

# Chapter 1

## Introduction

Stan Z. Li and Anil K. Jain

### 1.1 Face Recognition

Face recognition is a task that humans perform routinely and effortlessly in our daily lives. Wide availability of powerful and low-cost desktop and embedded computing systems has created an enormous interest in automatic processing of digital images in a variety of applications, including biometric authentication, surveillance, human-computer interaction, and multimedia management. Research and development in automatic face recognition follows naturally.

Face recognition has several advantages over other biometric modalities such as fingerprint and iris: besides being natural and nonintrusive, the most important advantage of face is that it can be captured at a distance and in a covert manner. Among the six biometric attributes considered by Hietmeyer [16], facial features scored the highest compatibility in a Machine Readable Travel Documents (MRTD) [27] system based on a number of evaluation factors, such as enrollment, renewal, machine requirements, and public perception, shown in Fig. 1.1. Face recognition, as one of the major biometric technologies, has become increasingly important owing to rapid advances in image capture devices (surveillance cameras, camera in mobile phones), availability of huge amounts of face images on the Web, and increased demands for higher security.

The first automated face recognition system was developed by Takeo Kanade in his Ph.D. thesis work [18] in 1973. There was a dormant period in automatic face recognition until the work by Sirovich and Kirby [19, 38] on a low dimen-

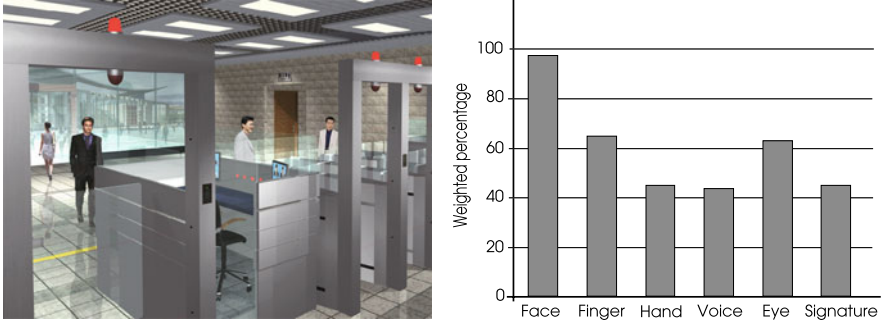
---

S.Z. Li (✉)

Center for Biometrics and Security Research & National Laboratory of Pattern Recognition,  
Institute of Automation, Chinese Academy of Sciences, Beijing, China  
e-mail: [szli@cbsr.ia.ac.cn](mailto:szli@cbsr.ia.ac.cn)

A.K. Jain

Michigan State University, East Lansing, MI 48824, USA  
e-mail: [jain@cse.msu.edu](mailto:jain@cse.msu.edu)



**Fig. 1.1** A scenario of using biometric MRTD systems for passport control (*left*), and a comparison of various biometric traits based on MRTD compatibility (*right*, from Hietmeyer [16] with permission)

sional face representation, derived using the Karhunen–Loeve transform or Principal Component Analysis (PCA). It is the pioneering work of Turk and Pentland on Eigenface [42] that reinvigorated face recognition research. Other major milestones in face recognition include: the Fisherface method [3, 12], which applied Linear Discriminant Analysis (LDA) after a PCA step to achieve higher accuracy; the use of local filters such as Gabor jets [21, 45] to provide more effective facial features; and the design of the AdaBoost learning based cascade classifier architecture for real time face detection [44].

Face recognition technology is now significantly advanced since the time when the Eigenface method was proposed. In the constrained situations, for example where lighting, pose, stand-off, facial wear, and facial expression can be controlled, automated face recognition can surpass human recognition performance, especially when the database (gallery) contains a large number of faces.<sup>1</sup> However, automatic face recognition still faces many challenges when face images are acquired under unconstrained environments. In the following sections, we give a brief overview of the face recognition process, analyze technical challenges, propose possible solutions, and describe state-of-the-art performance.

This chapter provides an introduction to face recognition research. Main steps of face recognition processing are described. Face detection and recognition problems are explained from a face subspace viewpoint. Technology challenges are identified and possible strategies for solving some of the problems are suggested.

## 1.2 Categorization

As a biometric system, a face recognition system operates in either or both of two modes: (1) face verification (or authentication), and (2) face identification (or recognition). Face verification involves a one-to-one match that compares a query face

<sup>1</sup>Most individuals can identify only a few thousand people in real life.

image against an enrollment face image whose identity is being claimed. Person verification for self-serviced immigration clearance using E-passport is one typical application.

Face identification involves one-to-many matching that compares a query face against multiple faces in the enrollment database to associate the identity of the query face to one of those in the database. In some identification applications, one just needs to find the most similar face. In a watchlist check or face identification in surveillance video, the requirement is more than finding most similar faces; a confidence level threshold is specified and all those faces whose similarity score is above the threshold are reported.

The performance of a face recognition system largely depends on a variety of factors such as illumination, facial pose, expression, age span, hair, facial wear, and motion. Based on these factors, face recognition applications may be divided into two broad categories in terms of a user's cooperation: (1) *cooperative* user scenarios and (2) *noncooperative* user scenarios.

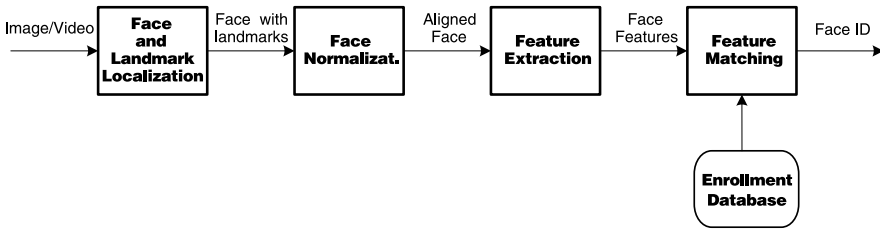
The cooperative case is encountered in applications such as computer login, physical access control, and e-passport, where the user is willing to be cooperative by presenting his/her face in a proper way (for example, in a frontal pose with neutral expression and eyes open) in order to be granted the access or privilege.

In the noncooperative case, which is typical in surveillance applications, the user is unaware of being identified. In terms of distance between the face and the camera, near field face recognition (less than 1 m) for cooperative applications (e.g., access control) is the least difficult problem, whereas far field noncooperative applications (e.g., watchlist identification) in surveillance video is the most challenging.

Applications in-between the above two categories can also be foreseen. For example, in face-based access control at a distance, the user is willing to be cooperative but he is unable to present the face in a favorable condition with respect to the camera. This may present challenges to the system even though such cases are still easier than identifying the identity of the face of a subject who is not cooperative. However, in almost all of the cases, ambient illumination is the foremost challenge for most face recognition applications.

### 1.3 Processing Workflow

Face recognition is a visual pattern recognition problem, where the face, represented as a three-dimensional object that is subject to varying illumination, pose, expression, and other factors, needs to be identified based on acquired images. While two-dimensional face images are commonly used in most applications, certain applications requiring higher levels of security demand the use of three-dimensional (depth or range) images or optical images beyond the visual spectrum. A face recognition system generally consists of four modules as depicted in Fig. 1.2: face localization, normalization, feature extraction, and matching. These modules are explained below.



**Fig. 1.2** Depiction of face recognition processing flow

*Face detection* segments the face area from the background. In the case of video, the detected faces may need to be tracked across multiple frames using a face tracking component. While face detection provides a coarse estimate of the location and scale of the face, *face landmarking* localizes facial landmarks (e.g., eyes, nose, mouth, and facial outline). This may be accomplished by a landmarking module or face alignment module.

*Face normalization* is performed to normalize the face geometrically and photometrically. This is necessary because state-of-the-art recognition methods are expected to recognize face images with varying pose and illumination. The geometrical normalization process transforms the face into a standard frame by face cropping. Warping or morphing may be used for more elaborate geometric normalization. The photometric normalization process normalizes the face based on properties such as illumination and gray scale.

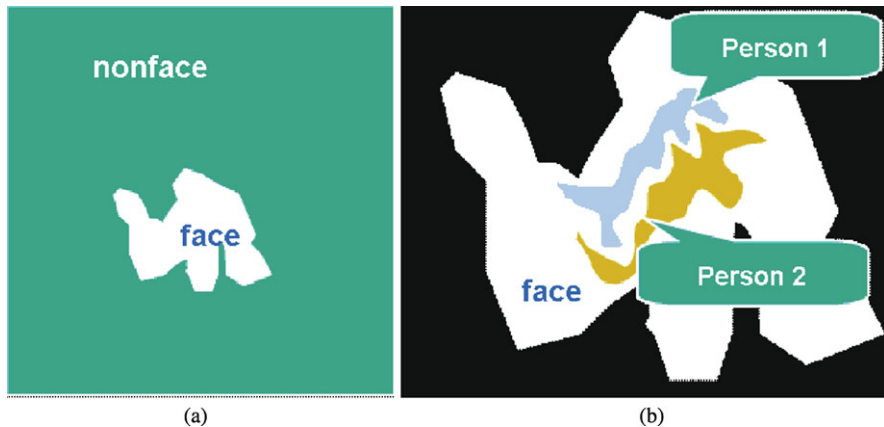
*Face feature extraction* is performed on the normalized face to extract salient information that is useful for distinguishing faces of different persons and is robust with respect to the geometric and photometric variations. The extracted face features are used for face matching.

In *face matching* the extracted features from the input face are matched against one or many of the enrolled faces in the database. The matcher outputs ‘yes’ or ‘no’ for 1:1 verification; for 1:N identification, the output is the identity of the input face when the top match is found with sufficient confidence or unknown when the tip match score is below a threshold. The main challenge in this stage of face recognition is to find a suitable similarity metric for comparing facial features.

The accuracy of face recognition systems highly depends on the features that are extracted to represent the face which, in turn, depend on correct face localization and normalization. While face recognition still remains a challenging pattern recognition problem, it may be analyzed from the viewpoint of face subspaces or manifolds, as follows.

## 1.4 Face Subspace

Although face recognition technology has significantly improved and can now be successfully performed in “real-time” for images and videos captured under favorable (constrained) situations, face recognition is still a difficult endeavor, especially



**Fig. 1.3** Face subspace or manifolds. **a** Face versus nonface manifolds. **b** Face manifolds of different individuals

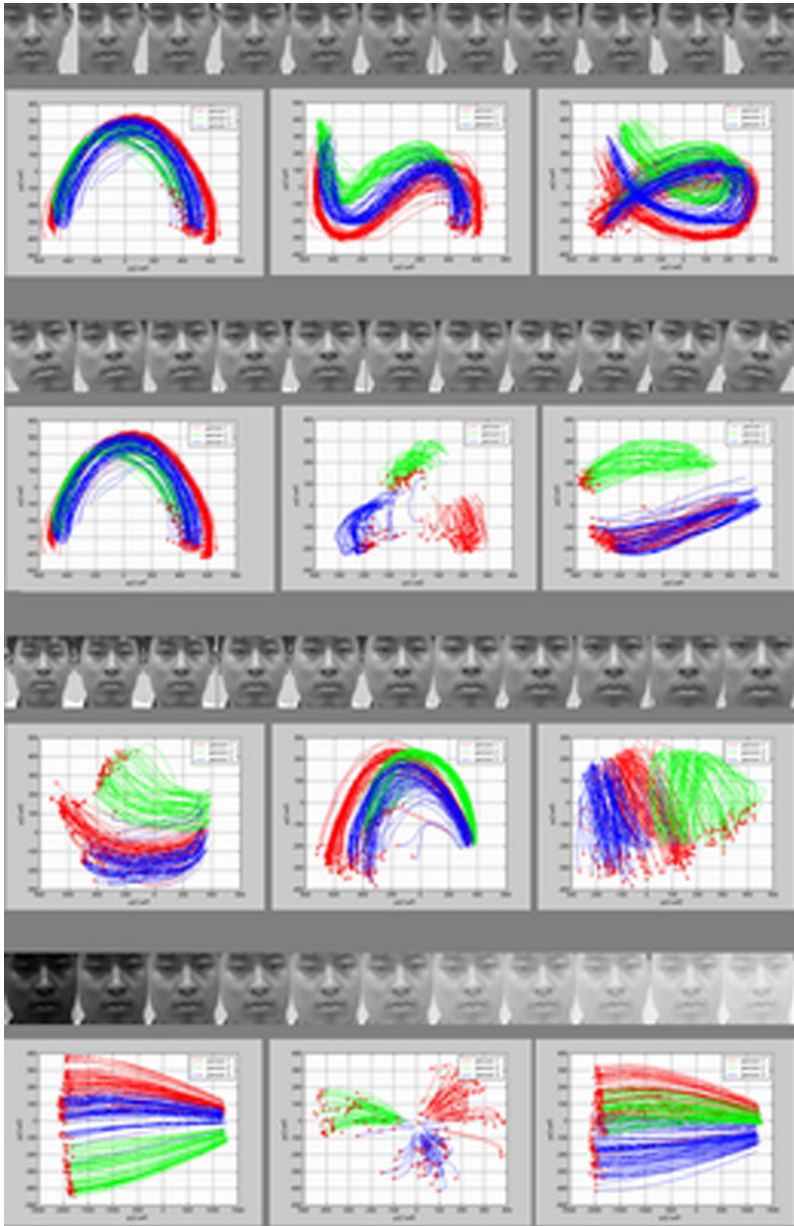
for unconstrained tasks where viewpoint, illumination, expression, occlusion, and facial accessories can vary considerably. This can be illustrated from face subspace or manifold viewpoint.

Subspace analysis techniques for face recognition are based on the fact that a class of patterns of interest, such as the face, resides in a subspace of the input image space. For example, a  $64 \times 64$  8-bit image with 4096 pixels can express a large number of pattern classes, such as trees, houses, and faces. However, among the  $256^{4096} > 10^{9864}$  possible “configurations,” only a tiny fraction correspond to faces. Therefore, the pixel-based image representation is highly redundant, and the dimensionality of this representation could be greatly reduced when only the face patterns are of interest.

The eigenface or PCA method [19, 42] derives a small number (typically 40 or lower) of principal components or eigenfaces from a set of training face images. Given the eigenfaces as basis for a face subspace, a face image is compactly represented by a low dimensional feature vector and a face can be reconstructed as a linear combination of the eigenfaces. The use of subspace modeling techniques has significantly advanced the face recognition technology.

The manifold or distribution of all the faces accounts for variations in facial appearance whereas the nonface manifold accounts for all objects other than the faces. If we examine these manifolds in the image space, we find them highly nonlinear and nonconvex [5, 41]. Figure 1.3(a) illustrates face versus nonface manifolds and Fig. 1.3(b) illustrates the manifolds of two individuals in the entire face manifold. Face detection can be considered as a task of distinguishing between the face and nonface manifolds in the image (subwindow) space and face recognition can be considered as a task of distinguishing between faces of different individuals in the face manifold.

Figure 1.4 further demonstrates the nonlinearity and nonconvexity of face manifolds in a PCA subspace spanned by the first three principal components, where the



**Fig. 1.4** Nonlinearity and nonconvexity of face manifolds under (from top to bottom) translation, rotation, scaling, and Gamma transformations

plots are drawn from real face image data. Each plot depicts the manifolds of three individuals (in three colors). The data consists of 64 frontal face images for each

individual. A transform (horizontal transform, in-plane rotation, size scaling, and gamma transform for the 4 groups, respectively) is performed on each face image with 11 gradually varying parameters, producing 11 transformed face images; each transformed image is cropped to contain only the face region; the 11 cropped face images form a sequence. A curve in this figure represents such a sequence in the PCA space, and so there are 64 curves for each individual. The three-dimensional (3D) PCA space is projected on three different 2D spaces (planes). We can observe the nonlinearity of the trajectories.

The following observations can be drawn based on Fig. 1.4. First, while this example is demonstrated in the PCA space, more complex (nonlinear and nonconvex) trajectories are expected in the original image space. Second, although these face images have been subjected to geometric transformations in the 2D plane and pointwise lighting (gamma) changes, more significant complexity of trajectories is expected for geometric transformations in 3D space (for example, out-of-plane head rotations) and ambient lights.

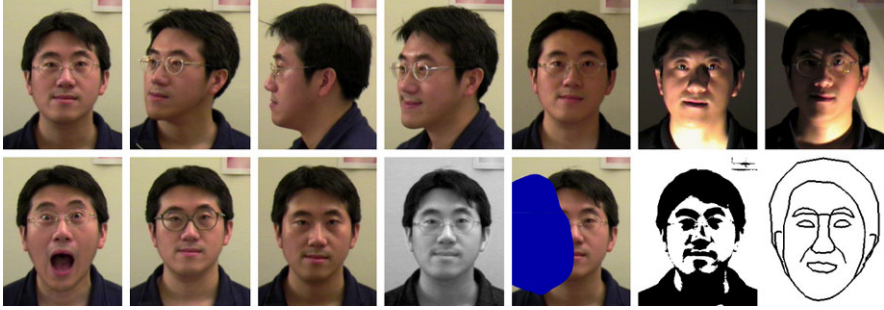
## 1.5 Technology Challenges

As shown in Fig. 1.3, the problem of face detection is highly nonlinear and nonconvex, even more so for face matching. Face recognition evaluation reports, for example Face Recognition Technology (FERET) [34], Face Recognition Vendor Test (FRVT) [31] and other independent studies, indicate that the performance of many state-of-the-art face recognition methods deteriorates with changes in lighting, pose, and other factors [8, 43, 50]. The key technical challenges in automatic face recognition are summarized below.

**Large Variability in Facial Appearance** Whereas shape and reflectance are intrinsic properties of a face, the appearance (i.e., the texture) of a face is also influenced by several other factors, including the facial pose (or, equivalently, camera viewpoint), illumination, and facial expression. Figure 1.5 shows an example of large intra-subject variations caused by these factors. Aging is also an important factor that leads to an increase in the intra-subject variations especially in applications requiring duplication of government issued photo ID documents (e.g., driver licenses and passports). In addition to these, various imaging parameters, such as aperture, exposure time, lens aberrations, and sensor spectral response also increase intra-subject variations. Face-based person identification is further complicated by possible small inter-subject variations (Fig. 1.6). All these factors are confounded in the image data, so “the variations between the images of the same face due to illumination and viewing direction are almost always larger than the image variation due to change in face identity” [30]. This variability makes it difficult to extract the intrinsic information about the face identity from a facial image.

**Complex Nonlinear Manifolds** As illustrated above, the entire face manifold is highly nonconvex, and so is the face manifold of any individual under various





**Fig. 1.5** Intra-subject variations in pose, illumination, expression, occlusion, accessories (e.g., glasses), color, and brightness. (Courtesy of Rein-Lien Hsu [17])

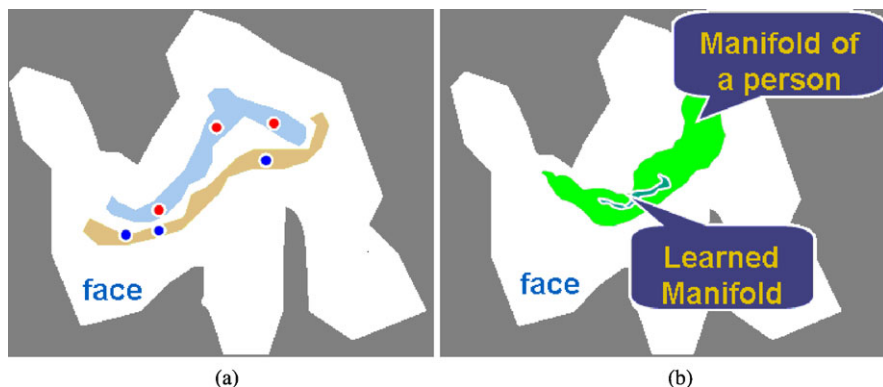


**Fig. 1.6** Similarity of frontal faces between **a** twins (downloaded from [www.marykateandashley.com](http://www.marykateandashley.com)); and **b** a father and his son (downloaded from BBC news, [news.bbc.co.uk](http://news.bbc.co.uk))

changes. Linear methods such as PCA [19, 42], independent component analysis (ICA) [2], and linear discriminant analysis (LDA) [3]) project the data linearly from a high-dimensional space (for example, the image space) to a low-dimensional subspace. As such, they are unable to preserve the nonconvex variations of face manifolds necessary to differentiate among individuals. In a linear subspace, Euclidean distance and, more generally, the Mahalanobis distance do not perform well for discriminating between face and nonface manifolds and between manifolds of different individuals (Fig. 1.7(a)). This limits the power of the linear methods to achieve highly accurate face detection and recognition in many practical scenarios.

**High Dimensionality and Small Sample Size** Another challenge in face recognition is the generalization ability, which is illustrated in Fig. 1.7(b). The figure depicts a canonical face image of size  $112 \times 92$  which resides in a 10,304-dimensional feature space. The number of example face images per person (typically fewer than 10, and sometimes just one) available for learning the manifold is usually much smaller





**Fig. 1.7** Challenges in face recognition from subspace viewpoint. **a** Euclidean distance is unable to differentiate between individuals. When using Euclidean distance, an inter-person distance can be smaller than an intra-person distance. **b** The learned manifold or classifier is unable to characterize (i.e., generalize) unseen images of the same face

than the dimensionality of the image space; a system trained on a small number of examples may not generalize well to unseen instances of the face.

## 1.6 Solution Strategies

There are two strategies for tackling the challenges outlined in Sect. 1.5: (i) extract invariant and discriminative face features, and (ii) construct a robust face classifier. A set of features, constituting a feature space, is deemed to be good if the face manifolds are simple (i.e., less nonlinear and nonconvex). This requires two stages of processing: (1) normalizing face images geometrically and photometrically (for example, using geometric warping into a standard frame and photometric illumination correction) and (2) extracting features in the normalized images, such as using Gabor wavelets and LBP (local binary pattern), that are stable with respect to possible geometric and photometric variations.

A powerful classification engine is still necessary to deal with difficult nonlinear classification and regression problems in the constructed feature space. This is because the normalization and feature extraction cannot solve the problems of nonlinearity and nonconvexity. Learning methods are useful tools to find good features and build powerful robust classifiers based on these features. The two stages of processing may be designed jointly using learning methods.

In the early development of face recognition [6, 13, 18, 36], geometric facial features such as eyes, nose, mouth, and chin were explicitly used. Properties of the features and relations (e.g., areas, distances, angles) between the features were used as descriptors for face recognition. Advantages of this approach include economy and efficiency when achieving data reduction and insensitivity to variations in illumination and viewpoint. However, facial feature detection and measurement

techniques developed to date are not sufficiently reliable for the geometric feature-based recognition [9]. Further, geometric properties alone are inadequate for face recognition because rich information contained in the facial texture or appearance is not utilized. These are the main reasons why early feature-based techniques were not effective.

Statistical learning methods are the mainstream approach that has been used in building current face recognition systems. Effective features and classifiers are learned from training data (appearance images or features extracted therefrom). During the learning, both prior knowledge about face(s) and variations encountered in the training data are taken into consideration. The appearance-based approach, such as PCA [42] and LDA [3] based methods, has significantly advanced face recognition technology. Such an approach generally operates directly on an image-based representation (i.e., array of pixel intensities). It extracts features in a subspace derived from training images. Using PCA, an “optimal” face subspace is constructed to represent only the face object; using LDA, a discriminant subspace is constructed to distinguish faces of different persons. It is now well known that LDA-based methods generally yields better results than PCA-based methods [3].

These linear, holistic appearance-based methods encode prior knowledge contained in the training data and avoid instability of manual selection and tuning needed in the early geometric feature-based methods. However, they are not effective in describing local variations in the face appearance and are unable to capture subtleties of face subspaces: protrusions of nonconvex manifolds may be smoothed out and concavities may be filled in, thereby losing useful information. Note that the appearance-based methods require that the face images be properly aligned, typically based on the eye locations.

Nonlinear subspace methods use nonlinear transforms to convert a face image into a feature vector in a discriminative feature space. Kernel PCA [37] and kernel LDA [29] use kernel tricks to map the original data into a high-dimension space to make the data separable. Manifold learning, which assumes that face images occupy a low-dimensional manifold in the original space, attempts to model such manifolds. These include ISOMAP [39], LLE [35], and LPP [15]. Although these methods achieve good performance on the training data, they tend to overfit and hence do not generalize well to unseen data.

The most successful approach to date for handling the nonconvex face distribution works with local appearance-based features extracted using appropriate image filters. This is advantageous in that distributions of face images in local feature space are less affected by the changes in facial appearance. Early work in this direction included local features analysis (LFA) [33] and Gabor wavelet-based features [21, 45]. Current methods are based on local binary pattern (LBP) [1] and many variants (for example ordinal feature [23], Scale-Invariant Feature Transform (SIFT) [26], and Histogram of Oriented Gradients (HOG) [10]). While these features are general-purpose and can be extracted from arbitrary images, face-specific local filters may be learned from images [7, 20].

A large number of local features can be generated by varying parameters associated with the position, scale, and orientation of the filters. For example, more than

400 000 local appearance features can be generated when an image of size  $100 \times 100$  is filtered with Gabor filters with five different scales and eight different orientation for all pixel positions. While some of these features are useful for face recognition, others may be less useful or may even degrade the recognition performance. Boosting based methods have been implemented to select good local features [46, 48, 49]. A discriminant analysis step can be applied to further transform the space of the selected local features to discriminative subspace of a lower dimensionality to achieve better face classification [22, 24, 25]. This leads to a framework for learning both effective features and powerful classifiers.

There have been only a few studies reported on face recognition at a distance. These approaches can be essentially categorized into two groups: (i) generating a super resolution face image from the given low resolution image [11, 32] and (ii) acquiring high resolution face image using a special camera system (e.g., a high resolution camera or a PTZ camera) [4, 14, 28, 40, 47].

The availability of high resolution face images (i.e., tens of megapixels per image) provides new opportunities in facial feature representation and matching. In the 2006 Face Recognition Vendor Test (FRVT) [31], the best face matching accuracies were obtained from the high resolution 2D images or 3D images. This underlines the importance of developing advanced sensors as well as robust feature extraction and matching algorithms in achieving high face recognition accuracy. The increasing popularity of infrared cameras also supports the importance of sensing techniques.

## 1.7 Current Status

For cooperative scenarios, frontal face detection and tracking in normal lighting environment is a reasonably well-solved problem. Assuming the face is captured with sufficient image resolution, 1:1 face verification also works satisfactorily well for cooperative frontal faces. Figure 1.8 illustrates an application of face verification at the 2008 Beijing Olympic Games. This system verifies the identity of a ticket holder (spectator) at entrances to the National Stadium (Bird's Nest). Each ticket is associated with a unique ID number, and the ticket holder is required to submit his registration form with a two-inch ID/passport photo attached. The face photo is scanned into the system. At the entrance, the ticket is read in by an RFID reader, and the face image is captured using a video camera, which is compared with the enrollment photo scan, and the verification result is produced.

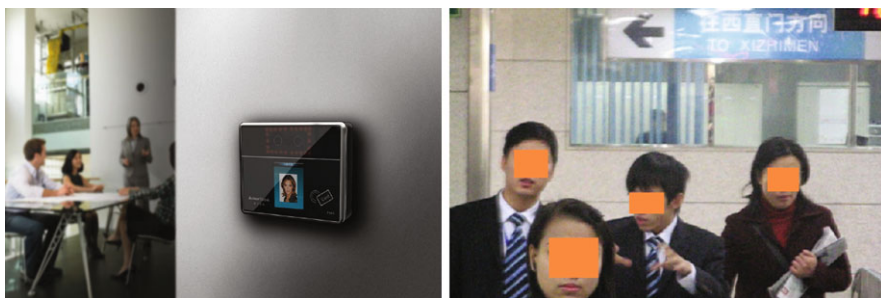
A novel solution to deal with uncontrolled illumination is to use active near infrared (NIR) face imaging to control the illumination direction and the strength. This enables the system to achieve high face recognition accuracy. The NIR face recognition technology has been in use at China–Hong Kong border<sup>2</sup> for self-service immigration clearance since 2005 (see Fig. 1.8).

---

<sup>2</sup>The ShenZhen (China)–Hong Kong border is the world's largest border crossing point, with more than 400 000 crossings every day.



**Fig. 1.8** 1:1 Face verification used at the 2008 Beijing Olympic Games, and 1:1 NIR face verification used at the China–Hong Kong border control since 2005



**Fig. 1.9** An embedded NIR face recognition system for access control in 1:N identification mode and watch-list face surveillance and identification at subways

One-to-many face identification using the conventional, visible band face images has not yet met the accuracy requirements of practical applications even for cooperative scenarios. The main problem is the uncontrolled ambient illumination. The NIR face recognition provides a good solution, even for 1:N identification. Embedded NIR face recognition based access control products (Fig. 1.9) have been on the market since 2008.

Face recognition in noncooperative scenarios, such as watch-list identification, remains a challenging task. Major problems include pose, illumination, and motion blur. Because of growing emphasis on security, there have been several watch-list identification application trials. On the right of Fig. 1.9, it shows a snapshot of 1:N watch-list face surveillance and identification at a Beijing Municipal Subways station, aimed at identifying suspects in the crowd. CCTV cameras are mounted at the subway entrances and exits, in such a way that images of frontal faces are more likely to be captured. The best system could achieve a recognition rate of up to 60% at a FAR = 0.1%.

## 1.8 Summary

Face recognition technology has made impressive gains, but it is still not able to meet the accuracy requirements of many applications. A sustained and collaborative effort is needed to address many of the open problems in face recognition.

## References

1. Ahonen, T., Hadid, A., Pietikainen, M.: Face recognition with local binary patterns. In: Proceedings of the European Conference on Computer Vision, pp. 469–481. Prague, Czech Republic (2004)
2. Bartlett, M.S., Lades, H.M., Sejnowski, T.J.: Independent component representations for face recognition. In: Proceedings of the SPIE, Conference on Human Vision and Electronic Imaging III, vol. 3299, pp. 528–539 (1998)
3. Belhumeur, P.N., Hespanha, J.P., Kriegman, D.J.: Eigenfaces vs. Fisherfaces: Recognition using class specific linear projection. *IEEE Trans. Pattern Anal. Mach. Intell.* **19**(7), 711–720 (1997)
4. Bernardin, K., v. d. Camp, F., Stiefelwagen, R.: Automatic person detection and tracking using fuzzy controlled active cameras. In: Proc. IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pp. 1–8 (2007)
5. Bichsel, M., Pentland, A.P.: Human face recognition and the face image set's topology. *CVGIP, Image Underst.* **59**, 254–261 (1994)
6. Brunelli, R., Poggio, T.: Face recognition: Features versus templates. *IEEE Trans. Pattern Anal. Mach. Intell.* **15**(10), 1042–1052 (1993)
7. Cao, Z., Yin, Q., Tang, X., Sun, J.: Face recognition with learning-based descriptor. In: Proceedings of IEEE Computer Society Conference on Computer Vision and Pattern Recognition (2010)
8. Chellappa, R., Wilson, C., Sirohey, S.: Human and machine recognition of faces: A survey. *Proc. IEEE* **83**, 705–740 (1995)
9. Cox, I.J., Ghosn, J., Yianilos, P.: Feature-based face recognition using mixture-distance. In: Proceedings of IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pp. 209–216 (1996)
10. Dalal, N., Triggs, B.: Histograms of oriented gradients for human detection. In: Proceedings of IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pp. 886–893 (2005)
11. Dedeoglu, G., Kanade, T., August, J.: High-zoom video hallucination by exploiting spatio-temporal regularities. In: Proceedings of IEEE International Conference on Computer Vision, pp. 151–158 (2004)
12. Etemad, K., Chellappa, R.: Face recognition using discriminant eigenvectors. In: Proceedings of the International Conference on Acoustic, Speech and Signal Processing (1996)
13. Goldstein, A.J., Harmon, L.D., Lesk, A.B.: Identification of human faces. *Proc. IEEE* **59**(5), 748–760 (1971)
14. Hampapur, A., Pankanti, S., Senior, A., Tian, Y.-L., Brown, L., Bolle, R.: Face cataloger: multi-scale imaging for relating identity to location. In: Proc. IEEE Conference Advanced Video and Signal Based Surveillance, pp. 13–20 (2003)
15. He, X., Yan, S., Hu, Y., Niyogi, P., Zhang, H.: Face recognition using laplacianfaces. *IEEE Trans. Pattern Anal. Mach. Intell.* **27**(3), 328–340 (2005)
16. Hietmeyer, R.: Biometric identification promises fast and secure processing of airline passengers. *ICAO J.* **55**(9), 10–11 (2000)
17. Hsu, R.-L.: Face detection and modeling for recognition. PhD thesis, Michigan State University (2002)

18. Kanade, T.: Picture processing system by computer complex and recognition of human faces. PhD thesis, Kyoto University (1973)
19. Kirby, M., Sirovich, L.: Application of the Karhunen-Loeve procedure for the characterization of human faces. *IEEE Trans. Pattern Anal. Mach. Intell.* **12**(1), 103–108 (1990)
20. Kumar, R., Banerjee, A., Vemuri, B.: Volterrafaces: discriminant analysis using Volterra kernels. In: *Proceedings of IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 150–155 (2009)
21. Lades, M., Vorbruggen, J., Buhmann, J., Lange, J., von der Malsburg, C., Wurtz, R.P., Konen, W.: Distortion invariant object recognition in the dynamic link architecture. *IEEE Trans. Comput.* **42**, 300–311 (1993)
22. Lei, Z., Liao, S., Pietikäinen, M., Li, S.Z.: Face recognition by exploring information jointly in space, scale and orientation. *IEEE Trans. Image Process.* **20**(1), 247–256 (2011)
23. Liao, S., Lei, Z., Zhu, X., Sun, Z., Li, S.Z., Tan, T.: Face recognition using ordinal features. In: *Proceedings of IAPR International Conference on Biometrics*, pp. 40–46 (2006)
24. Liao, S., Zhu, X., Lei, Z., Zhang, L., Li, S.Z.: Learning multi-scale block local binary patterns for face recognition. In: *Proceedings of IAPR International Conference on Biometrics*, pp. 828–837 (2007)
25. Liu, C.: Capitalize on dimensionality increasing techniques for improving face recognition grand challenge performance. *IEEE Trans. Pattern Anal. Mach. Intell.* **28**(5), 725–737 (2006)
26. Lowe, D.G.: Object recognition from local scale-invariant features. In: *Proceedings of IEEE International Conference on Computer Vision*, p. 1150, Los Alamitos, CA (1999)
27. Machine Readable Travel Documents (MRTD). <http://www.icao.int/mrtd/overview/overview.cfm>
28. Marchesotti, L., Piva, S., Turolla, A., Minetti, D., Regazzoni, C.: Cooperative multisensor system for real-time face detection and tracking in uncontrolled conditions. In: *Proceedings of SPIE Int'l Conf. Image and Video Communications and Processing* (2005)
29. Mika, S., Ratsch, G., Weston, J., Schölkopf, B., Müller, K.-R.: Fisher discriminant analysis with kernels. In: *Neural Networks for Signal Processing IX*, pp. 41–48 (1999)
30. Moses, Y., Adini, Y., Ullman, S.: Face recognition: The problem of compensating for changes in illumination direction. In: *Proceedings of the European Conference on Computer Vision*, vol. A, pp. 286–296 (1994)
31. NIST: Face Recognition Vendor Tests (FRVT) (2006). <http://www.frvt.org>
32. Park, J., Lee, S.: Stepwise reconstruction of high-resolution facial image based on interpolated morphable face model. In: *Proc. Int'l Conf. Audio-and Video-based Biometric Person Authentication*, pp. 102–111 (2005)
33. Penev, P., Atick, J.: Local feature analysis: A general statistical theory for object representation. *Neural Syst.* **7**(3), 477–500 (1996)
34. Phillips, P.J., Moon, H., Rizvi, S.A., Rauss, P.J.: The FERET evaluation methodology for face-recognition algorithms. *IEEE Trans. Pattern Anal. Mach. Intell.* **22**(10), 1090–1104 (2000)
35. Roweis, S., Saul, L.: Nonlinear dimensionality reduction by locally linear embedding. *Science* **290**(22), 2323–2326 (2000)
36. Samal, A., Iyengar, P.A.: Automatic recognition and analysis of human faces and facial expressions: A survey. *Pattern Recognit.* **25**, 65–77 (1992)
37. Schölkopf, B., Smola, A., Müller, K.R.: Nonlinear component analysis as a kernel eigenvalue problem. *Neural Comput.* **10**, 1299–1319 (1999)
38. Sirovich, L., Kirby, M.: Low-dimensional procedure for the characterization of human faces. *J. Opt. Soc. Am. A* **4**(3), 519–524 (1987)
39. Tenenbaum, J., Silva, V., Langford, J.: A global geometric framework for nonlinear dimensionality reduction. *Science* **290**(22), 2319–2323 (2000)
40. Tistarelli, M., Li, S., Chellappa, R. (eds.): *Handbook of Remote Biometrics for Surveillance and Security*. Springer, Berlin (2009)
41. Turk, M.: A random walk through eigenspace. *IEICE Trans. Inf. Syst.* **E84-D**(12), 1586–1695 (2001)
42. Turk, M.A., Pentland, A.P.: Eigenfaces for recognition. *J. Cogn. Neurosci.* **3**(1), 71–86 (1991)

43. Valentin, D., Abdi, H., O'Toole, A.J., Cottrell, G.W.: Connectionist models of face processing: A survey. *Pattern Recognit.* **27**(9), 1209–1230 (1994)
44. Viola, P., Jones, M.: Rapid object detection using a boosted cascade of simple features. In: *Proceedings of IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, p. 511 (2001)
45. Wiskott, L., Fellous, J., Kruger, N., v. d. Malsburg, C.: Face recognition by elastic bunch graph matching. *IEEE Trans. Pattern Anal. Mach. Intell.* **19**(7), 775–779 (1997)
46. Yang, P., Shan, S., Gao, W., Li, S.Z., Zhang, D.: Face recognition using Ada-boosted Gabor features. In: *Proceedings of International Conference on Automatic Face and Gesture Recognition*, pp. 356–361 (2004)
47. Yao, Y., Abidi, B., Kalka, N., Schmid, N., Abidi, M.: Improving long range and high magnification face recognition: Database acquisition, evaluation, and enhancement. *Comput. Vis. Image Underst.* **111**(2), 111–125 (2008)
48. Zhang, L., Li, S.Z., Qu, Z., Huang, X.: Boosting local feature based classifiers for face recognition. In: *Proceedings of First IEEE Workshop on Face Processing in Video*, Washington, DC (2004)
49. Zhang, G., Huang, X., Li, S.Z., Wang, Y., Wu, X.: Boosting local binary pattern (LBP)-based face recognition. In: Li, S.Z., Lai, J., Tan, T., Feng, G., Wang, Y. (eds.) *Advances in Biometric Personal Authentication*, vol. 3338, pp. 180–187. Springer, Berlin (2005)
50. Zhao, W., Chellappa, R., Phillips, P., Rosenfeld, A.: Face recognition: A literature survey. *ACM Comput. Surv.* 399–458 (2003)