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A Novel Face Recongnisation Algorithm Based On Low-Rank Matrix Decomposition



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Abstract

For the task of robust face recognition, we particularly focus on the scenario in which training and test image data are corrupted due to occlusion or disguise. Prior standard face recognition methods like Eigenfaces or state-of-the-art approaches such as sparse representation-based classification did not consider possible contamination of data during training, and thus their recognition performance on corrupted test data would be degraded. In this paper, we propose a novel face recognition algorithm based on low-rank matrix decomposition to address the aforementioned problem. Besides the capability of decomposing raw training data into a set of representative bases for better modeling the face images, we introduce a constraint of structural incoherence into the proposed algorithm, which enforces the bases learned for different classes to be as independent as possible. As a result, additional discriminating ability is added to the derived base matrices for improved recognition performance. Experimental results on different face databases with a variety of variations verify the effectiveness and robustness of our proposed method.

Index Terms— ***Face recognition, low-rank matrix decomposition, Images, Sparse Representation-Based Classificationand structural incoherence.***

INTRODUCTION

Among biometric approaches for identity recognition, the use of face images can be considered as the most popular one due to its low intrusiveness and high uniqueness [1]. Other physiological or behavioral biometrics (e.g., gait recognition) often requires cooperative subjects, which might not always be feasible for real-world applications. Generally, face images can be acquired actively by the user, or they can be captured passively by surveillance cameras. With the increasing needs for security-related applications such as computational forensics and anti-terrorism, face recognition has been an active topic for researchers in the areas of computer vision and image processing.

To address the problem of face recognition, one typically focuses on the extraction of facial features from training image data, and the learning of associated classification models.

Unseen test data from the same subjects of interest will be used to evaluate the recognition performance. It is worth noting that, most prior works on face recognition assume that both training and test image data are under pose, illumination, or expression variations. To further assess the robustness of the designed face recognition algorithm, only test images are considered to be corrupted due to occlusion or disguise in recent literatures [2] and [3]. In other words, while the test data might be corrupted, most

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prior works consider the training face images to be taken under a well controlled setting (i.e., under reasonable illumination, pose, etc. variations without occlusion or disguise). To apply these prior approaches for practical face recognition scenarios, one will need to discard corrupted training images and thus inevitably encounter small sample size and over-fitting problems. Moreover, the disregard of corrupted training face images might give up some valuable information for recognition. For example, in forensic identification, any available information extracted from face images could be the key to identification for forensic investigators [4].

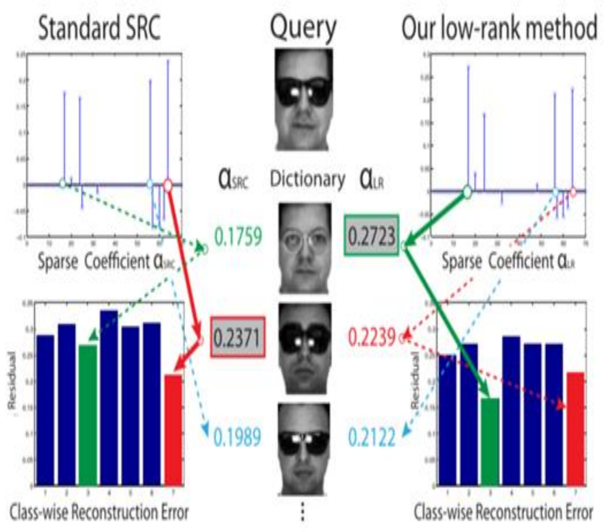

Fig. 1. Comparison between the standard SRC and our method.

The standard SRC classifies the Test input as the class with most similar training images even if they are occluded (e.g. due to sunglasses), while our approach alleviates this problem and is robust to such occlusions presented in both training and test data.

Recently, sparse representation-based classification (SRC) [2] has shown very promising results on face recognition, which considers each test image as a sparse linear combination of the training instances. SRC solves an L1 minimization problem for a test input by deriving the sparse coefficients for the training data, and recognition is achieved based on the minimum class-wise reconstruction error.

RELATED WORK

A. Robust PCA and Low-Rank Matrix Recovery

Principal component analysis (PCA) is a popular dimension reduction technique for data analysis applications such as reconstruction and classification. In spite of its effectiveness, PCA is known to be sensitive to sparse errors with large magnitudes [15]. A number of approaches have been proposed in literatures to address this problem, including the introduction of influence functions [9], alternating minimization techniques [10], and low-rank matrix recovery [11] (noted as LR in the remaining for this paper for conciseness). Among these methods (known as robust PCA), LR has been observed to be solved in polynomial time with performance guarantees [11]. Since our work in this paper is inspired by low-rank matrix decomposition, we briefly review its formulation for the sake of completeness.

Low-rank matrix recovery aims at decomposing a data matrix D into A + E, in which A is a low-rank matrix and E is the associated sparse error. More precisely, to derive the low-rank approximation of the input data matrix D, LR minimizes the rank of matrix A while reducing the L0-norm of E. As a result, one will need to solve the following minimization problem:

$$\min_{\mathbf{A},\mathbf{E}} \operatorname{rank}(\mathbf{A}) + \lambda\|\mathbf{E}\|_0 \quad \text{s.t.} \quad \mathbf{D} = \mathbf{A} + \mathbf{E}.$$

From the above formulation, we note that $\|\mathbf{E}\|_0$ calculates the number of non-zero elements in **E**. Since solving (1) involves the low-rank matrix completion and the $\_{0}$-norm minimization problems, it is NP-hard and thus is not easy to solve. To convert (1) into a more tractable optimization problem, Candes *et al.* [11] relax (1) by replacing rank *(***A***)* with its nuclear norm (i.e., the sum of the singular values of **A**). Instead of solving the minimization of L_0-norm, that of L_1-norm is now considered (i.e., the sum of the absolute values of each entry in **E**). Consequently, the

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convex relaxation of (1) has the following form:

$$\min_{\mathbf{A},\mathbf{E}} \|\mathbf{A}\|_* + \lambda\|\mathbf{E}\|_1 \quad \text{s.t.} \quad \mathbf{D} = \mathbf{A} + \mathbf{E}. \qquad (2)$$

It is shown in [11] that solving this convex relaxation version is equivalent to solving the original low-rank matrix approximation problem, as long as the rank of A to be recovered is not too large, and the number of non-zero elements in E is reasonably small (i.e., to be sufficiently sparse). To solve the optimization problem of (2), the technique of augmented Lagrange multipliers (ALM) [16] has been applied due to its computational efficiency. While many image processing applications can be casted as the low-rank matrix recovery problems (e.g., image alignment [17], subspace segmentation [18], collaborative filtering [11], and image tag transduction [19]), we are among the first to apply LR-based techniques for addressing the problem of robust face recognition.

B. Sparse Representation-Based Classification

Wright et al. [2] recently proposed a sparse representation-based classification (SRC) algorithm for face recognition. SRC considers each test image as a sparse linear combination of training image data by solving an L1-minimization problem. Very promising results were reported in [2], even if test image data are corrupted due to occlusion or noise. Several works have been proposed to further extend SRC for improved performance.

In other words, the test image y will be assigned to the class based on a class-wise minimum reconstruction error. The motivation behind this classification strategy is that the test image y should lie in the space spanned by the columns Dj of class j. As a result, most non-zero elements of α will mainly be presented in the non-zero elements of δ j (α), which results in the minimum reconstruction error. The framework of SRC is depicted by the red arrows in Fig. 3. Although impressive face recognition results were reported by SRC [2], SRC still requires clean (i.e., unconcluded) face images for training. In other words, it might not be preferable for real-world scenarios when corrupted face images are collected during training. As later verified by our experiments, this practical training scenario would result in degraded recognition performance for SRC due to the tendency of recognizing test images as the training ones with the same type of corruption presented. In the following section, we will introduce our proposed algorithm for robust face recognition,

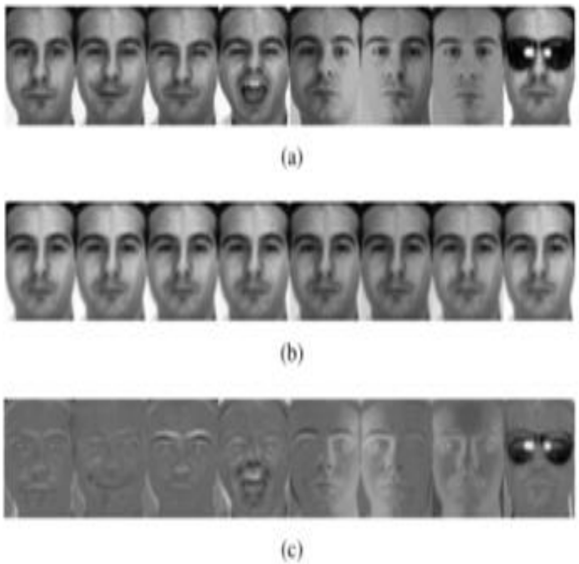

Fig. 2. Example results of low-rank matrix recovery. (a) Original images D. (b) Low-rank and approximated images A of (a). (c) Sparse error images E of (a).

LOW-RANK MATRIX RECOVERY WITH STRUCTURAL INCOHERENCE FOR FACE RECOGNITION

A. Face Recognition with Low-Rank Matrix Recovery

For face recognition in real-world scenarios, we cannot expect the training image data to be always collected under a well-controlled setting. In addition to illumination, pose, or expression variations, it is possible that one can be taking a scarf, gauze mask, or sunglasses, when his/her face image is taken by the camera. Using such images for training would make the learned face recognition algorithm over fit the extreme noise of occlusion, instead of modeling the face of the subject. As a result, the resulting recognition performance will be degraded.

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We note that low-rank matrix recovery (LR) can be applied to alleviate the aforementioned problem. Recall that LR decomposes the collected data matrix into two different parts, one is a representative basis matrix with a minimum rank and the other is the corresponding sparse error matrix.

It is worth noting that, in order to apply LR for face recognition, the face image data needs to be registered prior to the procedure of low-rank matrix decomposition. In our work, we only consider face images of frontal views (i.e., no pose variations), so that the extracted low-rank matrix would preserve the structure of the face images.

When applying LR for face recognition with N subjects of interest, one can collect training data D = [D1, D2, . . . , DN],where Di is the training data matrix (with the presence of occlusion or disguise) for subject i , as shown in Fig. 2(a). By performing low-rank matrix recovery, the data matrix D = [D1, D2, . . . , DN] will be decomposed into a low-rank matrix A = [A1, A2, . . . , AN] and the sparse error matrix E = [E1, E2, . . . , EN].

As shown in Fig. 2(b), the representative images in A can be considered as preprocessed data with sparse noise removed (see the corresponding images in Fig. 2(c)). Comparing Figs. 2(a) and 2(b), we can see that the low-rank matrix A has a better representative ability than the original data D does in describing the face images of the in which both training and test image data can be corrupted. Subject of interest. Since the face images are typically with high dimensionality, standard dimension reduction techniques such as PCA are typically applied to the face image data before training and testing.

Instead of using the Eigenfaces calculated by from the original data matrix D as most prior works did, one can apply PCA on the low-rank matrix A (as shown in Step 2 of Fig. 3), and the resulting subspace can be applied as the dictionary for training and testing purposes (see Step 3 in Fig. 3). Finally, one can apply SRC and the derived dictionary to classify test inputs, which performs classification based on class-wise minimum reconstruction error (as depicted by Step 4 in Fig. 3). Later in Section IV, in contrast to the direct use of raw data D we will verify that LR better handles the problem in which the input training data is under severe illumination variations or is corrupted by occlusion or disguise. Algorithm 1 and Fig. 3 summarize the procedure of integrating low-rank matrix recovery and SRC for face recognition.

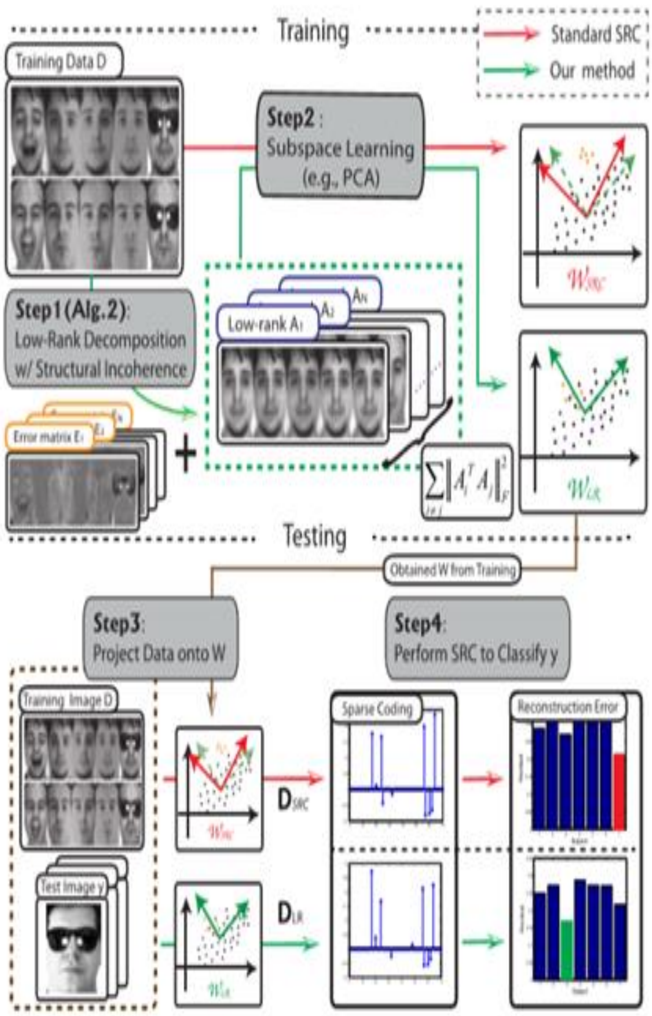

Fig. 3. Illustration of our proposed method.

Note that we promote the structural incoherence between low-rank matrices for better modeling and recognizing face images.

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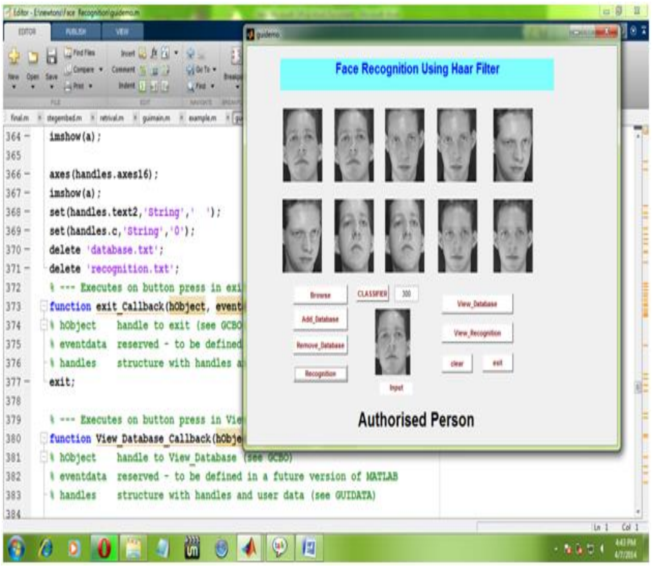
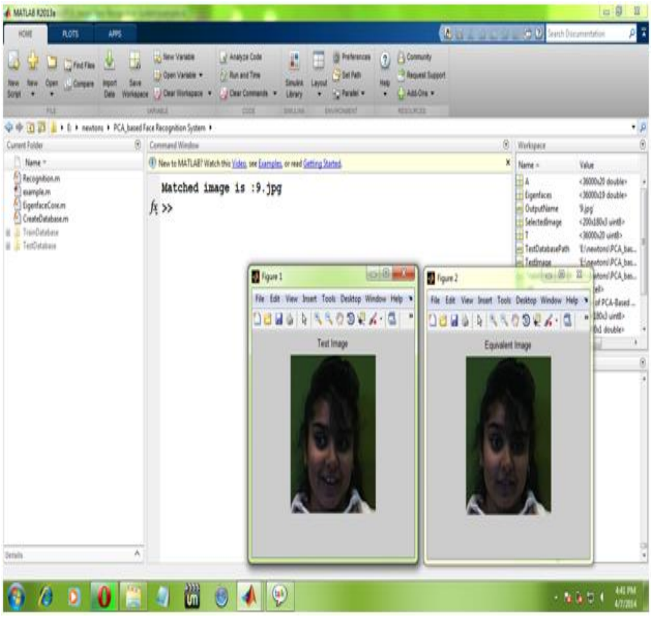
SIMULATION RESULTS



Face Recognition using Haar filter



Matched Image

CONCLUSION

We presented a low-rank matrix approximation algorithm with structural incoherence for robust face recognition. The introduction of structural incoherence between low-rank matrices promotes the discrimination between different classes, and thus the associated models exhibit excellent discriminating ability. We showed that the proposed optimization problem can be easily solved by advancing augmented Lagrange multipliers. Our experiments confirmed that our proposed LR approach is robust to severe illumination variations or corruptions such as occlusion and disguise, while our method has been shown to outperform state-of-the-art face recognition algorithms.

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