Information Sciences 394–395 (2017) 1–17

Contents lists available at ScienceDirect

Information Sciences

journal homepage: www.elsevier.com/locate/ins

Weighted sparse coding regularized nonconvex matrix regression for robust face recognition

Hengmin Zhang[a], Jian Yang[a,*], Jianchun Xie[a], Jianjun Qian[a], Bob Zhang[b]

[a] School of Computer Science and Engineering, Nanjing University of Science and Technology, Nanjing, PR China
[b] Department of Computer and Information Science, University of Macau, Macau, PR China

ARTICLE INFO

Article history:
Received 16 June 2016
Revised 8 February 2017
Accepted 10 February 2017
Available online 13 February 2017

Keywords:
Nonconvex matrix regression
Weighted sparse coding
Inexact augmented lagrange multiplier method
Face recognition

ABSTRACT

Most existing regression based classification methods for robust face recognition usually characterize the representation error using L_1-norm or Frobenius-norm for the pixel-level noise or nuclear norm for the image-level noise, and code the coefficients vector by l_1-norm or l_2-norm. To our best knowledge, nuclear norm can be used to describe the low-rank structural information but may lead to the suboptimal solution, while l_1-norm or l_2-norm can promote the sparsity or cooperativity but may neglect the prior information (e.g., the locality and similarity relationship) among data. To solve these drawbacks, we propose two weighted sparse coding regularized nonconvex matrix regression models including weighted sparse coding regularized matrix γ-norm based matrix regression (WSγMR) for the structural noise and weighted sparse coding regularized matrix γ-norm plus minimax concave plus (MCP) function based matrix regression (WSγM^{2}R) for the mixed noise (e.g, structural noise plus sparse noise). The MCP induced nonconvex function can overcome the imbalanced penalization of different singular values and entries of the error image matrix, and the weighted sparse coding can consider the prior information by borrowing a novel distance metric. The variants of inexact augmented Lagrange multiplier (iALM) algorithm including nonconvex iALM (NCiALM) and majorization-minimization iALM (MMiALM) are developed to solve the proposed models, respectively. The matrix γ-norm based classifier is devised for classification. Finally, experiments on four popular face image databases can validate the superiority of our methods compared with the-state-of-the-art regression methods.

1. Introduction

For the past several decades, it is well known that face recognition has received more and more applications in pattern recognition and computer vision. Many researchers around the world have proposed numerous methods to solve the difficulties that appear in face recognition. Among these methods, regression based classification methods have become a popular tool and received much attention in recent years. For example, sparse representation based classification (SRC) method [42] has gained great success and attraction by seeking a sparse solver of the testing sample over all the training samples. The striking performance of SRC has not only boosted research interest, but also brings a promising research direction especially in computer vision. Subsequently, Yang et al. [44] further provided a theoretical analysis on SRC for

* Corresponding author.
E-mail address: csjyang@njust.edu.cn (J. Yang).

http://dx.doi.org/10.1016/j.ins.2017.02.020

its effectiveness to image classification. Meanwhile, Zhang et al. [49] also analyzed the working mechanism of SRC and presented the collaborative representation based classification (CRC) method. Jia et al. [17] proposed a structured sparse representation based classification (SSRC) method, which extended SRC by introducing structured sparsity to characterize the spatially contiguous occlusion of error image. Based on the fundamental assumption that patterns from same subject should lie on a linear subspace, Naseem et al. presented a linear regression classifier (LRC) [29] and further extended it to the robust linear regression classifier (RLRC) [30], which can demonstrate the robustness of the huber estimator to address random pixel corruption and illumination changes in face images. To make the method more effective, Yang et al. [45] developed a robust sparse coding (RSC) method by borrowing the idea of robust regression [15]. By virtue of the induced robust error metric, another interesting work called correntropy based error sparse representation (CESR) was given by He et al. [12]. In addition, the half-quadratic-based iterative minimization (HQIM) regression method was also presented by He et al. [13] for robust sparse representation, which can obtain the inspiring results for face recognition. The aforementioned methods can improve the performance of face recognition in different aspects. However, there exist two limitations of these methods in real-world applications: One is these methods all use one-dimensional pixel-level noise based error regression models, which need to stretch the error image matrix to a vector in advance. Specially, these models assume that each pixel of the error image is independent of one another and also neglects the correlation information. The other is that they use l_1-norm or l_2-norm to code the coefficients vector to promote the sparsity or cooperativity, respectively. They consider the linear structure of data representation, but do not take much prior information (e.g., low-rank structural information of the error image matrix, locality structure and similarity relationship among data) into consideration. These limitations may restrict the effectiveness of these regression methods in practical applications.

Recently, considering that illumination and occlusion changes in the testing images generally yield a low-rank or approximately low-rank error image matrix, several nuclear norm based matrix regression (NMR) methods are proposed to make use of the low-rank structural noise (e.g., occlusions, illumination variations) in [5,43] and the mixed noise (i.e., structural noise plus additive noise) in [26,33] to overcome the aforementioned first limitation since they employ the dependence relationship of the error image matrix. In detail, these methods use nuclear norm as a criterion to measure the low-rank structural information and matrix L_1-norm or Frobenius-norm as the measurements of sparse noise or gaussian noise in the error image matrix. They indeed obtain good experimental results in [5,26,33,43] over the pixel-level noise based regression methods for face recognition especially for structural noise and mixed noise. However, we observe that when the occlusion area and illumination variation become much larger, the performance is relatively lower since the rank function approximated by nuclear norm may not satisfy the incoherence assumptions [4,34]. In addition, nuclear norm as the convex relaxation of the rank function usually over-penalizes several large singular values of the error image matrix, which may lead to the suboptimal solution. Moreover, these methods still use l_1-norm or l_2-norm to code the coefficients vector, which also has the similar disadvantage as the above second limitation. After carefully studying these regression based methods, we know that selecting the proper measurement rule to the error image matrix [13,17,26,43,45] can help to improve their performance, while using more prior information of the data (e.g., the local structure, similarity relationship) for the characterization of coefficients vector can also help to achieve better performance [8,23,38,46].

To obtain a better approximation the matrix rank function, there are some nonconvex relaxations of rank function such as weighted nuclear norm [10], truncated nuclear norm [14], Ky Fan $p-k$-norm$(0 < p < 1)$ [18] and schatten-p norm$(0 < p < 1)$ [31]. Additionally, some nonconvex surrogate functions of the l_0-norm listed in [24,25] have been extended to approximate the rank function, such as smoothly clipped absolute deviation (SCAD) [7] and minimax concave plus (MCP) [47]. The above mentioned nonconvex rank relaxations can be used to overcome the limitations of nuclear norm. Most importantly, they can obtain nearly unbiased approximation of rank function and lead to the local solution although it is not optimal in general. As far as we know, there are some inspiring results discussed by Wang et al. [39] and Liu et al. [21] for robust principle component analysis (RPCA) and matrix completion (MC), respectively, in which they use matrix γ-norm as rank approximation and matrix MCP function as matrix L_0-norm relaxation. This can motivate us adopt matrix MCP function and matrix γ-norm as nonconvex relaxation of the error image matrix for sparse noise and structural noise, respectively. By doing this, the error image matrix can be better characterized over the convex counterparts such as L_1-norm, Frobenius-norm and nuclear norm. On the other hand, the coding coefficients vector measured by l_1-norm or l_2-norm can lead to unstable performance as explained in [23,38,46] since that the local structure of data becomes more critical than sparsity, and the sparse coding does not guarantee the use of the local information. Inspired by [23,48], we define a novel distance metric to describe the similarity relationship between the training samples and testing samples, and then integrate it into the sparse coding to form a unified coding formulation namely weighted sparse coding (WSC), which can be regarded as an extension of sparse coding. Similar to [23], WSC can overcome the above second limitation, and it takes both locality and similarity information of data into consideration, while seeking the sparse linear representation. As a result, they are conducive to improving the performance of classification. Note that nonconvex rank relaxations and WSC for the error characterization and coefficients coding can only overcome the above mentioned limitations, independently.

It follows from the aforementioned improvements that we can use the low rank and sparse regularizers (i.e., matrix-γ norm and MCP function) instead of convex ones for the error image matrix description, and WSC for the coefficients vector characterization instead of l_1-norm or l_2-norm. Based on further analysis of NMR methods [5,26,33,43] and motivated by [21,23,39,48], this paper proposes a novel and unified nonconvex matrix regression method called weighted sparse coding regularized nonconvex matrix regression: one is named as WSγMR for dealing with the structural noise, while the other is WSγM^{2}R for the mixed noise. It should be noted that the proposed models are all nonconvex, this means