CSIC5011 Mini-Project 1: Robust PCA on video surveillance

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1. Introduction

Robust principal component analysis (RPCA) appears in a wide range of applications, including video and voice background subtraction, sparse graphs clustering, 3D reconstruction, and fault isolation. However, RPCA problem is ill-posed without any additional conditions. Thus, many algorithms computationally rather expensive to solve, even for medium size matrices. Robust PCA regards the original dataset as the sum of a low rank matrix L and a sparse matrix S by solving the optimization problem called Stable Principal Component Pursuit (SPCP). We will compare some optimization algorithms on this task.

2. Dataset

We use surveillance video clip named “shopping mall” to perform RPCA. The video shows people walking around in the shopping mall and the angle of view is fixed. So, RPCA could decompose each frame into low rank background and sparse foreground. The video has 1000 frames with 320*256 resolution. The scale of the dataset is large and suitable for testing speed of optimization algorithms.

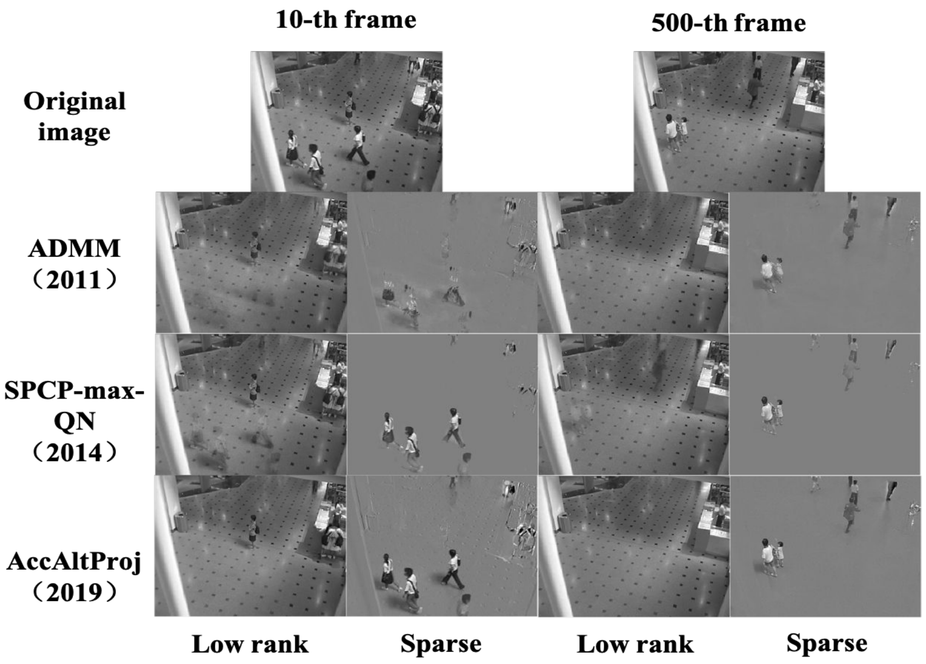
3. Methods

ADMM: an algorithm that solves convex optimization problems by breaking them into smaller pieces. Can be used as a basic algorithm for solving principal component decomposition. The optimizer is the Alternating Direction Method of Multipliers (ADMM), which regard the whole optimizer into several sub optimization problems.

SPCP-max-QN: A new convex formulation called SPCP-max is introduced for SPCP to decompose noisy signals into low-rank and sparse representations. It change the objective function from sum of nuclear norm of low rank matrix and l1 norm of sparse matrix to maximum of them. To solve this problem, a new quasi-Newton method called SPCP-max-QN is introduced.

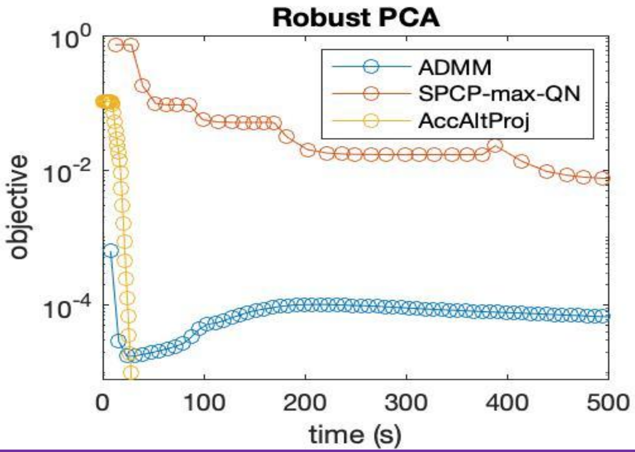
AccAltProj: an accelerated algorithm for RPCA. Alternating projections (AltProj) can be used to solve RPCA: the projection of a matrix onto the space of low rank matrices can be computed by the singular value decomposition (SVD) followed by truncating out small singular values, while the projection of a matrix onto the space of sparse matrices can be computed by the hard thresholding operator. AccAltProj circumvents the high computational cost of the SVD and is able to reduce the per-iteration computational cost of AltProj significantly (AltProj requires to compute the SVD of a full size matrix).

4. Visualization



After decomposition, the original data can be regarded as the sum of the a low rank matrix (background) and a sparse matrix (foreground) shown as above. Note that one person appears in the tenth frame since he didn’t move in the beginning of the video, then he has been treated as background.

5. Result and Conclusion



It is clear that AccAltProj is much faster than previous algorithm. Although ADMM solves the problem fast at early stage, the convergence speed is not guaranteed in a long term. As for SPCP-max-QN, it is always the slowest one. Thus, the final performance of it is the worst in our comparison.

6. References

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7. Contribution

DONG Hanze: AccAltProj method + part of poster
LI Donghao: SPCP-max-QN method + part of poster
WU Jiamin: ADMM method + part of poster