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Overview on Face Recognition based Automation Systems

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Abstract— The face is the identity of a person. The methods to exploit this physical feature have seen a great change since the advent of image processing techniques. Face recognition techniques are now being widely used in a large number of automated systems. These systems are increasingly being deployed in a wide range of practical applications. This paper provides a survey on face recognition approaches. It also covers the relative analysis between all the approaches. Finally this paper concludes by extending the use of face recognition in various automated systems.

Key words: Face Recognition, Face Recognition Approaches, Appearance-Based and Model-Based Algorithms

I. INTRODUCTION

In recent advances in computer vision, pattern recognition and image processing, face recognition is one of the most popular research topics. It is easy to use, can be used efficiently for mass scanning and also increases user-friendliness in human-computer interaction. Moreover its wide range of surveillance, access control and law enforcement applications and availability of executable technologies after vigorous research in last few decades has made it gain significant attention. Face recognition approaches can be divided into appearance-based and model-based algorithms. Appearance-based methods represent a face in terms of several raw intensity images. An image is considered as a high-dimensional vector. Then statistical techniques are usually used to derive a feature space from the image distribution. The sample image is compared to the training set. On the other hand, the model-based approach tries to model a human face. The new sample is fitted to the model, and the parameters of the fitted model are used to recognize the image. Appearance-based methods can be classified as linear or non-linear, while model-based methods can be 2D or 3D. Linear appearance-based methods perform a linear dimension reduction. The face vectors are projected to the basis vectors, the projection coefficients are used as the feature representation of each face image. Examples of this approach are PCA, LDA or ICA. Non-linear appearance-based methods are more complicated. In fact, linear subspace analysis is an approximation of a nonlinear manifold. KernelPCA (KPCA) is a method widely used. Model-based approaches can be 2-Dimensional or 3-Dimensional. These algorithms try to build a model of a human face. These models are often morphable. A morphable model allows classifying faces even when pose changes are present. 3D models are more complicated, as they try to capture the three dimensional nature of human faces. Examples of this approach are Elastic Bunch Graph Matching or 3D Morphable Models.

II. LITERATURE SURVEY

Principal component analysis (PCA) has been proven to be an efficient method in pattern recognition and image analysis. It has been extensively employed for face recognition algorithms, such as eigenface and fisherface. Many PCA-based face-recognition systems have also been developed. However, existing PCA-based face recognition systems are hard to scale up because of the computational cost and memory-requirement burden. To overcome this limitation, an incremental approach is usually adopted. Incremental PCA (IPCA) methods have been studied for many years in the machine-learning community. The major limitation of existing IPCA methods is that there is no guarantee on the approximation error. In view of this limitation, Zhao, Haitao, et al. proposed a new IPCA method in [1]. This method is based on the idea of a singular value decomposition (SVD) updating algorithm, namely an SVD updating-based IPCA (SVDU-IPCA) algorithm. In the proposed SVDU-IPCA algorithm, they have mathematically proved that the approximation error is bounded. A complexity analysis on the proposed method is also presented. Another characteristic of the proposed SVDU-IPCA algorithm is that it can be easily extended to a kernel version. A kernel principal component analysis (KPCA) is a nonlinear extension of a PCA. The basic idea is to first map the input space into a feature space via nonlinear mapping and then compute the principal components in that feature space. In [12], the kernel PCA is adopted as a mechanism for extracting facial features. Through adopting a polynomial kernel, the principal components can be computed within the space spanned by high-order correlations of input pixels making up a facial image, thereby producing a good performance. Kernel-PCA is used to represent nonlinear mappings in a higher-dimensional feature space in [13]. Several parameters of Kernel functions are investigated and expected to affect the recognition performance. The k-nearest neighbor classifier with Euclidean distance is used in the classification step. Gabor-based kernel principal component analysis (PCA) with doubly nonlinear mapping is proposed for human face recognition in [15]. In this approach, the Gabor wavelets are used to extract facial features, then a doubly nonlinear mapping kernel PCA (DKPCA) is proposed to perform feature transformation and face recognition. The conventional kernel PCA nonlinearly maps an input image into a high-dimensional feature space in order to make the mapped features linearly separable. However, this method does not consider the structural characteristics of the face images. A new method of nonlinear mapping, which is performed in the original feature space, is defined. The proposed nonlinear mapping not only considers the statistical property of the input features, but also adopts an eigenmask to emphasize those important facial feature points. Therefore, after this mapping, the transformed features have a higher discriminating power, and the relative importance of the features adapts to the spatial importance of the face images. This new nonlinear mapping is combined with the conventional kernel PCA to be called “doubly” nonlinear mapping kernel PCA. Another technique coined two-dimensional principal component analysis (2DPCA) is proposed by Yang, Jian, et.al in [2]. As opposed to PCA, 2DPCA is based on 2D image matrices rather than 1D vector so the image matrix does not need to be transformed into a vector prior to feature extraction. Instead, an image covariance matrix is constructed directly using the original image matrices and its eigenvectors are derived for image feature extraction. In contrast to the covariance matrix of traditional PCA, the size of the image covariance matrix using 2DPCA is much smaller. As a result, it is easier to evaluate the covariance matrix accurately, computation cost is reduced and the performance is also improved. In an effort to improve and perfect the performance efface recognition system, Nhat, Vo Dinh Minh, and SungYoung Lee proposed a Kernel-based 2DPCA (K2DPCA) method in [14]. K2DPCA method can extract nonlinear principal components based directly on input image matrices. Similar to Kernel PCA, K2DPCA can extract nonlinear features efficiently instead of carrying out the nonlinear mapping explicitly. Another technique called Diagonal principal component analysis DiaPCA which is much more accurate than both PCA and 2DPCA is proposed in [3]. In contrast to standard PCA, Diagonal principal component analysis DiaPCA directly seeks the optimal projective vectors from diagonal face images without image-to-vector transformation. While in contrast to 2DPCA, DiaPCA reserves the correlations between variations of rows and those of columns of images.

Linear Discriminant Analysis (LDA) is a popular feature extraction technique for face recognition. However, it often suffers from the “small sample size” (SSS) problem when dealing with the high dimensional face data. Some approaches have been proposed to overcome this problem, but they are often unstable and have to discard some discriminative information. A dual-space LDA approach [4] for face recognition is proposed to take full advantage of the discriminative information in the face space. Based on a probabilistic visual model, the eigenvalue spectrum in the null space of within-class scatter matrix is estimated, and discriminant analysis is simultaneously applied in the principal and null subspaces of the within-class scatter matrix. The two sets of discriminative features are then combined for recognition. It outperforms existing LDA approaches. Another LDA method that attempts to address the SSS problem is proposed in [5]. In addition, a scheme of expanding the representational capacity of face database is introduced to overcome the limitation that the LDA-based algorithms require at least two samples per class available for learning. In [6], an innovative algorithm named 2D-LDA is proposed. 2D-LDA directly extracts the proper features from image matrices based on Fisher’s Linear Discriminant Analysis. Linear techniques such as those based on principal component analysis (PCA) or linear discriminant analysis (LDA) cannot provide reliable and robust solutions to those face recognition problems with complex face variations. A kernel machine-based discriminant analysis method proposed in [7] deals with the nonlinearity of the face patterns’ distribution. The proposed method also effectively solves the “small sample size” (SSS) problem, which exists in most face recognition tasks. To improve the generalization capability of LDA when only few samples per class are available, a face recognition method based on PCA (Principal Component Analysis) and LDA (Linear Discriminant Analysis) is proposed in [8]. The method consists of two steps: First, the face image from the original vector space is projected to a face subspace via PCA. Second, LDA is used to obtain a linear classifier.

The basis images found by PCA depend only on pair wise relationships between pixels in the image database. In a task such as face recognition, in which important information may be contained in the high-order relationships among pixels, it seems reasonable to expect that better basis images may be found by methods sensitive to these high-order statistics. Independent component analysis (ICA), a generalization of PCA, is one such method. In [9], Bartlett, Marian Stewart, et al. used a version of ICA derived from the principle of optimal information transfer through sigmoidal neurons. ICA was performed on face images in the FERET database under two different architectures, one which treated the images as random variables and the pixels as outcomes, and a second which treated the pixels as random variables and the images as outcomes. The first architecture found spatially local basis images for the faces. The second architecture produced a factorial face code. Both ICA representations were superior to representations based on PCA for recognizing faces across days and changes in expression. A classifier that combined the two ICA representations gave the best performance. Typically, face representations obtained by ICA involve unsupervised learning and high-order statistics. In [10], Kwak, Keun-Chang, and Witold Pedrycz developed an enhancement of the generic ICA by augmenting this method by the Fisher linear discriminant analysis (LDA); abbreviated as FICA. The FICA is systematically developed and presented along with its underlying architecture. A comparative analysis explores four distance metrics, as well as classification with support vector machines (SVMs). The work demonstrated that the FICA approach leads to the formation of well-separated classes in low-dimension subspace and is endowed with a great deal of insensitivity to large variation in illumination and facial expression. To be well suited for classification problems, Kwak, Nojun, et al. explored a new method of feature extraction for face recognition by utilizing class information [11]. By using ICA in solving supervised classification problems, they obtained new features which were made as independent from each other as possible and which conveyed the class information faithfully.

EBGM [16] is a model-based face recognition method. By manual interaction, some of the features are selected on face. Based on this features, a bunch graph is produced. Node of the bunch graph represent facial landmark. Displacement between test image features and closest train image features is measured by comparing it to all test images and by finding closest measure within it. Face graph is calculated for each test image and train image by extracting landmark features from face. The graph contains location of node and value of those nodes of graph which is created from facial landmark feature.

Recent work in face recognition has demonstrated that Morphable Models of 3D faces provide a promising technique for face recognition under uncontrolled imaging conditions. The process of 3D shape reconstruction by fitting the Morphable Model to an image gives a full solution of the 3D vision problem. For face recognition, however, a full 3D reconstruction may not always be necessary. In those cases, the Morphable Model may help to improve existing image-based classifier systems by preprocessing the gallery or probe images. The main concepts of Morphable Models of 3D faces are summarized in [17]. The description of two algorithms for 3D surface reconstruction and face recognition is also provided. The first algorithm is based on an analysis-by-synthesis technique that estimates shape and pose by fully reproducing the appearance of the face in the image. The second algorithm is based on a set of feature point locations, producing high resolution shape estimates in computation times of 0.25 seconds. A variety of different application paradigms for model-based face recognition have also been discussed. Another approach based on a 3D morphable face model is presented in [18]. The proposed approach is used for recognizing faces in images taken from different directions and under different illumination. For face identification, the shape and texture parameters of the model that are separated from imaging parameters, such as pose and illumination are used. Experimental results for more than 4000 images from the publicly available CMUPIE database are presented. A method proposed in [19] estimates 3D shape and texture of faces from single images by fitting a statistical, morphable model of 3D faces to images. The model is learned from a set of textured 3D scans of heads. The proposed method recognizes face across variations in pose, ranging from frontal to profile views, and across a wide range of illuminations, including cast shadows and specular reflections. Results obtained with 4,488 images from the publicly available CMU-PIE database and 1,940 images from the FERET database are presented.

III. COMPARATIVE ANALYSIS

The comparative analysis of the different approaches which are used for face recognition have been shown in Table I. Different types of methods are considered in this analysis like SVDU-IPCA, PCA + Kernel-PCA, 2DPCA, DiaPCA, 2D-LDA, Kernel machine-based discriminant analysis method, Hybrid classifier using PCA and LDA, ICA, FICA, Feature extraction based on independent component analysis, LDA/KDA, Kernel SVM with linear Preprocessing (PCA/LDA).

Algorithm	Database	Analysis
SVDU-IPCA [1]	FERET,AR, Yale B	SVDU-IPCA method gives close approximation to the batch-mode PCA method.
PCA + Kernel-PCA [13]	ORL	Kernel-PCA with Gaussian function can give a correct recognition rate similar to PCA and higher than Kernel-PCA with polynomial function.
2DPCA [2]	FERET,AR Yale B	The recognition rate is higher using 2DPCA than PCA. Extraction of image features is computationally more efficient using 2DPCA than PCA.
DiaPCA [3]	FERET	DiaPCA is much more accurate than PCA and 2DPCA.
2D-LDA [6]	ORL	2D-LDA achieves the best performance compared to 2D-PCA, Eigenfaces and Fisherfaces.
Kernel machine-based discriminant analysis method [7]	UMIST	Error rate of Kernel machine-based discriminant analysis method is approximately 34% and 48% of kernel-PCA (KPCA) and the generalized discriminant analysis (GDA), respectively.
Hybrid classifier using PCA and LDA [8]	FERET	Significant improvement when principal components rather than original images are fed to the LDA classifier.
ICA [9]	FERET	ICA representations are superior to representations based on PCA for recognizing faces across days and changes in expression.
FICA [10]	FERET	FICA has improved classification rates compared to eigenface, fisherface, and ICA.
Feature extraction based on ICA [11]	YALE AT and T	Feature extraction based on independent component analysis outperforms principal component analysis (PCA) and Fisher's linear discriminant (FLD).
LDA/KDA [20]	UMIST	LDA/KDA outperform PCA/KPCA because of the inherent discrimination ability of the former
Kernel SVM with linear Preprocessing [20]	UMIST	In SVM classifier, kernel SVM with linear preprocessing (PCA/LDA) performs better than Linear SVM with non-linear preprocessing (KPCA/KDA)

Table 1: Comparative Analysis of Face Recognition Approaches

IV. CONCLUSION

A survey on appearance-based and model-based algorithms for face recognition shows that LDA is generally supposed to be better than PCA but this is not true for small data set. ICA is the generalization of PCA and in most of the cases outperforms PCA. A relative analysis between linear and kernel-based methods for face recognition done on UMIST database shows that LDA/KDA outperform PCA/KPCA because of the inherent discrimination ability of the former. The SVM classifier outperforms the Nearest Neighbor algorithm in all the methods used for feature extraction. In SVM classifier, we find that kernel SVM with linear preprocessing (PCA/LDA) performs better than Linear SVM with non-linear preprocessing (KPCA/KDA), though in spirit both are similar. The lowest error performance was achieved by using LDA with RBF SVM classifier. Morphable Models of 3D faces provide a promising technique for face recognition under uncontrolled imaging conditions. This model is versatile and efficient for facial representation.

Face recognition is a technology just reaching sufficient maturity for it to experience a rapid growth in its practical applications. Much research effort around the world is being applied to expanding the accuracy and capabilities of this biometric domain, with a consequent broadening of its application in the near future. Verification systems for physical and electronic access security are available today, but the future holds the promise of passive customization and automated surveillance systems enabled by face recognition.

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