SPARSE CLASSIFICATION FOR OCCLUDED FACES

[1]Afreen Bari, [2]Yojana yadav
CSIT,DURG
Email: [1]Afreeen.bari@gmail.com, [2]yojanayadav@csitdurg.in

ABSTRACT

In these paper various survey has been done related to face recognition. The proposed technique first divides the images of a few subjects, sparse representation which involves high dimensional feature vector is computationally expensive. The sparse representations of all the test images are determined with respect to the training set by computing the l1-minimization. This survey illustrates different FR practices that laid foundations on the issue of partial occlusion dilemma where faces are disguised to cheat the security system.

KEYWORDS:

Sparse representation, face recognition, compressed sensing, feature selection.

INTRODUCTION:

Face recognition has been a relevant area of research in computer vision, making many important contributions since the 1990s. In recent years the focus of face recognition algorithms has been shifted to deal with unconstrained conditions including variability in ambient lighting, pose, expression, face size and distance from the camera . In the last few years, many approaches have been proposed to deal with the afore mentioned problems.

The methods that can handle the occlusion problem roughly fall into three groups: completion-based method, partition-based method, and holistic method. The completion-based method detects the occluded part and rectifies them before classification. These methods need an additional procedure of occlusion detection and completion. The partition based method partitions the images into several blocks and computes the local similarity. The optimal partition of the face images is still unknown. More popular are the holistic methods which directly manipulate the occluded images.

Challenges in face recognition

Face recognition is sensitive under the conditions written below

- Large variation in pose
- Drastic change in illumination
- Face under Partial occlusion

Partial Occlusion

Hindrance in the view of an image refers to Occlusion. It may be natural, as well as synthetic. Natural hindrance refers to hindrance of perspectives between the two picture objects without any intension while manufactured hindrances refer to a fake barricade of purposefully blanket the picture's perspective with a white/dark solid rectangular piece. Fractional occlusion has been found in numerous areas of picture handling. It is seen in iris recognition where the eyelashes impede the iris;

distinguishing proof through ear can likewise be impeded by the ornaments. Indeed continuously requisition face picture gets blocked by means of extra accessories (sunglasses/scarf/ hair or even by hand). Other than biometric picture processing, it is additionally experienced in the medicinal field where the supply routes may be blocked because of elevated cholesterol level.
When there is drastic change in the environment or target face is under partial occlusion, the recognition of the faces becomes a tedious task. Previously proposed methods and algorithm fail to make an impact under such challenging conditions. To make the recognition process robust, there is need of algorithm which can tackle these challenges well.

Recently, the theory of sparse representation and compressed sensing has shed some new light on this challenging problem. Indeed, there is a very natural notion of sparsity in the face recognition problem: one always tries to find only a single subject out of a large database of subjects that best explains a given query image. In this chapter, we will discuss how tools from compressed sensing, especially `1-minimization and random projections, have inspired new algorithms for face recognition. In particular, the new computational framework can simultaneously address the most important types of variation in face recognition.

Nevertheless, face recognition diverges quite significantly from the common compressed sensing setup. On the mathematical side, the data matrices arising in face recognition often violate theoretical assumptions such as the restricted isometry property or even incoherence. Moreover, the physical structure of the problem (especially misalignment) will occasionally force us to solve the sparse representation problem subject to certain nonlinear constraints.

On the practical side, face recognition poses new non-trivial challenges in algorithm design and system implementation. First, face images are very high-dimensional data (e.g., a 1000 _ 1000 gray-scale image has 106 pixels). Largely due to lack of memory and computational resource, dimensionality reduction techniques have largely been considered as a necessary step in the conventional face recognition methods. Notable holistic feature spaces include Eigenfaces , Fisherfaces, Laplacianfaces and their variants. Nevertheless, it remains an open question: what is the optimal low-dimensional facial feature space that is capable of pairing with any Nwelldesigned classifier and leads to superior recognition performance?

Second, past face recognition algorithms often work well under laboratory conditions, but their performance would degrade drastically when tested in less-controlled environments – partially explaining some of the highly publicized failures of these systems. A common reason is that those face recognition systems were only tested on images taken under the same laboratory conditions (even with the same cameras)

as the training images. Hence, their training sets do not represent well variations in illumination for face images taken under different indoor and outdoor environments, and under different lighting conditions. In some extreme cases, certain algorithms have attempted to reduce the illumination effect from only a single training image per subject. Despite these efforts, truly illumination-invariant features are in fact impossible to obtain from a few training images, let alone a single image [21, 4, 1]. Therefore, a natural question arises: How can we improve the image acquisition procedure to guarantee sufficient illuminations in the training images that can represent a large variety of real-world lighting conditions?

In this chapter, under the overarching theme of the book, we provide a systematic exposition of our investigation over the past few years into a new mathematical approach to face recognition, which we call sparse representation-based classification (SRC).We will start from a very simple, almost simplistic, problem formulation that is directly inspired by results in compressed sensing.

TOPOLOGY BASED ON GRAPH

1) Face Graph: Graph GR = (VR, ER) is used to represent the face. 400 example graphs and geometric mean of node sizes and edge distances are used to design face graph. Size and position of components are used to design each example graph.

2) Designing of Graph: Firstly graph GD is constructed from detected components. A node v ε VD is face components and an edge e ε ED is used to connect nodes. Deviation is represented by the two measures of each node pairs.

3) Labeling of Connected Components: Many connected components of face are consisted by graph GD.

4) Matching of Graph: There is different size and location of components consisted by each graph GC. Matching process is done and matched subgraph find out in this step. Low similarity combinations should be removed. A component v ε VW, without size and distance information is introduced for completion of face. All subgraphs = (,) with minimum two different detected components are selected from the resulting graph.

5) Wildcard Estimation: Several wildcard components are included in the resulted matched graph after the graph matching step. Facial components coordinates are required to estimate the face region. Reference graph, orientation information and detected components are used to estimate missing coordinates.

6) Face Localization: Subgraph components and reference graph are used to estimate the face region. Subgraph components are left eye L, right eye R, nose N, and mouth M. The rectangle b= (x, y, w, h) is used to describe the face region, where w is width, h is height and (x, y)T is center.

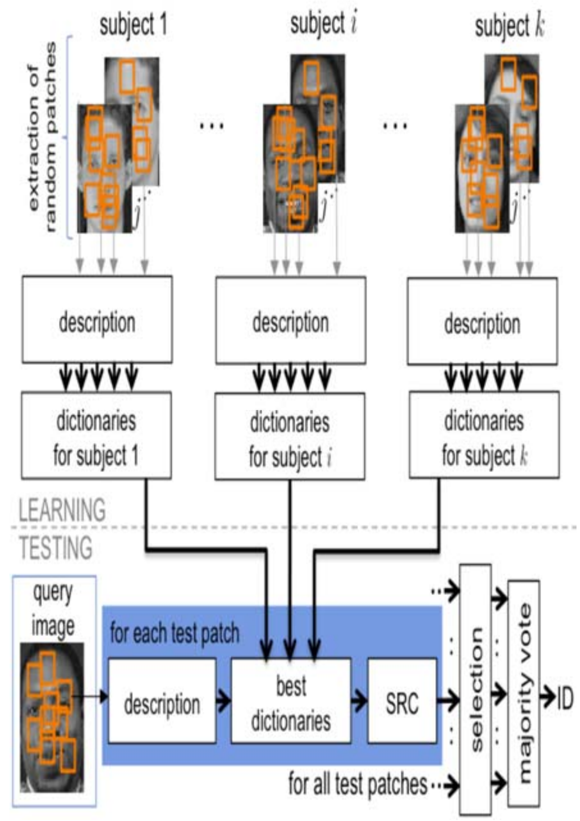

Fig. 1. Overview of proposed method.

CONCLUSION : In this paper, we have proposed sparse classification for occluded faces and topology verification method for completion of occluded face and partial distance measure for recognition task. Viola and Jones approach is used to detect individual components. Specific graph model is used to describe the topology of different components. Size and distance ratios are considered by graph model. The recognition rate improved under partial occlusion of scarf and glass by proposed method. Proposed face recognition algorithm has limitation of resolution, so future work will concentrate to overcome the resolution limitation automatic estimation of components.

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