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Evaluation of Face Recognition Methods in Unconstrained Environments

Amrit Kumar Agrawal[a], Yogendra Narain Singh[b]

[a]*Apollo Institute of Technology, Kanpur, 209402, India.*
[b]*Institute of Engineering & Technology, Lucknow, 226021, India.*

Abstract

Face recognition is one of the most challenging applications of image analysis and pattern recognition. Face recognition methods perform well on the images that are collected with careful cooperation of the subjects. Whereas, the challenges of change in illumination, expression, pose make this problem harder. Age changes the facial texture and shape while occluded images left partial facial features for processing, thus making the problem of face recognition much harder. This paper presents an overview and a general classification of face recognition methods along with their pros and cons. We present a comparison across different methods and conclude by discussing possible future directions.

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Keywords: face recognition; feature extraction; pose; illumination.

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1. Introduction

Human face is one of the most informative means of communication in our societal life. Unlike, face recognition by humans to comprehend their peers possess a natural phenomenon, but recognizing facial geometry through machine is still a challenging problem. Face recognition is the task of recognizing an individual using digital facial image. The progress of face recognition technology over the past two decades has been substantial, as benchmarked by the National Institute of Standards and Technology (NIST)[1]. The release of the Multiple Biometric Evaluation 2010 report of NIST shows that the most accurate face recognition technique (FRT), the chance of identifying the unknown subject is about 92% when searching a gallery of 1.6 million faces. For other population sizes, this accuracy rate decreases linearly with the logarithm of the population size[2].

Face recognition techniques (FRT) are more accurate on the images that are collected with careful cooperation of the subjects, active compliance by the photographer to the image collection under controlled environment, and a proper review by an official. The compressed facial images such as passport, visa and ID card are subject to losses, while less compressed images such as mugshot are generally of higher resolution, exhibit considerable pose, illumination and expression variations. Identifying person in an uncontrolled environment is still a challenge for facial recognition reliability. The FRT performance deteriorates significantly when variations are found in illumination, facial pose and expression[3,4]. Other factors such as image resolution, orientation and blurring, time delay or facial aging, and occlusion such as partial covering of face by clothing, shadows and obstructions also contribute to face recognition errors[5].

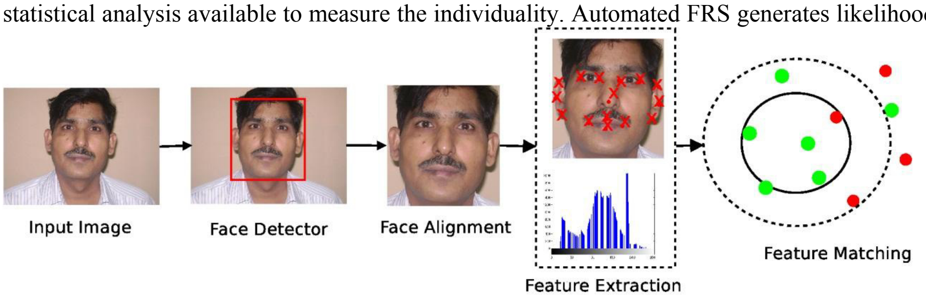
This paper presents an evaluation of face recognition methods available in the literature [1-58]. An overview of popular face recognition methods and their general classification is also presented. We compare these methods on the technique used, database used and the achieved recognition results. The rest of the paper is organized as follows. An overview of automated facial recognition system is given in Section 2. The classification and evaluation of face recognition method are presented in Section 3. The challenges faced by a face recognition system are outline in Section 4. Finally the conclusion and the possible future directions required for an efficient face recognition system is drawn in Section 5.

2. Automated facial Recognition

Automatic facial recognition can be seen as a pattern recognition problem, which is very challenging due to its nonlinearity[3]. In particular, it can be viewed as a template matching problem, where matching has to be performed in a high dimensional space. Higher the dimension of the space, resulted more the computation we need to find a true match. A face recognition system (FRS) is typically designed to measure the similarity between probe and gallery facial images. An automated FRS typically involves localization of facial landmarks such as eyes, nose, mouth, and facial outline, normalizing the facial geometry and appearance such as illumination and gray scale properties, choosing a suitable facial feature representation, selection of distinguished feature combinations and developing of an accurate and scalable matching techniques[6,7]. The schematic of the major steps involved in automatic FRS is described in Fig. 1.

Face recognition systems are also looking at ways to apply the latest advances in FRT to uncontrolled environments, where state-of-the-art face detectors can achieve about 50-70% detection rate, with about 0.5-3% of the detected faces being false positives[8]. When considering face recognition in video frames the issues such as segmenting the face images in varying illuminations[9] and compression artifacts[10] must be considered. Improving success rates in videos and films is especially important for law enforcement for example, identifying suspects from reviewing security tapes and other forensic scenarios.

In order to distinguish between two faces, the critical elements on which the recognition is based are, individuality and matching[11]. Individuality refers to the likelihood of biometric patterns among non-mates are sufficiently similar. In other words, it is a measure of likelihood that a given biometric template is sufficiently similar to the templates of a target population. The major challenge in identifying people by their facial geometry is the lack of statistical analysis available to measure the individuality. Automated FRS generates likelihoods of match on subjective basis depending on the chosen method without



having the actual statistical framework of individuality of faces. The matching process in a FRS generates the similarity score from some probe image for each image in the gallery and taking the decision on the closest match in contrary to a human that examines the top-most matches.

Fig. 1. Face recognition system[12]

3. Face Recognition Methods

A number of face recognition methods have been developed during the past decades. We can classify these methods in two groups that include appearance-based methods and model based methods. Former methods use holistic texture features that are applied to either whole-face or specific regions in a face image whereas latter methods employ shape and texture of the face. The classification of these methods is shown in Fig. 2.

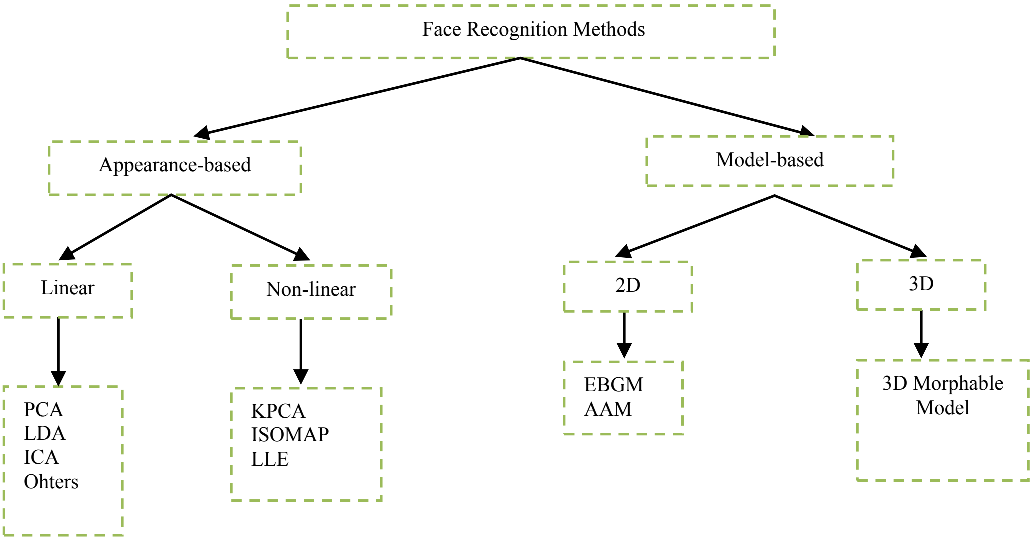


Fig. 2. A general classification of face recognition techniques

3.1. Appearance-based Face Recognition Methods

Face recognition problem can be considered as a space-searching problem in combination with machine learning problem. The most popular methods of appearance-based face recognition are: Principal component analysis (PCA), independent component analysis (ICA) and linear discriminant analysis (LDA). The PCA[13], finds a set of the most representative projection vectors such that the projected samples retain most information about original samples. The ICA[14], captures both second and higher order statistics and projects the input data onto the basis vectors that are statistically independent as possible. The LDA uses the class information and finds a set of vectors that maximize the between-class scatter while minimizing the within-class scatter[15,16]. The PCA and LDA methods have demonstrated their success in face detection, recognition and tracking. The representations in these subspace methods are based on second order statistical of the image set that do not address higher order statistical dependencies such as the relationships among three or more pixels. A new method for performing a nonlinear form of Principal component analysis is used as kernal PCA[17].

The pros and cons of appearance-based methods are as follows: Primarily, the face recognition problem is transformed to a face space analysis problem, where a number of well known statistical methods can be tried out. Special aspect of this model is its applicability to low resolution or poor quality images. A flaw in this model is that to have a sufficient data for sample underlying distribution successfully. Prior knowledge of the human faces is not utilized in this model. Impact of facial variations due to illumination, pose and expression is subjected to its limitations. Correspondence needs to be established in advance, although the tangent distance may be used to tolerate small correspondence displacements.

3.2. Model-based Face Recognition Methods

The model-based face recognition scheme is aimed at constructing a model of the human face, which is able to capture the facial variations. The prior knowledge of human face is highly utilized to design the model. For example, feature-based matching derives distance and relative position features from the placement of internal facial elements (e.g., eyes). A more recent feature-based system, based on elastic bunch graph matching, was developed by Wiskott et al.[18]. By integrating both shape and texture, Cootes et al.[19,20] developed a 2D morphable face model[21], through which the face variations are learned. A more advanced 3D morphable face model is explored to capture the true 3D structure of human face surface. The 3D model is better for representing faces, especially to handle facial variations, such as pose, illumination. Blanz et al.[22,23] proposed a method based on a 3D morphable face model that encodes shape and texture in terms of model parameters, and an algorithm that recovers these parameters from a single image of a face.

The pros and cons of model-based face recognition methods are as follows: The model has intrinsic physical relationship with real faces. An explicit modeling of face variations, such as pose, illumination and expression gives the possibility to handle these variabilities in practice. The problem of model construction is a challenging task. Facial feature points are difficult to extract automatically with robustness. Model fitting is a searching process, prone to be trapped into local minimum; recognition results highly depend on the fitting results. Fitting process is time consuming. Relatively high resolution and good quality face images and an appropriate boost in initialization is needed.

3.4 Unconstrained Face Recognition Methods

We present a review of unconstrained face recognition methods that are known in recent past. Park et al.[24], proposed an key point detection method which enhanced the accuracy on the 1000 tattoo images. Experimental result has shown that the method is superior than the SIFT key point. A two level illumination estimation framework is proposed by Zhang et al.[25]. Experimental result shows the satisfactory performance against various datasets. Min et al.[26], presented the possibility to explore face recognition in the presence of partial occlusions such as sunglass and scakrf. The proposed method identified the occluded parts t the pixel level and applying face recognition on non-occlued parts only. Experimental result shows that the proposed method is superior to KLD-LGBPHS, S-LNME, OA-LBP and RSC. Cassio et al.[27], proposed five approach to determine whether the subject of test sample is enrolled in face gallery. Out of these approaches, three have been presented a good result. The approaches have been identified on feature explored in the data, scalability and accuracy. For face recognition the approaches have been tested on standard databases namely FRGC and Pubfig83. Various assumptions has been made by the authors before the approaches apply on the datasets. Indhumathi et al.[28], proposed an algorithm for face detection using distance images. The effectiveness of the recognizing blurred and poorly well-lighted faces are also addressed by the author and shown good recognition rate than LBP operator. Bhattacharjee[29], presented an automatic face recognition system using adaptive polar transformation and wavelet based fusion method. In which visual and thermal face images have been effectively combined by the fusion method on robust manner. Experimental result has shown good performance in recognizing against various possible complicacies. A Component based representation in automated face recognition has been demonstrated by Bonnen et al.[30]. Experimental result shown that the method is robust to change in facial pose, and recognition accuracy on occulded face is enhanced in forensic scenarios.

Niinuma et al.[31], proposed a fully automatic method for multi-view face recognition using synthetic target face images. To align the synthetic target images and query images, procrustes analysis has been applied. The method performed well against different state of art matchers. Brendan et al.[32], proposed a method for heterogeneous face recognition in which nonlinear prototype face images are used. The HFR also addressed the issue from the small sample size problem by using the random sampling. Finally, the method has been demonstrated on different scenarios, such as near infrared to photograph, thermal to photograph etc. Yi et al.[33], proposed a 3D model fitting algorithm to find the pose of face images. PCA method has been applied on the pose adaptive Gabor features to find the similarity between them using cosine metric. Experimental result show that method performs well against LFW. Connor et al.[34], proposed an algorithm based on local binary pattern and random forest, where the sign and magnitude feature has been fused. The performance of the method is validated on different datasets. Arashloo et al.[35], proposed a pose-invariant face recognition method using MRF matching to reduce the inference time. The method is evaluated on different databases in verification, identification and unseen pair-matching paradigms.

Liao et al.[36], proposed an alignment-free face representation method which is based on MKD. Descriptor size of a face has been identified by using the original content of the image. The method requires no any facial component in the image. Experimental results shown that the method is superior than other method in terms of recognizing both holistic and partial face under different databases. Carlos et al.[37], proposed a method for making the process of gallery maintenance making more efficient, which is based on one-against-some classification rule. Han et al.[38], proposed a 3D face texture modeling method using frontal and profile face images. The 2D face recognition has been also utilized in different scenarios. Superior performance has been shown on FERET database in experimental result. Fischer et al.[39], proposed a method for pose-invariant face recognition algorithm which is based on PLS approach. Different parameters such as size, location and the selection of the local blocks are considered for the good performance using PLS approach. Experimental results show that the recognition rate of the proposed method is very good.

Li et al.[40], proposed a cross-pose face recognition method based on regressor. Experimental result show that the recognition performance is good against various face databases. Maturana et al.[41], proposed two methods for face recognition using histogram of LBP. The pose variation and misalignment cases have been considered for the proposed work. Sharma et al.[42], proposed an pose-invariant face recognition method. Projection direction for the different poses has been identified in such a way that projected images of the same subject in different poses are highly correlated in the latent space. Out of three methods PLS, BLM and CCA, the performance of the CCA is better than other two.

Shyam et al.[43], have evaluated and presented that the some of the traditional methods such as Eigenface and Fisherface may be performed better in constrained environments when they are computed on Bray Curtis dissimilarity as a distance measures. In[44], Shyam et al. have nicely presented the multimodal biometrics, in which the matching score of the traditional and feature based methods have been fused at the information level. In[45], Shyam et al. have theoretically and practically illustrated a variant of Local Binary Pattern, for handling the challenge of unconstrained environments.

A summary of the discussed methods is presented in Table 1.

Table 1. Face recognition methods at a glance

Author and Year	**Technique used**	**Database used**	**Result**
Park et.al, 2014	SIFT, High order SIFT	Tatto image dataset of 1000 images	Accuracy=98.8%
Zhang et al, 2014	Subject-independent illumination estimation method	CAS-PEAL, CMU-PIE	Accuracy=97.39%
Min et. al, 2014	OA-LGBPS	AR face database	Identification rate for clean=99.17%, scarf=95.83% Sunglass=87.08%
Cassio et.al, 2014	LS,SVM-Single, CI, SVM- All, RBF, BK-set, SVM- All poly	FRGC & PubFig83	Average AUC=79.2 for LS
Indhumathi et.al,2014	DRBF, IRPF	Own dataset with blurred image/ private dataset	-
Bonnen et. al, 2013 algorithm, RS-LDA	Component based	AR, FERET	Efficiency of occlusion with fused component=96.67% against FERET database
Niinuma et.al, 2013	Pose regulation + MLBP	Color FERET, PubFig	Face identification rate=77% on FERET database using MKD-SRC matcher
Brendan et.al, 2013	P-RS, D-RS	CHUX, XM2VTS, FERET	Accuracy=99% on P-RS framework

Yi et.al, 2013	PCA, LFW, PAF	FERET, PIE	Mean classification accuracy=87.77%
Connor et.al, 2013	LBP+RF, MLBP	MORPH	Accuracy(N:1)=32.96% at 6 X 5 patches Accuracy(1:N)=40.71% at 6 X7 patches
Arashloo et. al, 2013	Multi-resolution analysis based o RGT, Daisy features, multi-resolution LBP histogram	XM2VTS, FERET & LFW	Mean accuracy = 80.08%
Liao et.al, 2013	GTP, MKD-SRC	FRGCV 2.0, AR, LFW, PubFig	Detection rate=98.33% on PubFig database
Carlos et.al, 2013	PLS (Partial Least Square)	FRGC, PubFig83	Recognition rate=99.30% for FRGC dataset one against some
Han et.al, 20123	Dmodeling from two images, MLBP	FERET	Face authentication accuracy Capability enhancement on FaceVACS=98% Recognition rate=91.6% ofaceVACS after face normalization
Fischer et.al, 2012	Partial Least Square	CME, Multi-PIE dataset	Recognition rate=90.1% for frontal and 82.0 % for all pose
Li et.al, 2012	Linear regression	FERET, CMU+PIE	Recognition rate=100% on CMU PIE database and 97.5% on FERET database
Sharma et.al, 2012	Discriminant Multiple couple latent subspace framework	CMU PIE & FERET MultiPIE	Accuracy for DMCLS= 93.25%
Maturana et.al, 2009	LBP, SPM, SNBNN, Eig, Fish, AH, SPM	AT & T-ORK, Yale, Georgia Tech, Ext. Yale B (Frontal)	Accuracy =99.98% against Ext. Yale B dataset
Shyam et.al, 2014	Eigenfaces with BCD Fisherfaces with BCD	ORL	Accuracy=95.45% and 97.50%
Shyam et.al, 2014	Fisherfaces + LBP	ORL	Accuracy =99.87%
Shyam et.al, 2014	ALBP with BCD	Ext. Yale, Yale	Accuracy=86.45 and 71.9%

4. Challenges of Face Recognition

The challenges of face recognition are outlined as follows: (1) Illumination where variations in illumination sometimes result in larger image differences than the variations due to identity. Different methods address the issue of varying lighting conditions[46,47,48]. (2) Occlusion where non-invasive nature of face recognition confronts the occlusion problem. People use accessories such as sunglasses, scarfs, and hats which partially occlude the face region. Local region-based methods have been successfully used in partial occlusion problem. Earlier works on literature that address the issue of occlusion are described in[49,50,51]. (3) Expression where facial expression changes the geometry of the face and impacts recognition accuracy. Local region-based or patch-based methods that use a histogram of features have been successfully used for expression invariant face recognition. Li et al.[52] described expression invariant face recognition method. (4) Age that changes the facial texture and shape. There is a change in shape of the cranium from infancy to teenage and changes in skin texture during adulthood. This is an issue even on controlled face recognition because the passport and visa face images are not updated frequently. The work of [53,54], addressed the issue of age progression in face recognition. In[54], the authors proposed age invariant feature descriptors named as GOP (Gradient Orientation Pyramid) in which they use gradient directions at multiple scales for age invariance in face images. (5) Pose that refers to out-of-plane rotation, a challenge found in face recognition systems due to the 3D nature of a face. The differences due to pose are, sometimes, larger than inter-person differences within the images. However, in non-intrusive, uncontrolled settings such as surveillance, a subject can be found looking up, down, left or right, causing an out-of-plane rotation. Local region-based approaches such as EBGM[18] and LBP [55,56], are more robust to pose variations than holistic approaches such as PCA and LDA. The work of face recognition in pose variations is found in [57,58] .

5. Conclusion

This paper has presented an evaluation of face recognition methods in unconstrained environments. A comparative study on image based face recognition system along with their pros and cons are presented. The state-of-the art face recognition methods for unconstraint environments such as pose, illumination, expression variations are also discussed. In view of this discussion and sensitiveness of face recognition methods the facial geometry is a moderate biometric identity. But, due to its user friendly nature the automatic face recognition offers a wide range of applications ranging from commercial, civilian and forensic applications.

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