Robust Matrix Completion By Exploiting Dynamic Low-Dimensional Structures

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Research

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Abstract

This paper studies the robust matrix completion problem for time-varying models. Leveraging the low-rank property and the temporal information of the data, we develop novel methods to recover the original data from partially observed and corrupted measurements. We show that the reconstruction performance can be improved if one further leverages the information of the sparse corruptions in addition to the temporal correlations among a sequence of matrices. The dynamic robust matrix completion problem is formulated as a nonconvex optimization problem, and the recovery error is quantified analytically and proved to decay in the same order as that of the state-of-the-art method when there is no corruption. A fast iterative algorithm with convergence guarantee to the stationary point is proposed to solve the nonconvex problem. Experiments on synthetic data and real video dataset demonstrate the effectiveness of our method.

Full Text

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Figures

Figure 1

Relative recovery error of the convex relaxation and Algorithm 1 according to different d .

Figure 2

Relative recovery error of the LOWEMS [21], the convex relaxation, and Algorithm 1 ($d = 3$).

Figure 3

Relative recovery error of Algorithm 1 according to different standard deviation of the perturbation noise ($d = 3$).

Figure 4

Video frames only including the first RGB value. (first row: original frames; second row: frames with 15% random corruptions and 15% missing; third row: frames with 20% block corruptions and 15% missing).

Figure 5

Relative recovery error of our method according to different d.

Figure 6

Relative recovery error of our method according to different d (20% block corruptions).

Figure 7

Relative recovery error according to different corruption rate ($d = 2$).

Figure 8

Box-plot-diagram of relative recovery error when the average erasure rate changes (Corruption rate= 5%, $d = 2$).

Figure 9

The performance of our method on a public video dataset (20% corruptions).

Figure 10

Recovery Visualization (first row: original frames; second row: frames with 20% random corruptions and 30% missing; third row: the recovery using our method with $d = 3$).