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A Survey of Face Recognition Techniques

Rabia Jafri* and Hamid R. Arabnia*

Abstract: Face recognition presents a challenging problem in the field of image analysis and computer vision, and as such has received a great deal of attention over the last few years because of its many applications in various domains. Face recognition techniques can be broadly divided into three categories based on the face data acquisition methodology: methods that operate on intensity images; those that deal with video sequences; and those that require other sensory data such as 3D information or infra-red imagery. In this paper, an overview of some of the well-known methods in each of these categories is provided and some of the benefits and drawbacks of the schemes mentioned therein are examined. Furthermore, a discussion outlining the incentive for using face recognition, the applications of this technology, and some of the difficulties plaguing current systems with regard to this task has also been provided. This paper also mentions some of the most recent algorithms developed for this purpose and attempts to give an idea of the state of the art of face recognition technology.

Keywords: *Face Recognition, Person Identification, Biometrics*

1. Problem Definition

The face recognition problem can be formulated as follows: Given an input face image and a database of face images of known individuals, how can we verify or determine the identity of the person in the input image?

2. Why Use the Face for Recognition

Biometric-based techniques have emerged as the most promising option for recognizing individuals in recent years since, instead of authenticating people and granting them access to physical and virtual domains based on passwords, PINs, smart cards, plastic cards, tokens, keys and so forth, these methods examine an individual's physiological and/or behavioral characteristics in order to determine and/or ascertain his identity. Passwords and PINs are hard to remember and can be stolen or guessed; 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.

Biometric-based technologies include identification based on physiological characteristics (such as face, fingerprints, finger geometry, hand geometry, hand veins, palm, iris, retina, ear and voice) and behavioral traits (such as gait, signature and keystroke dynamics) [1]. Face recognition appears to offer several advantages over other biometric methods, a few of which are outlined here: Almost all these technologies require some voluntary action by the user, i.e., the user needs to place his hand on a hand-rest for fingerprinting or hand geometry detection and has to stand in a fixed position in front of a camera for iris or retina identification. However, face recognition can be done passively without any explicit action or participation on the part of the user since face images can be acquired from a distance by a camera. This is particularly beneficial for security and surveillance purposes. Furthermore, data acquisition in general is fraught with problems for other biometrics: techniques that rely on hands and fingers can be rendered useless if the epidermis tissue is damaged in some way (i.e., bruised or cracked). Iris and retina identification require expensive equipment and are much too sensitive to any body motion. Voice recognition is susceptible to background noises in public places and auditory fluctuations on a phone line or tape recording. Signatures can be modified or forged. However, facial images can be easily obtained with a couple of inexpensive fixed cameras. Good face recognition algorithms and appropriate preprocessing of the images can compensate for noise and slight variations in orientation, scale and illumination. Finally, technologies that require multiple individuals to use the same equipment to capture their biological characteristics potentially expose the user to the transmission of germs and impurities from other users. However, face recognition is totally non-intrusive and does not carry any such health risks.

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Corresponding Author: Hamid R. Arabnia
* Dept. of Computer Science, University of Georgia, Athens, Georgia, U.S.A. ({jafri, hra}@cs.uga.edu)

3. Applications

Face recognition is used for two primary tasks:

1. Verification (one-to-one matching): When presented with a face image of an unknown individual along with a claim of identity, ascertaining whether the individual is who he/she claims to be.
2. Identification (one-to-many matching): Given an image of an unknown individual, determining that person's identity by comparing (possibly after encoding) that image with a database of (possibly encoded) images of known individuals.

There are numerous application areas in which face recognition can be exploited for these two purposes, a few of which are outlined below.

- Security (access control to buildings, airports/seaports, ATM machines and border checkpoints [2, 3]; computer/ network security [4]; email authentication on multimedia workstations).
- Surveillance (a large number of CCTVs can be monitored to look for known criminals, drug offenders, etc. and authorities can be notified when one is located; for example, this procedure was used at the Super Bowl 2001 game at Tampa, Florida [5]; in another instance, according to a CNN report, two cameras linked to state and national databases of sex offenders, missing children and alleged abductors have been installed recently at Royal Palm Middle School in Phoenix, Arizona [6]).
- General identity verification (electoral registration, banking, electronic commerce, identifying newborns, national IDs, passports, drivers' licenses, employee IDs).
- Criminal justice systems (mug-shot/booking systems, post-event analysis, forensics).
- Image database investigations (searching image databases of licensed drivers, benefit recipients, missing children, immigrants and police bookings).
- "Smart Card" applications (in lieu of maintaining a database of facial images, the face-print can be stored in a smart card, bar code or magnetic stripe, authentication of which is performed by matching the live image and the stored template) [7].
- Multi-media environments with adaptive human-computer interfaces (part of ubiquitous or context-aware systems, behavior monitoring at childcare or old people's centers, recognizing a customer and assessing his needs) [8, 9].
- Video indexing (labeling faces in video) [10, 11].
- Witness face reconstruction [12].

In addition to these applications, the underlying techniques in the current face recognition technology have also been modified and used for related applications such as gender classification [13-15], expression recognition [16, 17] and facial feature recognition and tracking [18]; each of these has its utility in various domains: for instance, expression recognition can be utilized in the field of medicine for intensive care monitoring [19] while facial feature recognition and detection can be exploited for tracking a vehicle driver's eyes and thus monitoring his fatigue [20], as well as for stress detection [21].

Face recognition is also being used in conjunction with other biometrics such as speech, iris, fingerprint, ear and gait recognition in order to enhance the recognition performance of these methods [8, 22-34].

4. General Difficulties

Face recognition is a specific and hard case of object recognition. The difficulty of this problem stems from the fact that in their most common form (i.e., the frontal view) faces appear to be roughly alike and the differences between them are quite subtle. Consequently, frontal face images form a very dense cluster in image space which makes it virtually impossible for traditional pattern recognition techniques to accurately discriminate among them with a high degree of success [35].

Furthermore, the human face is not a unique, rigid object. Indeed, there are numerous factors that cause the appearance of the face to vary. The sources of variation in the facial appearance can be categorized into two groups: intrinsic factors and extrinsic ones [36]. A) Intrinsic factors are due purely to the physical nature of the face and are independent of the observer. These factors can be further divided into two classes: intrapersonal and interpersonal [37]. Intrapersonal factors are responsible for varying the facial appearance of the same person, some examples being age, facial expression and facial paraphernalia (facial hair, glasses, cosmetics, etc.). Interpersonal factors, however, are responsible for the differences in the facial appearance of different people, some examples being ethnicity and gender. B) Extrinsic factors cause the appearance of the face to alter via the interaction of light with the face and the observer. These factors include illumination, pose, scale and imaging parameters (e.g., resolution, focus, imaging, noise, etc.).

Evaluations of state-of-the-art recognition techniques conducted during the past several years, such as the FERET evaluations [7, 38], FRVT 2000 [39], FRVT 2002 [40] and the FAT 2004 [41], have confirmed that age variations, illumination variations and pose variations are three major problems plaguing current face recognition systems [42].

Although most current face recognition systems work well under constrained conditions (i.e., scenarios in which at least a few of the factors contributing to the variability between face images are controlled), the performance of most of these systems degrades rapidly when they are put to work under conditions where none of these factors are regulated [43].

5. Face Recognition Techniques

The method for acquiring face images depends upon the underlying application. For instance, surveillance applications may best be served by capturing face images by means of a video camera while image database investigations may require static intensity images taken by a standard camera. Some other applications, such as access to top security domains, may even necessitate the forgoing of the non-intrusive quality of face recognition by requiring the user to stand in front of a 3D scanner or an infra-red sensor. Therefore, depending on the face data acquisition methodology, face recognition techniques can be broadly divided into three categories: methods that operate on intensity images, those that deal with video sequences, and those that require other sensory data such as 3D information or infra-red imagery. The following discussion sheds some light on the methods in each category and attempts to give an idea of some of the benefits and drawbacks of the schemes mentioned therein in general (for detailed surveys, please see [44, 45]).

5.1 Face Recognition from Intensity Images

Face recognition methods for intensity images fall into two main categories: feature-based and holistic [46-48]. An overview of some of the well-known methods in these categories is given below.

5.1.1 Featured-based

Feature-based approaches first process the input image to identify and extract (and measure) distinctive facial features such as the eyes, mouth, nose, etc., as well as other fiducial marks, and then compute the geometric relationships among those facial points, thus reducing the input facial image to a vector of geometric features. Standard statistical pattern recognition techniques are then employed to match faces using these measurements.

Early work carried out on automated face recognition was mostly based on these techniques. One of the earliest such attempts was by Kanade [49], who employed simple image processing methods to extract a vector of 16 facial parameters - which were ratios of distances, areas and angles (to compensate for the varying size of the pictures) - and used a simple Euclidean distance measure for matching to achieve a peak performance of 75% on a database of 20 different people using 2 images per person (one for reference and one for testing).

Brunelli and Poggio [46], building upon Kanade's approach, computed a vector of 35 geometric features (Fig. 1) from a database of 47 people (4 images per person) and reported a 90% recognition rate. However, they also reported 100% recognition accuracy for the same database using a simple template-matching approach.

More sophisticated feature extraction techniques involve deformable templates ([50], [51], [52]), Hough transform methods [53], Reisfeld's symmetry operator [54] and Graf's filtering and morphological operations [55]. However, all of these techniques rely heavily on heuristics such as restricting the search subspace with geometrical constraints [56]). Furthermore, a certain tolerance must be given to the models since they can never perfectly fit the structures in the image. However, the use of a large tolerance value tends to destroy the precision required to recognize individuals on the basis of the model's final best-fit parameters and makes these techniques insensitive to the minute variations needed for recognition [37]. More recently, Cox et al. [57] reported a recognition performance of 95% on a database of 685 images (a single image for each individual) using a 30-dimensional feature vector derived from 35 facial features (Fig. 2). However, the facial features were manually extracted, so it is reasonable to assume that the recognition performance would have been much lower if an automated, and hence less precise, feature extraction method had been adopted. In general, current algorithms for automatic feature extraction do not provide a high degree of accuracy and require considerable computational capacity [58].

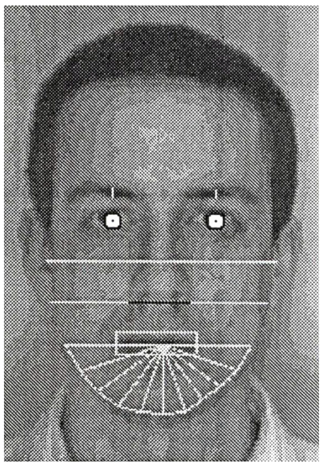


Fig. 1. Geometrical features (white) used in the face recognition experiments [46]. (©1993 IEEE)

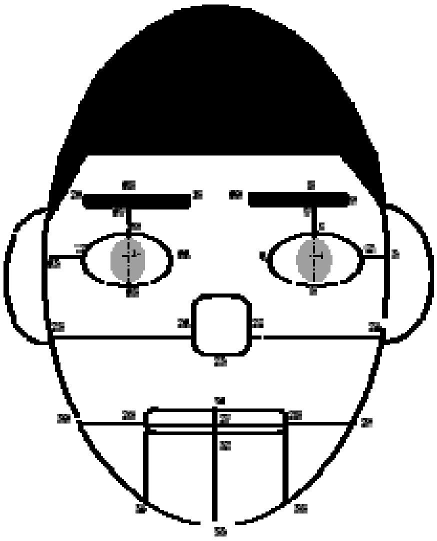


Fig. 2. 35 manually identified facial features [57]. (©1996 IEEE)

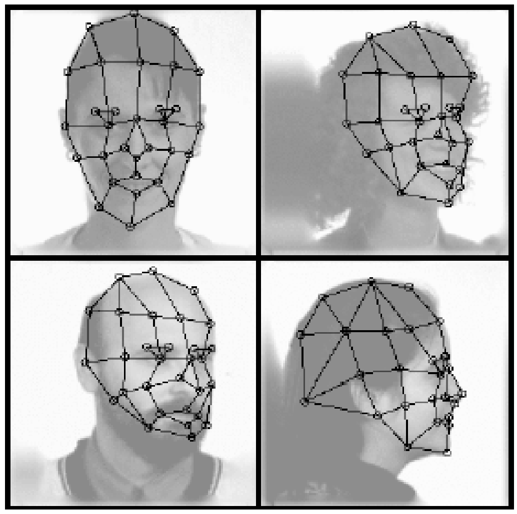


Fig. 3. Grids for face recognition [61]. (©1999 IEEE)

Another well-known feature-based approach is the elastic bunch graph matching method proposed by Wiskott et al. [59] . This technique is based on Dynamic Link Structures [60]. A graph for an individual face is generated as follows: a set of fiducial points on the face are chosen. Each fiducial point is a node of a full connected graph, and is labeled with the Gabor filters' responses applied to a window around the fiducial point. Each arch is labeled with the distance between the correspondent fiducial points. A representative set of such graphs is combined into a stack-like structure, called a *face bunch graph*. Once the system has a face bunch graph, graphs for new face images can then be generated automatically by Elastic Bunch Graph Matching. Recognition of a new face image is performed by comparing its image graph to those of all the known face images and picking the one with the highest similarity value. Using this architecture, the recognition rate can reach 98% for the first rank and 99% for the first 10 ranks using a gallery of 250 individuals. The system has been enhanced to allow it to deal with different poses (Fig. 3) [61] but the recognition performance on faces of the same orientation remains the same. Though this method was among the best performing ones in the most recent FERET evaluation [62, 63], it does suffer from the serious drawback of requiring the graph placement for the first 70 faces to be done manually before the elastic graph matching becomes adequately dependable [64]. Campadelli and Lanzarotti [65] have recently experimented with this technique, where they have eliminated the need to do the graph placement manually by using parametric models, based on the deformable templates proposed in [50], to automatically locate fiducial points. They claim to have obtained the same performances as the elastic bunch graph employed in [59]. Other recent variations of this approach replace the Gabor features by a graph matching strategy [66] and HOGs (Histograms of Oriented Gradients [67].

Considerable effort has also been devoted to recognizing faces from their profiles [68-72] since, in this case, feature extraction becomes a somewhat simpler one-dimensional problem [57, 71]. Kaufman and Breeding [70] reported a recognition rate of 90% using face profiles; however, they used a database of only 10 individuals. Harmon et al. [68] obtained recognition accuracies of 96% on a database of 112 individuals, using a 17-dimensional feature vector to describe face profiles and utilizing a Euclidean distance measure for matching. More recently, Liposcak and Loncaric [71] reported a 90% accuracy rate on a database of 30 individuals, using subspace filtering to derive a 21-dimensional feature vector to describe the face profiles and employing a Euclidean distance measure to match them (Fig. 4).

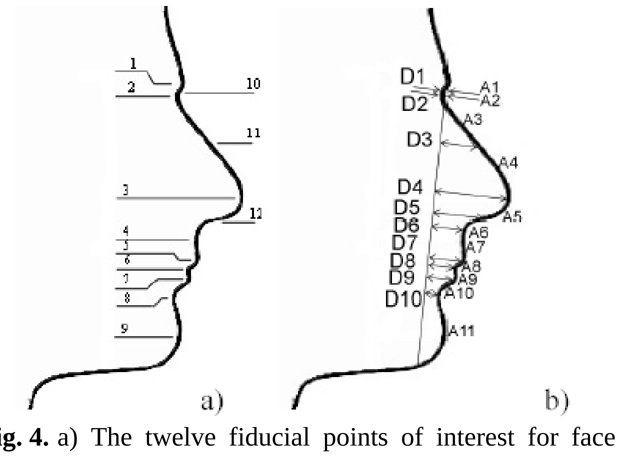


Fig. 4. a) The twelve fiducial points of interest for face recognition; b) Feature vector has 21 components; ten distances D1-D10 (normalized with /(D4+D5)) and eleven profile arcs A1-A11 (normalized with /(A5+A6)) [71]. (Courtesy of Z. Liposcak and S. Loncaric)

5.1.1.1 Advantages and Disadvantages

The main advantage offered by the featured-based techniques is that since the extraction of the feature points precedes the analysis done for matching the image to that of a known individual, such methods are relatively robust to position variations in the input image [37]. In principle, feature-based schemes can be made invariant to size, orientation and/or lighting [57]. Other benefits of these schemes include the compactness of representation of the face images and high speed matching [73].

The major disadvantage of these approaches is the difficulty of automatic feature detection (as discussed above) and the fact that the implementer of any of these techniques has to make arbitrary decisions about which features are important [74]. After all, if the feature set lacks discrimination ability, no amount of subsequent processing can compensate for that intrinsic deficiency [57].

5.1.2 Holistic

Holistic approaches attempt to identify faces using global representations, i.e., descriptions based on the entire image rather than on local features of the face. These schemes can be subdivided into two groups: statistical and AI approaches. An overview of some of the methods in these categories follows.

5.1.2.1 Statistical

In the simplest version of the holistic approaches, the image is represented as a 2D array of intensity values and recognition is performed by direct correlation comparisons between the input face and all the other faces in the database. Though this approach has been shown to work [75] under limited circumstances (i.e., equal illumination, scale, pose, etc.), it is computationally very expensive and suffers from the usual shortcomings of straightforward correlation-based approaches, such as sensitivity to face orientation, size, variable lighting conditions, background clutter, and noise [76]. The major hindrance to the direct-matching methods' recognition performance is that they attempt to perform classification in a space of very high dimensionality [76]. To counter this curse of dimensionality, several other schemes have been proposed that employ statistical dimensionality reduction methods to obtain and retain the most meaningful feature dimensions before performing recognition. A few of these are mentioned below.

Sirovich and Kirby [77] were the first to utilize Principal Components Analysis (PCA) [78, 79] to economically represent face images. They demonstrated that any particular face can be efficiently represented along the eigenpictures coordinate space, and that any face can be approximately reconstructed by using just a small collection of eigenpictures and the corresponding projections ('coefficients') along each eigenpicture.

Turk and Pentland [80, 81] realized, based on Sirovich and Kirby's findings, that projections along eigenpictures could be used as classification features to recognize faces. They employed this reasoning to develop a face recognition system that builds eigenfaces, which correspond to the eigenvectors associated with the dominant eigenvalues of the known face (patterns) covariance matrix, and then recognizes particular faces by comparing their projections along the eigenfaces to those of the face images of the known individuals. The eigenfaces define a feature space that drastically reduces the dimensionality of the original space, and face identification is carried out in this reduced space. An example training set, the average face and the top seven eigenfaces derived from the training images are shown in (Figs. 5, 6 and 7), respectively. The method was tested using a database of 2,500 images of 16 people under all combinations of 3 head orientations, 3 head sizes or scales, and 3 lighting conditions and various resolutions. Recognition rates of 96%, 85% and 64% were reported for lighting, orientation and scale variation. Though the method appears to be fairly robust to lighting variations, its performance degrades with scale changes.

The capabilities of Turk and Pentland's system have

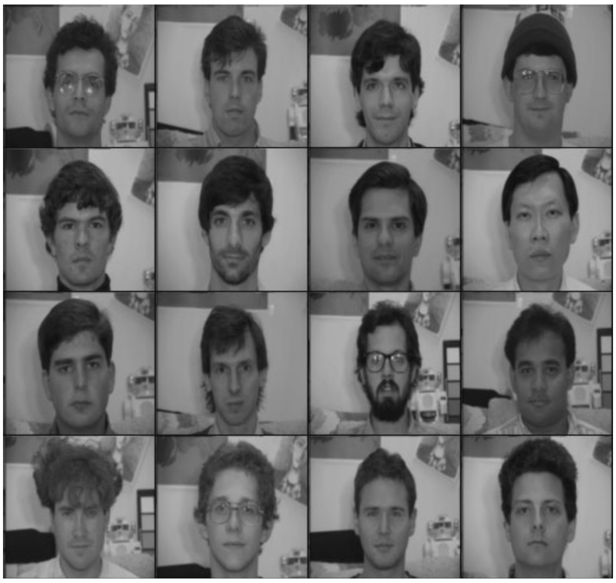


Fig. 5. An example training set [81]. (With kind permission of MIT Press Journals)

Fig. 6. The average face [81]. (With kind permission of MIT Press Journals)

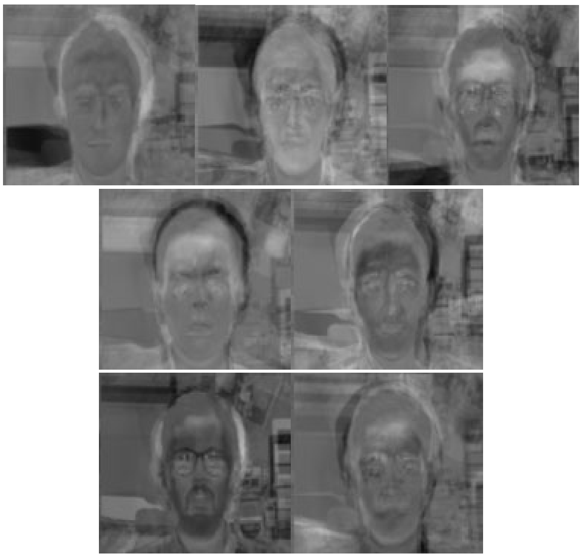
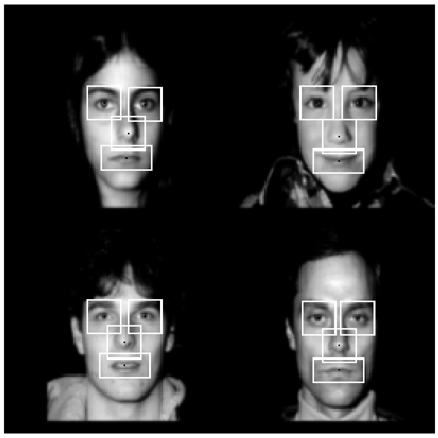
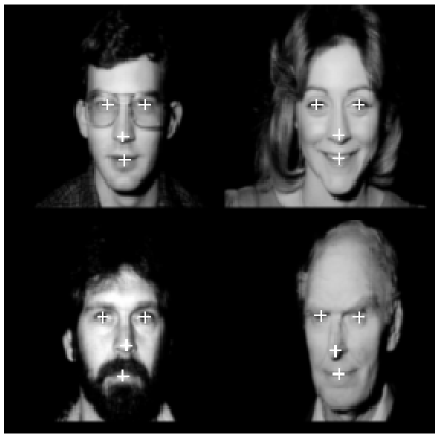


Fig. 7. Seven of the eigenfaces calculated from the images of Fig. 5, without the background removed [81]. (With kind permission of MIT Press Journals)

been extended in several ways in [82] and tested on a database of 7,562 images of approximately 3,000 people. A "multiple observer" method has been suggested to deal with large changes in pose: Given *N* individuals under *M* different views, one can either do recognition and pose estimation in a universal eigenspace calculated from the combination of *NM* images (parametric approach) or, alternatively, one can build a set of *M* separate eigenspaces, one for each of the *N* views (the view-based approach). The view-based approach is reported to have yielded better results than the parametric one. A modular "eigenfeatures" approach has also been proposed to deal with localized variations in the facial appearance where a low-resolution description of the whole face is augmented by additional higher resolution details in terms of the salient facial features (Fig. 8). This system is reported to have produced slightly better results than the basic eigenfaces approach (Figs. 9, 10). Though no implementation has been reported, it has however been suggested in [81] that variation in scale be dealt with by employing multi-scale eigenfaces or by rescaling the input image to multiple sizes and using the scale that results in the smallest distance measure to the face space. PCA appears to work well when a single image of each individual is available, but when multiple images per person are present, then Belhumeur et al. [83] argue that by choosing the projection which maximizes total scatter, PCA retains unwanted variations due to lighting and facial expression. As stated by Moses et al. [84], "the variations between the images of the same face due to illumination and lighting direction are almost always larger than image variations due to a change in face identity" (see Fig. 11 for an example of this.) Therefore, they propose



(a)



(b)

Fig. 8. (a) Examples of facial feature training templates used and (b) the resulting typical detections [82]. (©1994 IEEE)

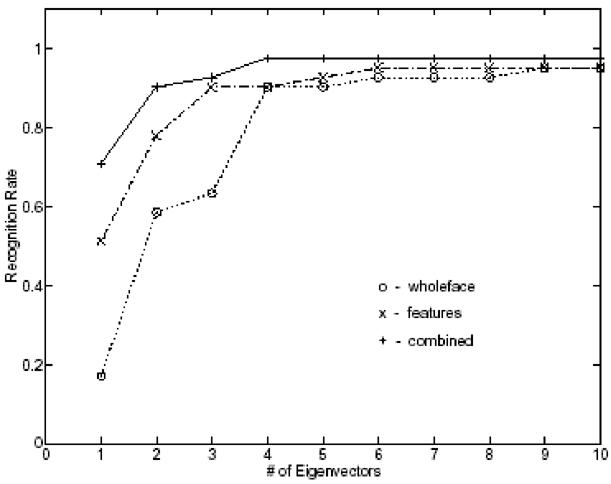


Fig. 9. Recognition rates for eigenfaces, eigenfeatures, and the combined modular representation [82]. (©1994 IEEE)

using Fisher's Linear Discriminant Analysis [85], which maximizes the ratio of the between-class scatter and the

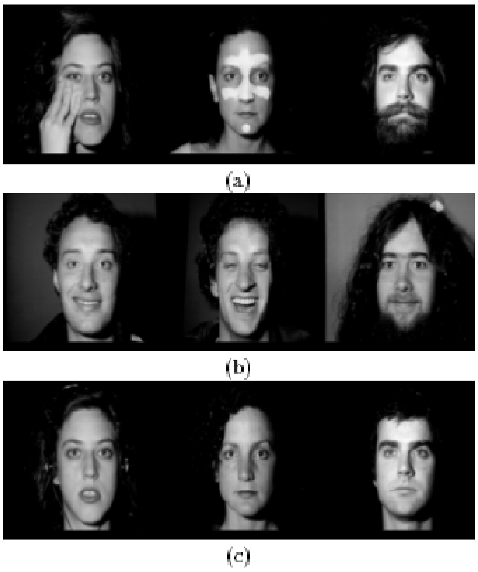


Fig. 10. (a) Test views, (b) Eigenface matches, (c) Eigenfeature matches [82]. (©1994 IEEE)

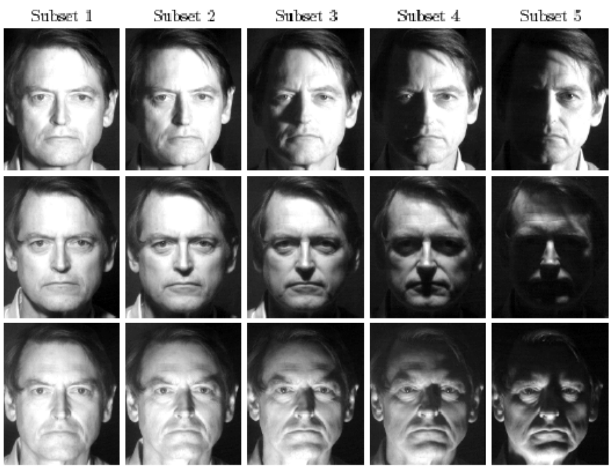


Fig. 11. The same person seen under varying light conditions can appear dramatically different [83]. (©1997 IEEE)

within-class scatter and is thus purportedly better for classification than PCA. Conducting various tests on 330 images of 5 people (66 of each), they report that their method, called Fisherfaces, which uses subspace projection prior to LDA projection (to prevent the within-class scatter matrix from becoming degenerate), is better at simultaneously handling variations in lighting and expression. Swets and Weng [86] previously reported similar results when employing the same procedure not only for faces but also for general objects (90% accuracy on a database of 1316+298 images from 504 classes) (Fig. 12 shows some examples of eigenfaces and Fisherfaces and how Fisherfaces capture discriminatory information better than eigenfaces). It should be noted, however, that some recent work [87] shows that when the training data set is small,

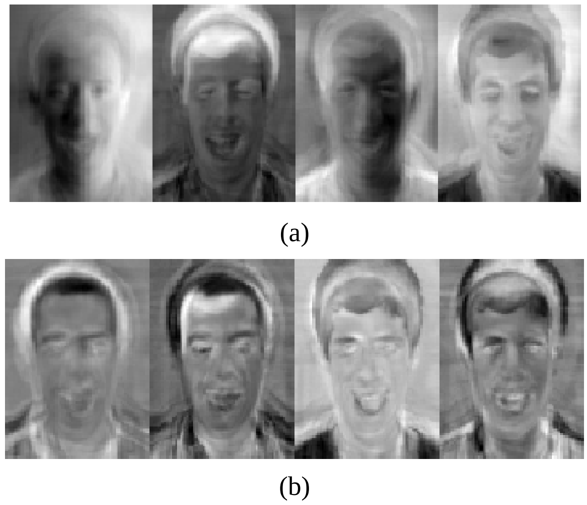


Fig. 12. (a) This sample of eigenfaces shows the tendency of the principal components to capture major variations in the training set such as lighting direction; (b) The corresponding sample of Fisherfaces shows the ability of Fisherfaces to discount those factors unrelated to classification [86]. (©1996 IEEE).

PCA can outperform LDA and also that PCA is less sensitive to different training sets.

The standard eigenfaces and the Fisherfaces approaches assume the existence of an optimal projection that projects the face images to distinct non-overlapping regions in the reduced subspace where each of these regions corresponds to a unique subject. However, in reality, that assumption may not necessarily be true since images of different people may frequently map to the same region in the face space and, thus, the regions corresponding to different individuals may not always be disjoint.

Moghaddam et al. [88] propose an alternative approach which utilizes difference images, where a difference image for two face images is defined as the signed arithmetic difference in the intensity values of the corresponding pixels in those images. Two classes of difference images are defined: *intrapersonal*, which consists of difference images originating from two images of the same person, and *extrapersonal,* which consists of difference images derived from two images of different people.

It is assumed that both these classes originate from discrete Gaussian distributions within the space of all possible difference images. Then, given the difference image between two images I_1 and I_2, the probability that the difference image belongs to the intrapersonal class is given by Bayes Rule as follows:

$$P(\Omega_I \mid d(I_1, I_2)) = \frac{P(d(I_1, I_2) \mid \Omega_I) P(\Omega_I)}{P(d(I_1, I_2) \mid \Omega_I) P(\Omega_I) + P(d(I_1, I_2) \mid \Omega_E) P(\Omega_E)} \quad (1)$$

where

$d(I_1, I_2)$ = the difference image between two images I_1 and I_2

Ω_I = the intrapersonal class

Ω_E = the extrapersonal class

The formulation of the face recognition problem in this manner converts it from an *m*-ary classification problem (where *m* is the number of individuals in the database of known face images) into a binary classification problem which can be solved using the maximum a posteriori (MAP) rule – the two images are declared to belong to the same individual if $P(\Omega_I|d(I_1, I_2)) > P(\Omega_E|d(I_1, I_2))$ or, equivalently, if $P(\Omega_I|d(I_1, I_2)) > ½$. For a computationally more expedient approach, Moghaddam and Pentland [89] also suggest ignoring the extrapersonal class information and calculating the similarity based only on the intrapersonal class information. In the resulting maximum likelihood (ML) classifier, the similarity score is given only by $P(d(I_1, I_2)| \Omega_I)$.

Numerous variations on and extensions to the standard eigenfaces and the Fisherfaces approaches have been suggested since their introduction. Some recent advances in PCA-based algorithms include multi-linear subspace analysis [90], symmetrical PCA [91], two-dimensional PCA [92, 93], eigenbands [94], adaptively weighted sub-pattern PCA [95], weighted modular PCA [96], Kernel PCA [97, 98] and diagonal PCA [99]. Examples of recent LDA-based algorithms include Direct LDA [100, 101], Direct-weighted LDA [102], Nullspace LDA [103, 104], Dual-space LDA [105], Pair-wise LDA [106], Regularized Discriminant Analysis [107], Generalized Singular Value Decomposition [108, 109], Direct Fractional-Step LDA [110], Boosting LDA [111], Discriminant Local Feature Analysis [112], Kernel PCA/LDA [113, 114], Kernel Scatter-Difference-based Discriminant Analysis [115], 2D-LDA [116, 117], Fourier-LDA [118], Gabor-LDA [119], Block LDA [120], Enhanced FLD [121], Component-based Cascade LDA [122], and incremental LDA [123], to name but a few. All these methods purportedly obtain better recognition results than the baseline techniques.

One main drawback of the PCA and LDA methods is that these techniques effectively see only the Euclidean structure and fail to discover the underlying structure if the face images lie on a non-linear submanifold in the image space. Since it has been shown that face images possibly reside on a nonlinear submanifold [124-130] (especially if there is a perceivable variation in viewpoint, illumination or facial expression), some nonlinear techniques have consequently been proposed to discover the nonlinear structure of the manifold, e.g., Isometric Feature Mapping (ISOMAP) [130], Locally Linear Embedding (LLE) [126, 131], Laplacian Eigenmap [132], Locality Preserving Projection (LPP) [133], Embedded Manifold [134], Nearest Manifold Approach [135], Discriminant Manifold Learning [136] and Laplacianfaces [137].

The eigenvectors found by PCA depend only on pair-wise relationships between the pixels in the image database. However, other methods exist that can find basis vectors that depend on higher-order relationships among the pixels, and it seems reasonable to expect that utilizing such techniques would yield even better recognition results. Independent component analysis (ICA) [138], a generalization of PCA, is one such method that has been employed for the face recognition task. ICA aims to find an independent, rather than an uncorrelated, image decomposition and representation. Bartlett et al. [139] performed ICA on images in the FERET database under two different architectures: one treated the images as random variables and the pixels as outcomes; conversely, the second treated the pixels as the random variables and the images as outcomes. Both ICA representations outperformed PCA representations for recognizing faces across days and changes in expression. A classifier that combined both ICA representations gave the best performance. Others have also experimented with ICA [140-146] and have reported that this technique, and variations of it, appear to perform better then PCA under most circumstances.

Other subspace methods have also been exploited for the face recognition task: Foon et al. [147] have integrated various wavelet transforms and non-negative matrix factorizations [148] and claim to have obtained better verification rates as compared to the basic eigenfaces approach. In [149], an intra-class subspace is constructed, and the classification is based on the nearest weighted distance between the query face and each intra-class subspace. Experimental results are presented to demonstrate that this method performs better than some other nearest feature techniques.

A study and comparison of four subspace representations for face recognition, i.e., PCA, ICA, Fisher Discriminant Analysis (FDA), and probabilistic eigenfaces and their 'kernalized' versions (if available), is presented in [150]. A comprehensive review of recent advances in subspace analysis for face recognition can be found in [151].

5.1.2.2 AI

AI approaches utilize tools such as neural networks and machine learning techniques to recognize faces. Some examples of methods belonging to this category are given below.

In [152], 50 principal components were extracted and an auto-associative neural network was used to reduce those components to five dimensions. A standard multi-layer perceptron was exploited to classify the resulting representation. Though favorable results were received, the database used for training and testing was quite simple: the pictures were manually aligned, there was no lighting variation, tilting, or rotation, and there were only 20 people in the database.

Weng et al. [153] made use of an hierarchical neural network which was grown automatically and not trained on the traditional gradient descent method. They reported good results on a database of 10 subjects.

Lawrence et al [58] reported a 96.2% recognition rate on the ORL database (a database of 400 images of 40 individuals) using a hybrid neural network solution which combines local image sampling, a self-organizing map [154, 155] neural network (which provides dimensionality reduction and invariance to small changes in the image sample), and a convolutional neural network (which provides partial invariance to translation, rotation, scale and deformation). The eigenfaces method [80, 81] produced 89.5% recognition accuracy on the same data. Replacing the self-organizing map by the Karhunen-Loeve transform and the convolutional network by a multi-layer perceptron resulted in a recognition rate of 94.7% and 60% respectively (Fig. 13).

Eleyan and Demirel [156] used principal components analysis to obtain feature projection vectors from face images which were then classified using feed forward neural networks. Some tests on the ORL database using various numbers of training and testing images showed that the performance of this system was better than the eigenfaces [80, 81] one in which a nearest neighbor classifier was used for classification.

Li and Yin [157] introduced a system in which a face image is first decomposed with a wavelet transform to three levels. The Fisherfaces method [83] is then applied to each of the three low-frequency sub-images. Then, the individual classifiers are fused using the RBF neural network. The resulting system was tested on images of 40 subjects from the FERET database and was shown to outperform the individual classifiers and the direct Fisherfaces method.

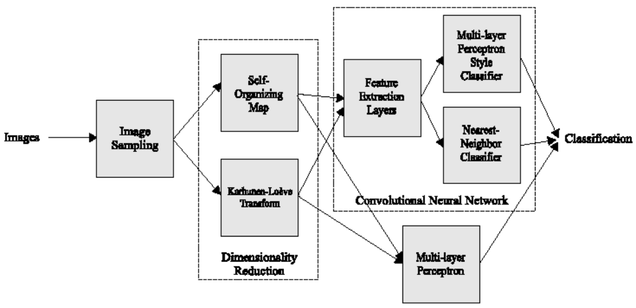


Fig. 13. A high-level diagram of the system used for face recognition [58]. (©1997 IEEE)

Melin et al. [158] divided the face into three regions (the eyes, the mouth, and the nose) and assigned each region to a module of the neural network. A fuzzy Sugeno integral was then used to combine the outputs of the three modules to make the final face recognition decision. They tested it on a small database of 20 people and reported that the modular network yielded better results than a monolithic one.

Recently, Zhang et al. [159] proposed an approach in which a similarity function is learned describing the level of confidence that two images belong to the same person, similar to [88]. The facial features are selected by obtaining Local Binary Pattern (LBP) [160] histograms of the sub-regions of the face image and the Chi-square distances between the corresponding LBP histograms are chosen as the discriminative features. The AdaBoost learning algorithm, introduced by Freund and Schapire [161], is then applied to select the most efficient LBP features as well as to obtain the similarity function in the form of a linear combination of LBP feature-based weak learners. Experimental results on the FERET frontal image sets have shown that this method yields a better recognition rate of 97.9 % by utilizing fewer features than a previous similar approach proposed by Ahonen et al. [162].

Some researchers have also used the one-against-one approach [163] for decomposing the multi-class face recognition problem into a number of binary classification problems. In this method, one classifier is trained for each pair of classes, ignoring all the remaining ones. The outputs of all the binary classifiers are then combined to construct the global result. For binary classifiers with probabilistic outputs, *pair-wise coupling* (PWC) [164] can be used to couple these outputs into a set of posterior probabilities. Then, the test example is assigned to the class with the maximum posterior probability. One main disadvantage of PWC is that when a test example does not belong to either of the classes related to a binary classifier, then the output of that classifier is meaningless and can damage the global result. In [165], a new algorithm called PWC-CC (where CC stands for correcting classifier) is presented to solve this problem: for each binary classifier separating class c_i from class c_j, a new classifier separating the two classes from all other classes is trained. Even though PWC-CC performs better than PWC, it has its own drawbacks. In [166], a novel PWC-CC (NPWC-CC) method is proposed for the face recognition problem and the results of tests on the ORL database are presented to support the claim that it outperforms PWC-CC. In [167], the optimal PWC (O-PWC) approach is introduced and is shown to have better recognition rates that the PWC method. Feature extraction is done by using principal components analysis in [166] and by wavelet transform in [167]. In both [166] and [167], Support Vector Machines

(SVMs) were employed as binary classifiers and the SVM outputs were mapped to probabilities by using the method suggested by Platt [168].

It should be noted that Support Vector Machine (SVM) is considered to be one of the most effective algorithms for pattern classification problems [169]. In general, it works as follows for binary problems [170]: First, the training examples are mapped to a high-dimensional feature space *H*. Then, the optimal hyperplane in *H* is sought to separate examples of different classes as much as possible, while maximizing the distance from either class to the hyperplane. SVM has been employed for face recognition by several other researchers and has been shown to yield good results [169, 171-175].

Hidden Markov models [176] have also been employed for the face recognition task. Samaria and Harter [177] used a one-dimensional HMM to obtain a peak recognition accuracy of 87% on the ORL database. They later upgraded the one-dimensional HMM to a pseudo two-dimensional HMM [178] and achieved a best recognition performance of 95% on the same database using half the images for training and the other half for testing. Nefian and Hayes III [179] reported a best recognition rate of 98% on the same training and testing sets using embedded HMM [180] face models, and they also claimed that their system was much faster than that of Samaria [178] and invariant to the scale of the face images.

Some other AI approaches utilized for the face recognition task include evolutionary pursuit [181, 182] and techniques [183, 184] based on boosting [161, 185]. These schemes have reportedly yielded promising results for various difficult face recognition scenarios.

5.1.2.3 Multiple Classifier Systems

Since the performance of any classifier is more sensitive to some factors and relatively invariant to others, a recent trend has been to combine individual classifiers in order to integrate their complementary information and thereby create a system that is more robust than any individual classifier to variables that complicate the recognition task. Such systems have been termed as multiple classifier systems (MCSs) [186] and are a very active research area at present. Examples of such approaches proposed for face recognition include the following: Lu et al. [187] fused the results of PCA, ICA and LDA using the sum rule and RBF network-based [188] integration strategy (Fig. 14); Marcialis and Roli [189-191] combined the results of the PCA and LDA algorithms (Fig. 15); Achermann and Bunke [192] utilized simple fusion rules (majority voting, rank sum, Baye's combination rule) to integrate the weighted outcomes of three classifiers based on frontal and profile views of faces; Tolba and Abu-Rezq [193] employed a

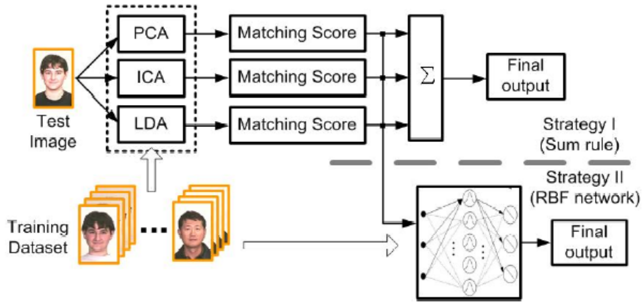


Fig. 14. Classifier combination system framework [187]. (©2003 IEEE)

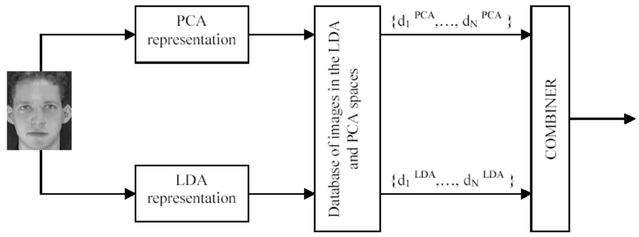


Fig. 15. Overview of the fusion methodology [191]. (With kind permission of Springer Science and Business Media)

simple combination rule for fusing the decisions of RBF and LVQ networks; Wan et al. [194] used a SVM and HMM hybrid model; Kwak and Pedrycz [195] divided the face into three regions, applied the Fisherfaces method to the regions as well as to the whole face and then integrated the classification results using the Choquet fuzzy integral [196]; Haddadnia et. al. [197] used PCA, the Pseudo Zernike Moment Invariant (PZMI) [198, 199] and the Zernike Moment Invariant (ZMI) to extract feature vectors in parallel, which were then classified simultaneously by separate RBF neural networks and the outputs of these networks were then combined by a majority rule to determine the final identity of the individual in the input image.

5.1.2.4 Advantages and Disadvantages

The main advantage of the holistic approaches is that they do not destroy any of the information in the images by concentrating on only limited regions or points of interest [37]. However, as mentioned above, this same property is their greatest drawback, too, since most of these approaches start out with the basic assumption that all the pixels in the image are equally important [74]. Consequently, these techniques are not only computationally expensive but require a high degree of correlation between the test and training images, and do not perform effectively under large variations in pose, scale and illumination, etc. [200]. Nevertheless, as mentioned in the above review, several of these algorithms have been modified and/or enhanced to compensate for such variations, and dimensionality reduction techniques have been exploited (note that even though such techniques increase generalization capabilities, the downside is that they may potentially cause the loss of discriminative information [151]), as a result of which these approaches appear to produce better recognition results than the feature-based ones in general. In the latest comprehensive FERET evaluation [62, 63], the probabilistic eigenface [88], the Fisherface [83] and the EBGM [59] methods were ranked as the best three techniques for face recognition (Even though the EBGM method is feature-based in general, its success depends on its application of holistic neural network methods at the feature level).

5.2 Face Recognition from Video Sequences

Since one of the major applications of face recognition is surveillance for security purposes, which involves real-time recognition of faces from an image sequence captured by a video camera, a significant amount of research has been directed towards this area in recent years.

A video-based face recognition system typically consists of three modules: one for detecting the face; a second one for tracking it; and a third one for recognizing it [201]. Most of these systems choose a few good frames and then apply one of the recognition techniques for intensity images to those frames in order to identify the individual [202]. A few of these approaches are briefly described below.

Howell and Buxton [203] employed a two-layer RBF network [204, 205] for learning/training and used Difference of Gaussian (DoG) filtering and Gabor wavelet analysis for the feature representation, while the scheme from [206] was utilized for face detection and tracking. Training and testing were done using two types of image sequences: 8 primary sequences taken in a relatively constrained environment, and a secondary sequence recorded in a much more unconstrained atmosphere (Figs. 16, 17). The image sequences consisted of 62 to 94 frames. The use of Gabor wavelet analysis for feature representation, as opposed to DoG filtering, seemed to yield better recognition results. The recognition accuracies reported varied quite a

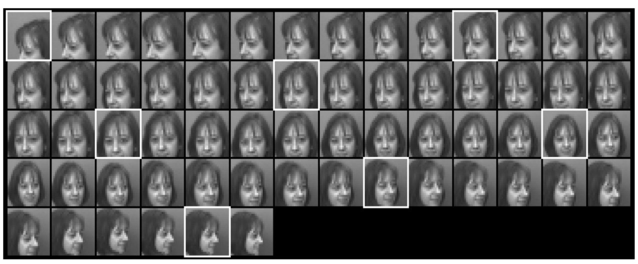


Fig. 16. A complete Primary sequence for the class Carla, after segmentation but before preprocessing [203]. (©1996 IEEE)

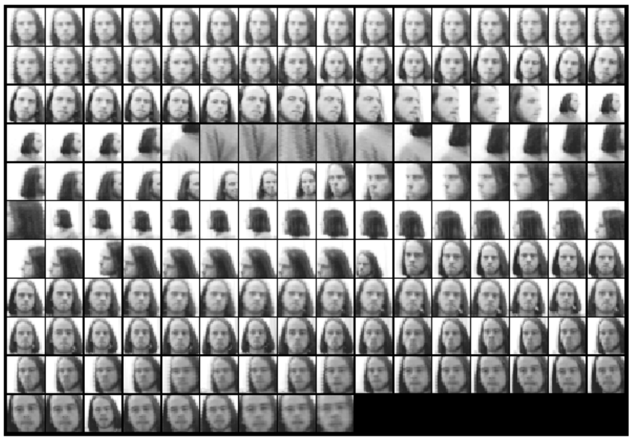


Fig. 17. A complete Secondary sequence for the class Steve, after segmentation but before preprocessing [203]. (© 1996IEEE)

bit, ranging from 99%, using 278 images for training and 276 for testing, to 67%, using 16 training and 538 testing images.

de Campos et al. [207] propose a recognition system which uses skin color modeling [208] to detect the face, then utilizes GWN [209] to detect prominent facial landmarks (i.e., the eyes, nose, and mouth) and to track those features. For each individual frame, eigenfeatures [82] are then extracted and a feature selection algorithm [210] is applied over the combination of all the eigenfeatures, and the best ones are selected to form the feature space. A couple of classifiers described in [211] are then applied to identify the individual in the frame and, finally, a super-classifier based on a voting scheme [212] performs the final classification for the entire video sequence (Figs. 18, 19). Good recognition results (97.7% accuracy) have been reported using 174 images of the eyes of 29 people (6 images per person).

Biuk and Loncaric [213] take image sequences in which the pose of the person's face changes from -90 degrees to 90 degrees (Fig. 20). The sequences are projected into eigenspace to give a prototype trajectory for each known individual. During the recognition phase, an unknown face trajectory is compared with the prototype trajectories to determine the identity of the individual (Fig. 21). They tested the system on a database of 28 individuals (11 frames per person) and found that the system yielded excellent recognition results when all frames and 4 or more eigenfaces were used, but that the performance decreased when either parameter was decreased. They, however, propose a matching method which associates a score to each trajectory point and then makes the final match based on the maximum score: They claim that this enhancement enables their system to achieve better performance when a smaller number (< 4) of eigenfaces is used.

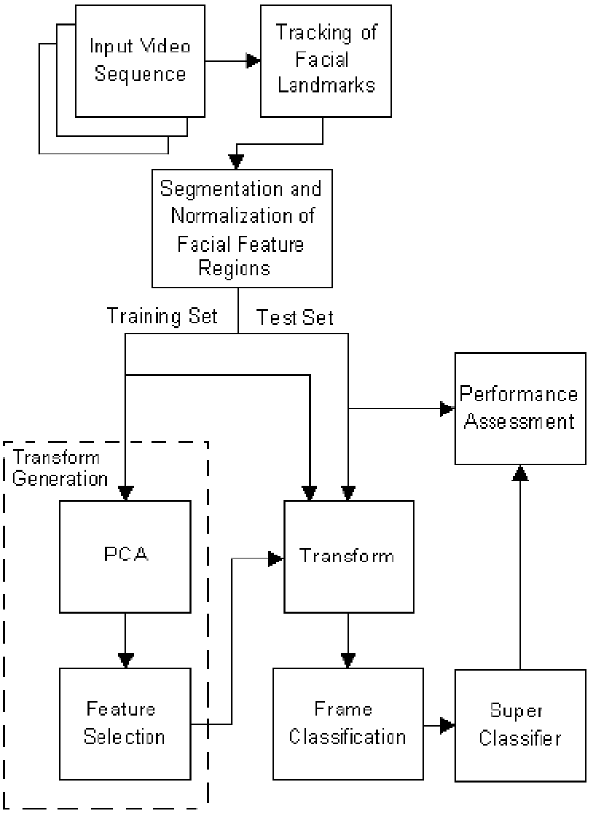


Fig. 18. Overview of the project [207]. (Courtesy of T. E. de Campos, R. S. Feris and R. M. Cesar Jr.)

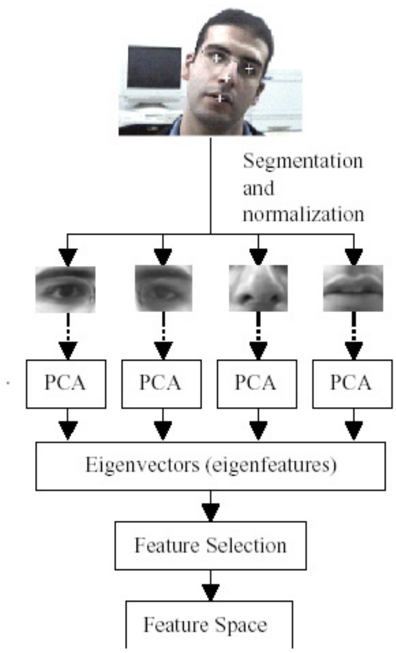


Fig. 19. Feature space generation [207]. (Courtesy of T. E. de Campos, R. S. Feris and R. M. Cesar Jr.)

Fig. 20. Face images taken from different viewing angles (profile to profile) [213]. (©2001 IEEE)

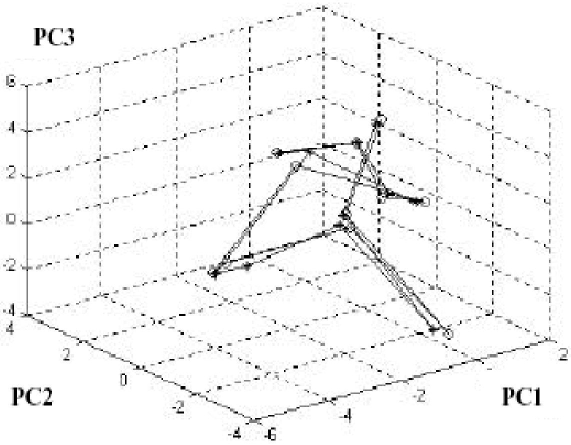


Fig. 21. Pattern trajectories for two sequences of the same person represented with the first three principal components [213]. (©2001 IEEE)

Recently, some approaches [214, 215] have employed a video-to-video paradigm in which information from a sequence of frames from a video segment is combined and associated with one individual. This notion involves a temporal analysis of the video sequence and a condensation of the tracking and recognition problems. Such schemes are still a matter of ongoing research since the reported experiments were performed without any real variations in orientation and facial expressions [216].

It is worth mentioning that several schemes have incorporated information from other modalities in order to recognize facial images acquired from video clips. For instance, [217] makes use of stereo information and reports a recognition accuracy of 90%, while [8] exploits both audio and video cues as well as 3D information about the head to achieve a 100% accuracy rate for 26 subjects. (For more information about recognition based on audio and video, see the Proceedings of the AVBPA Conferences [218]).

A detailed survey of recent schemes for face recognition from video sequences is provided in [219].

5.2.1 Advantages and Disadvantages

Dynamic face recognition schemes appear to be at a disadvantage relative to their static counterparts in general, since they are usually hampered by one or more of the following: low quality images (though image quality may be enhanced by exploiting super-resolution techniques [220-223]); cluttered backgrounds (which complicate face detection [224]); the presence of more than one face in the picture; and a large amount of data to process [71]. Furthermore, the face image may be much smaller than the size required by most systems employed by the recognition modules [202].

However, dynamic schemes do have the following advantages over static techniques: the enormous abundance of data empowers the system to choose the frame with the best possible image and discard less satisfactory ones [203]. Video provides temporal continuity [203], so classification information from several frames can be combined to improve recognition performance. Moreover, video allows the tracking of face images such that variations in facial expressions and poses can be compensated for, resulting in improved recognition [225]. Dynamic schemes also have an edge over static ones when it comes to detecting the face in a scene, since these schemes can use motion to segment a moving person's face [71].

5.3 Face Recognition from Other Sensory Inputs

Though the bulk of the research on face recognition has been focused on identifying individuals from 2D intensity images, in recent years some attention has nevertheless been directed towards exploiting other sensing modalities, such as 3D or range data and infra-red imagery, for this purpose.

5.3.1 3D Model-based

The main argument in favor of using 3D information for face recognition appears to be that it allows us to exploit features based on the shape and the curvature of the face (such as the shape of the forehead, jaw line, and cheeks) without being plagued by the variances caused by lighting, orientation and background clutter that affect 2D systems [37, 226, 227]. Another argument for the use of depth data is that "at our current state of technology, it is the most straightforward way to input or record complex shape information for machine analysis" [228]. The obvious drawbacks of such approaches are their complexity and computational cost [202].

The following techniques are currently being used to obtain 3D information [226]:

- Scanning systems: Laser face scanners produced by companies like Cyberware Inc. [229] and 3D Scanners Ltd. [230] seem to be producing highly accurate results; however, the cost of these commercial scanning services is obviously substantial.
- Structured light systems: These systems make use of the principles of stereo vision to obtain the range data. Their main advantage is that the only equipment they require is cameras and some kind of projection system. The primary drawback with such systems is that they can experience difficulty in resolving the shape of the pattern in the camera image.
- Stereo vision systems: These are systems that attempt to extract 3D information from two or more 2D images of the same object taken from different angles. They are limited to objects which will "generate a sufficient number of image features to allow for conclusive stereo matching. In the case of trying to establish the shape of a reasonably smooth object, such as the human face, these systems would be unable to generate an accurate surface shape. (Smooth surfaces can be 'roughed up' by the projection of a textured pattern onto the face)" [226].
- Reverse rendering/shape from shading: These techniques endeavor to construct the shape of an object using knowledge about illumination and the physical properties of the object.

Until recently, there appear to have been very few papers that describe attempts to recognize faces based mainly on range data or 3D data about the subjects' faces. However, lately, there has been a revival of interest in this area and several new schemes of this sort have been proposed in the past few years. One of the earliest of such approaches is described in [228], where the principle curvatures of the face surface are calculated from range data (Fig. 22), after which this data - supplemented by a priori information about the structure of the face - is used to locate the various facial features (i.e., the nose eyes, forehead, neck, chin, etc.). The faces are then normalized to a standard position and re-interpolated onto a regular cylindrical grid. The volume of space between two normalized surfaces is used as a similarity measure. The system was tested using the face images of 8 people (3 images per person). Features

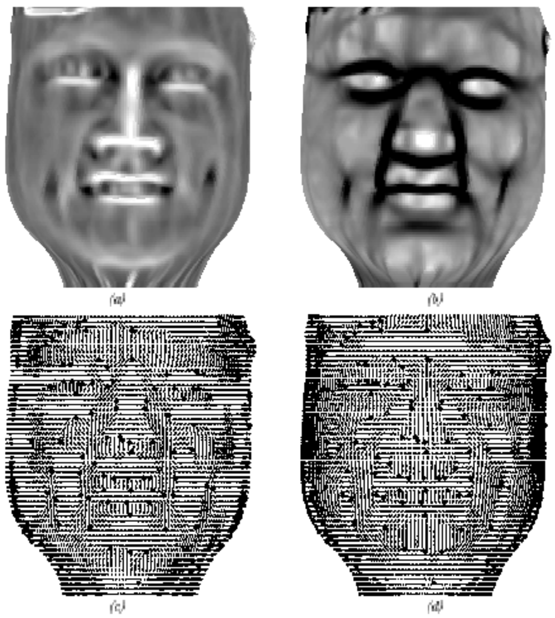


Fig. 22. Principle curvatures for a single face: magnitude (a) and direction (c) of maximum curvature, magnitude (b) and direction (d) of minimum curvature. Umbilic points are marked in (c) and (d); filled circles are points with a positive index and open circles are points with a negative index [228]. (Courtesy of G. Gordon)

were detected adequately for all faces. Recognition rates of 97% and 100% were reported for individual features and the whole face respectively.

Another approach described in [200] uses profiles (which have external contours consisting of rather rigid parts) instead of frontal images, captures 3D data by triangulation, and then does a 3D comparison of the profile data (Figs. 23, 24). This method requires a good deal of user cooperation and restrictions on the background, etc. in order for it to work.

[37] uses 3D data to normalize the results obtained from the face detection algorithm to a form more appropriate for the recognition engine, i.e., in this case, the 3D data is just being used to supplement rather than supplant existing face detection and recognition algorithms.

Some examples of more recent face recognition approaches based on 3D data include the following: Castellani et al. [231] approximate the range images of faces obtained by stereoscopic analysis using Multi-level B-Splines [232], and SVMs are then used to classify the resulting approximation coefficients. Some other techniques [227, 233, 234] first project the 3D face data onto a 2D intensity image, whereupon the projected 2D images are processed as standard intensity images. Yet other methods have been proposed for 3D face recognition based on local features [235], local and global geometric cues [236], profiles [237-240], and the rank-based decision fusion of various shape-based classifiers [241].

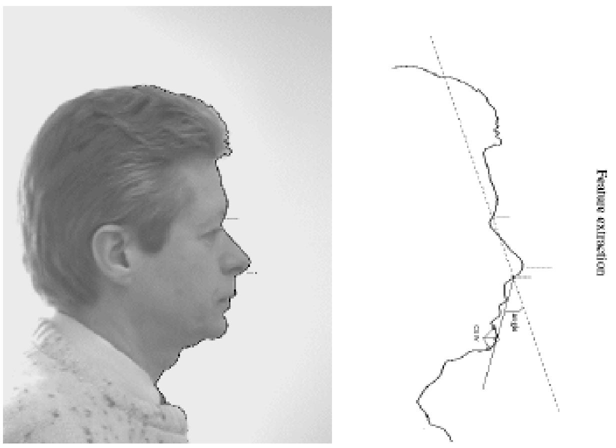


Fig. 23. (a) Profile image (b) Contour extraction, nose and eye localization, feature extraction [200]. (Courtesy of C. Beumier and M. Acheroy)

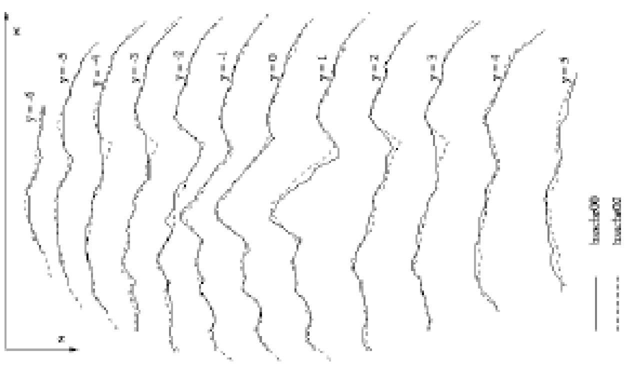


Fig. 24. 3D comparison by parallel planar cuts [200]. (Courtesy of C. Beumier and M. Acheroy)

Several approaches have also been proposed that integrate 2D texture and 3D shape information. Such methods make use of the PCA of intensity images [242-244], facial profile intensities [245], Iterative Closest Point (ICP [246]) [247, 248], Gabor wavelets [249], and Local Feature Analysis [250], etc. For instance, Wang et al. [249] extract 3D shape templates from range images and texture templates from grayscale images of faces, apply PCA separately to both kinds of templates to reduce them to lower-dimensional vectors, then concatenate the shape and texture vectors and, finally, apply SVMs to the resulting vectors for classification. In general, experiments with such systems indicate that combining shape and texture information reduces the misclassification rates of the face recognizer.

Comprehensive recent surveys of literature on 3D face recognition can be found in [251] and [252].

5.3.2 Infra-red

Since thermal infra-red imagery of faces is relatively insensitive to variations in lighting [253], such images can hence be used as an option for detecting and recognizing faces. Furthermore, [254] argues that since infra-red facial images reveal the vein and tissue structure of the face which is unique to each individual (like a fingerprint), some of the face recognition techniques for the visible spectrum should therefore yield favorable results when applied to these images. However, there exist a multitude of factors that discourage the exploitation of such images for the face recognition task, among which figure the substantial cost of thermal sensors, the low resolution and high level of noise in the images, the lack of widely available data sets of infra-red images, the fact of infra-red radiation being opaque to glass (making it possible to occlude part of the face by wearing eyeglasses) [255] and, last but not least, the fact that infra-red images are sensitive to changes in ambient temperature, wind and metabolic processes in the subject [256] (Note that in [257], the use of blood perfusion data is suggested to alleviate the effect of ambient temperature).

In [254], the eigenface technique [80, 81] was applied to a database of 288 hand-aligned low-resolution (160x120) images of 24 subjects taken from 3 viewpoints. The following recognition rates were reported: 96% for frontal views, 96% for 45 degrees views, and 100% for profile views.

Wilder et al. [258] compared the performance of three face recognition algorithms on a database of visible and infra-red images of 101 subjects and concluded that the recognition results for one modality were not significantly better than those for the other.

Socolinsky et al. [259] tested the eigenfaces [80, 81] and the ARENA [260] algorithms on a database of visible and infrared images of 91 distinct subjects (captured under various illumination conditions, with varying facial expressions, and with or without glasses using a sensor capable of imaging both modalities simultaneously [Figs. 25, 26 and 27]), and reported that the infra-red imagery significantly outperformed the visible one in all the classification experiments conducted under the various above-mentioned conditions.

Selinger and Socolinsky [256] used the same database of 91 subjects and tested the performance of four face recognition algorithms (PCA, LDA, LFA and ICA) under the afore-mentioned conditions and reached the same conclusion, although they did concede that the apparent superiority of the infra-red approach may stem from the fact that their data did not contain sufficiently challenging situations (i.e., changes in temperature, wind, etc.) for the infra-red imagery, whereas it did so for the visible images.

Chen et al. [262] collected several datasets of images (both in infra-red and the visible spectrum) of 240 distinct subjects under various expressions and lighting conditions at different times (some of the images were taken in the same session while others were taken over a period of ten weeks [Fig. 28]). They studied the effect of temporal changes in facial appearance on the performance of the eigenfaces algorithm in both modalities and concluded that though the recognition accuracy was approximately the same for images taken in the same session, visible images

Fig. 25. Sample imagery taken from the database. Note that LWIR images are not radio-metrically calibrated [259]. (©2001 IEEE)

Fig. 26. First five visible eigenfaces [259]. (© 2001 IEEE)

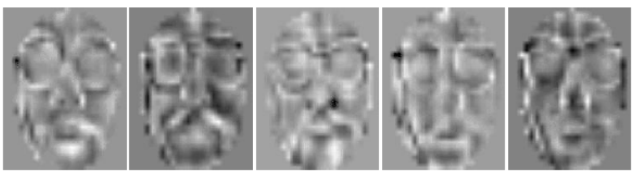


Fig. 27. First five LWIR eigenfaces [259]. (©2001 IEEE)

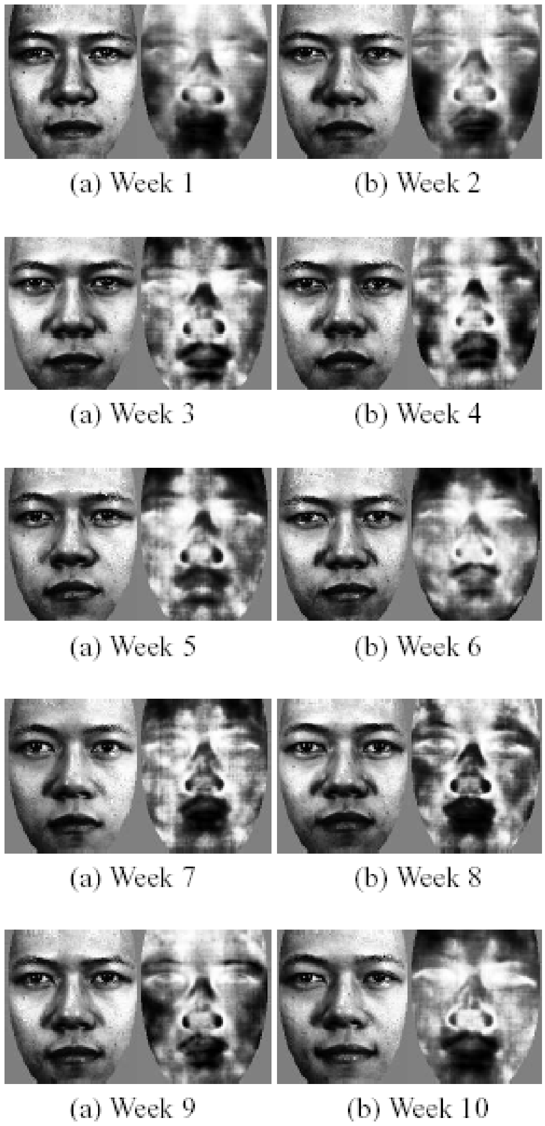


Fig. 28. Normalized face images of one subject in visible and IR across ten weeks [261]. (Reprinted from Computer Vision and Image Understanding, 99(3), X. Chen, P. Flynn and K. Bowyer, IR and Visible Light Face Recognition, 332-358, Copyright (2005), with permission from Elsevier).

outperformed the infra-red ones when there was a significant lapse in the time between which the training and test images were acquired. They attributed the lower performance of the infra-red imagery to variations in the thermal patterns of the same subject and the sensitivity of the infra-red imagery to the manual location of the eyes. They also found that the FACEIT [263] software performed better than eigenfaces in both modalities. However, the combination of the two classifiers using the sum rule [264] outperformed the individual classifiers as well as the FACEIT program. Latter experiments conducted by Chen et al. [261] on a larger set of data reconfirmed these results.

Other approaches have also been proposed recently which explore the fusion of face images captured under visible and infrared light spectrum to improve the performance of face recognition [255, 265-267].

A comprehensive review of recent advances in face recognition from infra-red imagery may be found in [268].

6. Conclusions

Face recognition is a challenging problem in the field of image analysis and computer vision that has received a great deal of attention over the last few years because of its many applications in various domains. Research has been conducted vigorously in this area for the past four decades or so, and though huge progress has been made, encouraging results have been obtained and current face recognition systems have reached a certain degree of maturity when operating under constrained conditions; however, they are far from achieving the ideal of being able to perform adequately in all the various situations that are commonly encountered by applications utilizing these techniques in practical life. The ultimate goal of researchers in this area is to enable computers to emulate the human vision system and, as has been aptly pointed out by Torres [225], “Strong and coordinated effort between the computer vision, signal processing, and psychophysics and neurosciences communities is needed” to attain this objective.

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Rabia Jafri

She received a B.S. degree in Mathematics and Physics from Islamia University, Pakistan in 1995 followed by B.S. and Ph.D. degrees from the University of Georgia, U.S.A. in 1999 and 2008, respectively. Her research interests include face recognition, gait recognition, multi-biometric classification systems and image processing.

Hamid R. Arabnia

Hamid R. Arabnia received a Ph.D. degree in Computer Science from the University of Kent (Canterbury, England) in 1987. He is currently a Full Professor of Computer Science at University of Georgia (Georgia, USA), where he has been since October 1987. His research interests include Parallel and distributed processing techniques and algorithms, interconnection networks, and applications. He has chaired national and international conferences and technical sessions in these areas; he is the chair of WORLDCOMP annual research congress. He is Editor-in-Chief of The Journal of Supercomputing (Springer) and is on the editorial and advisory boards of 26 other journals and magazines. He has received a number of awards, including, the Distinguished Service Award "in recognition and appreciation of his contributions to the profession of computer science and his assistance and support to students and scholars from all over the world" and an "Outstanding Achievement Award in Recognition of His Leadership and Outstanding Research Contributions to the Field of Supercomputing". Prof. Arabnia has published extensively in journals and refereed conference proceedings. He has over 300 publications (journals, proceedings, editorship, editorials) in his area of research. He has been a Co-PI on $7,139,525 externally funded projects/initiatives (mainly via Yamacraw - includes some UGA matching). He has also contributed projects for justification for equipment purchase (grant proposals worth over $3 Million). In addition, during his tenure as Graduate Coordinator of Computer Science (August 2002 - January 2009), he secured the largest level of funding in the history of the Department for supporting the research and education of graduate students (PhD, MS). Prof. Arabnia has delivered numerous number of keynote lectures at international conferences; most recently at (since September 2008): The 14th IEEE International Conference on Parallel and Distributed Systems (ICPADS'08, Australia); International Conference on Future Generation Communication and Networking (FGCN 2008 / IEEE CS, Sanya/China); The 10th IEEE International Conference on High Performance Computing and Communications (HPCC-08, Dalian/China). He has also delivered a number of "distinguished lectures" at various universities.