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Sparse representation-based robust face recognition by graph regularized low-rank sparse representation recovery

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ABSTRACT

This paper proposes a graph regularized low-rank sparse representation recovery (GLRSRR) method for sparse representation-based robust face recognition, in which both the training and test samples might be corrupted because of illumination variations, pose changes, and occlusions. On the one hand, GLRSRR imposes both the lowest-rank and sparsest constraints on the representation matrix of the training samples, which makes the recovered clean training samples discriminative while maintaining the global structure of data. Simultaneously, GLRSRR explicitly encodes the local structure information of data and the discriminative information of different classes by incorporating a graph regularization term, which further improves the discriminative ability of the recovered clean training samples for sparse representation. As a result, a test sample is compactly represented by more clean training samples from the correct class. On the other hand, since the error matrix obtained by GLRSRR can accurately and intuitively characterize the corruption and occlusion of face image, it can be used as occlusion dictionary for sparse representation. This will bring more accurate representations of the corrupted test samples. The experimental results on several benchmark face image databases manifest the effectiveness and robustness of GLRSRR.

1. Introduction

Face recognition (FR) has caught a lot of attention in computer vision and machine learning fields due to its numerous real-world applications such as card identification, access control, security monitoring, etc. As we all know, although face images are usually with high dimensionality, they possibly reside on a low dimensional subspace. Many subspace learning methods, such as principle component analysis (PCA) [1], linear discriminant analysis (LDA) [2], locality preserving projections (LPP) [3], marginal Fisher analysis (MFA) [4], local discriminant embedding (LDE) [5], have been proposed for reducing the dimension of face image. Subsequently, a classifier, such as the nearest neighbor classifier (NNC) or support vector machine (SVM), is usually used for classification. Although subspace learning methods have been successfully used in FR, they are not robust to face image with corruption [6], such as occlusion, disguise and pixel contamination. Especially, when the amount of training samples is small, the learned subspace will be deflective [7].

Recently, a new robust FR framework, namely sparse representation-based classification (SRC) [8], was presented. SRC sparsely encodes a test sample over a dictionary consisting of the training samples by l_1-norm optimization techniques, and then classifies a test sample to the class that generates the minimal reconstruction error. When all the training samples are undercontrolled (i.e., under reasonable pose and illumination, no corruption and occlusion), SRC is robust to test sample with occlusion and corruption, and achieves a high face recognition accuracy. Unfortunately, the performance of SRC might be dropped when some training and test samples are both corrupted [9]. Recently, Zuo et al. [10] declared that using non-convex l_p-norm sparse coding can obtain better results than using the convex l_1-norm sparse coding for image classification problems, and proposed a generalized iterated shrinkage algorithm (GISA) for l_p-norm nonconvex sparse coding.

To address the problem that the training samples are corrupted, Ref. [9] adopts low-rank recovery (LR) [11] technique to recover the clean low-rank data matrix from the corrupted data matrix, and then uses the clean data matrix as dictionary for SRC to classify a test data. Since LR assumes all the data residing on a single subspace [12], it might not work well while the data come

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from multiple subspaces. Therefore, Ref. [9] uses LR to remove noises from training data class by class. This procedure is computationally expensive for a great number of classes. In addition, although Ref. [9] introduces a structure incoherence regularization term into LR to promote the incoherence between different classes, the data structure might not be maintained. Recently, Zhao et al. [13] proposed a generative RPCA model to recovery low-rank data matrix under the Bayesian framework by modeling data noise as a mixture of Gaussians, which is able to fit a wide range of noises. Liu et al. [12] presented a Low-rank representation (LRR) method, which can effectively reveal the global structure of data that are drawn from multiple subspaces. This implies that LRR can effectively recover the clean data from the corrupted data by correcting the noises and corruptions [12]. Nevertheless, LRR does not consider the local structure of data while recovering the subspace, which perhaps make the recovery performance deteriorated. To solve this issue, Lu et al. [14] incorporated a graph regularization term into the LRR to encode the local structure information of data. Recently, Zhang et al. [15] also used LR [11] to decompose the feature vectors of images within each class into a low-rank matrix and a sparse error matrix, and then used LLC [16] method to encode the feature vectors of images over the dictionary that is composed of the low-rank matrix and sparse error matrix. Finally, they used linear SVM for image classification. Additionally, Zhang et al. [17] proposed a low-rank sparse coding (LRSC) method, which considers the local structure information among features of an image for image classification, and represents densely sampled SIFT [18] descriptors as a low-rank and sparse linear combination of codewords.

In the case of test sample with corruption or occlusion, SRC introduces an identity matrix as occlusion dictionary to cope with corruption and occlusion of test sample. However, the dimensionality of the identity matrix is usually very high, which makes the sparse coding procedure computationally expensive [19]. To solve this issue, Deng et al. [20] proposed an extended SRC (ESRC) method, in which an intra-class variant matrix, determined by subtracting the class centroid from the samples of the same class, is used as occlusion dictionary. The dimensionality of occlusion dictionary used in ESRC is much smaller than that of occlusion dictionary used in SRC. However, the intra-class variant matrix might not accurately depict corruption and occlusion of face image. In [21], the sparse error matrix obtained by LR [11] is used as occlusion dictionary, and the superior FR performance has achieved. Recently, Yang and Zhang et al. [22] pointed out it may not be enough that SRC [8] measures the representation fidelity by l_2-norm or l_1-norm of coding residual, because such fidelity term assumes that the coding residual obeys Gaussian or Laplacian distribution, which may not be true in real-world applications. Based on this viewpoint, they proposed a robust sparse coding (RSC) [22] method for robust FR by modeling the sparse coding as a sparsity-constrained robust regression problem. Subsequently, they also proposed a regularized robust coding (RRC) [23] method for robust FR, which is a substantial extension of RSC. Moreover, He et al. [24] replaced the representation fidelity term of SRC with the correntropy based Gaussian-kernel fidelity term and proposed a correntropy-based sparse representation (CESR) method for robust FR. Although both RSC [22], RRC [23], and CESR [24] are more robust to deal with the test sample with corruption or occlusion, they also need all the training samples under-controlled.

In this paper, we present a graph regularized low-rank sparse representation recovery method to address the problem of sparse representation-based robust FR, in which both training and test samples might be corrupted. As mentioned above, using the corrupted training samples as dictionary may lead to poor FR performance. To overcome this issue, we construct a graph regularized low-rank sparse representation recovery (GLRSRR) model to recover the clean training samples from the corrupted training samples. Unlike LRR merely imposes the lowest-rank constraint on the representation matrix of the training samples, GLRSRR imposes both lowest-rank and sparsest constraints on the representation matrix of the training samples. As observed in [25], low-rankness can reveal the global structure of data, while sparsity helps to identify the class to which a data belongs. Hence, the recovered clean training samples are discriminative while maintaining the global structure of data. Furthermore, a supervised nearest neighbor graph is built to encode the local structure information of data and the discriminative information of different classes, and then a graph regularization term is incorporated into the GLRSRR model. By considering both the local structure information and discriminative information, the recovered clean training samples have more discriminative ability for sparse representation. As a result, using the recovered clean training samples to constitute a dictionary, a test sample is compactly represented as linear combination of more clean training samples from the correct class. In addition, since the error matrix obtained by GLRSRR can accurately and intuitively characterize the corruption and occlusion of face image, it can be used as occlusion dictionary to deal with corruption or occlusion of test sample. This will bring more accurate representations of the corrupted test samples.

It is worth noting that there are some mainly differences between our work and the works of [15,17], though our work is closely related to them. The mainly differences are as follows. (a) Our work designs a novel recovery method, namely GLRSRR, to separate the corrupted training data matrix into a clean training data matrix and a sparse error matrix, while [15] uses the existing method of LR [11] to decompose the training feature matrix into a low-rank feature matrix and a sparse error matrix; (b) The work of [17] proposed a low-rank sparse coding (LRSC) method, which is utilized to encode the local features of a sub-region in an image over a given codebook, while our proposed GLRSRR method aims to recover the clean training data matrix from the corrupted training data matrix by using the corrupted training data matrix itself as dictionary. In other words, GLRSRR is used for recovery but LRSC [17] for coding; (c) The LRSC [17] imposes both the lowest-rank and sparsest constraints on the representation matrix, while our GLRSRR not only imposes both lowest-rank and sparest constraints on the representation matrix, but also introduces a graph regularization term to make the representations more discriminative. That is to say, the optimization problem of GLRSRR is different from that of LRSC.

Several advantages of our proposed GLRSRR method are summarized as follows:

- It recovers the clean training samples with more discriminative ability from the corrupted training samples by not only imposing both lowest-rank and sparsest constraints on the representation matrix of the training samples, but also introducing a graph regularization term to explicitly encode the local structure information of data and the discriminative information of different classes.
- The error matrix obtained by GLRSRR model can accurately depict the corruption and occlusion of face image. So it can be used as occlusion dictionary to deal with the corruption or occlusion of test sample.
- Using the recovered clean training data matrix and the error matrix as dictionary and occlusion dictionary, a corrupted test sample can be sparsely represented by more clean training samples from the correct class and the corresponding errors. This brings a more accurate identification of the corrupted test sample for SRC.

The remainder of this paper is outlined as follows. Section 2 reviews related works on SRC algorithm and low-rank matrix recovery algorithms. Section 3 presents our GLRSRR method for sparse