Review on Sparse based Face Recognition Methods in Uncontrolled Environment

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***Abstract*—Face recognition has been found to be the minimally invasive method among the available biometric identification schemes. It aims to identify or verify a person's identity by matching input face image against the faces in a database. It is one of the important research areas due to its large practical applications. Most of the systems could well handle the images captured under controlled situations. But practical face recognition systems have a number of challenges as the real world images are captured under uncontrolled environments. These challenges are due to variations in orientations, expressions, occlusions, illumination conditions and image resolutions. In this paper, different methods used for face recognition in challenging environments in the literature are summarized.**

Keywords-Sparse based Classification, Face recognition in uncontrolled environments, Occlusion, Pose, Low resolution face images

I. INTRODUCTION

Biometric authentication [18] is a robust remedy for many security violations. It is usually used in areas like manufacturing, stock exchange, internet security, defense, banking, public sector, retailing, health industry, airport security. Face recognition has been found to be the minimally invasive method among the available biometric identification schemes. It has a wide range of real-world applications including surveillance, duplication of identity documents (e.g., passport, license), access control, photo-management, and person tracking and also in emerging online scenarios such as image tagging and image search. Over the past two decades, variety of face recognition approaches has been proposed. Face recognition systems either perform face verification, i.e., classify face images as belonging to the same individual or not, or perform face identification, i.e., classify unknown faces with respect to some training set. Today various advanced face recognition systems have appeared in the literature. These face recognition techniques work well in the face images taken in controlled environments with cooperating subjects. But in real scenarios, it is not the case. We have to recognize the images of non-cooperating subjects taken in unconstrained environments. Face images of single person will vary due to occlusions, illumination changes, physical changes like expression changes and aging effect. So practical face recognition applications are very difficult and it poses a serious challenge to researchers.

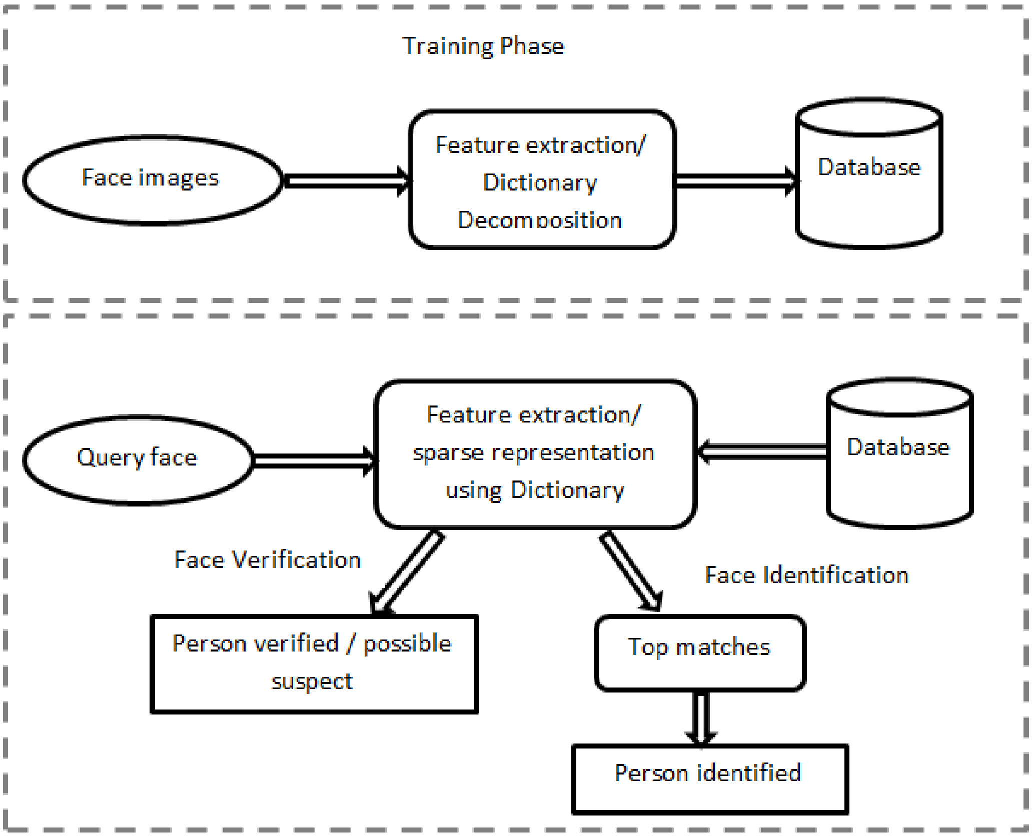
Labeled samples may not be available for training, and it is one of the major challenges for practical face recognition systems. High cost of human effort is needed for labeling training samples. In some cases a class may not have more than one face images. For example, in order to recognize a culprit, there may be only one sample available, e.g. his/her ID photo. And the differences between the testing image and the small number of training images will be greater i.e., the training image may be a front face photo with normal lighting conditions, but the testing images may include different type of occlusions (e.g. may wear a mask or sunglasses) and contain worse lighting conditions [1].

Surveillance cameras are of very low-resolution, and the images captured will contain various poses and bad illumination conditions. Real world face recognition systems will be very poor on these data. When the images are of low resolution, works that addresses the problem of matching faces across changes in pose and illumination cannot be applied.

Changes in pose, expressions or partial occlusions create great changes in face images. In uncontrolled situations, such variations are common. In those cases only parts of the facial appearance change largely while others are less affected. It is highly unpredictable where and how these local deformations may occur in the facial appearance. So Face recognition in such cases is very challenging. [2].

Normally real world face recognitions will be performed in unconstrained scenarios with non-cooperating subjects. A lot of works in this area have been proposed in the literature. None of the algorithms are robust enough to cope with the variations and face recognition performance for real application is significantly diminishing. To represent a query image, Sparse Representation based Classifier (SRC) [19], use training samples of all classes collaboratively. Due to l1-norm minimization of the representation error, SRC can even recognize a face image heavily corrupted by noise and occlusions. Impressive and significant face recognition results have been obtained by SRC. But if the training images are not carefully controlled and sufficient training samples of each class is not present, then the method may fail or performance may affected badly. In this paper, some recent sparse based methods in face recognition that handle real world face images with challenging environments are analyzed and summarized. Section 1 discusses the introduction and a general framework of face recognition system, Section 2 summarizes recent face recognition methods for real world images from the literature and Section 3 concludes the paper.

1.1 General Framework of Sparse based Face Recognition System



In the training phase face images of different classes are used., Features will be extracted from the face images before they fed into classifiers. Sparse Representation based Classifiers (SRC) use l1 norm optimization of the training data and decomposes the dictionary so that a test image can be represented using sparse coefficients in the dictionary. For verifying a face the features are extracted from query image and it is compared with the trained database. For face identification the face is classified to any of the class using a classifier. In order to represent the test image by limited training images, a sparse coefficient vector was introduced in SRC. This model was formulated by minimizing the reconstruction error along with the l1 norm calculation on the sparse coefficient vector. The class which gives the minimum error is identified as the recognized class.

II. REVIEW OF FACE RECOGNITION METHODS FOR REAL WORLD IMAGES IN CHALLENGING ENVIRONMENTS

Author	Method/ Paper	Technique used	Advantages	Databases used	Performance (RR)
Xavier Fontaine, Achanta, Sabine Susstrunk[3]	Face Recognition In Real World Images	Automatic alignment using landmark detection, modified Robust Sparse Coding (RSC) algorithm for classification	Can be trained using very few training samples,Computationally efficient	Labeled Faces in the Wild (LFW)	95.0%
M. Saad Shakeel; Kin-Man-Lam[4]	Recognition of LR face images using sparse coding of local features	Gabor features extraction from a LR gallery image and a query image at different scales and orientations, Projects the features separately into a low-dimensional feature space using sparse coding	Recognition of Low Resolution face images without using super-resolution technique.	ORL, Extended -Yale B, and CAS-PEAL-R1	93% 94.73 % 97.22 %
Jian Yang, Lei Luo, Jianjun Qian, Ying Tai, Fanlong Zhang, Yicheng Gao[5]	Nuclear Norm based Matrix Regression	Nuclear norm of representation error minimization, To calculate the regression coefficients Alternating Direction Method of Multipliers (ADMM) and Classification with Nuclear Norm based Matrix Regression (NMR)	Better results in recognition of images with real world occlusions and high illumination changes	Extended Yale B, AR, EURECOM, Multi-PIE and FRGC	Average 93%
Soma Biswas, Gaurav Aggarwal, Patrick J. Flynn, and Kevin W. Bowyer[6]	Pose-Robust Recognition of Low-Resolution Face Images	Simultaneously transform the features from the poor quality probe images and the high-quality gallery images using multidimensional scaling, Facial landmark localization using Tensor analysis and Automatic feature localization	Application of tracking and recognition in surveillance videos, Perform well in LR uncontrolled probe images	Multi-PIE	Average 90%
Jing Wang, Canyi Lu, Meng Wang, Peipei Li, Shuicheng Yan, Xuegang Hu[7]	Robust Face Recognition via Adaptive Sparse Representation (ASRC)	ASRC selects the most discriminative samples for representation if correlation of samples low; Otherwise correlation concept is used	Take advantage of both sparsity and correlation; Solve problems such as motion segmentation, activity recognition, subspace learning	Yale, ORL, AR and sampled from the UCI repository	83.17 % 95.85 % 9.71% 93%
Qingxiang Feng; Chun Yuan; Jar-Ferr Yang; Chou; Yicong Zhou; Weifeng Li[8]	Superimposed Sparse Parameter Classifiers	Superimposed sparse parameter (SSP) classifier based on Two Phase Test Sample Sparse Representation (TPTSSR) and Linear Regression Classification (LRC),	Iterative removal of most unlikely classes to improve the SR, Good in Face Recognition on Noise Face with pose, expressions variations.	CASIA ORL AR	36% 92% 95%
Yuan Gao; Jiayi Ma; Alan L. Yuille [9]	Semi-Supervised SRC with Insufficient Labeled Samples	Faces are represented in terms of two dictionaries Gallery dictionary, and a Variation dictionary, GMM and SRC .	Deal with both linear and non-linear variations between training and testing samples.	AR, Multi-PIE, CAS-PEAL, and LFW	95.2% 74.6% 92.5%

Maria Marsico, Michele Nappi, Daniel Riccio, and Wechsler,[10]	Face Analysis for Commercial Entities (FACE)	Pose and Illumination Normalization, Pose (SP) and Illumination (SI) quality indices used to discard images , Localized version of the correlation and reliability indices SRR I,SRR II	Improved accuracy for Uncontrolled Pose and Illumination Changes, Do not require expensive training to learn face space,	Celebrity DBLFW , SCface, FERET	87% 61% 89%
Ali Moeini, Hossein Moeini [11]	Real-World and Rapid Face Recognition towards Pose and Expression Variations via Feature Library Matrix	3D Probabilistic Facial Expression Recognition Generic Elastic Model (3D PFER-GEM), automatic head pose estimation by CLM, Feature Library Matrix (FLM), iterative scoring classification using the SVM.	Better face recognition under pose and expression variations from only a single frontal image, Very rapid and real-time.	Bosphor us FERET, CMU-PIE LFW	91. 4% 99% 98.2% 93.16 %
Changxing Ding, Chang Xu; Dacheng Tao [12]	Multi-task Pose-Invariant Face Recognition PBPR-MtFTL	3D method is for face pose normalization, un occluded facial texture detection, Patch-Based Face Representation, PCA, Multi-Task Feature Transformation Learning	Full range of pose variations are handled within ±90° of yaw, effectively uses all un occluded face texture and correlation b/w different poses	CMU-PIE MULTI-PIE LFW	99.6% 93.2% 92.95 %
Chia-Po Wei; Yu-Chiang Frank Wang [13]	Under sampled Face Recognition via Robust Auxiliary Dictionary Learning	Robust Sparse coding, Auxiliary Dictionary Learning, Normalization	Though one or few images per subject are available during training recognition on occlusions, illumination and expressions variations is good.	AR CAS-PEAL Multi-PIE	95. 4% 93.63 % 94.0%
Shu Zhang; Man Zhang; Ran He; Zhenan Sun [14]	Transform-invariant dictionary learning for face recognition	Transform-Invariant Basis Matrix Learning, Sparse Coding, Appearance Consistent Error Term Based Optimization	Recognizing face images with large transformation variations, transform-invariance, discriminability	Extended Yale B LFW	94.17 % 80%
Chia-Po Wei; Chih-Fan Chen; Yu-Chiang Frank Wang [15]	Structurally Incoherent Low-Rank Matrix Decomposition	Low-Rank Matrix Decomposition with Structural Incoherence, Optimization via ALM	Better performance even when training and test image data are corrupted due to occlusion or disguise	Extended Yale, AR CMU MULTI-PIE	95% 83% 90.55 %
Xudong Jiang; Jian Lai [16]	Sparse and Dense Hybrid Representation via Dictionary Decomposition (SDR-SLR)	Low-rank (SLR) dictionary decomposition in supervised mode, Sparse and Dense Representation, Class specific component along with the non-class-specific components is used by a sample to compete against others.	Work well even in the absence of representative samples for every class, Handles corrupted training data.	CMU Multi-PIE Extended Yale B AR FERET	87.2% 84.5% 97.6% 90.6%
Massimo Tistarelli; Yunlian Sun; Norman Poh [17]	Use of Discriminative Cohort Score Normalization	Picture-specific cohort score normalization, cohort polynomial regression	Facilitate the pairwise face matching, work in Unconstrained conditions	FRGC 2.0 LFW	93% 80%

III. . CONCLUSION

Face recognition in unconstrained environments is very challenging due to variations in orientations, expressions, occlusions, illumination conditions and low image resolutions. Researchers have proposed several novel face recognition techniques for handling real world applications. In order to overcome different challenges caused by non-cooperating subjects different methods have been used. But performance of these methods is significantly less in complex real time scenarios. The general classification target is well matched with the Sparse representation based classification. It give better results even when images are heavily corrupted by noise and occlusions. So Comparing to normal classifications methods, Sparse Representation based methods obtain better Recognition in most of the practical face recognition problems. In this paper sparse based techniques for performing real time face recognition in uncontrolled scenarios are discussed.

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