effect of age variation or age factor is not commonly considered in face recognition research [70, 71]. One of the main reasons for the small number of studies concerning face recognition realised in the context of age factor is the absence of representative public databases with images containing individuals of different ages as well as the low quality of old images as documented in the literature [72, 73]. As it is very difficult to collect a dataset for face images that contains images for the same person taken at different ages along his/her life.
- *Facial expression/facial style:* The appearance of faces is directly affected by a person's facial expression as shown in Fig. 3*d*. Facial hair such as beard and moustache can alter facial appearance and features in the lower half of the face, specifically near the mouth and chin regions. Moreover, hair style can be changed to alter the appearance of the face image or hide facial features [74]. Aleix [75] formulates the problem of face recognition under facial expression as 'how can we robustly identify a person's face for whom the learning and testing face images differ in facial expression?'
- *Occlusion:* Faces may be partially occluded by other objects. In an image with a group of people, some faces or other objects may partially occlude other faces, which in turn results in only a small part of the face is available in many situations [75]. However, this makes the face (i.e. face detection) by the system location a difficult task, and even if the face is found, recognition itself might be difficult because of some hidden facial parts, making features difficult to recognise [76, 77].

The challenges and problems because of image acquisition and imaging conditions have been the focus of face recognition research for decades, but they are still not well resolved. No current system can claim to handle all of these challenges well and none of the current algorithms is 100% correct [78, 79], as the performance of the current face recognition systems is still very sensitive to any variability in the face area. In addition, face recognition represents an ongoing set of key scientific challenges. For instance, a large number of popular face recognition methods usually assume that there are multiple samples for each person available for feature extraction during the training phase. However, in real-world face recognition applications such as law enhancement and ID card identification, this assumption may not hold because there is only a single sample per person recorded in these systems [80, 81].

Furthermore, extracting robust and discriminant features which make the intra-person faces compact and enlarge the margin among different persons is a critical and difficult problem in the face recognition field [12, 82]. Moreover, how can we match or exceed the performance of a human face on real-world face recognition tasks (e.g. recognition of people known to the human viewer)? How can we learn a good model of the face from a small number of examples? How can we achieve the level of robustness exhibited by the human face recognition? How can we make face recognition robust to the effects of ageing the faces? These questions and an ever-increasing demand for the technology promise to keep face recognition active for a long time in the future [17].

3.2 Benchmark datasets and evaluation protocols

Systematic data collection and evaluation of face recognition systems on a fair basis are also considered a kind of challenges and problems that are related to research in the face recognition field [83]. In this respect, varieties of recognition benchmarks have recently been published to facilitate the development of methods for face recognition under different imaging conditions in both 2D and 3D. Table 2 lists the most widely used 2D benchmarks in performance evaluation of face recognition systems, whereas Table 3 lists 3D and video databases.

Table 2 Available and widely used 2D databases in performance evaluation of face recognition systems

Name of database	Image size	#Images	#Subject	Colour/grey	Imaging conditions	Web address
FERET	256 × 384	14.126	1564	colour	controlled	http://www.itl.nist.gov/iad/humanid/feret/feret_master.html
ORL	92 × 112	400	10	grey	controlled	http://www.cl.cam.ac.uk/research/dtg/facedatabase.html
AR	768 × 576	4	126	colour	uncontrolled	http://www2.ece.ohiostate.edu/aleix/ARdatabase.html
MIT-CBCL	115 × 115	2	10	colour	controlled +3D models	http://www.cbcl.mit.edu/heisele/facerecognition-database.html
SCface		4.16	130	colour	uncontrolled	http://www.scface.org/
Yale B	640 × 480	5.76	10	grey	uncontrolled	http://www.vision.ucsd.edu/leekc/ExtYaleDatabase/ExtYaleB.html
extended Yale B	640 × 480	16.128	28	grey	uncontrolled	http://www.vision.ucsd.edu/leekc/ExtYaleDatabase/ExtYaleB.html
CAS-PEAL	360 × 480	99.594	1.04	grey	uncontrolled	http://www.jdl.ac.cn/peal/index.html
FRGC	1704 × 2272 1200 × 1600	12.776	688	colour	controlled +3D models	http://www.nist.gov/itl/iad/ig/frgc.cfm
FEI	640 × 480	2800	200	colour	controlled	http://www.fei.edu.br/cet/facedatabase.html
BioID	382 × 288	1.521	23	grey	uncontrolled	http://www.bioid.com/
MIW		154	125	colour	uncontrolled	http://www.antitza.com/makeup-datasets.html
CVL	640 × 480	114	7	colour	uncontrolled	http://www.lrv.fri.uni-lj.si/facedb.html
LFW	250 × 250	13.233	5.749	colour	uncontrolled	http://www.vis-www.cs.umass.edu/lfw/
LFW-*a* NIST (MID)	250 × 250			colour	uncontrolled	http://www.openu.ac.il/home/hassner/data/lfwa/
		1573	1573	grey	controlled	http://www.nist.gov/srd/nistsd18.cfm
KinFaceW	64 × 64	156, 134, 116	pairs of kinship	colour		http://www.kinfacew.com/index.html
NUAA PI	640 × 480		15	colour	anti-spoofing	http://www.thatsmyface.com/
CASIA	640 × 480		50	colour	anti-spoofing	http://www.cbsr.ia.ac.cn/english/FaceAntiSpoofDatabases.asp

IET Comput. Vis., 2015, Vol. 9, Iss. 4, pp. 614–626

Table 3 Available 3D face model and video databases

Name of database	Data size	#Images	#Subject	3D models/subject	Imaging conditions	Web address
3D RMA		4	120	3	3D models	http://www.sic.rma.ac.be/beumier/DB/3d_rma.html
BFM		4	200		3D models	http://www.faces.cs.unibas.ch/bfm/
GavabDB		549	61	9	3D models	http://www.gavab.etsii.urjc.es/recursos_en.html
Bosphorus		4.666	105		3D models	http://www.bosphorus.ee.boun.edu.tr/default.aspx
Texas 3DFRD	1149	105	105		3D models	http://www.live.ece.utexas.edu/research/texas3dfr/
UMB-DB		1.473	143		3D models	http://www.ivl.disco.unimib.it/umbdb/description.html
UMB	1473	143			occluded	http://www.ivl.disco.unimib.it/umbdb/
3DMAD			17		anti-spoofing	http://www.idiap.ch/dataset/replayattack
YouTube		3425	1595		video	http://www.cs.tau.ac.il/wolf/ytfaces/
McGillFaces		18 000	60	31 F + 29 M	video	https://www.mcgill-unconstrained-face-video-database/

In these lists, we focus only on face recognition databases; there are many other databases, but they are used mainly for other tasks such as face detection. These types of databases are beyond the scope of this paper. It should be noted that today face recognition algorithms can achieve too optimistic a 97% accuracy and the underlying false accept rate may still be high (e.g. 3%) with these benchmark datasets, remaining a very limited room for algorithm development [84]. Consequently, in spite of the endeavour for collecting the listed datasets, more realistic datasets should be introduced to help facilitate larger-scale explorations in real-world face recognition. Furthermore, the popularity of face recognition has raised concerns about face spoof attacks, thus new face spoof databases are needed in public domain for cross-database benchmark. Moreover, a face spoof database captured with smart phones is especially important to facilitate spoof detection research on mobile phone applications.

4 Literature review

4.1 Traditional face recognition approaches

Much research work has been done over the past decade into developing reliable face recognition algorithms. The traditional face recognition algorithms can be categorised into two categories; holistic features and local feature approaches as illustrated in Fig. 5. In the first category, algorithms can also be divided into linear projection methods such as principal component analysis (PCA) [85], independent component analysis (ICA) [86], linear discriminate analysis (LDA) [87, 88], 2DPCA [89] and linear regression classifier (LRC) [90]. Non-linear methods use approaches like kernel PCA (KPCA), kernel LDA (KLDA) [91] or locally linear embedding (LLE) [92]. The main difference between PCA, LDA and LRC is that PCA and LDA focus on the global structure of the Euclidean

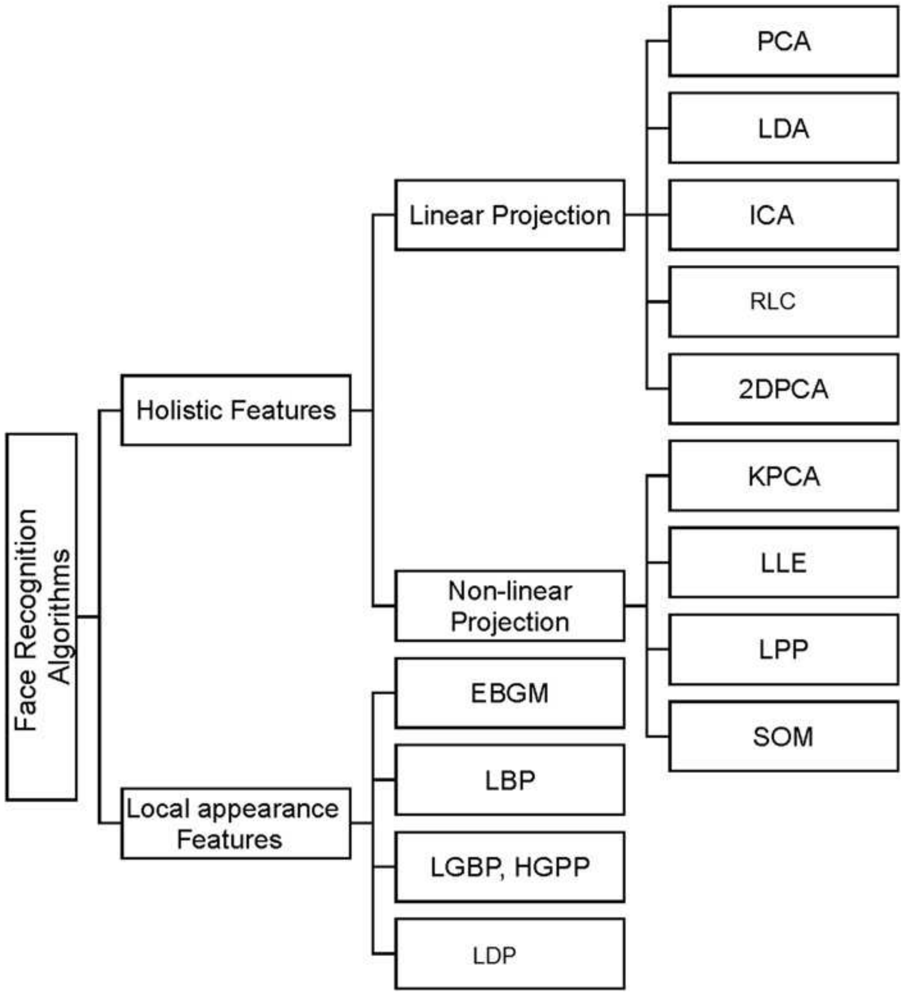

Fig. 5 *Categories of traditional face recognition algorithms*

space, whereas LRC focuses on local structure of the manifold, but they are all considered as linear subspace learning algorithms. These methods project face onto a linear subspace spanned by the eigenface images. The distance from face space is the orthogonal distance to the plane, whereas the distance in face space is the distance along the plane from the mean image. Both distances can be turned into Mahalanobis distances and given probabilistic interpretations [93]. The linear projection appearance-based methods have shown good results in many applications.

However, these methods may fail to adequately represent the faces when large variations in illumination conditions, facial expression and other factors are present. This is due to the fact that face patterns lie on a complex non-linear and non-convex manifold in the high-dimensional space. To deal with such cases, non-linear extensions have been proposed. For this, the kernel techniques are used; the idea consists of mapping the input face images into a higher-dimensional space in which the manifold of the faces is linear and simplified. Then, those traditional linear methods can be applied. Following these lines, KPCA [94], kernel ICA [95] and generalised linear discriminant analysis [96] have been developed. Despite the powerful theoretical foundation of kernel-based methods, the practical application of these methods in face recognition problems, however, do not produce a significant improvement compared with linear methods. Another family of non-linear projection methods has been introduced, which inherit the simplicity from the linear methods and the ability to deal with complex data from the non-linear ones. Among these methods are LLE [97] and locality preserving projection (LPP) [98]. However, these methods produce a projection scheme for training data only, while their capability to project new data items is questionable.

In the second category, local appearance features have certain advantages over holistic features. These methods are more stable to local changes such as expression, occlusion and misalignment. Local binary patterns (LBPs) [99, 100] are a representative method, which describes the neighbouring changes around the central pixel in a simple but effective way. It is invariant monotonic intensity transformation and small illumination variations. Many LBP variants are proposed to improve the original LBP such as histogram of Gabor phase patterns [101] and local Gabor binary pattern histogram sequence [102]. Generally, The LBP is utilised to model the neighbouring relationship jointly in spatial, frequency and orientation domains [103]. In this way, discriminant and robust information, as much as possible, could be explored. The discriminant common vectors (DCVs) [104] represent a further development of the previous subspace approaches. The main idea of the DCV consists in collecting the similarities among the elements in the same class dropping their dissimilarities. Consequently, each class can be represented by a common vector computed from the within scatter matrix. When an unknown face has to be tested, the corresponding feature vector is computed and associated to the class with the nearest common vector. For the face recognition task, kernel discriminative common vectors are employed in [105]. Moreover, an improved discriminative common vectors and support vector machine (SVM)-based face recognition method is introduced in [106]. Several global subspaces methods that were explored to represent facial structure and geometry are mentioned in chapter 7 of [6].

In [107, 108], two approaches called neighbourhood preserving projection (NPP) and orthogonal NPP (ONPP) are introduced in a way that is similar to the LLE method. These approaches preserve the local structure between samples. Data driven weights are used by solving a least-squares problem to reflect the intrinsic geometry of the local neighbourhoods. ONPP forces the mapping to be orthogonal and solves an ordinary eigenvalue problem, whereas the NPP imposes a condition of orthogonality on the projected data such that it requires solving a generalised eigenvalue problem. On the other hand, sparsity preserving projections [109] and LPPs [110] are also applied for face recognition. However, it is still unclear in these approaches how to select the neighbourhood size and how to assign optimal values for other hyper-parameters for them [109]. In an approach, which is different from preserving projection methods, a multi-linear extension of the LDA method called discriminant analysis with tensor representation is proposed by Lu *et al.* [111]. The method implements discriminant analysis directly on the natural tensorial data to preserve the neighbourhood structure of tensor feature space. Abeer *et al.* [112] introduce another method of supervised and unsupervised multi-linear NPP (MNPP) for face recognition. The MNPP method operates directly on tensorial data rather than vectors or matrices, and solves problems of tensorial representation for multi-dimensional feature extraction and recognition. Multiple interrelated subspaces are obtained in the MNPP method by unfolding the tensor over different tensorial directions. The number of subspaces derived by MNPP is determined by the order of the tensor space. A recent survey of multi-linear methods with in depth analysis and discussion can be found in [113].

4.2 Neural networks-based face recognition

A further non-linear solution to the face recognition problem is addressed by using neural networks [91, 114, 115]. For instance, Li *et al.* [116] suggested the use of a non-convergent chaotic neural network to recognise human faces. Zhou *et al.* [117] suggested using a radial basis function neural network that is integrated with a non-negative matrix factorisation to recognise faces. Park *et al.* [118] utilise a momentum back propagation neural network for face and speech verifications. Bhavin and Martin [119] applied the non-negative sparse coding method to learning facial features using different distance metrics such as the L1-metric, L2-metric and normalised cross-correlation for face recognition.

In [120], a posterior union decision-based neural network approach is proposed as a complement to the above methods for recognising face images with partial distortion and occlusion. It has the merits of both neural networks and statistical approaches. Unfortunately, this approach, like other statistical based methods, is inaccurate to model classes given only a single or a small number of training samples [121, 122].

4.3 Gabor-based face recognition

The Gabor wavelets are biologically motivated convolution kernels in the shape of plane waves restricted by a Gaussian envelope function, whose kernels are similar to the response of the 2D receptive field profiles of the mammalian simple cortical cell. They exhibit desirable characteristics of capturing salient visual properties such as spatial localisation, orientation selectivity and spatial frequency [123, 124], and captures the local structure corresponding to specific orientation and spatial frequency. The Gabor wavelets take the form of a complex plane wave modulated by a Gaussian envelope function

$$\boldsymbol{\psi}_{u,v}(z) = \frac{||\boldsymbol{K}_{u,v}||^2}{\sigma^2} \quad \mathrm{e}^{\left(\left(||\boldsymbol{K}_{u,v}||^2||z||^2\right)/(2\sigma^2)\right)}\left[\mathrm{e}^{iz\boldsymbol{K}_{u,v}} - \mathrm{e}^{(\sigma^2/2)}\right] \qquad (1)$$

where $K_{u,v} = K_v \mathrm{e}^{i\phi u}$, $z = (x, y)$, u and v define the orientation and scale of the Gabor wavelets, $K_v = K_{\max}/f^v$ and $\phi_u = \pi u/8$, $K_{\max}$ is the maximum frequency and $f = \sqrt{2}$ is the spacing factor between kernels in the frequency domain. The response of an image I to a wavelet ψ is calculated as the convolution

$$G = I * \psi \qquad (2)$$

The coefficients of the convolution represent the information in a local image region, which should be more effective than isolated pixels. A great outburst of Gabor-based methods for biometrics occurred in the past few years; and different biometrics applications prefer different information of the Gabor feature. For instance, Gabor-based face recognition usually uses the magnitude that is directly associated with both the real and imaginary parts of the Gabor feature, whereas Gabor-based palmprint authentication usually exploits only the real part of the Gabor feature [125].

Gabor wavelets have been widely used for face representation by face recognition researchers [126–128], and Gabor features are recognised as better representation for face recognition in terms of (rank-1) recognition rate [129]. Moreover, it is demonstrated to be discriminative and robust to illumination and expression variations [130].

Kanan and Faez [131] propose an approach for face representation and recognition based on adaptively weighted sub-Gabor array when only one sample image per enrolled subject is available. Although Yu *et al.* [132] propose two kinds of strategies to capture Gabor texture information, namely Gabor magnitude-based texture representation (GMTR) and Gabor phase-based texture representation (GPTR). The GMTR is characterised by using the Gamma density to model the Gabor magnitude distribution, whereas GPTR is characterised by using the generalised Gaussian density to model the Gabor phase distribution, where the estimated model parameters serve as texture representation of the face.

In [133], the Gabor wavelet is applied at fixed positions, in correspondence of the nodes of a square-meshed grid superimposed to the face image. Each sub-pattern of the partitioned face image is defined as the extracted Gabor features that belong to the same row of the square-meshed grid which are then projected to lower dimension space by Karhunen–Loeve transform. The obtained features of each sub-pattern, which are weighted using genetic algorithm (GA), are used to train a Parzen Window Classifier. Finally, matching process is done by combining the classifiers using a weighted sum rule. A manifold learning approach based on Gabor features and kernel supervised Laplacian faces for face recognition under the classifier fusion framework is introduced by Zhao *et al.* [134]. They tackle the Gabor features obtained from each channel as a new sample of the same class and then adopt the classifier fusion strategy to make the decision, which is useful for improving the performance of the recognition results.

Histogram of Gabor phase feature is proposed by Zhang *et al.* [135] for face recognition, where the quadrant-bit codes are extracted from faces based on the Gabor transform. The spatial histograms of non-overlapping rectangular regions are extracted and concatenated into an extended histogram feature to represent the original image. In [136], the patch-based histograms of local patterns are concatenated together to form the representation of the face image via learned local Gabor patterns. Ren *et al.* [137] deal with the feature representation problem by providing a learning method instead of simple concatenation or histogram feature. In [138], the Gabor features were adopted for the sparse representation (SR)-based classification and a Gabor occlusion dictionary was learned under the well-known SR framework. A different approach-based Gabor ordinal measures is introduced by Chai *et al.* [139], which integrates the distinctiveness of Gabor features and the robustness of ordinal measures as a promising solution to jointly handle inter-person similarity and intra-person variations in face images.

In spite of their superior performance, the drawback of Gabor-based methods is that the dimensionality of the Gabor feature space is overwhelmingly high since the face images are convolved with a bank of Gabor filters. To overcome the high dimensionality of the Gabor feature, selecting the most discriminative Gabor features has been studied via the employed Adaboost algorithm [140] and using entropy and GAs [141]. However, for all the proposed methods in this direction, it is very time consuming to select the most useful ones from so many Gabor features [140]. Furthermore, extracting the Gabor features is computationally intensive, so the features are impractical for real-time applications such as mobile phone applications [142]. A simplified version of Gabor wavelets is introduced in [143]. Unfortunately, the simplified Gabor features are slightly more sensitive to lighting variations than the original Gabor features are.

4.4 Face descriptor-based face recognition

Describing face images based on local features provides a global description; since local features of the image are evaluated in the neighbouring pixels and then aggregated to form the final global description [144, 145]. This is unlike global methods in which the entire image is utilised to produce each feature, where the first steps start with the description of the face realised at a pixel level by making use of the local neighbourhood of each pixel. After that the image is divided into a number of sub-regions and from each sub-region a local description is formed as a histogram of the pixel level descriptions calculated in the previous step. Then, the information of the regions is combined into the final face descriptor by concatenating the partial histograms [73].

Developing image descriptors that are able to improve classification performance of multi-option recognition as well as pair matching of face images is investigated in the literature [144, 146, 147]. The main idea behind developing image descriptors of these works is to learn the most discriminant local features that can minimise the difference of the features between images of a same individual and maximise that between images from other people depending on the nature of these descriptors, which compute an image representation from local patch statistics. Wolf *et al.* [82] propose an approach for face verification in the wild that combines multiple local descriptors, designed to capture statistics of local patch similarities, with learned statistics from background context. Its face verification accuracy ranked first on the LFW benchmark. In [148], a learning-based discriminant face descriptor is proposed for enhancing the face recognition performance by introducing the discriminative learning into three steps of LBP-like feature extraction. The discriminant image filters, the optimal soft sampling matrix and the dominant patterns are all learned from images. It has been demonstrated that these new methods are discriminative and robust to illumination and expression changes. Furthermore, the resulting face representation, learning-based descriptor, is compact, highly discriminative and easy to extract. Face recognition based on the local descriptor idea has been recently recognised as the state-of-the-art design framework for face identification and verification task [149].

4.5 3D-based face recognition

As 3D capturing process is becoming cheaper and faster [150], and it is commonly thought that the use of 3D sensing has the potential for greater recognition accuracy than 2D, recent works attempt to solve the problem directly on 3D face models [151]. The advantage behind using 3D data is that depth information does not depend on pose and illumination, and therefore the representation of the object does not change with these parameters, making the whole system more robust. Besides, 3D face recognition has been regarded as a natural solution to pose variation problem [152]. Given a sufficiently accurate 3D model, the 3D-based techniques can achieve better robustness to pose variation problem than 2D-based ones.

The work of Bowyer *et al.* [153] provides a comprehensive survey of the 3D face recognition approaches. Blanz and Vetter [154] present a method for face recognition across variations in pose, which combines deformable 3D models with a computer graphics simulation of projection and illumination. To account for variations in the face pose, the algorithm simulates the process of image formation in 3D space using computer graphics, and it estimates 3D shape and texture of faces from single images. The estimate is achieved by fitting a statistical, morphable model of 3D faces to images. The model is learned from a set of textured 3D scans of heads. The shape and albedo parameters of the model are computed by fitting the morphable model to the input image. In this method, faces are represented by model parameters for 3D shape and texture. Their 3D morphable models are combined with spherical harmonics illumination representation by Zhang and Samaras [155] to recognise faces under arbitrary unknown lighting.

Using similar direction, an automatic 3D face recognition approach able to differentiate between expression deformations and interpersonal disparities, and hence recognise faces under any facial expression is presented in [156], where the expression model is learned from pairs of neutral and non-neutral faces of each

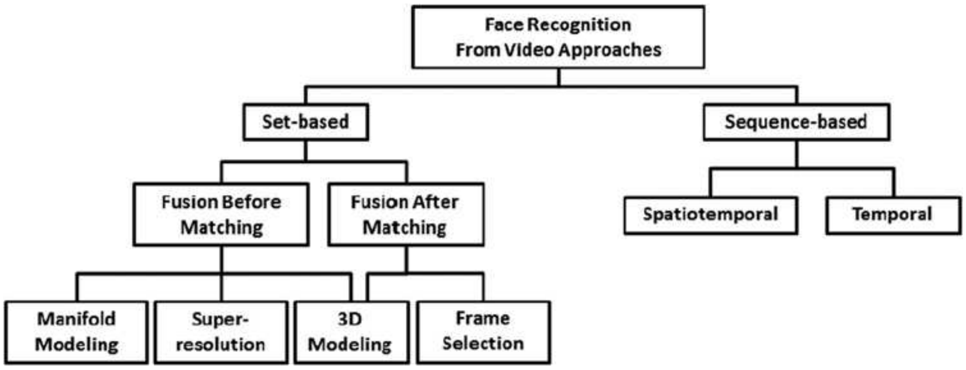

Fig. 6 *Categories of VFR approaches*

individual in the gallery. After that a PCA subspace is constructed using the shape residues of the finely registered pairs of faces. The learned model is then used to morph out any expression deformation from a non-neutral face. Although in [157], Passalis *et al.* propose using facial symmetry to handle pose variation in 3D face recognition. They employ an automatic landmark detector that estimates pose and detects occluded areas for each facial scan. Subsequently, an annotated face model is registered and fitted to the scan. During fitting, facial symmetry is used to overcome the challenges of missing data [158].

Similarly, Prabhu *et al.* [159] propose a generic 3D elastic model for pose invariant face recognition. They first construct a 3D model for each subject in the database using only a single 2D image by applying the 3D generic elastic model (3DGEM) approach. These 3D models comprise an intermediate gallery database from which novel 2D pose views are synthesised for matching. Before matching, an initial estimate of the pose of the test query is obtained using a linear regression approach based on automatic facial landmark annotation. Each 3D model is subsequently rendered at different poses within a limited search space about the estimated pose, and the resulting images are matched against the test query. Finally, the distances between the synthesised images and test query are computed by using a simple normalised correlation matcher to show the effectiveness of the pose synthesis method to real-world data.

In [160], a geometric framework for analysing 3D faces, with the specific goals of comparing, matching and averaging their shapes, is proposed to represent facial surfaces by radial curves emanating from the nose tips. Then, the elastic shape analysis of these curves is utilised to develop a Riemannian framework for analysing shapes of full 3D facial surfaces. Moreover, another 3D face recognition approach based on local geometrical signatures called facial angular radial signature (ARS) that can approximate the semi-rigid region of the 3D face is proposed in [161]. The authors employed KPCA to map the raw ARS facial features to mid-level features to improve the discriminating power. Finally, the resulting mid-level features are combined into one single feature vector and fed into the SVM to perform face recognition. Both are plausible approaches for using 3D information to assist in face recognition under large pose variations. For further reading on using 3D data in face recognition, more detailed surveys about various 3D face recognition methods can be found in [162–165].

On the other side, the drawback of using 3D data in face recognition is that these face recognition approaches need all the elements of the system to be well calibrated and synchronised to acquire accurate 3D data (texture and depth maps). Moreover, the existing 3D face recognition approaches rely on a surface registration or on complex feature (surface descriptor) extraction and matching techniques. They are, therefore, computationally expensive and not suitable for practical applications. Moreover, they require the cooperation of the subject making them not useful for uncontrolled or semi-controlled scenarios where the only input of the algorithms will be a 2D intensity image acquired from a single camera.

4.6 Video-based face recognition

On the other hand, the analysis of video streams of face images has received increasing attention in biometrics [166]. An immediate advantage in using video information is the possibility of employing redundancy present in the video sequence to improve still image systems. Although significant amount of research has been done in matching still face images, use of videos for face recognition is relatively less explored [167]. The first stage of video-based face recognition (VFR) is to perform re-identification, where a collection of videos is cross-matched to locate all occurrences of the person of interest [168]. For instance, in tragic events such as the Boston bombing incident, which happened in 2013, all available videos (both CCTV and amateur video) needed to be cross-matched to find all instances of the suspected attackers. Thus, the collection of videos of a subject can be used to query legacy face image databases.

Generally, VFR approaches can be classified into two categories based on how they leverage the multitude of information available in a video sequence: (i) sequence-based and (ii) set-based, where at a high-level, what most distinguishes these two approaches is whether or not they utilise temporal information [169]. Fig. 6 illustrates the classification of VFR approaches in the literature [170].

Zhang and Martinez [171] extend the formulation of a probabilistic appearance-based face recognition approach, which was originally defined to do recognition from a single still image as previously explained, to work with multiple images and video sequences. Although, Cevikalp and Triggs [172] constrained the subspace spanned from face images of a clip into a convex hull, and then calculate the nearest distance of two convex hulls as the between-set similarity. Thus, each test and training example is a set of images of a subject's face, not just a single image, so recognition decisions need to be based on comparisons of image sets.

Following different directions, Cui *et al.* [173] converted VFR task into the problem of measuring the similarity of two image sets, where the examples from a video clip construct one image set. The authors consider face images from each clip as an ensemble and formulate VFR into the joint sparse representation (JSR) problem. In JSR, to adaptively learn the sparse representation of a probe clip, they simultaneously consider the class-level and atom-level sparsity, where the former structurises the enrolled clips using the structured sparse regulariser and the latter seeks for a few related examples using the sparse regulariser. VFR approaches are beyond this work; thus for more details, readers are referred to the recent survey on this topic – chapter 8 of [174] and [170, 175, 176].

5 Future research directions

The joint efforts of the whole face recognition research community have made few applications of real-world face recognition achievable, but there are still several challenges to address and opportunities to explore for designing mature face recognition systems that can work in highly challenging environments and with images typically found within the social media environment. Hence, significant new research is required to address the aforementioned technical challenges of face recognition. To address these issues, either invariant features should be extracted to describe face image or devolve modern machine learning algorithms for learning robust representation of the face. Besides, the following points can be investigated as research directions to enhance face recognition performance to deal with emerging new and more demanding scenarios as well as working in outdoor conditions.

For the illumination problem, the human face can be treated as a combination of a sequence of small and flat facets. For each facet, the effect of the illumination can be modelled using effective mathematical representation or by extracting facial features which are invariant to illumination variations. In this context, there are some trials that attempted to construct a generative 3D face model that can be used to render face images with different poses and under varying lighting conditions [177].

Despite much attention to face illumination preprocessing, there are few systemic comparative studies on existing approaches that present fascinating insights and conclusions in how to design better illumination preprocessing methods [55]. Moreover, adding specifically designed preprocessing method before feature extraction can effectively increase the performance of face recognition system in a case of sever variations as well as developing methods that utilise colour information instead of using grey images. Moreover, most of the existing works that address the problem of matching faces across changes in pose and illumination cannot be applied when the gallery and probe images are of different resolutions [178]. There is a need for approaches that can match an LR probe image with a high-resolution gallery via using, for example, super-resolution techniques to construct a higher resolution image from the probe image and then perform matching.

Face recognition, similarly to other domains, for example, optical character recognition, has been known to benefit from the combination of multiple sources of information. Such information sources may include analysis of facial skin texture, shape of various shape parts, ratios of distances in the face, facial symmetry or lack thereof etc. Wolf *et al.* [82] show that combining several descriptors from the same LBP family boosts recognition performance. This suggests that, even though the development of new descriptors is an experimental science which is guided by best practices more than by solid theory, there is room for the introduction of new face encoding methods. Recent studies [179] have shown that fractional differential operator, which is a generalisation of the integer-order differentiation, can strengthen high-frequency marginal information and extract more detailed information contained in objects where grey scales intensively change and textural information in those areas. Fractional differential operator has not been investigated for face representation/recognition. In fact, face images contain rich textural information and edge information, thus, fractional differential operator may extract facial visual features of local regions such as eyes, nose and mouth etc.

Soft biometric traits embedded in a face such as demographic information (e.g. gender and ethnicity) and facial marks (e.g. scars, moles and freckles) are ancillary information and are not fully distinctive by themselves in face recognition tasks [180]. This information can be explicitly combined with face matching score to improve the overall face recognition accuracy. Moreover, in visual surveillance application, where a face image is occluded or is captured in off-frontal pose, soft biometric traits can provide even more valuable information for face matching [181]. On the other hand, facial marks can be useful to differentiate identical twins whose global facial appearances are very similar. We believe that using soft biometric traits can improve face image matching and recognition performance.

Currently, the available face recognition approaches that use the 2D information of face images, suffer from low reliability because of their sensitivity to illumination conditions, facial expressions and changes in pose [182]. The inadequate performance of these approaches should come as no surprise as these 2D-based algorithms ignore the fact that the human face is naturally a complex 3D object characterised by distinguishing features such as eyes, mouth and nose and by skin pigmentation; consequently, it needs to be described by a 3D model taking into account geometrical information of the 3D face [183]. In this context, the 3D structure of the human face intuitively provides high discriminatory information and is less sensitive to variations in environmental conditions like illumination or viewpoint. Besides, historically 3D face recognition has been criticised for lack of real-world 3D sensory cameras; this issue may be resolved in few years with inexpensive 3D sensors. Therefore we argue for further research towards using new modalities captured by 3D sensors such as infrared and depth images to enhance the performance of face recognition systems.

A further path of future research would be the implementation of the algorithms on parallel processing units such as GPU. One drawback of several current face recognition methods (e.g. Gabor) is their computational complexity, which keeps these methods from being widely used in real-world commercial products. Without any doubt, if one could perform classification in frame rate, such methods would be put into more practical use. Moreover, one can enhance matching by combining top-down and bottom-up information concurrently. For example, the detection and segmentation performed in the top layers can guide the bottom layer matching process and the bottom layer can enhance the segmentation in the upper layer.

Exploring the effectiveness of the current methods on a large-scale unconstrained real-world face recognition problem based on images taken from the Facebook social networking web site, Flickr, YouTube etc. is necessary to design successful systems. As well as, more study needs to be carried out on utilising the face recognition in conjunction with other biometrics such as iris, fingerprint, speech and ear recognition in order to enhance the recognition performance of these approaches (recent research [184]). Finally, there is much work to be done in order to realise methods that reflect how humans recognise faces and optimally make use of the temporal evolution of the appearance of the face for recognition.

6 Conclusions

Face recognition is a challenging problem in the field of computer vision, which has received a great deal of attention over the past years because of its several applications in various domains. Although research efforts have been conducted vigorously in this area, achieving mature face recognition systems for operating under constrained conditions, they are far from achieving the ideal of being able to perform adequately in all various situations that are commonly encountered by applications in the real world. This paper on face recognition serves as a reference point towards an objective evaluation of the community's progress on face recognition research and to better address the challenges of face recognition in the real-world scenarios. In this paper, we have reviewed the current achievements in face recognition and discussed several challenges and key factors that can significantly affect performance of the face recognition systems. Moreover, this paper aims to exploit the use of face recognition technology in other scientific and daily life applications. Also several possible research directions for improving the performance of the state-of-the-art face recognition systems are suggested as future directions. Finally, this paper concludes by arguing that the next step in the evolution of face recognition algorithms will require radical and courageous steps forward in terms of the face representations/descriptors, as well as the learning algorithms used.

7 Acknowledgments

The authors thank the reviewers for their insightful and constructive comments and suggestions that helped them to improve this paper.

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