Face Recognition Using Appearance Based Approach: A Literature Survey

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ABSTRACT
With the development of artificial intelligence and machine vision, face recognition has become a hot topic of pattern recognition.This paper describes the review-based comparison and recognition of challenges using holistic and hybrid appearance based approaches and the recent techniques used for improving recognition accuracy. The accuracy or efficiency of the techniques depends on the situation where the system is used. In addition, several major issues for further research in the area of face recognition are also pointed out for further improvement.

General Terms
Face Recognition, Appearance based approach, Holistic Approach, Hybrid Approach

Keywords
PCA, IPCA, LDA, SVM, BPNN, 2DRPCA, BAYESIAN

1. INTRODUCTION
One of the most remarkable abilities of human vision is that of face recognition. It develops over several years of childhood, is important for several aspects of our social life, and together with related abilities, such as estimating the expression of people with which the human interact, has played an important role in the course of evolution. The problem of face recognition was considered in the early stages of computer vision and is now undergoing a revival after nearly 20 years. Different specific techniques were proposed recently. Among those, one may cite neural networks, Elastic Template Matching, Karhunen-Loeve expansion, Algebraic moments, Principal Component Analysis, Discriminant Analysis, Local Binary Pattern, Higher order Derivative Pattern. Typically, the relation of these techniques with standard approaches and their relative performance has not been characterized well or at all. Even absolute performance has been rarely measured with statistical significance on meaningful databases. For many applications, the performance of face recognition systems in controlled environments has now reached a satisfactory level; however, there are still many challenges posed by uncontrolled environments. Some of these challenges are posed by the problems caused by variations in illumination, face pose, expression, and etc.

The effect of variation in the illumination conditions in particular, which causes dramatic changes in the face appearance, is one of those challenging problems [30] that a practical face recognition system needs to face. The variations of both global face appearance and local facial features also cause problems for automatic face detection/ localization, which is the prerequisite for the subsequent face recognition stage. Therefore the situation is even worse for a fully automatic face recognition system. Moreover, in a practical application environment, the illumination variation is always coupled with other problems such as pose variation and expression variation, which increase the complexity of the automatic face recognition problem.

The paper attempts here a comparative analysis of appearance based approaches to face recognition. The famous face recognition techniques are appearance based [22]; here represent an image of size n x m pixels by a vector of n x m dimensional space. Feature extraction from original data is an important step in pattern recognition tasks and it poses the input data onto feature space. Feature extraction is to map the original data on a discriminative feature space, in which the samples from different classes are clearly separated.

A number of face recognition approaches have been proposed in the past years. The proposed paper categorizes the appearance based approach into two main categories. We call the approaches in the first category as "Holistic" approaches. These methods use the whole face region as the raw input to a recognition system. One of the most widely used representations of the face region is Eigen pictures, which are based on principal component analysis. The other category contains "Hybrid" approaches, just as the human perception system uses both local features and the whole face region to recognize a face, a machine recognition system should use both. One can argue that these methods could potentially offer the better of the two types of methods. The review presented in this paper is more extensive than previous reviews and covers more recent techniques in both groups.

In this paper, comparison is done over different face recognition systems which might be good for one technique while a little erroneous for the other one.

2. APPEARANCE BASED APPROACH
Appearance based face recognition techniques [22] have received significant attention from a wide range of research areas such as biometrics, pattern recognition, computer vision and machine mining [5]. Although humans can recognize faces easily, building automated face recognition systems remains a great challenge in computer-based automated recognition research. To have a clear and high-level categorization, instead follow a guideline suggested by the psychological study of how humans use holistic and local features. Specifically, the proposed papers have the following categorization: Holistic approaches and Hybrid approaches. Figure.1. shows the flexible appearance model of a Face Recognition scheme. It shows that, for an input image, all three types of information, including extracted shape parameters, shape-free image parameters, and local profiles, are used to compute a Mahalanobis distance for classification.

2.1. Holistic Approaches

Among appearance-based holistic approaches, Eigenfaces [6] and Fisher faces [18] have proved to be effective in experiments with large databases. In holistic approaches, several authors have taken either whole faces as features or Gabor wavelet filtered whole faces.

2.1.1. Principal Component Analysis

Starting from the successful low dimensional reconstruction of faces using KL or PCA [8] projections, Eigen pictures have been one of the major driving forces behind face representation, detection, and recognition. It is well known that there exist significant statistical redundancies in natural images. Principal Component Analysis (PCA) [Mayank Agarwal et al, 2010] [38] is global structure preserving, the Eigen face method uses PCA for dimensionality reduction and maximize the total scatter across all classes. PCA retains unwanted variations due to lighting and facial expressions. The PCA projects original data onto lower dimensional subspace spanned by Eigen vectors and corresponding largest Eigen values of the covariance matrix for data of all classes. Eigen faces are the Eigen vectors of the set of the faces. Principal component analysis for face recognition is based on the information theory approach in which the relevant information in a face image is extracted as efficiently as possible. For calculating the eigenface PCA algorithm [20], was used. One of the best global compact representations is KL/PCA, Which decorrelates the outputs. More specifically, sample vectors x can be expressed as linear combinations of the orthogonal basis as in equation (1)

$$\Phi i : \mathrm{x} = \sum\nolimits^{n}{}_{i=1} a_i\, \Phi i \approx \sum\nolimits^{m}{}_{i=1} a_i\, \Phi i \qquad (1)$$

(Typically $m \leq n$) by solving the Eigen problem

$$\mathrm{C}\ \Phi = \Phi\Delta \qquad (2)$$

where C is the covariance matrix for input x as in equation (2). An advantage of using such representations is their reduced sensitivity to noise. Finally, the previously extracted features are used to represent the regions (eyes or mouth) during the classification. In this, each of the three regions is classified separately in good or bad. The adopted classification approach is a Support Vector Machine (SVM) [27]. After the classifier is trained with samples of good eyes/mouth and bad eyes/mouth, it is able to categorize the individual faces.

2.1.2. Linear Discriminant Analysis

Linear Discriminant Analysis (LDA) [12], which is based on Fisher Linear Discriminant (FLD) [45], is a popular face recognition technique. It aims to find the most discriminative features maximizing the ratio of determinant of between-class variations to within-class variations. A number of LDA-based methods have been proposed in face recognition. However, due to their parametric nature which assumes that the samples satisfy normal distribution, all these methods suffer from serious performance degeneration for cases of non-normal distribution. In [13], a nonparametric technique is proposed to overcome this problem for the case of two classes, in which a nonparametric between-class scatter is defined. However, it does not give a definition for multi-class problems. To apply it to face recognition, which is a typical multi-class recognition problem, a novel algorithm called nonparametric discriminant analysis [43] (NDA) which extends the definition of the nonparametric between-class scatter matrix to the multi-class problem. For high dimensional problems, there are often not enough training samples to guarantee the within class scatter matrix non-singularity. Inspired by the idea of the unified subspace [40], propose a novel method called principal nonparametric subspace analysis (PNSA) to extract nonparametric discriminating features within the principal subspace of within class scatter matrix, This will help to stabilize the transformation and thus improve the recognition performance.

Shufu Xie proposed that, block-based Fisher's linear discriminant (BFLD) [37] to reduce the dimensionality of the proposed descriptor and at the same time enhance its discriminative power. Finally, by using BFLD, fuse local patterns of Gabor magnitude and phase for face recognition. The fusion of magnitude and phase further enhance the recognition accuracy when they are encoded by local patterns and combined with BFLD.

The classical LDA cannot be directly applied due to the singularity problem of scatter matrix. Several extensions of LDA, including pseudo-inverse LDA, Direct LDA, and LDA/QR were proposed in recent years to deal with this problem. Rong-Hua Li, Eddie, C.L. Chan and George Baciu [3] proposed a well-known feature extraction algorithm for human face images which deals with the classical singularity problem of scatter matrices. Linear Discriminant Analysis via QR decomposition (LDA/QR) and Direct Linear Discriminant Analysis (DLDA) are two types of LDA algorithms to solve this singularity problem. And also they verified the equivalence relationship among these two LDAs. The DLDA and LDA/QR algorithms achieve the same classification accuracy on both ORL and Yale face dataset, which verify the theoretical analysis.

2.1.3. Improved PCA

Jizeng Wang and Tang [25] proposed an Improved Principal Component Analysis (IPCA) face recognition.[42] Initially the eigenspace[6] is created with Eigen values and eigenvectors. From this space, the Eigen faces are constructed, and the most relevant Eigen faces have been selected using IPCA [29]. With these Eigen faces, unlike PCA, the input images are be classified based on Euclidian distance. As shown in the results, the proposed IPCA method has the greater accuracy with consistency than the existing methods. The recognition rate is greater even with the small number of training images which demonstrated an improvement in comparison with previous methods H. Lu and K N. Plataniotis [8], proposed Mulit-Linear Principal Component analysis can also be applied to face recognition by modelling each image as a linear combination of non-Gaussian random vectors where the weights of the linear combinations of the training and testing images are used for identification.

Changes in the illumination condition cause dramatic variation in face appearance and seriously affect the performance of face recognition systems. Hence, the effect of illumination variation is one of the challenging problems in a practical face recognition system. Shermina.J [7] proposed a novel idea to overcome the illumination variation during face recognition [9].In this paper, a methodology on illumination invariant face recognition [11] using Discrete Cosine transform (DCT) and Principal Component Analysis (PCA) is discussed through the process of normalization, compensation and recognition of face images. The technique DCT with PCA in Yale Database B proves good recognition rate. However, it is identified that the efficiency of the face recognition system could be increased by the fusion of the existing approaches in a system so that, the combinational results will outperforms the existing methods in face recognition. Therefore, in future work, the fusion of two illumination invariant face recognition approaches could be experimented for recognition efficiency in order to determine the most effective approach in face recognition across variations in illumination.

2.1.4. Incremental Reduction PCA

Sun,Gu and Fei et al, described that [27], the candid covariance free incremental PCA (CCIPCA) algorithm was developed to overcome the limitation of the batch PCA method. The above methods assume that the data is represented as a vector. Therefore, in face recognition problems this leads to high dimensional vector which are difficult to analyze. Yang et al [35] presented the two dimensional PCA (2DPCA) method which is based on 2D matrices rather than 1D vectors. Although the 2DPCA method [10] has superior face recognition performances in terms of computational efficiency, data representation and recognition accuracy, it requires a larger amount of memory for image representation. Within this context, Mutelo [19] developed the two dimensional reduction PCA (2D RPCA) method. The 2D RPCA method overcomes the memory limitation of the 2DPCA method by efficiently representing the data image matrices within a few rows and column. This is because the “intrinsic dimensionality” of the face data structure is much lower. However, developing an online face recognition system utilizing the spatial information still remains a difficult challenge. The 2DIRPCA [47] technique computes the image covariance matrix of each image matrix as it arrives sequentially. Therefore, the contribution of each image to the projection matrices is added to the existing projection matrices. In this way, the 2DIRPCA method overcomes the limitations such as the computational cost and memory requirements making it suitable for real time applications. The proposed 2DIRPCA method does not suffer from the common convergence problems.

2.1.5. Kernal PCA

As per [8] [20], PCA has become one of the most successful approaches in face recognition. However, PCA only uses the second order statistical information in data. As a result, it fails to perform well in nonlinear cases. Kernel PCA (KPCA) [5] is able to capture the nonlinear correlations among data points, and in some cases has been more successful than conventional PCA. Yanmei Wang and Tang, propose a method of feature extraction for facial recognition based on KPCA, and the nearest neighbor classifier making use of Euclidean distance is adopted. Experimental results show a high recognition rate of using KPCA. Kernel principal component analysis [5] [25] is a method of non-linear feature extraction. With the Cover’s theorem, as in equation (3), nonlinearly separable patterns in an input space will become linearly separable with high probability if the input space is transformed nonlinearly into a high-dimensional feature space. Thus, therefore, map an input variable into a high-dimensional feature space, and then perform PCA.

$$\Phi : R^N \rightarrow F.x. \rightarrow \Phi(x_i),\ i=1,2 \ldots..M \qquad (3)$$

Performing PCA in the high-dimensional feature space can obtain high-order statistics of the input variables, that is, also the initial motivation of the KPCA. However, it is difficult to directly compute both the covariance matrix and its corresponding eigenvectors and eigen values in the high-dimensional feature space. It is computationally intensive to compute the dot products of vectors with a high-dimension. Fortunately, kernel tricks can be employed to avoid this difficulty, which computes the dot products in the original low-dimensional input space by means of a kernel function.

2.2. Hybrid Approaches

Hybrid approaches [2] use both holistic and local features. For example, the modular eigenfaces approach uses both global eigenfaces and local Eigen features. The concept of eigenfaces can be extended to eigen features, such as eigen eyes, eigen mouth, etc. Using a limited set of images (45 persons, two views per person, with different facial expressions such as neutral vs. smiling), recognition performance as a function of the number of eigenvectors was measured for eigenfaces only and for the combined representation. For lower-order spaces, the Eigen features performed better than the eigenfaces [1]; when the combined set was used, only marginal improvement was obtained.

2.2.1. Contourlet Based PCA

Walid Riad Boukabou and Ahmed Bouridane [28] propose to investigate the usefulness of the multiscale and directionality properties of the Contourlet Transform with a view to extract more discriminant features in order to further enhance the performance of the well known PCA method when applied to face recognition. This paper proposes to employ Contourlet with PCA [44] in order to extract discriminant features and obtain higher recognition rates. The experiment results suggest that the Contourlet Transform outperforms significantly the original PCA method. Moreover, when combined with PCA [37], it yields much improved classification results than most existing and similar methods such as the Directional Filter Bank with PCA, Gabor Filter Bank with PCA [36], Contourlet with LDA [17] and Contourlet with ICA [20].

2.2.2. PCA &Linear Feature Analysis

It has been argued that practical systems should use a hybrid of PCA and LFA (Appendix B in Penev and Atick [1996]). LFA [24] is an interesting biologically inspired feature analysis method. It seems to be better to estimate Eigen modes/ eigenfaces that have large Eigen values (and so are more robust against noise), use LFA. In LFA, the whole face region stimulates a full 2D array of receptors, each of which corresponds to a location in the face, but some of these receptors may be inactive. To explore this redundancy, LFA is used to extract topographic local features from the global PCA modes. Unlike PCA kernels Φi which contain no topographic information (their supports extend over the entire grid of images), LFA kernels $K(xi , y)$ at selected grids xi have local support.

2.2.3. Fusion of PCA & Bayesian

Two-dimensional face recognition suffered from pose changes, while three-dimensional approaches are with high computational complexity. Besides the improvement in recognition rate, this system reduces the misclassification that could occur in traditional single-view systems. Shin-Yee Tsai and Angela Chih-Wei Tang [14] proposed a system that fuses the individual recognition results of two images of the same identity with different viewing angles based on Bayesian theory. Bayesian approach uses the similarity of each person and is trained by determining the reliability of each identity of the two channels. Different form traditional PCA based approaches, SVM classifiers [20] are used instead of minimum distance classifier to enhance the robustness. Experimental results show that this two-view face recognition system has achieved a higher recognition rate compared with traditional 2D single-view face recognition systems.

2.2.4. Weighted Eigen Face & BPNN

In existed Eigenface algorithm, which has a large calculating quantity and requires large computer store capability when computing covariance matrix of face image. These are bottleneck of K-L transform. Besides, eigenface method gives the same weight to each pixel in one image. This will alleviate important information while overrate unimportant information. In W. Zhao, R. Chellappa, P. J. Phillips, and A. Rosenfeld [30], a new algorithm that combined weighted eigenface and BP networks [24] was proposed. This method has less computational complexity, higher recognition rate, and more robust than traditional appearance based method. Face image normalization is very important to every face recognition algorithm. Weighted eigenface algorithm [21] normalizes face image to 96×96 pixels considering image blocking. Computational complexity and time will be reduced by dividing face image into sub blocks to decrease its dimension. Weighted eigenface algorithm reduces computational complexity of traditional K-L transform. Recognition rate increases by giving different weights to different parts of human face according to each importance in human face recognition. Within-class average face keeps within class information maximally, and enlarges different class information effectively. Adaptive learning step algorithm adjusts BP neural network to jump out of local optimization, reduces learning time and quickens convergence speed comparing with traditional algorithm.

2.2.5 Fusion of Local & Global discriminant features

It has been observed that facial changes are occurred due to variations in facial expression, illumination condition, pose, etc. and these changes are often appeared only some regions of the whole image. The global features extracted changes. To cope with the above facial changes face images are divided into a number of non-overlapping from the whole image are not able to cope with these facial smaller sub-images and discriminant features are extracted from these sub-images as well as from the whole image. All these extracted local and global features are fused to form a large feature vector. Shiladitya Chowdhury, Jamuna Kanta Sing, Dipak Kumar Basu, and Mita Nasipuri [4] have used generalized two-dimensional fisher's linear discriminate (G-2DFLD) method to extract these local and global discriminant features. They used the fisher's linear discriminate (FLD) method to extract lower dimensional discriminant features from the fused large feature vector. A Multi-class Support Vector Machine (SVM) is applied on these reduced feature vectors for classification. All of these extracted local and global discriminant features are fused to get a large feature vector and then its dimensionality is reduced while keeping its discriminant information. The discriminating power of the extracted global and local features may be complemented by fusing them to form a feature vector.

3. DISCUSSION AND CONCLUSION

An attempt has been made to carry out a realistic comparison of face recognition schemes and methods with different data base systems. It is obvious that an ideal common environment can neither be ensured nor assumed while drawing meaningful conclusions. This problem is as complex as the face recognition itself. Hence a typical qualitative assessment has been made for comparison. From the Table 1, it is apparent that methods adapting FERET data base seem to be the most accurate one in the case of Holistic approach. Similarly ORL data base appears to be the best choice for methods following hybrid path. However these conclusions can not be quite emphatic as the test image, its brightness, contrast and illuminating conditions and the resolution of image capturing devices can vary vastly between methods or even between measurements. However, for a set of constraints and application requirement, this work could be useful as a ready reckoner to save repeated measurements.

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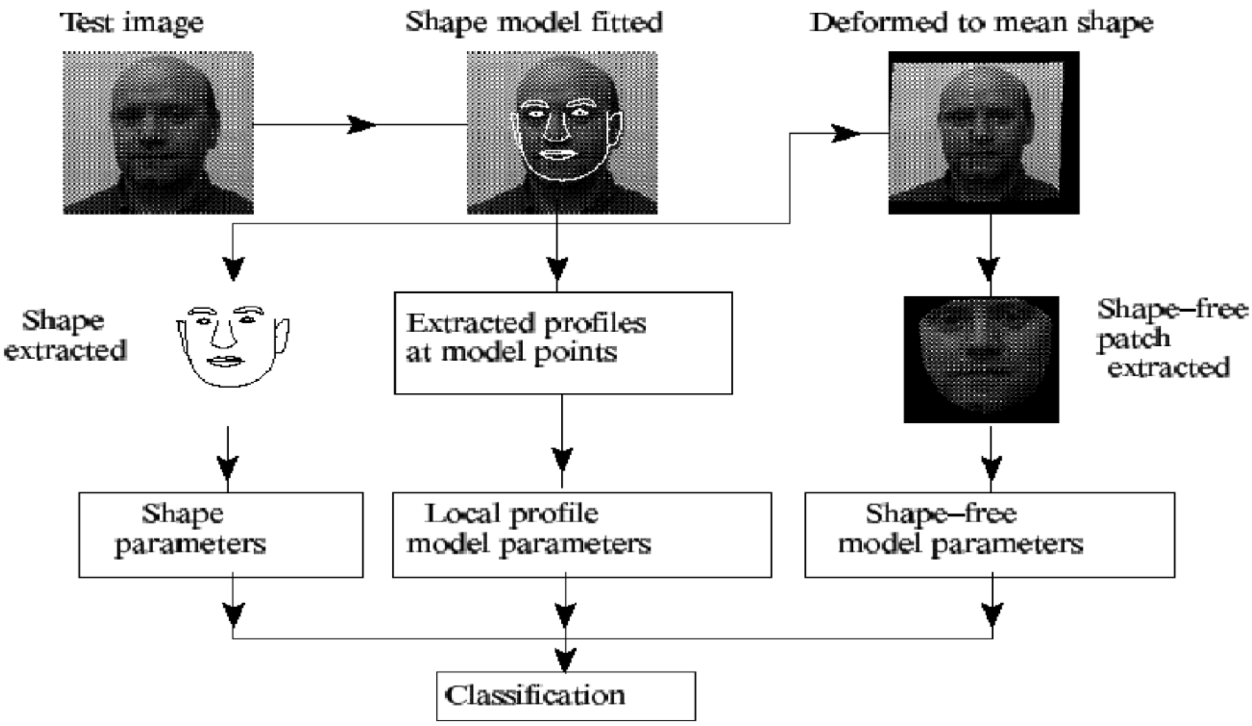

Fig. 1. Flexible Appearance Model Based Face Recognition Scheme

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Appearance based approach	Method	Recognition Rate %				
		YALE DataBase	ORL DataBase	FERET DataBase	CMU-PIE DataBase	AR Data Base
Holistic	PCA	77.8	94	98.1	71.66	72.8
	LDA	91.1	96	98	78.67	82.6
	DLDA/QR	-	95			
	ICA	93.3	-	99	-	84.3
	2DPCA	92%	92.5	99.5	-	97.79
	IPCA	96	97	99	-	-
	RPCA	-	93.5	-	-	-
	KPCA	96.94	-	-	-	-
Hybrid	Contourlet PCA	92	98	87	-	-
	Modular Eigenfaces	95	-	-	-	-
	MPCA-LDA	66.7	-	-	-	93.8
	PCA-SVM	91.1	86.88	93.8	-	51.4
	DCT&PCA	94.2	-	-	-	-
	PCA-BPNN	-	95.62	93.33	92.23	-
	KPCA-SVM	73.57	95	-	-	-
	LDA-NN	97	97	-	-	-

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