

Automated Face Recognition System for Criminals via Dictionary Learning

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Abstract- *The paper deals with the face recognition of criminals from the images and videos. It is the undersampled method because it does not use much images to perform the face recognition. Now-a-days crimes are increasing at it is difficult for the police to maintain their records and to handle them. So with the help of images and video they can perform the recognition. It allows the easy recognition without maintaining the paper record. We address the problem of robust face recognition with undersampled training data. Given only one or few training images available per subject, we present a novel recognition approach.*

Key Words: Undersampled, face recognition, subjects, robust, training data.

1. INTRODUCTION

Face recognition has been an active research topic, since it is difficult to recognize face images with illumination and expression variations as well as corruptions due to occlusion or disguise. A general solution is to collect a sufficient amount of training data in advance, so that the above intraclass variations can be properly handled. However, in practice, there is no guarantee that we get the satisfactory result. Moreover, for real-world applications, e.g. e-passport, driving license, or ID card identification, only one or very few face images of the subject of interest might be captured during the data acquisition stage. As a result, one would encounter the challenging task of undersampled face recognition.

Existing solutions to undersampled face recognition can be typically divided into two categories: patch-based methods and generic learning from external data. For patch-based methods, one can either extract discriminative information from patches collected by different images, or utilize/integrate the corresponding classification results for achieving recognition.

2. RELATED WORK

There are different techniques for face recognition. SRC and extended SRC is used in our work.

2.1 SRC

The problem of automatically recognizing human faces from frontal views with varying expression and illumination, as well as occlusion and disguise. The recognition problem as one of classifying among multiple linear regression models and argue that new theory from sparse signal representation offers the key to addressing this problem. Based on a sparse representation computed by l_1 -minimization, SRC propose a general classification algorithm for (image-based) object recognition. This new framework provides new insights into two crucial issues in face recognition: feature extraction and robustness to occlusion.

For feature extraction, show that if sparsity in the recognition problem is properly harnessed, the choice of features is no longer critical. What is critical, however, is whether the number of features is sufficiently large and whether the sparse representation is correctly computed. Unconventional features such as downsampled images and random projections perform just as well as conventional features such as Eigen faces and Laplacian faces, as long as

the dimension of the feature space surpasses certain threshold, predicted by the theory of sparse representation. This framework can handle errors due to occlusion and corruption uniformly by exploiting the fact that these errors are often sparse with respect to the standard (pixel) basis. The theory of sparse representation helps predict how much occlusion the recognition algorithm can handle and how to choose the training images to maximize robustness to occlusion.

2.2 EXTENDED SRC

Sparse Representation-Based Classification (SRC) is a face recognition breakthrough in recent years which has successfully addressed the recognition problem with sufficient training images of each gallery subject. In this extend SRC to applications where there are very few, or even a single, training images per subject. Assuming that the intraclass variations of one subject can be approximated by a sparse linear combination of those of other subjects, Extended Sparse Representation-Based Classifier (ESRC) applies an auxiliary intraclass variant dictionary to represent the possible variation between the training and testing images. The dictionary atoms typically represent intraclass sample differences computed from either the gallery faces themselves or the generic faces that are outside the gallery. The superior results of ESRC suggest that if the dictionary is properly constructed, SRC algorithms can generalize well to the large-scale face recognition problem, even with a single training image per class.

3. PORPOSED MODELLING

In this paper we are providing the techniques to perform face recognition from images as well as videos. With the video first we have to perform the detection of faces from it and then face recognition similar to that of recognition from images.

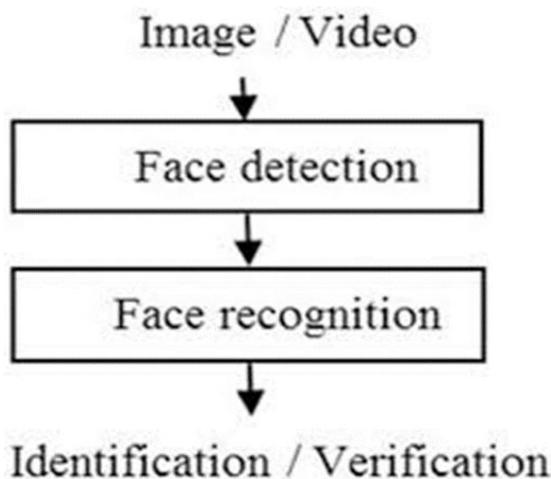


Fig.3.1 Proposed Model.

From the figure given above we can give the image or video as input. After giving the input as image and video the detection operation is performed. In detection the actual

faces from the image or videos are detected, and background is deleted. After the detection the actual face recognition is performed. For the recognition we use the face recognition via robust auxiliary dictionary, where auxiliary dictionary act as a supportive for face recognition. The actual face recognition is shown in the below figure.

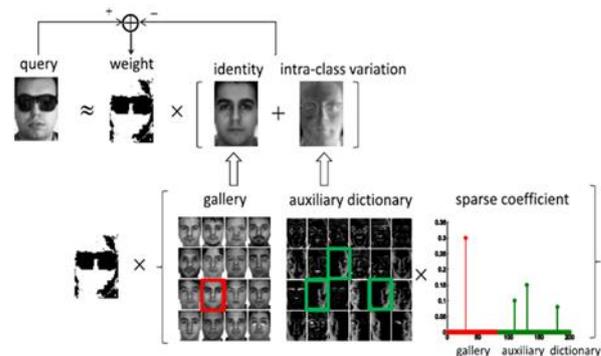


Fig.3.2 Face recognition via robust auxiliary dictionary learning.

The actual face recognition process is shown in the above figure. Firstly the query image is given, from that query image we have to remove the weight then we get the image of person without weight. With this query image we have to search the identical image from the gallery, which contain the neutral image of person, if we get the same then select that one and for any intraclass variation make use of auxiliary dictionary. To select the best one from the auxiliary dictionary we use the sparse coefficient, the one which is having the highest value of sparse coefficient we have to select that one. And finally the neutral image from gallery and the intraclass variation from auxiliary dictionary are combined to produce the final required image as that of the query image. If the neutral image of the query image is not present in the gallery then the final result will be produce that the person is not matched or recognized.

Suppose for example, let us consider that we have 20 persons, so the neutral image of face of this 20 persons we have to store in our gallery and out of 20 let us consider 10 persons face images with different intraclass variations such as illumination, expression, occlusion, etc. have to be save or store in the auxiliary dictionary that will act as a supportive for face recognition.

In this paper we require the prior knowledge of the occlusion, our approach eliminates such assumptions by introducing a novel classification method based on robust sparse coding. It is worth noting that existing dictionary learning algorithms like KSVD can also be used to learn dictionaries for images from external datasets. However, these learned dictionaries cannot guarantee the recognition performance for the subjects of interest, since KSVD only considers the representation ability of dictionaries.

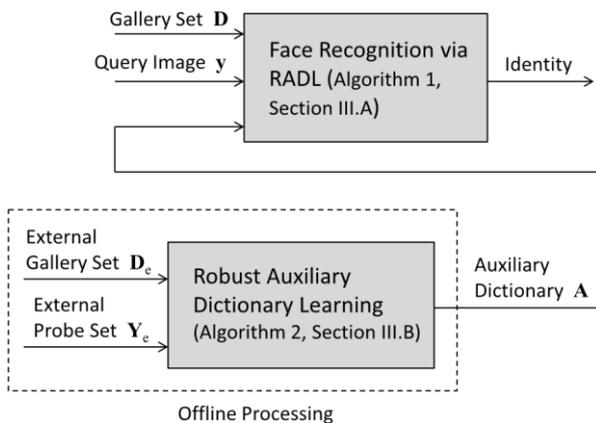


Fig. 3.3 Flowchart for our proposed framework for undersampled face recognition.

4. CONCLUSIONS

We presented a novel method for undersampled face recognition. We advocated the learning of an auxiliary dictionary from external data for modelling intraclass variation. As a result, the proposed model allows one to recognize occluded face images, or those with illumination and expressions variations, only one or few gallery images per subject are available during training.

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