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# Multiple Viewpoints Based Overview for Face Recognition

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Abstract. *Face recognition has the wide research and applications on many areas. Many surveys of face recognition are implemented. Different from previous surveys on from a single viewpoint of application, method or condition, this paper has a comprehensive survey on face recognition from practical applications, sensory inputs, methods, and application conditions. In the sensory inputs, we review face recognition from image-based, video-based, 3D-based and hypersprectral image based face recognition, and a comprehensive survey of face recognition methods from the viewpoints of signal processing and machine learning are implemented, such as kernel learning, manifold learning method. Moreover we discuss the single training sample based face recognition and under the variable poses. The prominent algorithms are described and critically analyzed, and relevant issues such as data collection, the influence of the small sample size, and system evaluation are discussed*

**Keywords:** Face recognition; single training sample; manifold learning; kernel method.

## 1. Introduction.

Face recognition have become a popular research topic in the computer vision, image processing, and pattern recognition areas. Recognition performance of the practical face recognition system is largely influenced by the variations in illumination conditions, viewing directions or poses, facial expression, aging, and disguises. Face recognition provides the wide applications in commercial, law enforcement, and military, and so on, such as airport security and access control, building surveillance and monitoring, human-computer intelligent interaction and perceptual interfaces, smart environments at home, office, and cars. Many application areas of face recognition are developed based on two primary verification (one-to-one) and identification (one-to-many) tasks as shown in Table 1.

## 2. Face recognition: Sensory Inputs.

TABLE 1. Face recognition applications

| | Areas | Taskes |
|---|---|---|
| 1 | Security[1] [2] | Access control to buildings,<br>Airports/seaports<br>ATM machines<br>Border checkpoints [6][7]<br>Computer/network security [8]<br>Smart Card [9] |
| 2 | Video indexing [3][ 4]. | Surveillance<br>Labeling faces in video<br>Forensics<br>Criminal justice systems<br>Mug-shot/booking systems<br>Post-event analysis |
| 3 | Image database investigations [5] | Licensed drivers managing<br>Benefit recipients<br>Missing children<br>Immigrants and police bookings<br>Witness face reconstruction |
| 4 | General identity verification | Electoral registration<br>Banking<br>Electronic commerce<br>Identifying newborns<br>National IDs<br>Passports<br>Drivers' licenses<br>Employee IDs). |
| 5 | HCI[10][11] | Ubiquitous aware<br>Behavior monitoring<br>Customer assessing |

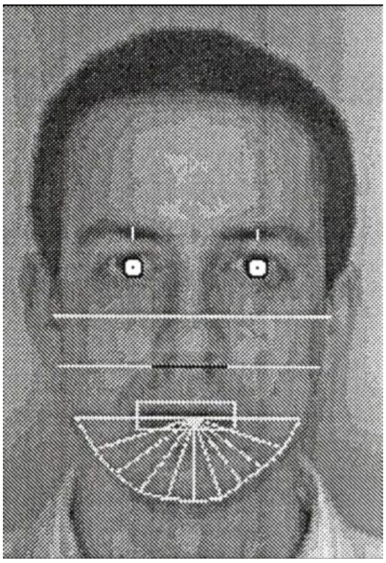

FIGURE 1. Geometrical features based face recognition in [12]

2.1. **Image-based face recognition.** Image-based face recognition methods can be divided into feature-based and holistic methods. On feature-based face recognition, geometry-based face recognition is the most popular method in the previous work. The work in [12] is a representative work, which computed a vector of 35 geometric features shown in Figure 1, and the 90%

recognition rate was reported. But the high 100% recognition accuracy is achieved by the the same database with the experiments under the template-based face recognition. Other methods were proposed for geometry based face recognition, including filtering and morphological operations [13], Hough transform methods [14] and deformable templates[15][16]. Researchers applied 30-dimensional feature vector derived from 35 facial features as shown in Figure 2 and reported a 95% recognition accuracy on 685 images of database. These facial features are marked manually and had its limitations on auto recognition in the practical face recognition system. In the following research work [18], researchers presented an automatic feature extraction but less recognition accuracy.

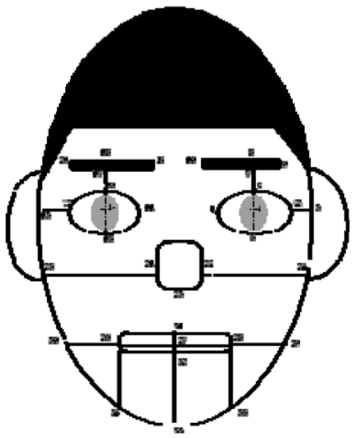

Figure 2. Manually mark facial features [17]

On holistic methods, which attempt to identify faces using global representations, i.e., descriptions based on the entire image rather than on local features of the face. Modular eigenfeatures based face recognition [19] deals with localized variations and a low-resolution description of the whole face in terms of the salient facial features as shown in Figure 3.

As the famous face recognition method, Principal Component Analysis (PCA) has been widely studied. Some recent advances in PCA-based algorithms include weighted modular PCA [20], adaptively weighted subpattern PCA [21], two-dimensional PCA [22, 23], multi-linear subspace analysis [24], eigenbands [25], symmetrical PCA [26].

2.2. **Video-based face recognition.** With the development of video surveillance, video-based face recognition have widely used in many areas. Video-based face recognition system typically consists of face detection, tracking and recognition [27]. In the practical video face recognition system, most of them applied a good frame to recognize a new face[28]. In [29], two types of image sequences were done in training and test procedure. As shown in Figure 4 and Figure 5, eight primary sequences were taken in a relatively constrained environment, and then a secondary sequence were recorded in unconstrained atmosphere.

2.3. **3D-based face recognition.** As shown in Figure 7, sixteen examples with full-color frontal and profile view photographs are shown. The profile images were converted to grayscale images. To prevent participants from matching the faces by hairstyles and forehead fringes, the distances between the lowest hair cue in the forehead and the concave of the nose of all the faces were measured [31]. The minimum distance among the faces in the same set was taken as the standard length for all the faces in the same set, and the faces in the same set were trimmed to the same extent based on the standard length.

2.4. **Hypersprectral image based face recognition.** Multispectral and hyperspectral imaging with remote sensing purposes are widely used in environment reconnaissance, agriculture, forest and mineral exploration. Multispectral and hyperspectral imaging obtains a set of spatially

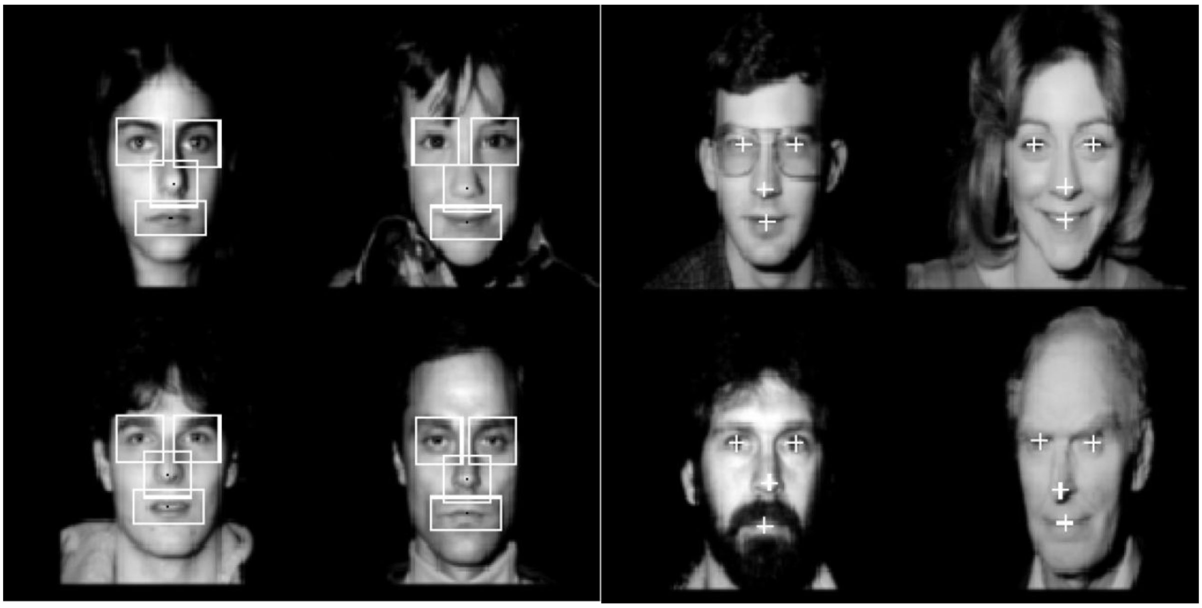

FIGURE 3. (a) Examples of facial feature training templates used and (b) the resulting typical detections [19]

FIGURE 4. A complete Primary sequence for the class Carla [29]

coregistered images with its spectrally contiguous wavelengths. Recently it has been applied to biometrics, skin diagnosis, etc. Especially, some studies on hyperspectral face recognition have been reported very recently [32]. Researchers built an indoor hyperspectral face acquisition system shown in Figure 8. For each individual, four sessions were collected at two different times (2 sessions each time) with an average time span of five months. The minimal interval is three months and the maximum is ten months. Each session consists of three hyperspectral cubesXfrontal, right, and left views with neutral expression. In the hyperspectral imaging system, the spectral range is from 400 to 720 nm with a step length of 10 nm with producing 33 bands in all. Some examples are shown in Figure 9.

## 3. Face recognition: Methods.

### 3.1. Signal processing based face recognition.

An excellent face recognition method should consider what features are used to represent a face image and how to classify a new face image based on this representation. Current feature extraction methods can be classified to signal processing and statistical learning methods. On signal processing based methods, feature extraction based Gabor wavelets are widely used to represent the face image [33][34], because the kernels of

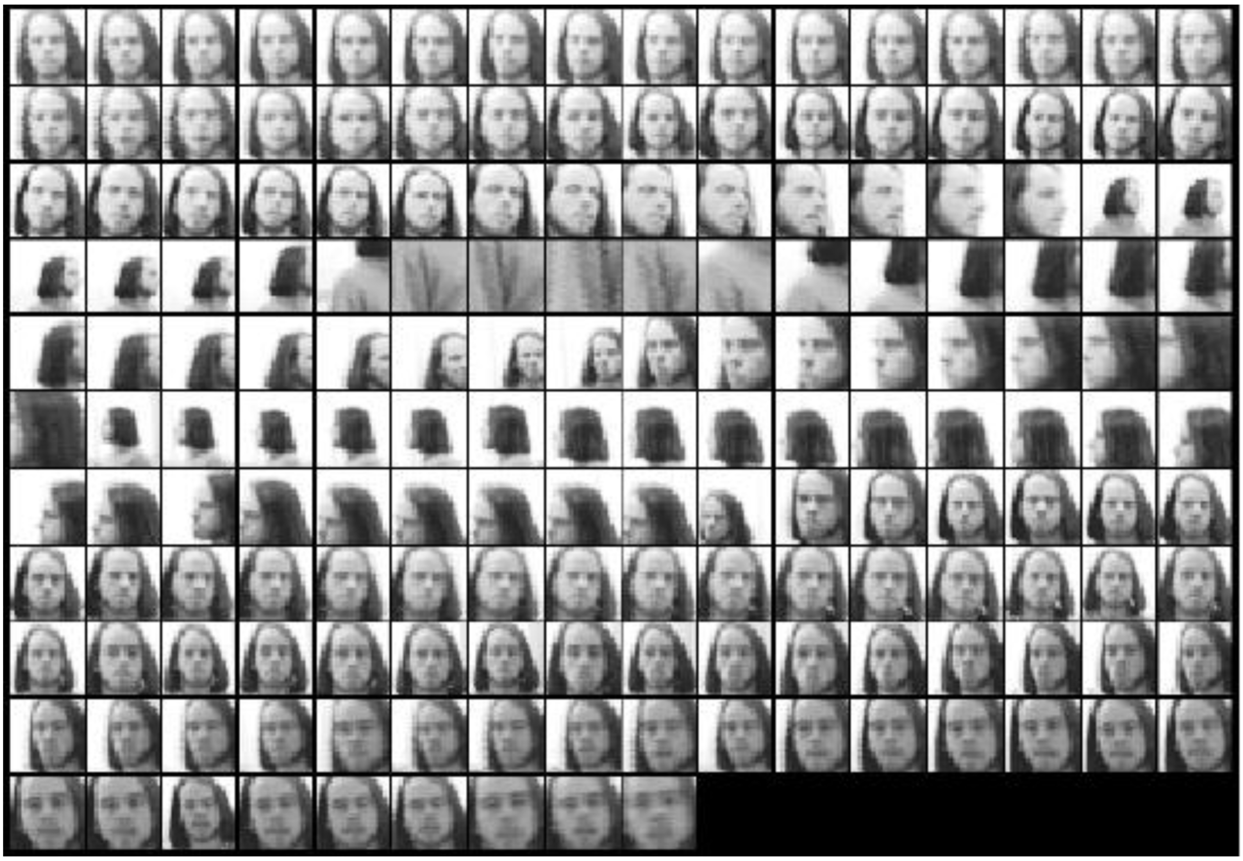

FIGURE 5. A complete Secondary sequence for the class Steve [29]

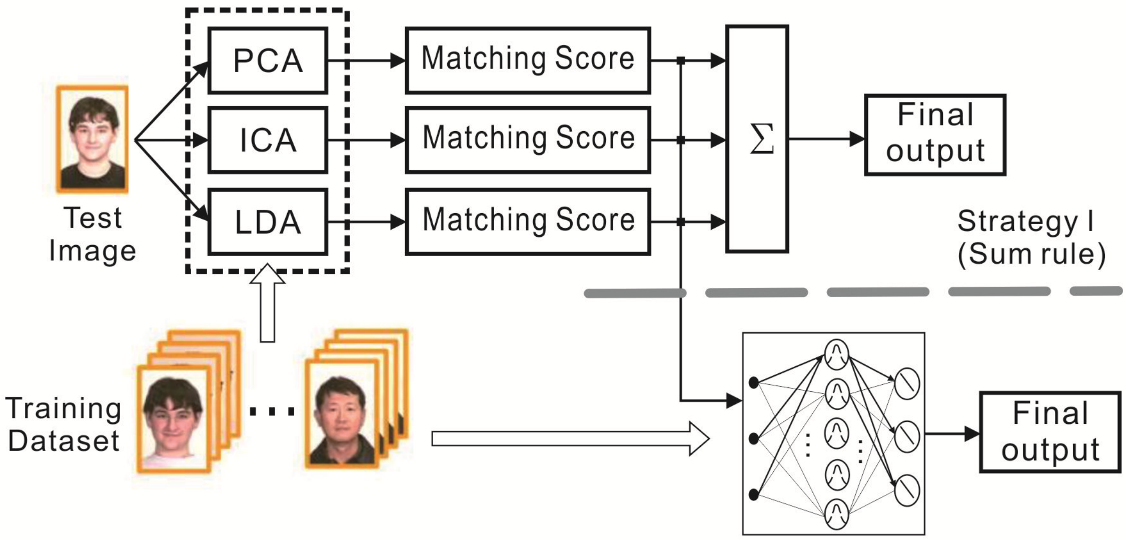


FIGURE 6. Combining Classifiers for Face Recognition[30]

Gabor wavelets are similar to two-dimensional receptive field profiles of the mammalian cortical simple cells, which captures the properties of spatial localization, orientation selectivity, and spatial frequency selectivity to cope with the variations in illumination and facial expressions. On the statistical learning based methods, the dimension reduction methods are widely used in

FIGURE 7. Examples of the front-view faces with their corresponding grayscale profiles [31]

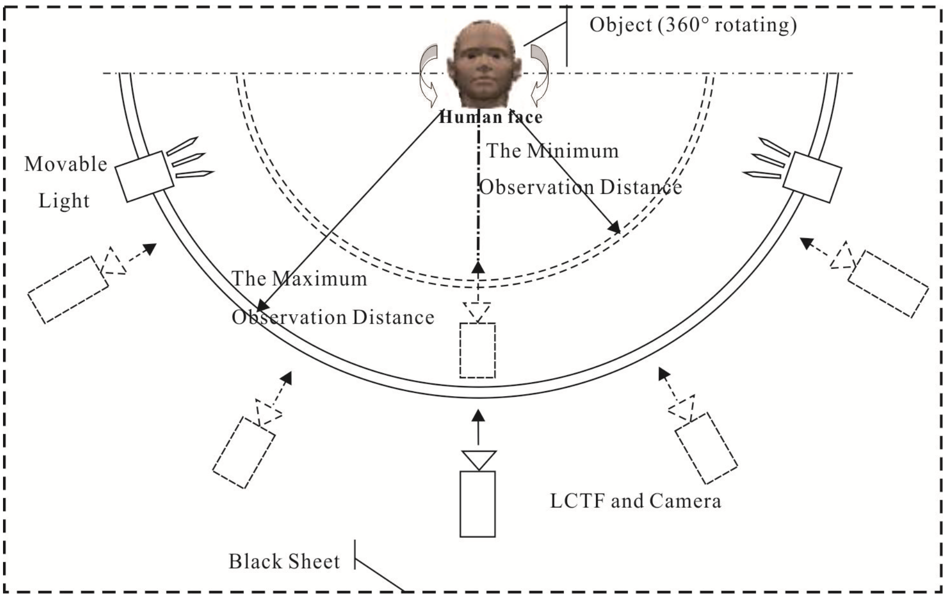


FIGURE 8. Established hyperspectral face imaging system[32]

the past works [35-40], and the PCA and LDA are widely used among the dimensionality reduction methods [41]. Recently kernel based nonlinear feature extraction methods were applied to face recognition[42-44], which has attracted much attention in the past research works[45-46].

Recently video-based technology have been developed and applied into many research topics including coding [47], [48], enhancing [49], [50] and face recognition as discussed in the previous section. This section, Gabor-based face recognition technology are discussed. The use of Gabor filter sets for image segmentation has attracted quite some attention in the last decades. Such filter sets provide a promising alternative in view of the amount and diversity of normal texture features proposed in the literature. Another reason for exploiting this alternative is the outstanding performance of our visual system, which is known by now to apply such a local spectral decomposition. However, it should be emphasized that a Gabor decomposition only represents the lowest level of processing in the visual system. It merely mimics the image coding from the input (cornea or retina) to the primary visual cortex, (cortical hypercolumns) which, in turn, can be seen as the input stage for further and definitively more complex cortical processing.The nonorthogonality of the Gabor wavelets implies that there is redundant information in the filtered images.

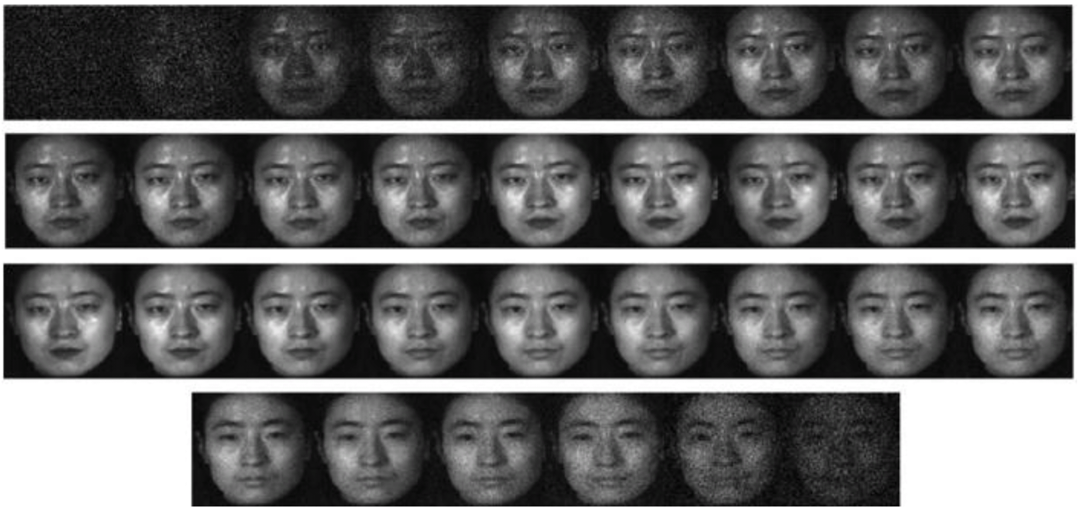

FIGURE 9. Exampls of a set of 33 bands of hyperspectral images from an person[32]

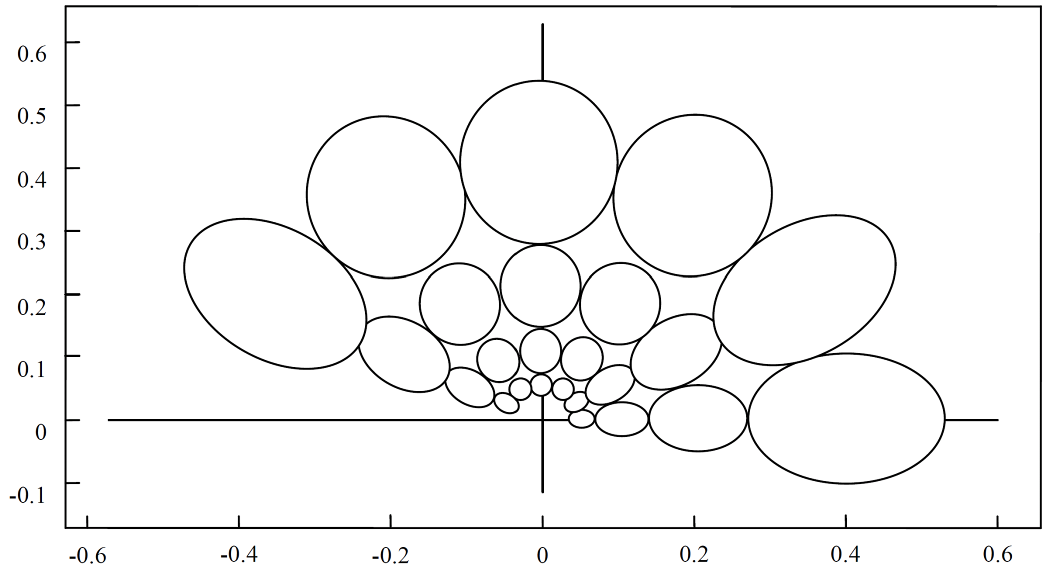


FIGURE 10. The contours indicate the half-peak magnitude of the filter responses in the Gabor filter dictionary.

Current Gabor-based face recognition can be divided into two major types including analytical methods and holistic methods[51]. The flow of analytical method is shown in Figure 11, and the one of holistic method as shown in Figure 12. Based on how they select the nodes, analytical methods can be divided into graph-matching based, manual detection (or other non-graph algorithms) and enhanced methods as shown in Table 2. As show in Figure 12, Holistic methods consider Gabor convolutions as a whole and therefore usually rely on an adequate preprocessing, like face alignment, size normalization and tilt correction. However these method still endure the dimensionality problem. So in the practical applications, dimensionality reduction methods such as PCA and LDA should be implemented to reduce the dimensionality of the vectors[52].

### 3.2. **Machine learning based face recognition.**

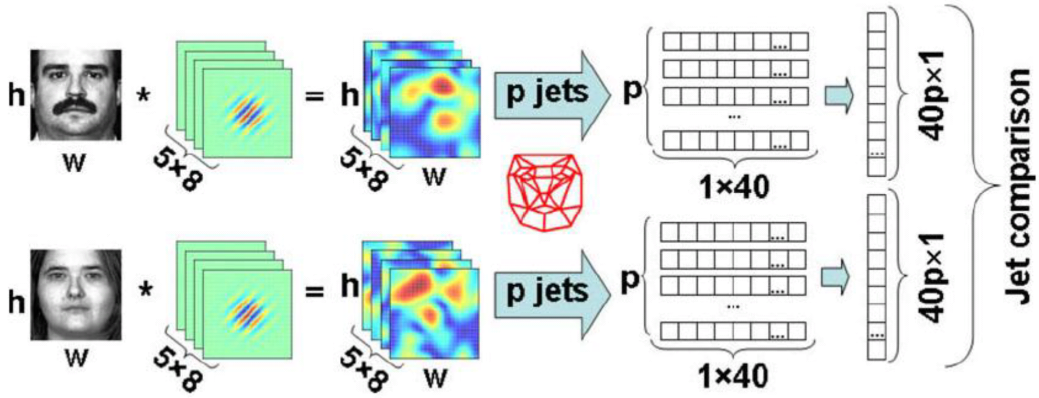


FIGURE 11. Outline of analytical methods[51]

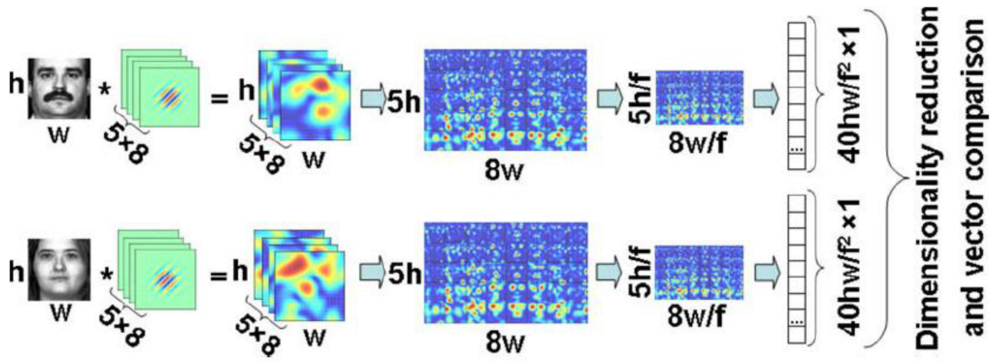


FIGURE 12. Outline of holistic methods[51]

3.2.1. *Manifold learning based face recognition.* Feature extraction with dimensionality reduction is an important step and essential process in embedding data analysis [53]. Linear dimensionality reduction aims to develop a meaningful low dimensional subspace in a high-dimensional input space such as PCA and LDA. LDA is to find the optimal projection matrix with Fisher criterion through considering the class labels, and PCA seeks to minimize the mean square error criterion. PCA is generalized to form the nonlinear curves such as principal curves [54] or principal surfaces [55]. Principal curves and surfaces are nonlinear generalizations of principal components and subspaces, respectively. The principal curves are essentially equivalent to self-organizing maps (SOM) [56]. With the extended SOM, ViSOM preserves directly the distance information on the map along with the topology [57], which represents the nonlinear data [58] and represents a discrete principal curve or surface through producing a smooth and graded mesh in the data space. Recently, researchers proposed other manifold algorithms such as Isomap [59], Locally Linear Embedding (LLE) [60] and Locality Preserving Projection (LPP) [61]. LPP project easily any new data point in the reduced representation space through preserving the local structure and intrinsic geometry of the data space [62]. Many improved LPP algorithms were proposed in recent years. Zheng et al. used the class labels of data points to enhance its discriminant power in the low-dimensional mapping space to propose Supervised Locality Preserving Projection (SLPP) for face recognition [63]. However, LPP is not orthogonal, which makes it difficult to reconstruct the data, so researchers applied the class information to present Orthogonal Discriminant Locality Preserving Projections (ODLPP) for face recognition through orthogonalizing the basis vectors of the face subspace [64]. Cai et al. proposed the orthogonal locality preserving projection (OLPP) to produce orthogonal basis functions with more power of preserving locality than LPP [65]. OLPP was reported to have more discriminating power than LPP. Yu et al. introduced a simple uncorrelated constraint into the objective

TABLE 2. Gabor-based face recognition[51]

| Types | Major methods |
|---|---|
| Graph-based | EBGM<br>DLA |
| Non-graph-based | Manual detection<br>Ridge/valley detection<br>Non-uniform sampling<br>Gaussian mixture models |
| Enhanced | Optimal Gabor parameters<br>Gabor + Adaboost |
| Downsampled Gabor+ PCA/LDA | GFC |
| | HEGFC |
| Downsampled Gabor kernel PCA/LDA | Gabor Kernel PCA<br>Gabor + KDDA |
| Gabor 2D Methods | Gabor + 2DPCA<br>Gabor + B2DPCA<br>Gabor + (2D)2PCA |
| Local Binary Patterns | LGBPHS<br>GBC<br>HGPP |
| No downsampling | Multichannel Gabor + PCA |

function to present Uncorrelated Discriminant Locality Preserving Projections (UDLPP) with the aim of preserving the within-class geometric structure but maximizing the between-class distance [66]. In order to improve the performance of LPP on the nonlinear feature extraction, researchers perform UDLPP in reproducing kernel Hilbert space to develop Kernel UDLPP for face recognition and radar target recognition. Feng et al. presented an alternative formulation of Kernel LPP (KLPP) to develop a framework of KPCA+LPP algorithm [67]. In recent research, Locality Preserving Projection and its improved methods are used in many areas, such as object recognition [68], [69],[70]. Face detection [71],[72]. Image analysis [73]. For any special image-based applications, such as face recognition, researchers proposed 2D LPP which extracts directly the proper features from image matrices without transforming one matrix into one vector [74], [75] and [76]. Both PCA and LPP are unsupervised learning methods, LDA is supervised learning method. One of the differences between PCA and LPP lies in the global or local preserving property, that is, PCA seeks to preserve the global property while LPP preserves the local structure. The locality preserving property leads to the fact that LPP outperforms PCA. Also as the global method, LDA utilizes the class information to enhance its discriminant ability which causes LDA to outperform PCA on classification. But the objective function of LPP is to minimize the local quantity, i.e., the local scatter of the projected data. This criterion cannot be guaranteed to yield a good projection for classification purposes. So it is reasonable to enhance LPP on classification using the class information like LDA.

3.2.2. *Kernel learning based face recognition.* Some algorithms using the kernel trick are developed in recent years, such as kernel principal component analysis (KPCA), kernel discriminant analysis (KDA) and support vector machine (SVM). KPCA was originally developed by Scholkopf et al. in 1998, while KDA was firstly proposed by Mika et al. in 1999. KDA has been applied in many real-world applications owing to its excellent performance on feature extraction. Researchers have developed a series of KDA algorithms (Juwei Lu[77], Baudat and Anouar [78], Liang and Shi [79],[80],[81], Yang [98],[83], J. Lu [82], Zheng [84], Huang [85], Wang [86] and Chen [87], Yixiong Liang [88], Yu-jie Zheng [89], Dacheng Tao[90], Yong Xu [91], Kamel Saadi [92], Dit-Yan Yeung [93], LinLin Shen [94], Bo Ma [95], Xiao-Hong Wu [96], Qingshan Liu[97]). Because the geometrical structure of the data in the kernel mapping space, which is totally determined by the kernel function, has significant impact on the performance of these KDA methods. The separability of the data in the feature space could be even worse if an inappropriate kernel is used. In order to improve the performance of KDA, many methods of optimizing the kernel parameters of the kernel function are developed in recent years (Huang [85], Wang [86] and Chen [87]). However, choosing the parameters for kernel just from a set of discrete values of the parameters doesnt change the geometrical structures of the data in the kernel mapping space. In order to overcome the limitation of the conventional KDA, we introduce a novel kernel named quasiconformal kernel which were widely studied in the previous work [99][100][101][102], where the geometrical structure of data in the feature space is changeable with the different parameters of the quasiconformal kernel. The optimal parameters are computed through optimizing an objective function designed with the criterion of maximizing the class discrimination of the data in the kernel mapping space.

4. **Face recognition: Application conditions.** Face recognition has its limitations in practical applications including poses and training samples collection. As shown in Table 3, the current methods are divided into the following types including pose transformation in image space, pose transformation in feature space, general algorithms, generic shape-based methods, feature-based 3D reconstruction, 2D techniques for face recognition across pose and local approaches.

The performance of face recognition system is influenced by many factors. And the limited number of training sample per person is a major factor. Now it is a still question whether it deserves further investigation. Firstly the extreme case of one sample per person really commonly happens in real scenarios and this problem needs be carefully addressed. Secondly storing only one sample per person in the database has several advantages desired by most real world applications. In fact, the practical face recognition system with only single training sample per person has its advantage owing to the following factors of easy sample collection, storage cost saving, and computational cost saving. Current algorithms can be divided into three types including holistic methods, local methods and hybrid methods[140][141].

Holistic methods. These methods identify a face using the whole face image as input. The main challenge faced by these methods is how to address the extremely small sample problem.

Local methods. These methods use the local facial features for recognition. Care should be taken when deciding how to incorporate global configurational information into local face model. Hybrid methods. These methods use both the local and holistic features to recognize a face. These methods have the potential to offer better performance than individual holistic or local methods, since more comprehensive information could be utilized. Table 4 summarizes algorithms and representative works for face recognition from a single image. Below, we discuss the motivation and general approach of each category first, and then, we give the review of each method, discussing its advantages and disadvantages.

In many practical applications, owing to the difficulties of collecting samples or storage space of systems, only one sample image per person is stored in the system, so the research of face recognition from one sample per person, owing to its own advantages (easy collecting of samples, less storage and computational cost), has been a sub-research topic in the face recognition area. The traditional method such as Fisherface [143] fails when each person just has one training face sample available because of nonexistence of the intra-class scatter. Recently researchers have proposed many algorithms, such as (PC)2A [144], as shown in Figure 12, these two projections

Table 3. Face recognition methods across pose

| Main ideas | Methods |
|---|---|
| Pose transformation in image space | Parallel deformation [103]<br>Pose parameter manipulation [104]<br>Active appearance models [105,106]<br>Linear shape model [107]<br>Eigen light-field [108] |
| Pose transformation in feature space | Kernel methods(kernelPCA [109,110]<br>Kernel FDA [111,112])<br>Expert fusion [113]<br>Correlation filters [114]<br>Local linear regression [115]<br>tied factor analysis [116] |
| General algorithms | Principal component analysis [117,118,119]<br>Artificial neural network(convolutionalnetworks [120])<br>Line edgemaps [121]<br>Directional cornerpoint [122] |
| Generic shape-based methods | Cylindrical 3D pose recovery [123]<br>Probabilistic geometry assisted facerecognition [124]<br>Automatic texture synthesis [125] |
| Feature-based 3D reconstruction | Composite deformable model [126]<br>Jiang's method [127]<br>Multi-level quadratic variation minimisation [128]<br>Image-based 3D reconstruction<br>Morphable model [129,130]<br>Illumination cone model [131,132]<br>Stereo matching [133] |
| 2D techniques for face recognition | Real view-basedmatching<br>Beymer's method [134] |
| across pose | panoramicview [135] |
| Local approaches | Template matching [136]<br>Modular PCA [137]<br>Elastic bunch graph matching [138]<br>Local binary patterns [139] |

reflect the distribution of the salient facial features that are useful for face recognition. Other enhanced algorithms are E(PC)2A [145] and SVD perturbation [146], for face recognition with one training image per person. But these algorithms still endure some problem. For example, the procedure of E(PC)2A is divided into two stages: 1) constructing a new image by combining the first-order and second-order projected images and the original image; 2) performing PCA on the newly-combined training images. In the second stage, the combined image matrix should be mapped into a 1D vector in advance in order to perform PCA. This causes the high storage and computational cost. In order to enhance the practicability of the face recognition system, we propose a novel algorithm so-called 2D(PC)2A for face recognition with one training image per person in this letter. 2D(PC)2A performs principal component analysis on the set of combined training images directly without mapping the image matrix to 1D vector. Thus 2D(PC)2A can directly extract feature matrix from the original image matrix. This leads to that much less time is required for training and feature extraction. Further, experiments implemented on two popular databases show that the recognition performance of 2D(PC)2A is better than that of classical E(PC)2A.

5. **Conclusion.** Face recognition is an important but a challenging problem both in theory and for real-world applications. In this paper, we attempt to provide a comprehensive survey

Table 4. Current face recognition methods from a single training sample

| Main ideas | Methods |
| --- | --- |
| Local feature-based | Graph matching methods [150-153]<br>Use directional corner points (DCP) features for recognition [154] |
| Local appearance-based | Modified LDA method [155,156]<br>SOM learning based recognition [157,158]<br>l HMM method [159]<br>Local probabilistic subspace method [160]<br>Fractal-based face recognition [161]<br>Hybrid local features [162]<br>Local probabilistic subspace method [160]<br>Face recognition with local binary patterns [163] |
| Extensions of Principal-Component analysis (PCA) | Use noise model to synthesize new face[164]<br>Enrich face image with its projections [165]<br>Select discriminant eigenfaces for face recognition[166]<br>Two dimensional PCA [167] |
| Enlarge the size of training set | ROCA[147], Imprecisely location method [160], E(PC)2A [148]<br>View synthesis using prior class-specific information [149] |

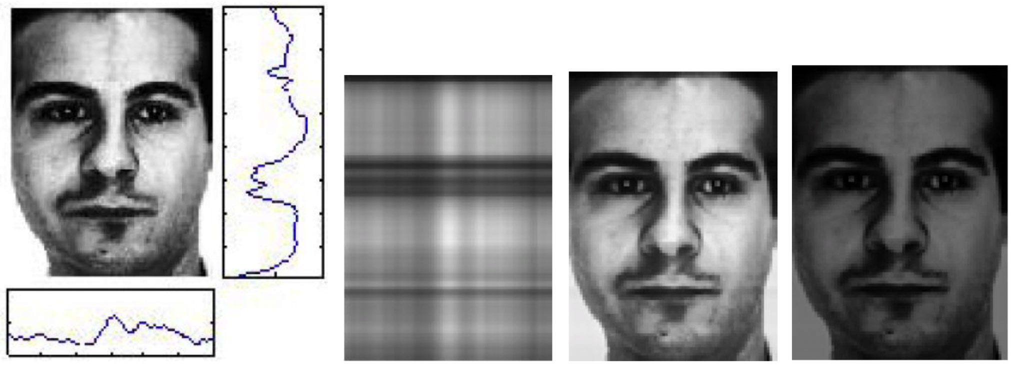

Figure 13. Some sample images in (PC)2A method. (a) original face image and its horizontal and vertical profiles. (b) first-ordered projection map (c) first-ordered projection-combined image (d) second-ordered combined image

of current researches on this problem. This paper is to have a comprehensive survey on face recognition from practical applications, sensory inputs, methods, and application conditions. Face recognition from image-based, video-based, 3D-based and hypersprectral image based face recognition are discussed and a novel face recognition method including kernel learning, manifold learning method.

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