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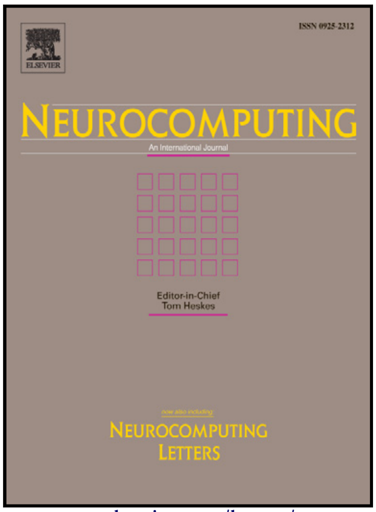

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Hengyou Wang, Ruizhen Zhao, Yigang Cen

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Rank Adaptive Atomic Decomposition for Low-Rank Matrix Completion and Its Application on Image Recovery

Wang Hengyou[1,2,3], Zhao Ruizhen[1,2 *], Cen Yigang[1,2]

[1]Institute of Information Science, Beijing Jiaotong University, Beijing 100044, China;

[2]Key Laboratory of Advanced Information Science and Network Technology of Beijing, Beijing 100044, China;

[3]School of Science, Beijing University of Civil Engineering and Architecture, Beijing 100044, China

Abstract: Recently, a greedy algorithm called Atomic Decomposition for Minimum Rank Approximation (ADMiRA) was proposed. It has solved the low-rank matrix approximation problem when the rank of the matrix is known. However, the rank of the matrix is usually unknown in practical application. In this paper, a Rank Adaptive Atomic Decomposition for Low-Rank Matrix Completion (RAADLRMC) algorithm is proposed based on the Atomic Decomposition for Minimum Rank Approximation. The advantage of RAADLRMC is that it works when the parameter rank-r of matrix is not given. Furthermore, the step size of iteration is decreased adaptively in order to improve the efficiency and accuracy. As illustrated by our experiments, our algorithm is robust, and the rank of matrix can be predicted accurately.

Key words: Matrix Completion, Rank Minimization, Atomic Decomposition, Image Recovery, Compressed Sensing

1. Introduction

In the recent years, studies in Compressed Sensing (CS) have shown that sparse signals can be exactly reconstructed. Furthermore, the solutions are guaranteed unique and stable. The reconstructed methods can be mainly classified into two types. One is based on the ℓ_1-norm. For example, Candès et al. proposed ℓ_1-MAGIC: recovery of sparse signals via convex programming [1]. Beck et al. presented fast iterative shrinkage-thresholding algorithm for linear inverse problems [2]. Another is based on ℓ_0-norm, such as matching pursuit [3], orthogonal matching pursuit [4], sparsity adaptive matching pursuit [5] and so on. ℓ_0-norm minimization method has attracted more attention for its simplicity and high speed in application. Since low-rank matrix approximation can be seen as the extension of compressed sensing in the case of matrix, what's the method of its reconstruction?

Recht et al. [6] studied rank minimization in the framework of compressed sensing and showed that rank minimization is analogous to ℓ_0-norm minimization in the case of vector. Most problem about ℓ_0-norm minimization is relaxed to ℓ_1-norm minimization. Analogously, rank minimization also can be relaxed to nuclear norm minimization. Based on this theory, several methods were proposed, such as singular value thresholding algorithm for matrix completion [7], the Inexact Augmented Lagrange Multiplier (IALM, also called Alternating Direction Methods (ADM)) [8] and so on [9-12].

Recently, Lee et al. [13] proposed a greedy algorithm called Atomic Decomposition for

*Corresponding author.