Chapter #

FUSION OF FACE RECOGNITION ALGORITHMS FOR VIDEO-BASED SURVEILLANCE SYSTEMS

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Abstract: It is widely acknowledged that face recognition could play an important role in advanced video-based surveillance systems, mainly because it is non-intrusive and does not require people cooperation. Unfortunately, face recognition algorithms showed to suffer a lot from the high variability of environmental conditions (e.g., variations of lighting, face pose and scale). This currently limits their application to real video-surveillance tasks. Recently, fusion of multiple face recognisers has been proposed to improve the robustness of face recognition systems to environmental conditions variability. In this chapter, fusion of two well-known face recognition algorithms, namely, PCA and LDA, is proposed. Experimental results that confirm the benefits of fusing PCA and LDA allow drawing some preliminary conclusions about the role of the fusion of face recognition algorithms in video-based surveillance applications.

Key words: Video Surveillance, Biometrics, Face Recognition, Fusion of Multiple Classifiers .

1. INTRODUCTION

It is widely acknowledged that face recognition could play an important role in advanced video-based surveillance systems, mainly because it is non intrusive and does not require people cooperation [1-2]. Unfortunately, face recognition algorithms showed to suffer a lot from the high variability of environmental conditions. As an example, the effectiveness of face recognition strongly depends on lighting conditions and on variations in the subject's pose and expression in front of the camera. This obviously limits their application to real video-surveillance tasks. On the other hand, face is considered a very good biometric. People recognize each other through the face, the acquisition process is non-intrusive, and does not require the collaboration of the subject to be recognized. Therefore, face recognition is a very active research field with many applications. For the purposes of this chapter, the face recognition applications can be subdivided in two types: applications in controlled and uncontrolled environments. One of the main applications of the first type is the so called "identity authentication". A person submits to the automatic identity verification system its face (frontal and/or profile view) and declares her/his identity. The system matches the acquired face with the "template" stored in its data base, and classifies the person as a "genuine" (i.e., the claimed identity is accepted) or an "impostor". Automatic identity verification based on face recognition is usually performed in controlled environments, and requires person cooperation.

Applications of the second type refer to the problem of recognition of an identity in a scene, and they are very useful for video-surveillance tasks. The recognition system first detects the face in the image and normalizes it with respect to the pose, lighting, and scale conditions. Then, it tries to associate the face to one or more faces stored in its database, and provides as outputs the set of faces that are considered as "nearest" to the detected face. This problem is much more complex than the previous "verification" problem. It is computationally expensive and needs of robust algorithms for detection, normalization, and recognition. In the context of video surveillance applications, the following problems can seriously affect face recognition performances:

- the scene complexity, that can strongly affect face detection performances [3];
- the quality of video sequence, that can be very low due to the poor performance of the surveillance cameras, and the very large variations of lighting conditions;
- the small size of acquired faces;
- the very large variations of face expression and pose.

Usually, each of the above problems is so complex that it must be addressed separately. In this chapter, we focus on the last stage of the face recognition process. We assume that the previous steps of face detection, restoration, and normalization have been already performed. In section 2, the state of the art of face recognition approaches is briefly reviewed, and the novel role of algorithm fusion is pointed out. In section 3, fusion of two well-known face recognition algorithms, namely, PCA and LDA, is proposed. In section 4, experimental results are reported. Conclusions are drawn in section 5.

2. FACE RECOGNITION SYSTEMS: A SHORT OVERVIEW

A good survey of the state-of-the-art of face recognition systems can be found in [4]. In the following, we briefly review the main works.

Many face recognition systems have been proposed in the last years. Each of them is based on a particular representation of face. For the purposes of this Chapter, we can identify two main types of approaches: the so called appearance-based approaches, where a feature vector for characterizing the face is derived from the input image, and the structural approaches, where a deformable model, like a graph, is used for face representation.

The term “appearance-based” has been proposed for distinguishing the statistical approaches from the structural ones [1-2]. The appearance-based methods describe the face with a feature vector derived from the original input image. The feature vector is computed by reducing the dimensionality of the original image space. Feature reduction is performed by applying some standard pattern recognition algorithms. The aim is to reduce the redundant and/or noisy information contained in the original image. Consequently, a compact and effective description of the face image is obtained.

The most used approach is the face representation by Principal Component Analysis (PCA), or “eigenface” approach, proposed by Turk and Pentland [5]. The face image is projected to a space where the correlation among the features is zero. Only the components with highest variance are used for characterizing the face. A transformation that satisfies this condition is the so-called Karhunen-Loeve transform. Another appearance-based approach is the face representation by Linear Discriminant Analysis (LDA), or “fisherface” approach, proposed by Kriegmann et al. [6]. The face image is projected to the so called Fisher space, in which the variability among the face-vectors of the same class is minimized, and the variability among the face-vectors of different classes is maximized. In this case, the face is represented by a number of components smaller than the one of the PCA. We discuss in more detail both “eigenface” and “fisherface” approaches in section 3. Usually, the matching between two face feature vectors is performed by applying some kind of metric like the Euclidean distance, the Mahalanobis distance, etc.

The Local Feature Analysis (LFA) by Penev and Atick [7] derives from the analysis of the local information around some critical points of the face (e.g., eyes, nose, lips). This local information can be computed through a kernel function centered on the given critical points. An example of such kernel function is given by the PCA transform. LFA is the face representation algorithm used in the face recognition system developed by Identix company.

With regard to the structural approaches, a well-known algorithm is the so called elastic bunch graph method [8] that refers to the dynamic link architectures [9] proposed by Wiskott et al. A set of reference points, called "fiducial points", is selected in the face image. Each fiducial point is a node of a fully connected graph, and it is labelled by the Gabor filters responses computed in a window centered around the fiducial point. Each arch is labelled with the distance between the correspondent fiducial points. Recognition is performed by an elastic matching between two graphs.

It is worth noting that, from the viewpoint of video-surveillance applications using video sequences, the above algorithms can be applied within the so called "still-to-still" and "multiple-stills-to-still" face recognition paradigms. In the still-to-still paradigm, the recognition algorithm (e.g., the Local Feature Analysis) is applied only if a good "pose" (e.g., a frontal view of the person to be recognized) can be detected in the video sequence. Therefore, the video sequence is firstly processed in order to detect a frame associated to a good pose (usually, a frontal view). Then, the recognition algorithm is applied to such frame. This approach requires a good pose estimation algorithm. In the multiple-stills-to-still approach, templates associated to multiple poses and expressions are used to cover all possible variations of the face in the video sequence. Therefore, recognition can be attempted for the most of frames of video sequence. The problem of this approach is how to choose the most representative face poses, because of the very large cases to be handled.

In the above paradigms, no temporal information and correlation among images is used.

Recently, Krüger, Zhou [10] and Chellappa [11] proposed the "video-to-video" paradigm, where the whole sequence of faces acquired during a given time interval of the video sequence is associated to a class (identity). This concept implies the temporal analysis of the video sequence with dynamical models (e.g., Bayesian models), and the "condensation" of the tracking and recognition problems. These methods are a matter of on-going research, and the reported experiments were performed without "real" variations of pose and face expressions.

Other face recognition systems based on the still-to-still and multiple-stills-to-still paradigms have been proposed [12-13]. However, none of them is able to effectively handle the large variability of critical parameters, like pose, lighting, scale, face expression, some kind of forgery in the subject appearance (e.g., the beard). Effective handling of lighting, pose and scale variations is a matter of on-going research. Typically, a face recognition system is specialized on a certain type of face view (e.g. frontal views), disregarding the images that do not correspond to such view. Therefore, a powerful pose estimation algorithm is required. But this is often not sufficient, and an unknown pose can deceive the whole system. Therefore, a face recognition system can usually achieve good performance only at the expense of robustness and reliability.

In order to improve the performance and robustness of individual recognizers, the use of multiple classifier systems (MCSs) has been recently proposed. MCSs are currently a very active research field [14]. Multiple classifiers systems cover a wide spectrum of applications: handwritten character recognition, fingerprint classification and matching, remote-sensing images classification, etc. The effectiveness of this approach is documented by many experimental results [14].

Approaches for improving the performance and the robustness of face recognition using MCSs have been proposed. Achermann and Bunke [15] proposed the fusion of three recognizers based on frontal and profile faces. The outcome of each expert, represented by a score, i.e., a level of confidence about the decision, is combined with simple fusion rules (majority voting, rank sum, Bayes's combination rule). Lucas [16] used a n-tuple classifier for combining the decisions of experts based on sub-sampled images. Tolba [17] presented a simple combination rule for fusing the decisions of RBF and LVQ networkz. Marcialis and Roli [18-19] reported preliminary experiments on the fusion of two statistical approaches, PCA and LDA, for face verification and recognition.

3. FACE RECOGNITION BY FUSION OF STATISTICAL FACE REPRESENTATIONS

In this section, we present our methodology for fusing two appearance-based (or statistical) approaches to face recognition: the PCA representation ("eigenface" approach) and the LDA representation ("fisherface" approach). We already used the fusion of LDA and PCA for face verification with good results [19]. From the viewpoint of video surveillance applications, it is worth noting that our methodology should be applied according to the still-to-still paradigm (Section 2). Figure 1 gives an overview of the proposed method. It is implemented by the following steps:

- representation of the face image according to the PCA and the LDA approaches;
- the distance vectors d^{PCA} and d^{LDA} of the input image from all the N face templates stored in the database are computed;

- for the final decision, these two vectors are fused by a combination rule. We proposed two algorithms for the fusion phase: the K-Nearest Neighbors and the Nearest Mean.

In the following, we briefly describe the theoretical framework behind the two face representations.

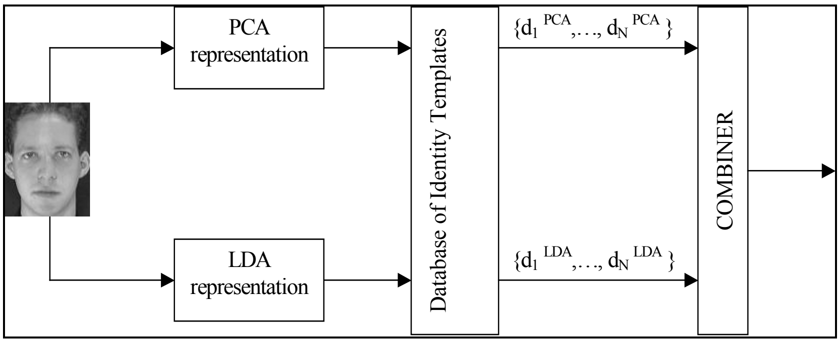

Figure #-1. The flow diagram of our Face Recognition System

3.1 PCA and LDA representations for Face Recognition

Let X be a *d*-dimensional feature vector. In our case, *d* is equal to the number of pixel of each face image. The high dimensionality of the related "image space" is a well-known problem for the design of a good face recognition algorithm. Therefore, methods for reducing the dimensionality of such image space are required. To this end, Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) are widely used.

Principal Component Analysis [5, 20] is defined by the transformation:

$$y_i = W^t x_i \tag{1}$$

Where $x_i \in X \subseteq \Re^d$, i = 1,…,n (n samples). W is a d-dimensional transformation matrix whose columns are the eigenvectors related to the eigenvalues computed according to the formula:

$$\lambda e_i = S e_i \tag{2}$$

S is the scatter matrix (i.e., the covariance matrix):

$$S = \sum_{i=1}^{n} (x_i - m) \cdot (x_i - m)^t \ , \qquad m = \frac{1}{n} \sum_{i=1}^{n} x_i \tag{3}$$

This transformation is called Karuhnen-Loeve transform. It defines the d-dimensional space in which the covariance among the components is zero, because the covariance matrix is diagonal. The eigenvalues correspond to the variances of each component in the transformed space. After ordering the eigenvalues by increasing order, it is possible to consider a small number of “principal” components exhibiting the highest variance. The principal components of the transformed space are also called the most expressive features, and the eigenvectors related to the most expressive features are called “eigenfaces”.

The Linear Discriminant Analysis (also called Fisher Discriminant Analysis) [6, 20] is defined by the transformation:

$$y_i = W^t x_i \tag{4}$$

The columns of W are the eigenvectors of $S_w^{-1} S_b$, where S_w is the *within-class scatter matrix*, and S_b is the *between-class scatter matrix*. It is possible to show that this choice maximizes the ratio $\det(S_b)/\det(S_w)$.

These matrices are computed as follows:

$$S_w = \sum_{j=1}^{c} \sum_{i=1}^{n_j} (x_i^j - m_j) \cdot (x_i^j - m_j)^t \ , \quad m_j = \frac{1}{n_j} \sum_{i=1}^{n_j} x_i^j \tag{5}$$

Where x_i^j is the i-th pattern of j-th class, and n_j is the number of patterns for the j-th class.

$$S_b = \sum_{j=1}^{c} (m_j - m) \cdot (m_j - m)^t \ , \quad m = \frac{1}{n} \sum_{i=1}^{n} x_i \tag{6}$$

The eigenvectors of LDA are called “fisherfaces”. LDA transformation is strongly dependent on the number of classes (c), the number of samples (n), and the original space dimensionality (d). It is possible to show that there are almost c-1 nonzero eigenvectors. c-1 being the upper bound of the discriminant space dimensionality. We need d+c samples at least to have a nonsingular S_w. It is impossible to guarantee this condition in real applications. Consequently, an intermediate transformation is applied to reduce the dimensionality of the image space. To this end, we used the PCA transform [21]. Other regularization techniques have been proposed [22-26].

3.2 Fusion of PCA and LDA for Face Recognition

Many works analyzed the differences between these two techniques (see, in particular, [6]), but no work investigated the possibility of fusing them. In our opinion, the apparent strong correlation of LDA and PCA, especially when frontal views are used and PCA is applied before LDA, discouraged the fusion of such algorithms. However, it should be noted that LDA and PCA are not so correlated as one can think, as the LDA transformation applied to the principal components can generate a feature space significantly different from the PCA one. Therefore, the fusion of LDA and PCA for face recognition and verification is worth of theoretical and experimental investigation.

We propose two kind of approaches to fuse PCA and LDA face representations: the K-Nearest Neighbor approach (KNN) and the Nearest Mean approach (NM) [20].

First of all, we normalize the distance vectors d^{PCA} and d^{LDA} in order to map the range of these distances to the interval [0,1]:

$$d_{norm} = \frac{d - d_{\min}}{d_{\max} - d_{\min}} \tag{7}$$

Then, a *combined distance vector d* that must contain both PCA and LDA informations is computed. To this end, the following two techniques can be used:

- the combined distance vector is computed as the mean vector:

$$d = \left\{ \frac{d_1^{PCA} + d_1^{LDA}}{2}, \ldots, \frac{d_N^{PCA} + d_N^{LDA}}{2} \right\} \tag{8}$$

- the combined distance vector is computed by appending the d^{PCA} and d^{LDA} vectors:

$$d = \left\{ d_1^{PCA}, \ldots, d_N^{PCA}, d_1^{LDA}, \ldots, d_N^{LDA} \right\} \tag{9}$$

where N is the number of images in the database. If C is the number of the identities, also called *classes*, an identity c is associated to each couple $\left(d_j^{LDA}, d_j^{PCA}\right)$, $j = 1,\ldots,N$.

After computing and ordering the combined distance vector d, we follow the KNN strategy: *the most frequent identity among the first K components of d is selected*. If the combined distance vector follows eq. (8), we call our algorithm "Mean-KNN" (M-KNN); if it follows eq. (9), we call our algorithm "Append-KNN" (A-KNN).

In the case of the NM approach, we first compute a template for each identity in the database. We selected the average image for both PCA and LDA representations. Consequently, our distance vectors d^{PCA} and d^{LDA} are composed by C components instead of N. These vectors are combined according to eq. (8) or (9). The identity associated to the smallest combined distance is selected. The related algorithms are called "Mean-NM" (M-NM), and "Append-NM" (A-NM), respectively.

4. EXPERIMENTAL RESULTS

In this section, we report our experiments on two well-known face data bases: the AT&T and the Yale datasets.

4.1 Data Sets

The AT&T data set is made up of ten different images of 40 distinct subjects. For some subjects, the images were taken at different times, varying the lighting, facial expressions (open/closed eyes, smiling/not smiling), and facial details (glasses/no glasses). All the images were taken against a dark homogeneous background with the subjects in an upright, frontal position (with tolerance for some side movement). The data set was subdivided into a training set, made up of 5 images per class/identity (200 images), and a test set, made up of 5 images per class (200 images). In order to assess recognition performances, we repeated our experiment for ten random partitions of the data set. Reported results refer to the average performance of such ten runs. Figure 2 shows an example of face images from the AT&T data set. AT&T data set is publicly available at the URL http://www.cam-orl.co.uk/facedatabase.html.

Figure #-2. Examples of face images from the AT&T data set.

The Yale data set is made up of 11 images per 15 classes/identities (165 total images). Each face is characterized by different facial expressions or configurations: center-light, with/without glasses, happy, left-light, w/no glasses, normal, right-light, sad, sleepy, surprised, and wink. The data set was subdivided into a training set, made up of 5 images per class (75 images), and a test set, made up of 6 images per class (90 images). We repeated our experiments for ten random partitions of the data set and reported the average performances. Figure 3 shows an example of face images from the Yale data set. Yale data set is publicly available at the URL: http://cvc.yale.edu/projects/yalefaces/yalefaces.html.

Figure #-3. Examples of face images from the Yale data set.

In both data sets the face images did not need pre-processing phases, such as re-scaling, rotation or normalization.

4.2 Results with the AT&T Data Set

Table 1 reports the results on the AT&T test set.

Table #-1. Percentage accuracy values on the AT&T test set.

Individual Algorithms		**Combined Algorithms**			
PCA	**LDA**	**A-KNN**	**M-KNN**	**A-NM**	**M-NM**
94.7%	96.1%	95.9%	**97.3%**	93.3%	96.1%

The average number of principal components for the PCA representation was 119, while we used all 39 components for the LDA representation.

It is worth noting that the best combination result (97.3%) is comparable with those reported in [16] and [17]. In [16], a 97.5% percentage accuracy is reported, but it is averaged only on five runs; in [17], a 99.5% percentage accuracy is reported, but with a rejection rate of 0.5%. Figure 2 shows the so called “rank” accuracy, i.e., the percentage accuracy that can be achieved by considering the M identities of the database nearest to the given input face. The input face is considered as correctly recognized if the right identity is one of the M identities. The rank is a reliability measure, and it is very important for video-surveillance applications in uncontrolled environments. Even in this case, the combination of PCA and LDA gives a sharp improvement of the performance, and a better identification reliability and robustness.

Another motivation for fusing PCA and LDA is the average correlation coefficient that we computed between the d^{PCA} and the d^{LDA} vectors. A very low value was obtained: 0.39. This suggests a strong complementarity of the information extracted by the PCA and LDA representations. This confirms that these two approaches are not so correlated as one could think. We think that PCA and LDA are weakly correlated thanks to the good quality of the images in terms of pose and lighting conditions.

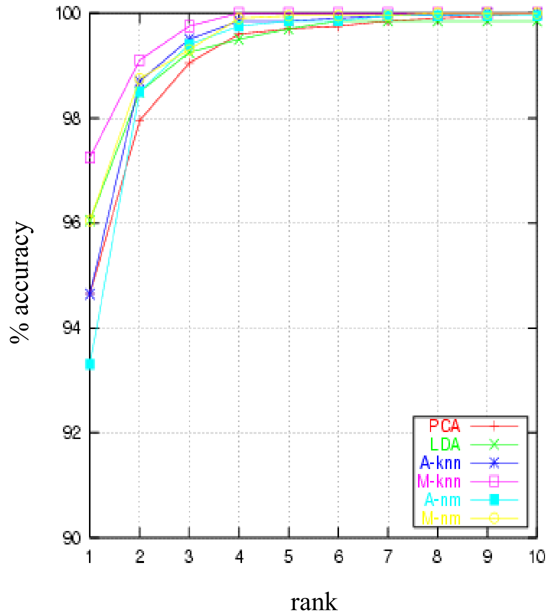

Figure #-4. Rank curves on the AT&T data set. Reported results show that the combination of PCA and LDA improves the reliability of the system

4.3 Results with the Yale Data Set

While the AT&T data set is characterized by small variations of pose and lighting, the Yale data set is characterized by strong variations of expression and lighting. This task is therefore more complex and the results are obviously worse, even if the number of identities is inferior.

Table 2 shows the percentage accuracy of our approaches on this data set.

Table #-2. Percentage accuracy on the Yale test set.

Individual Algorithms		**Combined Algorithms**			
PCA	**LDA**	**A-KNN**	**M-KNN**	**A-NM**	**M-NM**
83.0%	82.8%	**84.2%**	83.6%	83.6%	81.2%

Even in this case, the combination of PCA and LDA gives the best result. The gain is the same as for the AT&T data set (about 1.3%), but the final result is affected by the performances of PCA and LDA for this difficult task.

The average number of principal components is 33, while we used all 14 components for the LDA representation.

Unfortunately, in this case, we could not compare our results with others, because no work reported in the literature used the Yale data set for combining multiple algorithms for face recognition.

Even in this case, the rank-curves reported in Figure 3 show the effectiveness of the decision combination for improving the reliability of a face recognition system.

It should be noted that the average correlation coefficient in this case is high: a value of 0.69 was obtained. In our opinion, PCA and LDA are correlated because of the lighting and face expression variations in the images. The above variations can be considered as “noisy” information that limits the goodness of the feature extraction performed by PCA and LDA. However, the fusion algorithms overcomes partially this limitation. Performance accuracy is superior than that of the best individual recognition algorithm.

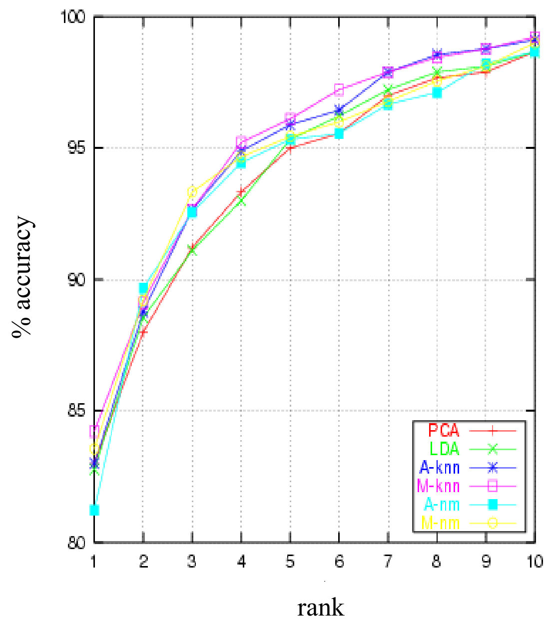

Figure #-5. Rank curves on the Yale data set. Reported results show that fusion improves the performance of the individual algorithms.

5. CONCLUSIONS

Although many face recognition systems have been proposed in the last years, none of them can completely overcome the limits due to the large variations of critical parameters, such as pose, lighting, scale. In the case of video-based surveillance systems, the poor quality of the acquired images and the variability of the scenarios are other critical problems to be addressed.

The orientation of the research community in this field is to perform recognition when certain constraints are satisfied in terms of pose, lighting, and scenario (still-to-still paradigm), but it is often impossible to guarantee these conditions for real video-surveillance tasks. On the other hand, the approaches based on multiple-stills-to-still and video-to-video paradigms are still a matter of on-going research. At present, an individual face recognition system can achieve good performance only at the expense of robustness and reliability.

In order to improve performances and robustness of face recognition systems for video-surveillance applications, the combination of multiple recognizers was recently proposed. But very few works investigated such fusion.

In this chapter, the fusion of two statistical approaches, namely PCA and LDA, for face representation and recognition has been investigated according to the still-to-still paradigm. Reported results confirm the benefits of such fusion. In particular, for the AT&T data set, these two representations proved to be complementary as shown by the low correlation coefficient. We combined PCA and LDA with the KNN-based combination rule and the NM-based combination rule. In general, the performance of the KNN rule is much better than that of the NM rule: this should mean that the average template (that can be viewed as a low-pass filtering in the domain of the PCA and LDA spaces) reduces the available information. The rank-curves show that the reliability of the recognition always increases with respect to the best individual approach.

Reported results are strongly dependent on the data set. A difficult task like the one presented by the Yale data set shows that the results of the individual classifiers decrease dramatically. However, they can be increased using fusion.

On the basis of the reported results, it is worth devoting further theoretical and experimental investigations to understand the behavior of PCA and LDA, in order to fuse them and to extend their application to real video-surveillance environments.

REFERENCES

1. A. Jain, R. Bolle, S. Pankanti Eds, BIOMETRIC – Personal Identification in Networked Society, Kluwer Academic Publishers, Boston/Dordrecht/London (1999).
2. H. Wechsler, J.P. Phillips, V. Bruce, F. Folgeman Soulie, T.S. Huang Eds., Face Recognition – From theory to applications, Springer, ASI NATO Series, vol.163, 1997.
3. M.H. Yang, D. Kriegman, N. Ahuja, Detecting Face Images: a Survey, IEEE Trans. on PAMI, 24 (1) 24-58, 2002.
4. W.Y. Zhao, R. Chellappa, A. Rosenfeld, and P.J. Philips, Face Recognition: a literature survey, UMD CfAR Technical Report CAR-TR-948, 2000.
5. M. Turk, and A. Pentland, Eigenfaces for Face Recognition, Journal of Cognitive Neuroscience, 3 (1) 71-86, 1991.
6. P.N. Belhumeur, J.P. Hespanha, and D.J. Kriegman, Eigenfaces vs. Fisherfaces: Recognition Using Class Specific Linear Projection, IEEE Trans. on PAMI, 19 (7) 711-720, 1997.
7. P.S. Penev and J. Atick, Local Feature Analysis: a general statistical theory for object representation, Network: Computation in Neural Systems, 7 (3) 477-500, 1996.
8. L. Wiskott, J.M. Fellous, N. Krüger, and C. von der Malsburg, Face Recognition by Elastic Bunch Graph Matching, IEEE Trans. on PAMI, 19 (7) 775-779, 1997.
9. M. Lades, J.C. Vorbrüggen, J. Buhmann, J. Lange, C. von der Malsburg, and W. Konen, Distortion invariant object recognition in the dynamic link architectures, IEEE Trans. on Computers, 42 (3) 300-311, 1993.
10. V. Krüger and S. Zhou, Exemplar-based Face Recognition from Video, Proc. of the Fifth IEEE International Conference on Automatic Face and Gesture Recognition (FGR'02), Washington D.C., U.S.A., 2002.
11. S. Zhou, V. Krüger, and R. Chellappa, Face Recognition from Video: a condensation approach, Proc. of the Fifth IEEE International Conference on Automatic Face and Gesture Recognition (FGR'02), Washington D.C., U.S.A., 2002.
12. A.J. Howell and H. Buxton, Towards Uncostrained Face Recognition from Image Sequences, Proc. of the IEEE International Conference on Automatic Face and Gesture Recognition (FGR'96), Killington, VT, pp.224-229, 1996.
13. Y. Li, S. Gong, H. Liddell, Support Vector Regression and Classification Based Multi-view Face Detection and Recognition, Proc. of the IEEE International Conference on Automatic Face and Gesture Recognition (FGR'00), Grenoble, France, pp.300-305, 2000.
14. F. Roli and J. Kittler Eds., Multiple Classifier Systems, Springer Verlag, LNCS 2364, 2002.
15. B. Achermann and H. Bunke, Combination of Classifiers on the Decision Level for Face Recognition, Technical Report IAM-96-002, Institut für Informatik und angewandte Mathematik, Universität Bern, January 1996.
16. SM. Lucas, Continuous n-Tuple Classifier and its Application to Real-time Face Recognition, IEE Proceedings of Visual Image and Signal Processing, 145 (5) 343-348, 1998.
17. AS. Tolba and AN. Abu-Rezq, Combined Classifier for Invariant Face Recognition, Pattern Analysis and Applications, 3 (4) 289-302, 2000.
18. G.L. Marcialis and F. Roli, Fusion of LDA and PCA for Face Recognition, Proceedings of the Workshop on Machine Vision and Perception, 8th Workshop of the Italian Association for Artificial Intelligence (AIIA'02), available at the URL: http://www-dii.ing.unisi.it/aiia2002.

19. G.L. Marcialis and F. Roli, Fusion of LDA and PCA for Face Verification, Proceedings of the Workshop on Biometric Authentication, M. Tistarelli, J. Bigun and A.K. Jain Eds., Springer LNCS 2359, Copenhagen, Denmark, pp.30-37, 2002.
20. R.O. Duda, P.E. Hart, and D.G. Stork, Pattern Classification, John Wiley & Sons, USA 2001.
21. W. Zhao, A. Krishnaswamy, R. Chellappa, D. Swets, and J. Weng, Discriminant Analysis of Principal Components for Face Recognition, in Face Recognition: From Theory to Applications, Eds. H. Wechsler, P.J. Phillips, V. Bruce, F.F. Soulie and T.S. Huang, Springer-Verlag, pp. 73-85, 1998.
22. L.F. Chen, H.Y.M. Liao, M.T. Ko, J.C. Lin, G.J. Yu, A new LDA-based face recognitions system which can solve the small sample size problem, Pattern Recognition 33 1713-1726, 2000.
23. F. Goudail, E.Lange, T. Iwamoto, K. Kyuma, N. Otsu, Face recognition system using local autocorrelation and multiscale integration, IEEE Trans. PAMI, 18 (10) 1024-1028, 1996.
24. K. Fukunaga, Introduction of Statistical Pattern Recognition, Academic Press, New York, 1990.
25. K. Liu, Y.Q. Cheng, J.Y. Yang, X. Liu, A generalised optimal set of discriminant vectors, Pattern Recognition, 25 (7) 731-329, 1992.
26. J. Yang, J. Yang, Why can LDA be performed in PCA transformed space?, Pattern Recognition, 36 (2) 563-566, 2003.