HANDBOOK OF ROBUST LOW-RANK AND SPARSE MATRIX DECOMPOSITION

Applications in Image and Video Processing

edited by

Thierry Bouwmans
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CRC Press
Taylor & Francis Group

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CRC Press
Taylor & Francis Group
Boca Raton London New York

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CRC Press
Taylor & Francis Group
6000 Broken Sound Parkway NW, Suite 300
Boca Raton, FL 33487-2742

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Printed on acid-free paper
Version Date: 20160411

International Standard Book Number-13: 978-1-4987-2462-3 (Hardback)

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Preface

Robust subspace learning and tracking by decomposition into low-rank and sparse matrices provide a suitable framework for computer vision applications. Thus, decomposition into low-rank and sparse matrices has been developed in different formulation problems such as robust principal component analysis, robust non-negative matrix factorization, robust matrix completion, subspace tracking, and low-rank minimization. These different approaches differ from the decomposition, the corresponding optimization problem, and the solvers. The optimization problem can be NP-hard in its original formulation, and it can be convex or not follow the constraints and the loss functions used. Thus, the key challenges concern the design of efficient relaxed models and solvers, which have to have as few iterations as possible, and be as efficient as possible.

As the advances in these different problem formulations are fundamental for computer vision applications, this field has witnessed a number of significant publications since the papers of Cands et al., and Chandrasekharan et al. in 2009. A representative example concerns the background/foreground separation in video surveillance. Up to now, many efforts have been made to develop methods that perform well visually with reduced computational cost. However, no algorithm has emerged that is able to simultaneously address all of the key challenges that accompany real-world videos. Thus, effective decompositions for robustness to deal with both real-life scenes with fixed cameras and mobile devices have recently been developed. Another feature of computer vision applications is that the decomposition has to be computed in real-time and low memory requirements. Algorithms have to be designed to meet these requirements.

In this context, this handbook solicited contributions to address this wide range of robust low-rank and sparse matrix decompositions for applications in image and video processing. Thus, it groups the works of the leading teams in this field over recent years. By incorporating both existing and new ideas, this handbook gives a complete overview of the concepts, theories, algorithms, and applications related to robust low-rank and sparse matrix decompositions. First, an introduction to robust principal component analysis via low-rank and sparse matrices decomposition for beginners is provided by surveying the different decompositions, loss functions, optimization problems, and solvers. Furthermore, leading methods and algorithms for robust low-rank and sparse matrix decompositions are presented. Moreover, an accompanying website[1] is provided. This website contains the list of chapters, their abstracts, and links to some software demonstrations. It allows the reader to have quick access to the main resources and codes in the field. Finally, with this handbook, we aim to bring a one-stop solution, i.e., access to a number of different decompositions, algorithms, implementations, and benchmarking techniques in a single volume.

The handbook consists of five parts. **Part I** presents an overall introduction to robust PCA via decomposition into low-rank and sparse matrices. Chapter 1 provides a first complete survey of the decomposition into low-rank and sparse matrices. Furthermore, the

[1] `https://sites.google.com/site/lowranksparsedecomposition/`

authors provide an accompanying website: the DLAM Website.[2] This website contains a full list of the references in the field, links to available datasets and codes. In each case, the list is regularly updated and classified according to the sections of this chapter. Chapter 2 gives a detailed review of algorithms for stable PCA. Chapter 3 investigates dual smoothing and value function techniques for variational matrix decomposition. Thus, the authors review some recent techniques in convex optimization and contribute several novel results. A distinguishing feature of Chapter 3 is the emphasis on a range of optimization formulations of the RPCA problem. When a few columns of the data matrix are generated by mechanisms different from the rest of the columns, the existence of these outlying columns tends to destroy the low-rank structure of the data matrix. Thus, Chapter 4 presents a low-rank and block-sparse matrix decomposition insensitive to column/row outliers. Chapter 5 focuses on the control of the sparsity in robust PCA.

Part II concerns robust matrix factorization/completion problems. Chapter 6 unifies nuclear norm and bilinear factorization for low-rank matrix decomposition. The authors present very convincing results in the several applications, such as background/foreground separation, structure from motion, face reconstruction, and motion estimation between photometric stereo sequences. Chapter 7 describes a robust non-negative matrix factorization under separability assumption. The algorithm called RobustXray is used for background/-foreground separation when illumination changes occur. Chapter 8 provides nonconvex approaches and efficient algorithms for robust matrix completion. The authors provide several results for image/video recovery and removing shadows from faces. Chapter 9 develops a factorized robust matrix completion. Results on video background subtraction show that this approach is robust against several challenges such as illumination changes and dynamic backgrounds.

Part III focuses on robust online subspace estimation, learning, and tracking. Chapter 10 develops online robust algorithms for robust PCA. Thus, the authors study the problem of sequentially recovering a sparse vector and a vector from a low-dimensional subspace from knowledge of their sum. Two main approaches are then presented: Recursive Projected Compressed Sensing (ReProCS) and Modified-PCP. A full evaluation is provided for background/foreground separation against state-of-the-art RPCA algorithms. Chapter 11 provides incremental methods for robust local subspace estimation. Furthermore, the authors generalize their model from a single low-rank subspace with a sparse set of possibly-large deviations, to a low-dimensional manifold with the same type of deviations. Thus, local subspace models and endogenous sparse representations are proposed to obtain a robust approximation of the backgrounds component of a video sequence captured by a non-stationary camera. Finally, a transform invariant incremental RPCA algorithm is described. Chapter 12 presents a Robust Orthonormal Subspace Learning called ROSL for efficient low-rank recovery. Different from convex methods using the nuclear norm, ROSL utilizes a novel rank measure on the low-rank matrix that imposes the group sparsity of its coefficients under orthonormal subspace. The authors present several applications such as in background/foreground separation and removing shadows from faces. Chapter 13 presents a unified view of nonconvex heuristic approaches. Then, the authors propose two non-convex models, i.e., l_p-norm heuristic recovery (pHR) and log-sum heuristic recovery (LHR) for corrupted matrix learning. Experimental results on noisy depth maps fusion for muti-view stereo show the robustness of these two non-convex models.

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[2] `https://sites.google.com/site/robustdlam/home`

Part IV concerns applications in image and video processing. Chapter 14 developed a variational approach. The authors evaluated their method on foreground detection in blurred and noisy video, and detection of network anomalies. Chapter 15 recovered low-rank and sparse matrices in the presence of missing and grossly corrupted observations. The authors present results on text removal, background/foreground separation, and face reconstruction. Collaborative filtering and subspace clustering are also investigated. Chapter 16 briefly presents the application of low-rank and sparse matrix decompositions in hyperspectral video processing. Chapter 17 investigates an accelerated dynamic MRI using low-rank plus sparse reconstruction with separation of background and dynamic components.

Part V presents resources and applications in background/foreground separation for video surveillance. Chapter 18 describes the LRSLibrary, which provides a collection of low-rank and sparse decomposition algorithms in MATLAB®. The library was designed for background/foreground separation in videos, but it can also be used or adapted for other computer vision. Currently the LRSLibrary contains a total of 72 matrix-based and tensor-based algorithms. The LRSLibrary was tested successfully in MATLAB R2013b in both the x86 and x64 versions. Chapter 19 develops a Dynamic Mode Decomposition (DMD) for Robust PCA. The DMD decomposition yields oscillatory time components of the video frames that have contextual implications. Furthermore, the authors present a multi-resolution DMD (MRDMD) that allows them to separate components that are happening on different time scales. Chapter 20 provides three algorithms for stochastic RPCA applied to background/-foreground separation. First, Markov Random Fields (MRF) are used to take into account the spatial constraints of the foreground objects. Then, multiple features and dynamic feature selection are added to improve the detection in the case of highly dynamic backgrounds. Finally, the authors present a depth-extended version which is robust in the presence of camouflage in color. Chapter 21 presents a Bayesian sparse estimation applied to background/foreground separation.

The handbook is intended to be a reference for researchers and developers in industries, as well as graduate students, who are interested in low-rank and sparse matrix decomposition applied to computer vision. Particularly, the application in image and video processing are presented, such as in image analysis, image denoising, motion saliency detection, video coding, key frame extraction, hyperspectral video processing and background/foreground separation. Thus, it can be suggested as a reading text for teaching graduate courses in subjects such as computer vision, image and video processing, real-time architecture, machine learning, and data mining. The editors of this handbook would like to acknowledge, with their sincere gratitude, the contributors, for their valuable chapters, and the reviewers, for the helpful comments concerning the chapters in this handbook. Particularly, we acknowledge Dr. Yuanqiang (Evan) Dong [3] from UtopiaCompression Corporation [4] for his review of the handbook. We also acknowledge the reviewers of the original handbook proposal for their hepful suggestions. Furthermore, we are very grateful for the help that we have received from Randi Cohen, Hayley Ruggieri, and others at CRC Press during the preparation of this handbook. Finally, we would like to acknowledge Shashi Kumar from Cenveo for his valuable support about the LaTeX issues.

[3] http://vigir.missouri.edu/~evan/index.htm

[4] http://www.utopiacompression.com/

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About the Editors

Thierry Bouwmans (http://sites.google.com/site/thierrybouwmans/) is an Associate Professor at the University of La Rochelle, France. His research interests consist mainly of the detection of moving objects in challenging environments. He has recently authored more than 30 papers in the field of background modeling and foreground detection. These papers investigated, in particular the use of fuzzy concepts, discriminative subspace learning models, and robust PCA. They also developed surveys on mathematical tools used in the field and particularly on decomposition in low-rank plus additive matrices. He has supervised five Ph.D. students in background/foreground separation. He is the creator and administrator of the Background Subtraction Website, and has served as a reviewer for numerous international conferences and journals.

Necdet Serhat Aybat (http://www.ie.psu.edu/AboutUs/FacultyStaff/Faculty/Profile/aybat.html) received his Ph.D. degree in Operations Research from Columbia University, Industrial Engineering and Operations Research Department. Currently, he is an assistant professor in the Industrial and Manufacturing Engineering Department at Pennsylvania State University, USA. His research, supported by the National Science Foundation (NSF), focuses on developing fast first-order algorithms for large-scale convex optimization problems coming from diverse application areas, such as compressed sensing, matrix completion, convex regression, and distributed optimization. In particular, he has devised algorithms, with provable computational complexity, for robust and stable principal component pursuit problems. He supervises Ph.D. students in this field, and actively serves as a reviewer for numerous academic journals and a session organizer for international conferences.

El Hadi Zahzah (http://sites.google.com/site/ezahzah/) is an Associate Professor at the University of La Rochelle, France. He obtained his Ph.D. at Toulouse Research Institute in Information Technology (IRIT) Lab. Since 1993, his research interests have consisted mainly in the spatio-temporal relations and detection of moving objects in challenging environments. He has authored more than 60 papers in the field of fuzzy logic, expert systems, image analysis, spatio-temporal modelization, and background modeling and foreground detection. His recent papers investigated the use of fuzzy concepts, discriminative subspace learning models, and robust Principal Component Analysis (PCA). He also develops surveys on mathematical tools and has supervised seven Ph.D. students.

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I

Robust Principal Component Analysis

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