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Double nuclear norm-based robust principal component analysis for image disocclusion and object detection

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ABSTRACT

Robust principal component analysis (RPCA) is usually used to remove structural error from low rank matrix. It assumes that the real data matrix has low rank and the error matrix is sparse. A new emerging method named double nuclear norm-based matrix decomposition (DNMD), which uses a unified low-rank assumption to characterize the real image data and continuous occlusions, is also applied to recover images and to model background. This paper presents a method called double nuclear norm-based robust principal component analysis (DNRPCA) for dealing with the occluded image. It not only assumes that the real data matrix has low rank, but also supposes the error matrix is sparse in vector space and each error image is a low-rank matrix, which can not only cope with the structural error but also the sparse error compared to DNMD. Experiments on removing occlusions from face images and object detection from monitoring videos demonstrate the advantages of our method compared to the state-of-the-art approaches.

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1. Introduction

As a common tool for high dimensional data processing and analysis, principal component analysis (PCA) has been widely applied in the community of pattern recognition, machine learning and computer vision [1–4]. It desires to extract a low rank dimensional subspace from the high dimensional data samples which might be relevant and redundant by some linear transformation techniques. With the increasing of data dimension, as an important means to solve the curse of dimensionality, PCA still has an important theoretical and analytical value, and it is still investigated and studied by many communities in recent years, such as 2D principal component analysis (2DPCA) [5] and its generalized *N*-dimensional principal component analysis (GND-PCA) [12], kernel principal component analysis [6], locality preserving projection [7], independent component analysis [9] and Euler principal component analysis (EPCA) [10].

Though PCA is effective to recover image from small Gaussian noise, it is sensitive to large outliers such as block occlusion. Thus, many robust principal component analysis approaches have been proposed to deal with the large outliers. L_1-norm PCA [11] was proposed by Ke and Kanade with applying maximum likelihood estimation to original data and diagonal principal component analysis with non-greedy L_1-norm maximization was proposed by Yu [8]. And rotational invariant L_1-norm PCA utilized Cauchy robust function and based on maximum correntropy criterion were presented in [13] and [14] respectively.

Another famous robust principal component analysis approach named principal component pursuit, which is referred as "PCP" in this paper, has been recently raised by Wright et al. [15], assuming that the data matrix is composed of a sparse error matrix and a low rank clean matrix. Its formulation can be optimized efficiently by augmented Lagrange multiplier or approximate proximal gradient method. As an important extension of PCP, the low-rank representation (LRR) [16] was presented to segment subspace from a union of multiple linear subspaces. LRR represents all columns of the low rank matrix as the linear combinations of the basis vectors in a dictionary and also assumes that the error matrix is sparse.

Unlike the approaches mentioned above characterizing the error term by L_1 or L_2 norm, He [17] depicts the error with non-convex M-estimators and Zhang [18] presents a double nuclear norm-based matrix decomposition (DNMD) method measuring the error images via nuclear norm. DNMD assumes that all image vectors form a low-rank matrix and each error image is also a low-rank image. It can recover the low rank data in image vector space and remove the low rank error in the image space simultaneously.

On one hand, nuclear norm is more reasonable than L_1 or L_2 norm for characterizing the structural error in image space, on the other hand, in the image vectors space, error term is sparse apparently. The robust principal component analysis approaches

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constraint the error term just by sparsity ignoring the low-rank structure in image space while DNMD characterizes each error image via nuclear norm neglecting the sparsity of error term in image vectors space. Thus, to unify these two properties, we propose a robust principal component analysis method based on double nuclear norm (DNRPCA). Like other subspace learning approaches, DNRPCA also assumes that the raw input data can be decomposed into a low-rank matrix and an error matrix. But in this assumption, the error term has to satisfy two constraints: sparsity in image vectors space and low rank in image space. A solution of DNRPCA model based on alternating direction method of multipliers has also been presented to recover the real low rank data and remove the error image in this paper.

The remainder of the paper is organized as follows. Section 2 introduces some closely related work. Our DNRPCA model is proposed and solved in Section 3. Comparative experiments with other methods on different datasets (face images and surveillance videos) are demonstrated in Section 4. Finally, the conclusion and discussion are offered in Section 5.

Notations: Let $X_i \in R^{m\times n}$ be an image with $m \times n$ pixels. Images matrix $X=[vec(X_1),\dots,vec(X_s)] \in R^{mn\times s}$ denotes observed data, where the vectorization operator $vec(\cdot)$ stacks the columns of an image into a vector, s is the number of images. X is assumed to be composed of two matrices $D=[vec(D_1),\dots,vec(D_s)] \in R^{mn\times s}$ and $E=[vec(E_1),\dots,vec(E_s)] \in R^{mn\times s}$, denoting the background images matrix and foreground errors respectively. And $D_i \in R^{m\times n}$, $E_i \in R^{m\times n}$ represent the corresponding background and object image of the ith observed image X_i. The nuclear norm of X is denoted as $\|X\|_* = \sum_{i=1}^{min\{m,n\}} \sigma_i$, where σ_i is the ith larger singular value of X. $\|X\|_0$ denotes the l_0 norm of X, i.e. the number of nonzero elements in X. The l_1 norm of X is represented as $\|X\|_1 = \sum_{i,j}|X_{ij}|$ and $\|X\|_F = \sqrt{\sum_{ij} X_{ij}^2}$ is the Frobenius norm of X.

2. Related works

Many approaches for matrix decomposition have been proposed so far, and we cannot describe all of them here. This section just introduced two methods of them, PCP and DNMD, which are very closely related to our DNRPCA model.

2.1. PCP

Given a set of observed samples $X_1,\dots,X_s \in R^{m\times n}$, where some of them are corrupted, such as be occluded, PCP assumes that the images matrix X is composed of two matrices D and E, and matrix D is supposed to have low rank and E is deemed to be sparse. The PCP model is formulated as

$$\min_{D,E} \|D\|_* + \lambda \|E\|_1, \quad \text{s.t. } X = D + E, \tag{1}$$

where the λ is a balance parameter between low rank and sparsity.

Many algorithms can be used to solve this model, such as accelerated proximal gradient approach, dual approach, and the methods of augmented Lagrange multipliers [24]. PCP has been applied in many applications, such as moving object detection, face recognition and other matrix completion problem, where a matrix with a fraction of entries missing is required to be completed.

2.2. DNMD

DNMD uses a unified low-rank assumption to characterize the real image data and continuous occlusion. It assumes that the recovered images, after being stacked into image vectors, form a low-dimensional vector space and the error images in the original image space are also low rank. The original data $X \in R^{mn\times s}$ can be divided into two parts $D \in R^{mn\times s}$ and $E \in R^{mn\times s}$, where D is a low rank matrix and each column in E is the vectorization of corresponding low rank error image $E_i \in R^{m\times n}$. The decomposition model of DNMD is given by

$$\min_{D,E} \|D\|_* + \lambda \sum_{i=1}^{s} \|E_i\|_*, \quad \text{s.t. } X = D + E. \tag{2}$$

The formulation of DNMD involves only the nuclear norm of matrix which can be solved by the singular value shrinkage operator. DNMD shows that nuclear norm is more reasonable than L_1 or L_2 norm for characterizing the structural error and it is effective on removing occlusion from face images and background modelling [18].

3. Double nuclear norm-based robust PCA

This section first presents the motivation and problem formulation of the double nuclear norm-based robust PCA model (DNRPCA), and then the algorithm based on the alternating direction method of multipliers is provided. Finally, some analyses on the convergence and complexity of the algorithm are given.

3.1. Formulation

Firstly, we give an intuitive impression that low rank hypothesis can better characterize the block occlusion through an instance. While the left face image in Fig. 1(a) is just mixed with some Gaussian noises, the one on the right is occluded by block. Our purpose is to recover the face images by removing the occlusions. Fig. 1(b) displays the corresponding recovered images and the error images are presented in Fig. 1(c), where the left is Gaussian error and the right is structural error. The corresponding singular values of Gaussian and structural error images are shown in Table 1, from where we can find the singular value of structural error falls more faster to zero than that of Gaussian error, which means fewer components can be applied to characterize the structural error image. So, for block occlusions, we suppose that the error image is low rank. Secondly, there are many similarities between the face images as they belong to the same class. Thus, if we stack the recovered images into column vectors of a matrix, it can be assumed to have low rank. Finally, because only a portion of images are occluded and the covered area is small, it is obvious that the matrix composed of vectorized error images is sparse. Therefore, taking into account the above points, to remove the

Fig. 1. Illustration of the low rank structure of occlusion error. (a) Observed images. (b) Recovered images. (c) Error images.

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