Full text available at: http://dx.doi.org/10.1561/2000000103

A Survey on the Low-Dimensional-Model-based Electromagnetic Imaging

Full text available at: http://dx.doi.org/10.1561/2000000103

Other titles in Foundations and Trends® in Signal Processing

Deep Learning in Object Recognition, Detection, and Segmentation
Xiaogang Wang
ISBN: 978-1-68083-116-0

Structured Robust Covariance Estimation
Ami Wiesel and Teng Zhang
ISBN: 978-1-68083-094-1

A Primer on Reproducing Kernel Hilbert Spaces
Jonathan H. Manton and Pierre-Olivier Amblard
ISBN: 978-1-68083-092-7

Deep Learning: Methods and Applications
Li Deng and Dong Yu
ISBN: 978-1-60198-814-0

Interactive Sensing and Decision Making in Social Networks
Vikram Krishnamurthy, Omid Namvar Gharehshiran and
Maziyar Hamdi
ISBN: 978-1-60198-812-6

Full text available at: http://dx.doi.org/10.1561/2000000103

A Survey on the Low-Dimensional-Model-based Electromagnetic Imaging

Lianlin Li

Martin Hurtado

Feng Xu

Bing Chen Zhang

Tian Jin

Tie Jun Cui

Marija Nikolic Stevanovic

Arye Nehorai

now
the essence of knowledge
Boston — Delft

Full text available at: http://dx.doi.org/10.1561/2000000103

Foundations and Trends® in Signal Processing

Published, sold and distributed by:
now Publishers Inc.
PO Box 1024
Hanover, MA 02339
United States
Tel. +1-781-985-4510
www.nowpublishers.com
sales@nowpublishers.com

Outside North America:
now Publishers Inc.
PO Box 179
2600 AD Delft
The Netherlands
Tel. +31-6-51115274

The preferred citation for this publication is

L. Li, M. Hurtado, F. Xu, B. .C. Zhang, T. Jin, T. J. Cui, M. Nikolic Stevanovic and A. Nehorai. *A Survey on the Low-Dimensional-Model-based Electromagnetic Imaging*. Foundations and Trends® in Signal Processing, vol. 12, no. 2, pp. 107–199, 2018.

ISBN: 978-1-68083-463-5
© 2018 L. Li, M. Hurtado, F. Xu, B. .C. Zhang, T. Jin, T. J. Cui, M. Nikolic Stevanovic and A. Nehorai

All rights reserved. No part of this publication may be reproduced, stored in a retrieval system, or transmitted in any form or by any means, mechanical, photocopying, recording or otherwise, without prior written permission of the publishers.

Photocopying. In the USA: This journal is registered at the Copyright Clearance Center, Inc., 222 Rosewood Drive, Danvers, MA 01923. Authorization to photocopy items for internal or personal use, or the internal or personal use of specific clients, is granted by now Publishers Inc for users registered with the Copyright Clearance Center (CCC). The 'services' for users can be found on the internet at: www.copyright.com

For those organizations that have been granted a photocopy license, a separate system of payment has been arranged. Authorization does not extend to other kinds of copying, such as that for general distribution, for advertising or promotional purposes, for creating new collective works, or for resale. In the rest of the world: Permission to photocopy must be obtained from the copyright owner. Please apply to now Publishers Inc., PO Box 1024, Hanover, MA 02339, USA; Tel. +1 781 871 0245; www.nowpublishers.com; sales@nowpublishers.com

now Publishers Inc. has an exclusive license to publish this material worldwide. Permission to use this content must be obtained from the copyright license holder. Please apply to now Publishers, PO Box 179, 2600 AD Delft, The Netherlands, www.nowpublishers.com; e-mail: sales@nowpublishers.com

Full text available at: http://dx.doi.org/10.1561/2000000103

Foundations and Trends® in Signal Processing
Volume 12, Issue 2, 2018

Editorial Board

Editor-in-Chief

Yonina Eldar
Technion
Israel

Editors

Pao-Chi Chang
National Central University

Pamela Cosman
University of California, San Diego

Michelle Effros
California Institute of Technology

Yariv Ephraim
George Mason University

Alfonso Farina
Selex ES

Sadaoki Furui
Tokyo Institute of Technology

Georgios Giannakis
University of Minnesota

Vivek Goyal
Boston University

Sinan Gunturk
Courant Institute

Christine Guillemot
INRIA

Robert W. Heath, Jr.
The University of Texas at Austin

Sheila Hemami
Northeastern University

Lina Karam
Arizona State University

Nick Kingsbury
University of Cambridge

Alex Kot
Nanyang Technical University

Jelena Kovacevic
Carnegie Mellon University

Geert Leus
TU Delft

Jia Li
Pennsylvania State University

Henrique Malvar
Microsoft Research

B.S. Manjunath
University of California, Santa Barbara

Urbashi Mitra
University of Southern California

Björn Ottersten
KTH Stockholm

Vincent Poor
Princeton University

Anna Scaglione
University of California, Davis

Mihaela van der Shaar
University of California, Los Angeles

Nicholas D. Sidiropoulos
Technical University of Crete

Michael Unser
EPFL

P.P. Vaidyanathan
California Institute of Technology

Ami Wiesel
The Hebrew University of Jerusalem

Min Wu
University of Maryland

Josiane Zerubia
INRIA

Full text available at: http://dx.doi.org/10.1561/2000000103

Editorial Scope

Topics

Foundations and Trends® in Signal Processing publishes survey and tutorial articles in the following topics:

- Adaptive signal processing
- Audio signal processing
- Biological and biomedical signal processing
- Complexity in signal processing
- Digital signal processing
- Distributed and network signal processing
- Image and video processing
- Linear and nonlinear filtering
- Multidimensional signal processing
- Multimodal signal processing
- Multirate signal processing
- Multiresolution signal processing
- Nonlinear signal processing
- Randomized algorithms in signal processing
- Sensor and multiple source signal processing, source separation
- Signal decompositions, subband and transform methods, sparse representations
- Signal processing for communications
- Signal processing for security and forensic analysis, biometric signal processing
- Signal quantization, sampling, analog-to-digital conversion, coding and compression
- Signal reconstruction, digital-to-analog conversion, enhancement, decoding and inverse problems
- Speech/audio/image/video compression
- Speech and spoken language processing
- Statistical/machine learning
- Statistical signal processing
  - Classification and detection
  - Estimation and regression
  - Tree-structured methods

Information for Librarians

Foundations and Trends® in Signal Processing, 2018, Volume 12, 4 issues. ISSN paper version 1554-057X. ISSN online version 1554-0588. Also available as a combined paper and online subscription.

Full text available at: http://dx.doi.org/10.1561/2000000103

Contents

Full text available at: http://dx.doi.org/10.1561/2000000103

A Survey on the Low-Dimensional-Model-based Electromagnetic Imaging

Lianlin Li[1], Martin Hurtado[2], Feng Xu[3], Bing Chen Zhang[4], Tian Jin[5], Tie Jun Cui[6], Marija Nikolic Stevanovic[7] and Arye Nehorai[8]

[1] *Peking University; lianlin.li@pku.edu.cn*
[2] *National University of La Plata; martin.hurtado@ing.unlp.edu.ar*
[3] *Fudan University; fengxu@fudan.edu.cn*
[4] *Institute of Electronics, Chinese Academy of Sciences; bczhang@mail.ie.ac.cn*
[5] *National University of Defense Technology; tianjin@nudt.edu.cn*
[6] *Southeast University; tjcui@seu.edu.cn*
[7] *University of Belgrade; mnikolic@etf.rs*
[8] *Washington University in St. Louis; nehorai@ese.wustl.edu*

ABSTRACT

The low-dimensional-model-based electromagnetic imaging is an emerging member of the big family of computational imaging, by which the low-dimensional models of underlying signals are incorporated into both data acquisition systems and reconstruction algorithms for electromagnetic imaging, in order to improve the imaging performance and break the bottleneck of existing electromagnetic imaging methodologies. Over the past decade, we have witnessed profound impacts of the low-dimensional models on electromagnetic imaging. However, the low-dimensional-model-based electromagnetic imaging remains at its early stage, and many

---

Lianlin Li, Martin Hurtado, Feng Xu, Bing Chen Zhang, Tian Jin, Tie Jun Cui, Marija Nikolic Stevanovic and Arye Nehorai (2018), "A Survey on the Low-Dimensional-Model-based Electromagnetic Imaging", Foundations and Trends® in Signal Processing: Vol. 12, No. 2, pp 107–199. DOI: 10.1561/2000000103.

Full text available at: http://dx.doi.org/10.1561/2000000103

important issues relevant to practical applications need to be carefully investigated. Especially, we are in the big-data era of booming electromagnetic sensing, by which massive data are being collected for retrieving very detailed information of probed objects. This survey gives a comprehensive overview on the low-dimensional models of structure signals, along with its relevant theories and low-complexity algorithms of signal recovery. Afterwards, we review the recent advancements of low-dimensional-model-based electromagnetic imaging in various applied areas. We hope this survey could bridge the gap between the model-based signal processing and the electromagnetic imaging, advance the development of low-dimensional-model-based electromagnetic imaging, and serve as a basic reference in the future research of the electromagnetic imaging across various frequency ranges.

Full text available at: http://dx.doi.org/10.1561/2000000103

1

Introduction

Electromagnetic imaging has been a powerful technique in various civil and military applications across medical imaging, geophysics, space exploration, resources and energy survey, etc., where the operational frequency ranges from the very low frequency (like tens of Hertz) through microwave, millimeter wave, and Therahertz, up to optical frequencies [47, 127, 23, 192, 96, 150, 70]. The electromagnetic imaging problem or the electromagnetic inverse scattering problem consists of determining the unknown features (including geometrical and physical parameters) of an object from processing measured electromagnetic data [127, 192]. Essentially, it is strongly nonlinear and ill-posed due to the complicated interaction between the electromagnetic wavefield and the imaging scene [127, 192]. In principle, this problem could be addressed by employing nonlinear iterative optimization methods, but these iterative methods are computationally prohibitive even for the moderate-scale problem [127]. In practice, one resorts to the linearized approximate solution to the rigorous inverse scattering problem, for example, Born-approximation [127, 23]. Nonetheless, the resulting inverse problem remains notoriously ill-posed since the measurements available are inadequate typically compared to the unknowns to be

Full text available at: http://dx.doi.org/10.1561/2000000103

retrieved. Especially, there are increasing continuously demands on the imaging resolution of detailed information of probed object nowadays, which broaden the gap between the unknowns of interest and the measurements available further. Moreover, the measurements are noisy and suffer from unknown ambiguous parameters, which makes the electromagnetic imaging problem more challenging.

Put formally, the electromagnetic imaging can be formulated as $\boldsymbol{y} = \boldsymbol{A}_{\boldsymbol{\theta}}(\boldsymbol{x}) + \boldsymbol{n}$, where the quantity $\boldsymbol{y}$ indicates the vectorized measurements corrupted with additive noise $\boldsymbol{n}$, $\boldsymbol{x}$ denotes the unknown (*e.g.*, the reflectivity of imaged scene) to be retrieved, $\boldsymbol{A}_{\boldsymbol{\theta}}$ is a mapping operator with the subscript $\boldsymbol{\theta}$ highlighting possible unknown ambiguous parameters [47, 127, 23, 192, 96, 150]. As argued above, the nonlinear inverse scattering, *i.e.* $\boldsymbol{A}_{\boldsymbol{\theta}}$ being nonlinear, is limited to the small-scale problem due to its very expensive computational cost. For this reason, we are restricted ourselves into the case of $\boldsymbol{A}_{\boldsymbol{\theta}}$ being linear. Furthermore, without the loss of generality, we assume no ambiguous parameters involved, implying that the subscript $\boldsymbol{\theta}$ vanishes. Consequently, $\boldsymbol{A}_{\boldsymbol{\theta}}$ becomes $\boldsymbol{A}$. Then, the electromagnetic imaging problem consists of retrieving the unknowns $\boldsymbol{x}$ from the noisy measurements $\boldsymbol{y}$. In probabilistic framework, the estimation of $\boldsymbol{x}$ amounts to evaluating the posterior probability of $\boldsymbol{x}$ conditional on $\boldsymbol{y}$ [157, 87, 166]:

$$\Pr(\boldsymbol{x}|\boldsymbol{y}) = \frac{1}{Z}\Pr(\boldsymbol{y}|\boldsymbol{x})\Pr(\boldsymbol{x}) \tag{1.1}$$

where $Z = \int \Pr(\boldsymbol{y}|\boldsymbol{x})\Pr(\boldsymbol{x})\,\mathrm{d}\boldsymbol{x}$ is the normalized factor (or the partition function), $\Pr(\boldsymbol{y}|\boldsymbol{x})$ is the likelihood function of $\boldsymbol{x}$, and $\Pr(\boldsymbol{x})$ is the prior knowledge on $\boldsymbol{x}$. Once obtaining the posteriori probability $\Pr(\boldsymbol{x}|\boldsymbol{y})$, we can numerically or analytically calculate desirable statistical quantities. We are particularly interested in the maximum a posteriori (MAP) mode denoted by $\boldsymbol{x}_{\mathrm{MAP}}$ [157, 87, 166]:

$$\begin{aligned}
\boldsymbol{x}_{\mathrm{MAP}} &= \arg\max_{\boldsymbol{x}} \log\Pr(\boldsymbol{x}|\boldsymbol{y}) \\
&= \arg\max_{\boldsymbol{x}} \left[\log\Pr(\boldsymbol{y}|\boldsymbol{x}) + \log\Pr(\boldsymbol{x})\right] \qquad (1.2)\\
&= \arg\min_{\boldsymbol{x}} \left[\frac{1}{2}\|\boldsymbol{y} - \boldsymbol{A}(\boldsymbol{x})\|_2^2 - \log\Pr(\boldsymbol{x})\right] \qquad (1.3)
\end{aligned}$$

As pointed out previously, Eq. 1.3 is ill-posed due to the inadequate

Full text available at: http://dx.doi.org/10.1561/2000000103

measurements compared to the unknowns to be retrieved, especially when the finer details of probed scene are desirable. Since the measurements are incomplete, an infinite number of solutions, however, being non-meaningful, match measurements. Therefore, one crucial task of electromagnetic imaging is to select the most meaningful solution out of the potential solutions. In terms of Bayesian analysis, the model function $\Pr(\boldsymbol{x})$ provides the speculative knowledge on the underlying signal $\boldsymbol{x}$, which is, if correct, helpful in suppressing remarkably the solution uncertainty by complementing the incomplete measurements. In this sense, one feasible approach to the above task is the exploration of the correct model $\Pr(\boldsymbol{x})$ in the design of imaging systems and imaging algorithms.

Most of real-world signals have low-dimensional models, known as being of the structured sparsity or structured compressibility [16, 62, 46, 10]. Here, we mean by structure that a transformed domain or manifold, being either deterministic or probabilistic, exists such that over which the transformed coefficients are sparse or compressible. By sparsity, we mean that a signal of length n has $k \ll n$ nonzero elements; in contrast, we mean by compressibility that a signal of length n can be approximated with certain accuracy by a signal with only $k \ll n$ nonzero coefficients [16]. Low-dimensional signal models affect significantly the data acquisition, analysis and later processing [63, 172, 59], which has profoundly broken bottlenecks set by the well-known Nyquist-Shannon theory founded by Kotelnikov, Nyquist, Shannon, Whittaker *et al.* A celebrated theory known as compressive sensing, founded by Candès, Tao, Romberg, Donoho *et al.*, states that the sparse or compressible signal can be accurately and efficiently retrieved from its low-dimensional projections [32, 31, 30, 29, 48]. Afterwards, many more realistic and richer low-dimensional signal models along with the guarantee of theories and algorithms have been discovered and investigated, which affect the data acquisition, analysis and processing significantly [59, 15, 80, 81, 64]. For instance, for tree- and block-structured signals, Baraniuk et al. established the theory of model-based compressive sensing (CS) along with reconstruction algorithms [80].

Low-dimensional-model based signal processing (model-based SP,

Full text available at: http://dx.doi.org/10.1561/2000000103

for short) differs from the Nyquist-Shannon theory based methods (conventional SP, for short) in several important aspects, as summarized in Table 1.1. As opposed to the conventional SP, which only uses the information provided by the measurement, model-based SP uses both the measurement and the prior knowledge, enabling us to break the limits in classical signal processing. For example, the number of measurements required by the Nyquist-Shannon theory can be dramatically reduced [80, 81, 64, 20], the Rayleigh resolution limit can be readily beat [35, 27], and so on. In addition, these two frameworks differ in the manner in which they deal with signal recovery. For conventional SP, the signal recovery is accomplished through simple sinc interpolation with marginal computational cost [46]. In contrast, the model-based signal recovery is achieved by implementing nonlinear iterative algorithms, which needs apparently expensive computational resources [80, 81, 64].

Table 1.1: Comparisons between two frameworks of conventional and low-dimensional-model-based signal processing.

	Conventional SP	Model-based SP
Data input	Measurements	Measurements plus prior knowledge
Math. Model $\boldsymbol{y} = \boldsymbol{A}\boldsymbol{x}$	$\dim(\boldsymbol{y}) \geq \dim(\boldsymbol{x})$	$\dim(\boldsymbol{y}) \ll \dim(\boldsymbol{x})$
Data acquisition	Nyquist sampling rate	RIP criterion
Data communication	Sampling followed by compression	Compressed sampling
Representation	Independent pixels	Structure or pattern
Statistical model	Gaussian	Non-Gaussian
Signal Recovery	Sinc interpolation	Nonlinear optimization
Resolution	Rayleigh limit	Better than Rayleigh limit

Over past years, we have witnessed the notable impacts of low-dimensional-model-based signal processing, more strictly, the sparse-model-based signal processing, on the electromagnetic imaging [30, 114, 113, 131, 85, 101, 151, 9, 144, 21, 176, 86, 149, 147, 125, 17, 37, 38,

Full text available at: http://dx.doi.org/10.1561/2000000103

84, 20]. Imaging techniques, that exploit low-dimensional-model of the underlying scene, are becoming more and more popular thanks to their ability to mitigate the theoretical and practical difficulties arising in the associated inverse problem, while properly complying with several common applicative requirements (*e.g.*, reduced computational costs, high spatial resolution, and robustness to the noise). Such an increased interest is proved by a vast of publications in several areas (*e.g.*, electromagnetic inverse scattering, radar, microwave imaging, and array synthesis), and special sessions in relevant international conferences, as well as special issues in leading-edge journals. Invoked by the concept of compressive sensing, Hunt et al. [85] and Li et al. [101] invented the single-pixel images for microwave imaging of sparse scenes, demonstrating the important potential of sparse-signal model of imaged scene in developing the apparatus of low-complexity and low-cost data acquisition. By now, the most affected issue related to electromagnetic imaging is the development of low-order model-based imaging algorithms. For instance, there are a large amount of efforts have been made to melt the sparsity-promoted regularization with the iterative algorithms of electromagnetic inverse scattering, being different in the selection of sparsifying transformations, leading to the feature-enhanced reconstruction. As argued above, the non-linear electromagnetic inverse scattering is limited to the small-scale problem due to very expensive computational complexity. For this reason, we leave the discussion about them out of this survey, and refer to [151, 9, 144, 21, 176] for detailed discussions. For the linearized electromagnetic imaging (Born-based tomography [86, 149, 147, 125] and signal-based radar imaging [17, 37, 38, 84, 180, 99, 195, 185]), the sparse-model (or compressible-model) of imaged scene have been exploited, and a large amount of low-order model-based imaging algorithms have been developed, demonstrating that the usefulness of sparse-model in enhancing the image quality and reducing the number of measurements. It is really appealing to incorporate low-dimensional models of underlying signals into the electromagnetic imaging, in order to reduce the number of measurements, improve the imaging resolution, enhance the capability of object recognition and classification, and so on. For this reason, we refer to this methodology of electromagnetic

Full text available at: http://dx.doi.org/10.1561/2000000103

imaging as the low-dimensional-model-based electromagnetic imaging (model-based electromagnetic imaging, for short). Here, we would like to give a formal description about it:

Definition 1: *The low-dimensional-model-based electromagnetic imaging is the object-oriented and feature-enhanced electromagnetic imaging methodology by incorporating the knowledge of the structured models of underlying signals into the data acquisition system and the reconstruction algorithm, in order to reducing the number of measurements, improve the imaging resolution, enhance the capability of object recognition and classification, and so on.*

Although the model-based signal processing by itself has arrived at relatively mature level with a solid body of theories [59, 32, 31, 30, 29, 48, 15, 80, 81, 64, 35, 27, 76, 34, 28, 54, 49, 50, 51, 52, 53] and algorithms [55, 159, 41, 94, 198, 33, 112, 115, 120, 183, 160, 168, 72, 161, 91], its interactions with electromagnetic imaging remains challenging and many important issues are deserved to be studied in-depth. The model-based electromagnetic imaging focuses on four major aspects as following.

First, it is desirable the development of the next-generation imaging system with low-cost, low-complexity and high efficiency by the way of the optimal design of the waveform, the programmable or reconfigurable antenna, the configuration of sparse sensor array, etc. For instance, the establishment of novel compressive radar is appealing for ultra-wideband (UWB) radar imaging [84, 180], since it is really too costly, or even physically impossible, to build devices capable of acquiring samples at the necessary rate in the context of classical signal processing.

Second, it is desirable to establish an easy-implementation of imaging formulations, which account for the real interaction between the electromagnetic wavefield and the probed scene. The interaction between the electromagnetic wavefield and the probed scene is nonlinear in essence; however, most of mathematical formulations of electromagnetic imaging considered so far are linear, failing to capture fully the undergoing physical mechanism in some practical cases [164, 26, 42].

Full text available at: http://dx.doi.org/10.1561/2000000103

Nikolic et al. attempted to link the electromagnetic mechanism and the sparse-signal model by using the equivalent electromagnetic currents, and demonstrated that with this model, the sparseness of imaged scene supports the reconstruction of non-convex shape of 2D PEC targets [123]. However, such methodology is limited to the single-frequency imaging configuration, since the equivalent currents vary with the operational frequencies.

Third, it is desirable to discover more realistic and richer low-dimensional models of the underlying electromagnetic information. By now, the low-dimensional models utilized in the area of electromagnetic imaging are nearly simple sparse or compressible models; more realistic and richer models are not fully investigated.

Fourth, we are in the deluge of massive electromagnetic data coming from the continuously increasing demands on retrieving very detailed information of objects nowadays. Therefore, it is crucial to develop efficient reconstruction algorithms for treating massive measurements and high-dimensional variables. From the aspect of computational complexity, it is also important to develop algorithmic frameworks trading off the imaging accuracy with the computational cost.

Full text available at: http://dx.doi.org/10.1561/2000000103

References

[1] Agarwal, K. and X. Chen. 2008. "Applicability of MUSIC-type imaging in twodimensional electromagnetic inverse problems". *IEEE Transactions on Antennas and Propagation*. 56(10): 3217–3223.

[2] Aharon, M., M. Elad, and A. Bruckstein. 2006. "K-SVD: An Algorithm for Designing Overcomplete Dictionaries for Sparse Representation". *IEEE Transactions on Signal Processing*. 54(11): 4311–4322.

[3] Ahmad, F., J. Qian, and M. G. Amin. 2014. "Wall Clutter Mitigation Using Discrete Prolate Spheroidal Sequences for Sparse Reconstruction of Indoor Stationary Scenes". *IEEE Transactions on Geoscience and Remote Sensing*. 53(3): 1549–1557.

[4] Ahmed, A., B. Recht, and J. Romberg. 2012. "Blind Deconvolution Using Convex Programming". *IEEE Transactions on Information Theory*. 60(3): 1711–1732.

[5] Ahn, S. and J. A. Fessler. 2003. "Globally convergent image reconstruction for emission tomography using relaxed ordered subsets algorithms". *IEEE Transactions on Medical Imaging*. 22(5): 613–626.

[6] Allenzhu, Z. and L. Orecchia. 2014. "Linear Coupling: An Ultimate Unification of Gradient and Mirror Descent". *Mathematics*.

Full text available at: http://dx.doi.org/10.1561/2000000103

[7] Amin, M. G., ed. 2011. *Through-the-wall radar imaging*. CRC Press.

[8] Amit, Y., M. Fink, N. Srebro, and S. Ullman. 2007. "Uncovering shared structures in multiclass classification". In: *Machine Learning, Proceedings of the Twenty-Fourth International Conference*. 17–24.

[9] Anselmi, N., M. Salucci, G. Oliveri, and A. Massa. 2015. "Wavelet-Based Compressive Imaging of Sparse Targets". *IEEE Transactions on Antennas and Propagation*. 63(11): 4889–4900.

[10] Bach, F., R. Jenatton, J. Mairal, and G. Obozinski. 2011. "Structured sparsity through convex optimization". *Statistical Science*. 27(4): 450–468.

[11] Bach, F., R. Jenatton, J. Mairal, and G. Obozinski. 2012. "Structured sparsity through convex optimization". *Statistical Science*. 27(4): 450–468.

[12] Bahlak, S., J. Gazalet, J. E. Lefebvre, T. Gryba, and V. Zhang. 2015. "Convex Optimization: Algorithms and Complexity". *Foundations and Trends in Machine Learning*. 8(3–4): 231–357.

[13] Bahmani, S. and J. Romberg. 2015. "Efficient Compressive Phase Retrieval with Constrained Sensing Vectors". *Mathematics*.

[14] Bai, C., P. E. Kinahan, D. Brasse, and C. Comtat. 2002. "Postinjection single photon transmission tomography with ordered-subset algorithms for whole-body PET imaging". *IEEE Transactions on Nuclear Science*. 49(1): 74–81.

[15] Baraniuk, R. G., V. Cevher, M. F. Duarte, and C. Hegde. 2010a. "Model-based compressive sensing". *IEEE Transactions on Information Theory*. 56(4): 1982–2001.

[16] Baraniuk, R. G., V. Cevher, and M. B. Wakin. 2010b. "Low-dimensional models for dimensionality reduction and signal recovery: A geometric perspective". *Proceedings of the IEEE*. 98(6): 959–971.

[17] Baraniuk, R. and P. Steeghs. 2007. "Compressive Radar Imaging". In: *Radar Conference*. 128–133.

Full text available at: http://dx.doi.org/10.1561/2000000103

[18] Beck, A. and M. Teboulle. 2009. “A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems”. *SIAM Journal on Imaging Sciences*. 2(1): 183–202.

[19] Becker, S., J. Bobin, and E. J. Candès. 2009. “NESTA: A Fast and Accurate First-order Method for Sparse Recovery”. *SIAM Journal on Imaging Sciences*. 4(1): 1–39.

[20] Bevacqua, M. T., L. Crocco, L. D. Donato, and T. Isernia. 2017. “Non-Linear Inverse Scattering via Sparsity Regularized Contrast Source Inversion”. *IEEE Transactions on Computational Imaging*. 3(2): 296–304.

[21] Bevacqua, M. T., L. Crocco, L. D. Donato, and T. Isernia. 2015. “Microwave Imaging of Nonweak Targets via Compressive Sensing and Virtual Experiments”. *IEEE Antennas and Wireless Propagation Letters*. 14: 1035–1038.

[22] Bingchen, Z., H. Wen, and W. Yirong. 2012. “Sparse microwave imaging: Principles and applications”. *Science China Information Sciences*. 55(8): 1722–1754.

[23] Born, M. and E. Wolf. 1980. *Principles of optics: electromagnetic theory of propagation, interference and diffraction of light*. Elsevier.

[24] Boyd, S., N. Parikh, E. Chu, B. Peleato, and J. Eckstein. 2011. “Distributed Optimization and Statistical Learning via the Alternating Direction Method of Multipliers”. *Foundations and Trends in Machine Learning*. 3(1): 1–122.

[25] Boyd, S. and L. Vandenberghe, eds. 2004. *Convex Optimization*. Cambridge University Press.

[26] Bucci, O. M. and T. Isernia. 2016. “Electromagnetic inverse scattering: Retrievable information and measurement strategies”. *Radio Science*. 32(6): 2123–2137.

[27] Candès, E. J. and C. Fernandez-Granda. 2012. “Towards a Mathematical Theory of Super-resolution”. *Communications on Pure & Applied Mathematics*. 67(6): 906–956.

[28] Candès, E. J. and Y. Plan. 2009. “Matrix Completion With Noise”. *Proceedings of the IEEE*. 98(6): 925–936.

Full text available at: http://dx.doi.org/10.1561/2000000103

[29] Candès, E. J., J. K. Romberg, and T. Tao. 2006. "Stable signal recovery from incomplete and inaccurate measurements". *Communications on Pure & Applied Mathematics*. 59(8): 1207–1223.

[30] Candès, E. J., J. Romberg, and T. Tao. 2004. "Robust uncertainty principles: exact signal reconstruction from highly incomplete frequency information". *IEEE Transactions on Information Theory*. 52(2): 489–509.

[31] Candès, E. J. and T. Tao. 2005. "Decoding by linear programming". *IEEE Transactions on Information Theory*. 51(12): 4203–4215.

[32] Candès, E. J. and T. Tao. 2006. *Near-Optimal Signal Recovery From Random Projections: Universal Encoding Strategies?* IEEE Press. 5406–5425.

[33] Candès, E. J., M. B. Wakin, and S. Boyd. 2007. "Enhancing sparsity by reweighted L1 minimization." *Journal of Fourier Analysis and Applications*. 14(5): 877–905.

[34] Candès, E. and B. Recht. 2012. "Exact Matrix Completion via Convex Optimization". *Foundations of Computational Mathematics*. 55(6): 111–119.

[35] Candès, E. J. and C. Fernandezgranda. 2013. "Super-Resolution from Noisy Data". *Journal of Fourier Analysis and Applications*. 19(6): 1229–1254.

[36] Catapano, I., L. Crocco, and T. Isernia. 2007. "On simple methods for shape reconstruction of unknown scatterers". *IEEE Transactions on Antennas and Propagation*. 55(5): 1431–1436.

[37] Cetin, M. and W. C. Karl. 2001. "Feature-enhanced synthetic aperture radar image formation based on non quadratic regularization". *IEEE Transactions on Image Processing*. 10(4): 623–31.

[38] Cetin, M., W. C. Karl, and D. A. Castanon. 2004. "Feature enhancement and ATR performance using non quadratic optimization based SAR imaging". *IEEE Transactions on Aerospace and Electronic Systems*. 39(4): 1375–1395.

Full text available at: http://dx.doi.org/10.1561/2000000103

[39] Cevher, V., S. Becker, and M. Schmidt. 2014. "Convex Optimization for Big Data". *Mathematics*. 17(1): 37–40.

[40] Charvat, G. L. 2014. *Small and short-range radar systems*. CRC Press. 102–103.

[41] Chen, S., D. L. Donoho, and M. A. Saunders. 1998. "Atomic decomposition by basis pursuit". *SIAM Journal on Scientific Computing*. 20(1): 33–61.

[42] Colton, D. and R. Kress. 2012. *Inverse Acoustic and Electromagnetic Scattering Theory*. Vol. 93. Springer Science & Business Media.

[43] Cotter, S. F., B. D. Rao, K. Engan, and K. Kreutz-Delgado. 2005. "Sparse solutions to linear inverse problems with multiple measurement vectors". *IEEE Transactions on Signal Processing*. 53(7): 2477–2488.

[44] Crocco, L., L. D. Donato, I. Catapano, and T. Isernia. 2013. "An improved simple method for imaging the shape of complex targets". *IEEE Transactions on Antennas and Propagation*. 61(2): 843–851.

[45] Darzentas, J. 1984. "Problem Complexity and Method Efficiency in Optimization". *Journal of the Operational Research Society*. 35(5): 455–455.

[46] Davenport, M. A., M. F. Duarte, Y. C. Eldar, and G. Kutyniok. 2012. "Introduction to compressed sensing". *Lecture Note*.

[47] Devaney, A. J. 2012. *Mathematical foundations of imaging, tomography and wavefield inversion*. Cambridge University Press.

[48] Donoho, D. L. 2006a. "Compressed sensing". *IEEE Transactions on Information Theory*. 52(4): 1289–1306.

[49] Donoho, D. L. 2006b. "For most large underdetermined systems of linear equations the minimal L1 norm solution is also the sparsest solution". *Communications on Pure and Applied Mathematics*. 59(6): 797–829.

[50] Donoho, D. L. and M. Elad. 2003. "Optimally sparse representation in general (nonorthogonal) dictionaries via L1 minimization". *Proceedings of the National Academy of Sciences*. 100(5): 2197–2202.

Full text available at: http://dx.doi.org/10.1561/2000000103

[51] Donoho, D. L. and M. Elad. 2006. "On the stability of the basis pursuit in the presence of noise". *Signal Processing*. 86(3): 511–532.

[52] Donoho, D. L., M. Elad, and V. N. Temlyakov. 2006. "Stable recovery of sparse overcomplete representations in the presence of noise". *IEEE Transactions on Information Theory*. 52(1): 6–18.

[53] Donoho, D. L. and J. Tanner. 2005. "Sparse nonnegative solution of underdetermined linear equations by linear programming". *Proceedings of the National Academy of Sciences*. 102(27): 9446–9451.

[54] Donoho, D. L. and J. Tanner. 2010. "Precise Undersampling Theorems". *Proceedings of the IEEE*. 98(6): 913–924.

[55] Donoho, D. L. and Y. Tsaig. 2008. "Fast Solution of L1 - Norm Minimization Problems When the Solution May Be Sparse". *IEEE Transactions on Information Theory*. 54(11): 4789–4812.

[56] Dremeau, A., C. Herzet, and L. Daudet. 2012. "Boltzmann Machine and Mean-Field Approximation for Structured Sparse Decompositions". *IEEE Transactions on Signal Processing*. 60(7): 3425–3438.

[57] Du, X., C. Duan, and W. Hu. 2013. "Sparse Representation Based Autofocusing Technique for ISAR Images". *IEEE Transactions on Geoscience and Remote Sensing*. 51(3): 1826–1835.

[58] Duan, H., L. Zhang, J. Fang, L. Huang, and H. Li. 2015. "Pattern-Coupled Sparse Bayesian Learning for Inverse Synthetic Aperture Radar Imaging". *IEEE Signal Processing Letters*. 22(11): 1995–1999.

[59] Duarte, M. F. and Y. C. Eldar. 2011. "Structured Compressed Sensing: From Theory to Applications". *IEEE Transactions on Signal Processing*. 59(9): 4053–4085.

[60] Duarte, M. F., M. A. Davenport, D. Takbar, J. N. Laska, T. Sun, K. F. Kelly, and R. G. Baraniuk. 2008. "Single-Pixel Imaging via Compressive Sampling". *IEEE Signal Processing Magazine*. 25(2): 83–91.

Full text available at: http://dx.doi.org/10.1561/2000000103

[61] Duarte-Carvajalino, J. M., G. Yu, L. Carin, and G. Sapiro. 2012. “Task-Driven Adaptive Statistical Compressive Sensing of Gaussian Mixture Models”. *IEEE Transactions on Signal Processing*. 59(12): 5842–5858.

[62] Elad, M. 2010. *Sparse and Redundant Representations: From Theory to Applications in Signal and Image Processing*. Springer Publishing Company.

[63] Elad, M. 2012. “Sparse and Redundant Representation Modeling - What Next?” *IEEE Signal Processing Letters*. 19(12): 922–928.

[64] Eldar, Y. C., P. Kuppinger, and H. Bolcskei. 2010. “Block-Sparse Signals: Uncertainty Relations and Efficient Recovery”. *IEEE Transactions on Signal Processing*. 58(6): 3042–3054.

[65] *Electronic Warfare and Radar Systems Engineering Handbook*. 1997. Naval Air Warfare Center. Point Mugu, CA.

[66] Fenn, A. J., D. H. Temme, W. P. Delaney, and W. E. Courtney. 2000. “The Development of Phased-Array Radar Technology”. *Lincoln Laboratory Journal*: 321–340.

[67] Fercoq, O., Z. Qu, P. Richtárik, and M. Takáč. 2014. “Fast distributed coordinate descent for non-strongly convex losses”. In: *IEEE International Workshop on Machine Learning for Signal Processing (MLSP)*. 1–6.

[68] Fercoq, O. and P. Richtárik. 2013. “Accelerated, Parallel and Proximal Coordinate Descent”. *SIAM Journal on Optimization*. 25(4).

[69] Figueiredo, M. A. T. and R. D. Nowak. 2003. “An EM algorithm for wavelet-based image restoration”. *IEEE Transactions on Image Processing*. 12(8): 906–916.

[70] Fornaro, G., F. Lombardini, A. Pauciullo, D. Reale, and F. Viviani. 2014. “Tomographic processing of interferometric SAR data: Developments, applications, and future research perspectives”. *IEEE Signal Processing Magazine*. 31(4): 41–50.

[71] Frey, J. 2004. “Introduction to Stochastic Search and Optimization: Estimation, Simulation, and Control”. *Journal of the American Statistical Association*. 18(468): 101–102.

Full text available at: http://dx.doi.org/10.1561/2000000103

[72] Friedman, J., T. Hastie, and R. Tibshirani. 2010. "A note on the group LASSO and a sparse group LASSO". *Tech. rep.* arXiv:1001.0736. URL: https://arxiv.org/abs/1001.0736.

[73] Gilboa, G. and S. Osher. 2008. "Nonlocal Operators with Applications to Image Processing". *SIAM Journal on Multiscale Modeling and Simulation*. 7(3): 1005–1028.

[74] Goldstein, T., C. Studer, and R. Baraniuk. 2015. "A Field Guide to Forward-Backward Splitting with a FASTA Implementation". arXiv:1411.3406v3.

[75] Gopi, S., P. Netrapalli, P. Jain, and A. Nori. 2013. "One-bit compressed sensing: Provable support and vector recovery". In: *International Conference on Machine Learning*. 154–162.

[76] Gribonval, R., V. Cevher, and M. E. Davies. 2012. "Compressible Distributions for High-Dimensional Statistics". *IEEE Transactions on Information Theory*. 58(8): 5016–5034.

[77] Gurbuz, A. C., J. H. Mcclellan, and W. R. Scott. 2009a. "A Compressive Sensing Data Acquisition and Imaging Method for Stepped Frequency GPRs". *IEEE Transactions on Signal Processing*. 57(7): 2640–2650.

[78] Gurbuz, A. C., J. H. Mcclellan, and W. R. Scott. 2009b. "Compressive sensing for subsurface imaging using ground penetrating radar". *Signal Processing*. 89(10): 1959–1972.

[79] Hardle, W., P. Hall, and H. Ichimura. 1991. "Optimal Smoothing in Single-Index Models". *Core Discussion Papers*. 21(1): 157–178.

[80] He, L. and L. Carin. 2009. "Exploiting Structure in Wavelet-Based Bayesian Compressive Sensing". *IEEE Transactions on Signal Processing*. 57(9): 3488–3497.

[81] He, L., H. Chen, and L. Carin. 2010. "Tree-Structured Compressive Sensing With Variational Bayesian Analysis". *IEEE Signal Processing Letters*. 17(3): 233–236.

[82] Hristache, M., A. Juditsky, and V. Spokoiny. 2001. "Direct Estimation of the Index Coefficient in a Single-Index Model". *Annals of Statistics*. 29(3): 595–623.

Full text available at: http://dx.doi.org/10.1561/2000000103

[83] Huang, J. and T. Zhang. 2010. "The benefit of group sparsity". *Ann. Statist.* 38(4): 1978–2004.

[84] Huang, Q., L. Qu, B. Wu, and G. Fang. 2010. "UWB Through-Wall Imaging Based on Compressive Sensing". *IEEE Transactions on Geoscience and Remote Sensing*. 48(3): 1408–1415.

[85] Hunt, J. and D. R. Smith. 2013. "Metamaterial apertures for computational imaging". *Science*. 339(6117): 310–313.

[86] Hurtado, M., N. Von Ellenrieder, C. Muravchik, and A. Nehorai. 2011. "Sparse modeling for polarimetric radar". In: *Statistical Signal Processing Workshop*. 17–20.

[87] Idier, J. 2013. *Bayesian approach to inverse problems*. John Wiley & Sons.

[88] Jacob, L., G. Obozinski, and J. P. Vert. 2009. "Group Lasso with Overlaps and Graph Lasso". In: *International Conference on Machine Learning*. 433–440.

[89] Jenatton, R., J. Y. Audibert, and F. Bach. 2010. "Structured Variable Selection with Sparsity-Inducing Norms". *Journal of Machine Learning Research*. 12(10): 2777–2824.

[90] Ji, S., D. Dunson, and L. Carin. 2009. *Multitask Compressive Sensing*. Vol. 57. No. 1. 92–106.

[91] Ji, S., Y. Xue, and L. Carin. 2008. "Bayesian Compressive Sensing". *IEEE Transactions on Signal Processing*. 56(6): 2346–2356.

[92] Jolliffe, I. T. 1986. *Principal Component Analysis*. Springer-Verlag. 41–64.

[93] Kim, D. and J. A. Fessler. 2016. "Optimized first-order methods for smooth convex minimization". *Mathematical Programming*. 159(1): 81–107.

[94] Koh, K., S. J. Kim, and S. Boyd. 2007. "An Interior-Point Method for Large-Scale L1 - Regularized Logistic Regression". *IEEE Journal of Selected Topics in Signal Processing*. 8(4): 1519–1555.

[95] Komodakis, N. and J. C. Pesquet. 2014. "Playing with Duality: An overview of recent primal-dual approaches for solving large-scale optimization problems". *IEEE Signal Processing Magazine*. 32(6): 31–54.

Full text available at: http://dx.doi.org/10.1561/2000000103

[96] Kunitsyn, V. E. and E. D. Tereshchenko. 2003. *Ionospheric tomography*. Springer Science & Business Media.

[97] Lagunas, E., M. G. Amin, F. Ahmad, and M. Najar. 2013. "Joint Wall Mitigation and Compressive Sensing for Indoor Image Reconstruction". *IEEE Transactions on Geoscience and Remote Sensing*. 51(2): 891–906.

[98] Lavielle, M. 1993. "Bayesian deconvolution of Bernoulli-Gaussian processes". *Signal Processing*. 33(1): 67–79.

[99] Leigsnering, M., F. Ahmad, M. G. Amin, and A. M. Zoubir. 2013. "Compressive sensing based specular multipath exploitation for through-the-wall radar imaging". In: *Proc. IEEE International Conference on Acoustics, Speech, and Signal Processing*. 6004–6008.

[100] Leigsnering, M., F. Ahmad, M. G. Amin, and A. M. Zoubir. 2015. "Compressive Sensing-Based Multipath Exploitation for Stationary and Moving Indoor Target Localization". *IEEE Journal of Selected Topics in Signal Processing*. 9(8): 1469–1483.

[101] Li, F., K. Yao, L. Li, and T. J. Cui. 2015. "Far-field imaging beyond diffraction limit using single sensor in combination with a resonant aperture". *Optics Express*. 23(1): 401–12.

[102] Li, L. 2012. "Note on RIP-based Co-sparse Analysis". preprint arXiv:1202.2037.

[103] Li, L., W. Zhang, and F. Li. 2008. "Tomographic Reconstruction Using the Distorted Rytov Iterative Method With Phaseless Data". *Analytica Chimica Acta*. 5(3): 479–483.

[104] Li, L., H. Zheng, and F. Li. 2009. "Two-Dimensional Contrast Source Inversion Method With Phaseless Data: TM Case". *IEEE Transactions on Geoscience and Remote Sensing*. 47(6): 1719–1736.

[105] Li, L. 2014. "Sparsity-Promoted Blind Deconvolution of Ground-Penetrating Radar (GPR) Data". *Geoscience and Remote Sensing Letters IEEE*. 11(8): 1330–1334.

Full text available at: http://dx.doi.org/10.1561/2000000103

[106] Li, L., B. Jafarpour, and M. R. Mohammad-Khaninezhad. 2013. "A simultaneous perturbation stochastic approximation algorithm for coupled well placement and control optimization under geologic uncertainty". *Computational Geosciences*. 17(1): 167–188.

[107] Liang, M., Y. Li, H. Meng, M. A. Neifeld, and H. Xin. 2015. "Reconfigurable Array Design to Realize Principal Component Analysis (PCA)-Based Microwave Compressive Sensing Imaging System". *IEEE Antennas and Wireless Propagation Letters*. 14: 1039–1042.

[108] Liu, H., J. Bo, H. Liu, and Z. Bao. 2014. "A Novel ISAR Imaging Algorithm for Micromotion Targets Based on Multiple Sparse Bayesian Learning". *IEEE Geoscience and Remote Sensing Letters*. 11(10): 1772–1776.

[109] Liu, Z., P. You, X. Wei, and X. Li. 2013. "Dynamic ISAR Imaging of Maneuvering Targets Based on Sequential SL0". *IEEE Geoscience and Remote Sensing Letters*. 10(5): 1041–1045.

[110] Long-Gang Wang, L. L. and T. J. Cui. 2017. "Compressive Microwave Imager Using 1-bit Programmable Coding Metasurface at Single Frequency". unpublished.

[111] Maleki, A., L. Anitori, Z. Yang, and R. G. Baraniuk. 2013. "Asymptotic Analysis of Complex LASSO via Complex Approximate Message Passing (CAMP)". *IEEE Transactions on Information Theory*. 59(7): 4290–4308.

[112] Mallat, S. G. and Z. Zhang. 1993. "Matching pursuits with time-frequency dictionaries". *IEEE Transactions on Signal Processing*. 41(12): 3397–3415.

[113] Massa, A., P. Rocca, and G. Oliveri. 2015. "Compressive Sensing in Electromagnetics - A Review". *IEEE Antennas and Propagation Magazine*. 57(1): 224–238.

[114] Massa, A. and F. L. Teixeira. 2015. "Guest Editorial: Special Cluster on Compressive Sensing as Applied to Electromagnetics". *IEEE Antennas & Wireless Propagation Letters*. 14: 1022–1026.

Full text available at: http://dx.doi.org/10.1561/2000000103

[115] Needell, D. and J. A. Tropp. 2009. "CoSaMP: Iterative Signal Recovery From Incomplete and Inaccurate Samples". *Applied and Computational Harmonic Analysis*. 26(3): 301–321.

[116] Needell, D., N. Srebro, and R. Ward. 2013. "Stochastic gradient descent and the randomized Kaczmarz algorithm". *Mathematical Programming*: 1–25.

[117] Nemirovski, A., A. Juditsky, G. Lan, and A. Shapiro. 2009. "Robust Stochastic Approximation Approach to Stochastic Programming". *Siam Journal on Optimization*. 19(4): 1574–1609.

[118] Nesterov, Y. 2005a. "Excessive Gap Technique in Nonsmooth Convex Minimization". *SIAM Journal on Optimization*. 16(1): 235–249.

[119] Nesterov, Y. 2005b. "Smooth minimization of non-smooth functions". *Mathematical Programming*. 103(1): 127–152.

[120] Nesterov, Y. 2013. *Introductory lectures on convex optimization: A basic course*. Springer Science & Business Media.

[121] Nesterov, Y. 2010. "Efficiency of Coordinate Descent Methods on Huge-Scale Optimization Problems". *Siam Journal on Optimization*. 22(2010002): 341–362.

[122] Nikolic, M., A. Nehorai, and A. R. Djordjevic. 2012. "Iterative sparse through-the-wall imaging". In: *IEEE Sensor Array and Multichannel Signal Processing Workshop*. 345–348.

[123] Nikolic, M., A. Nehorai, and A. R. Djordjevic. 2013. "Electromagnetic Imaging of Hidden 2D PEC Targets Using Sparse-Signal Modeling". *IEEE Transactions on Geoscience and Remote Sensing*. 51(5): 2707–2721.

[124] Nikolic, M., G. Tang, and A. Nehorai. 2010. "3D Electromagnetic imaging using compressive sensing". In: *IEEE Sensor Array and Multichannel Signal Processing Workshop*. 37–40.

[125] Oliveri, G., P. Rocca, and A. Massa. 2011. "A Bayesian Compressive Sampling Based Inversion for Imaging Sparse Scatterers". *IEEE Transactions on Geoscience and Remote Sensing*. 49(10): 3993–4006.

Full text available at: http://dx.doi.org/10.1561/2000000103

[126] Oliveri, G., D. H. Werner, and A. Massa. 2015. "Reconfigurable Electromagnetics Through Metamaterials–A Review". *Proceedings of the IEEE*. 103(7): 1034–1056.

[127] Pastorino, M. 2010. *Microwave imaging*. Vol. 208. John Wiley & Sons.

[128] Peleg, T., Y. C. Eldar, and M. Elad. 2012. "Exploiting Statistical Dependencies in Sparse Representations for Signal Recovery". *IEEE Transactions on Signal Processing*. 60(5): 2286–2303.

[129] Plan, Y. and R. Vershynin. 2011. "One-Bit Compressed Sensing by Linear Programming". *Communications on Pure and Applied Mathematics*. 66(8): 1275–1297.

[130] Plan, Y. and R. Vershynin. 2012. "Robust 1-bit Compressed Sensing and Sparse Logistic Regression: A Convex Programming Approach". *IEEE Transactions on Information Theory*. 59(1): 482–494.

[131] Potter, L. C., E. Ertin, J. T. Parker, and M. Cetin. 2010. "Sparsity and Compressed Sensing in Radar Imaging". *Proceedings of the IEEE*. 98(6): 1006–1020.

[132] Pournaghi, R. and X. Wu. 2014. "Coded Acquisition of High Frame Rate Video". *IEEE Transactions on Image Processing*. 23(12): 5670–5682.

[133] Qiu, W., E. Giusti, A. Bacci, M. Martorella, F. Berizzi, H. Z. Zhao, and Q. Fu. 1988. "Compressive sensing-based algorithm for passive bistatic ISAR with DVB-T signals." In: *International Conference on Enity-Relationship Approach: A Bridge To the User*. 207–225.

[134] Qu, Z., P. Richtárik, and T. Zhang. 2015. "Randomized Dual Coordinate Ascent with Arbitrary Sampling". *Mathematics*: 865–873.

[135] Rasmussen, C. and C. Williams. 2006. *Gaussian processes for machine learning*. MIT Press. 69–106.

[136] Ravishankar, S. and Y. Bresler. 2013. "Learning Sparsifying Transforms". *IEEE Transactions on Signal Processing*. 61(5): 1072–1086.

Full text available at: http://dx.doi.org/10.1561/2000000103

[137] Ravishankar, S. and Y. Bresler. 2015. "Efficient Blind Compressed Sensing Using Sparsifying Transforms with Convergence Guarantees and Application to MRI". *Mathematics*. 2(3): 294–309.

[138] Ravishankar, S. and Y. Bresler. 2016. "Data-Driven Learning of a Union of Sparsifying Transforms Model for Blind Compressed Sensing". *IEEE Transactions on Computational Imaging*. 2(3): 294–309.

[139] Recht, B., M. Fazel, and P. A. Parrilo. 2010. *Guaranteed Minimum-Rank Solutions of Linear Matrix Equations via Nuclear Norm Minimization*. Society for Industrial and Applied Mathematics. 471–501.

[140] Richtarik, P. and M. Takac. 2014. "Iteration complexity of randomized block-coordinate descent methods for minimizing a composite function". *Mathematical Programming*. 144(1): 1–38.

[141] Robbins, H. and S. Monro. 1985. *A Stochastic Approximation Method*. Springer New York. 400–407.

[142] Rubinstein, R., M. Zibulevsky, and M. Elad. 2010. "Double Sparsity: Learning Sparse Dictionaries for Sparse Signal Approximation". *IEEE Transactions on Signal Processing*. 58(3): 1553–1564.

[143] Samadi, S., M. Cetin, and M. A. Masnadi-Shirazi. 2011. "Sparse representation-based synthetic aperture radar imaging". *IET Radar Sonar Navigation*. 5(2): 182–193.

[144] Scapaticci, R., P. Kosmas, and L. Crocco. 2014. "Wavelet-based regularization for robust microwave imaging in medical applications". *IEEE Transactions on Biomedical Engineering*. 62(4): 1195–1202.

[145] Shervashidze, N. and F. Bach. 2015. "Learning the Structure for Structured Sparsity". *IEEE Transactions on Signal Processing*. 63(18): 4894–4902.

[146] Slavakis, K., S. J. Kim, G. Mateos, and G. B. Giannakis. 2014. "Stochastic Approximation vis-a-vis Online Learning for Big Data Analytics [Lecture Notes]". *IEEE Signal Processing Magazine*. 31(6): 124–129.

Full text available at: http://dx.doi.org/10.1561/2000000103

[147] Soldovieri, F., R. Solimene, and F. Ahmad. 2012. "Sparse Tomographic Inverse Scattering Approach for Through-the-Wall Radar Imaging". *IEEE Transactions on Instrumentation and Measurement*. 61(12): 3340–3350.

[148] Soldovieri, F., R. Solimene, L. L. Monte, M. Bavusi, and A. Loperte. 2011. "Sparse Reconstruction From GPR Data With Applications to Rebar Detection". *IEEE Transactions on Instrumentation and Measurement*. 60(3): 1070–1079.

[149] Solimene, R., F. Ahmad, and F. Soldovieri. 2012. "A Novel CS-TSVD Strategy to Perform Data Reduction in Linear Inverse Scattering Problems". *IEEE Geoscience and Remote Sensing Letters*. 9(9): 881–885.

[150] Solimene, R., I. Catapano, G. Gennarelli, A. Cuccaro, A. Dell' Aversano, and F. Soldovieri. 2014. "SAR imaging algorithms and some unconventional applications: A unified mathematical overview". *IEEE Signal Processing Magazine*. 31(4): 90–98.

[151] Stevanovic, M. N., L. Crocco, A. R. Djordjevic, and A. Nehorai. 2016a. "Higher Order Sparse Microwave Imaging of PEC Scatterers". *IEEE Transactions on Antennas and Propagation*. 64(3): 988–997.

[152] Stevanovic, M. N., J. Dinkic, J. Music, and A. Nehorai. 2016b. "Sparse microwave breast imaging with differently polarized arrays". In: *European Signal Processing Conference (EUSIPCO)*. 355–358.

[153] Su, W., S. Boyd, and E. J. Candès. 2015. "A Differential Equation for Modeling Nesterov's Accelerated Gradient Method: Theory and Insights". *Advances in Neural Information Processing Systems*. 3(1): 5312–5354.

[154] Suksmono, A. B., E. Bharata, A. A. Lestari, A. G. Yarovoy, and L. P. Ligthart. 2010. "Compressive Stepped-Frequency Continuous-Wave Ground-Penetrating Radar". *IEEE Geoscience and Remote Sensing Letters*. 7(4): 665–669.

Full text available at: http://dx.doi.org/10.1561/2000000103

[155] Tan, Z., Y. C. Eldar, and A. Nehorai. 2013. "Direction of Arrival Estimation Using Co-Prime Arrays: A Super Resolution Viewpoint". *IEEE Transactions on Signal Processing*. 62(21): 5565–5576.

[156] Tang, G. and A. Nehorai. 2015. "Computable Performance Bounds on Sparse Recovery". *IEEE Transactions on Signal Processing*. 63(1): 132–141.

[157] Tarantola, A. 2005. *Inverse Problem Theory and Methods for Model Parameter Estimation*. Society for Industrial and Applied Mathematics. DOI: 10.1137/1.9780898717921.

[158] Thrampoulidis, C., E. Abbasi, and B. Hassibi. 2015. "The LASSO with Non-linear Measurements is Equivalent to One With Linear Measurements". *Statistics*.

[159] Tibshirani, R. J. 1996. "Regression shrinkage and selection via the LASSO". *Journal of the Royal Statistical Society*. 58: 267–288.

[160] Tibshirani, R., M. Saunders, S. Rosset, J. Zhu, and K. Knight. 2005. "Sparsity and smoothness via the fused LASSO". *Journal of the Royal Statistical Society*. 67(1): 91–108.

[161] Tipping, M. E. 2001. "Sparse bayesian learning and the relevance vector machine". *Journal of Machine Learning Research*. 1(3): 211–244.

[162] Tosic, I. and P. Frossard. 2011. "Dictionary Learning". *Signal Processing Magazine IEEE*. 28(2): 27–38.

[163] Trandinh, Q. and V. Cevher. 2015. "An optimal first-order primal-dual gap reduction framework for constrained convex optimization". *Mathematics*.

[164] Tsang, L., J. A. Kong, and R. T. Shin. 1985. *Theory of microwave remote sensing*. Wiley.

[165] Tseng, P. 2008. "On accelerated proximal gradient methods for convex-concave optimization". *SIAM Journal on Optimization*.

[166] Tveito, A., H. P. Langtangen, B. F. Nielsen, and X. Cai. 2010. "Parameter Estimation and Inverse Problems". *International Geophysics*. 67: 411–421.

Full text available at: http://dx.doi.org/10.1561/2000000103

[167] Vaidyanathan, P. P. and P. Pal. 2011. "Theory of Sparse Coprime Sensing in Multiple Dimensions". *IEEE Transactions on Signal Processing*. 59(8): 3592–3608.

[168] Van Den Berg, E., M. Schmidt, M. P. Friedlander, and K. Murphy. 2008. "Group sparsity via linear-time projection". *Tech. rep.* Department of Computer Science, University of British Columbia.

[169] Varshney, K. R., M. Cetin, J. W. Fisher III, and A. S. Willsky. 2006. "Joint image formation and anisotropy characterization in wide-angle SAR". In: *Defense and Security Symposium*. Vol. 6237. 62370D.

[170] Vidal, R., Y. Ma, and S. S. Sastry. 2005. "Generalized Principal Component Analysis". *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 27(12): 1945–59.

[171] Vila, J. and P. Schniter. 2011. "Expectation-maximization Bernoulli Gaussian approximate message passing". In: *Conference Record of the Forty Fifth Asilomar Conference on Signals, Systems and Computers (ASILOMAR)*. 799–803.

[172] Wainwright, M. J. 2014. "Structured Regularizers for High-Dimensional Problems: Statistical and Computational Issues". *Annual Review of Statistics & Its Application*. 1(1): 233–253.

[173] Wang, L., L. Zhao, G. Bi, and C. Wan. 2015. "Sparse Representation Based ISAR Imaging Using Markov Random Fields". *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*. 8(8): 3941–3953.

[174] Wang, L., L. Zhao, G. Bi, C. Wan, and L. Yang. 2014. "Enhanced ISAR Imaging by Exploiting the Continuity of the Target Scene". *IEEE Transactions on Geoscience and Remote Sensing*. 52(9): 5736–5750.

[175] Watts, C. M., D. Shrekenhamer, J. Montoya, G. Lipworth, J. Hunt, T. Sleasman, S. Krishna, D. R. Smith, and W. J. Padilla. 2014. "Terahertz compressive imaging with metamaterial spatial light modulators". *Nature Photonics*. 8(8): 605–609.

Full text available at: http://dx.doi.org/10.1561/2000000103

[176] Winters, D. W., B. D. Van Veen, and S. C. Hagness. 2010. "A Sparsity Regularization Approach to the Electromagnetic Inverse Scattering Problem." *IEEE Transactions on Antennas and Propagation*. 58(1): 145–154.

[177] Wu, Q., Y. D. Zhang, F. Ahmad, and M. G. Amin. 2015. "Compressive-Sensing-Based High-Resolution Polarimetric Through the Wall Radar Imaging Exploiting Target Characteristics". *IEEE Antennas and Wireless Propagation Letters*. 14: 1043–1047.

[178] Yang, J., T. Jin, X. Huang, J. Thompson, and Z. Zhou. 2014. "Sparse MIMO Array Forward-Looking GPR Imaging Based on Compressed Sensing in Clutter Environment". *IEEE Transactions on Geoscience and Remote Sensing*. 52(7): 4480–4494.

[179] Yoon, Y. S. and M. G. Amin. 2008. "Compressed sensing technique for high-resolution radar imaging". In: *SPIE Defense and Security Symposium*. 69681A-69681A-10.

[180] Yoon, Y. S. and M. G. Amin. 2010. "Through-the-Wall Radar Imaging using compressive sensing along temporal frequency domain". In: *IEEE International Conference on Acoustics, Speech and Signal Processing*. 2806–2809.

[181] Yu, G. and G. Sapiro. 2011. *Statistical Compressed Sensing of Gaussian Mixture Models*. IEEE Press. 5842–5858.

[182] Yu, Y. 2013. "Better approximation and faster algorithm using the proximal average". *Advances in Neural Information Processing Systems*: 458–466.

[183] Yuan, M. and Y. Lin. 2006. "Model selection and estimation in regression with grouped variables". *Journal of the Royal Statistical Society*. 68(1): 49–67.

[184] Yun, B. L., L. L. Lian, B. G. Cai, C. Qiang, and T. J. Cui. 2015. "Holographic leaky-wave metasurfaces for dual-sensor imaging". *Scientific Reports*. 5: 18170.

[185] Zhang, L., Z. J. Qiao, M. Xing, Y. Li, and Z. Bao. 2011a. "High-Resolution ISAR Imaging With Sparse Stepped-Frequency Waveforms". *IEEE Transactions on Geoscience and Remote Sensing*. 49(11): 4630–4651.

Full text available at: http://dx.doi.org/10.1561/2000000103

[186] Zhang, L., Z. J. Qiao, M. Xing, Y. Li, and Z. Bao. 2011b. "High-Resolution ISAR Imaging With Sparse Stepped-Frequency Waveforms". *IEEE Transactions on Geoscience and Remote Sensing*. 49(11): 4630–4651.

[187] Zhang, L., M. Xing, C. W. Qiu, J. Li, and Z. Bao. 2009. "Achieving Higher Resolution ISAR Imaging With Limited Pulses via Compressed Sampling". *IEEE Geoscience and Remote Sensing Letters*. 6(3): 567–571.

[188] Zhang, S., W. Zhang, Z. Zong, Z. Tian, and T. S. Yeo. 2015. "High-Resolution Bistatic ISAR Imaging Based on Two Dimensional Compressed Sensing". *IEEE Transactions on Antennas and Propagation*. 63(5): 2098–2111.

[189] Zhang, W., L. Li, and F. Li. 2011c. "Reducing the Number of Elements in Linear and Planar Antenna Arrays With Sparseness Constrained Optimization". *IEEE Transactions on Antennas and Propagation*. 59(8): 3106–3111.

[190] Zhang, Z. and B. D. Rao. 2012. "Recovery of block sparse signals using the framework of block sparse Bayesian learning". In: *IEEE International Conference on Acoustics, Speech and Signal Processing*. 3345–3348.

[191] Zhao, T., Y. C. Eldar, A. Beck, and A. Nehorai. 2013. "Smoothing and Decomposition for Analysis Sparse Recovery". *IEEE Transactions on Signal Processing*. 62(7): 1762–1774.

[192] Zhdanov, M. S. 2009. *Geophysical electromagnetic theory and methods*. Vol. 43. Elsevier.

[193] Zhong, L. W. and J. T. Y. Kwok. 2014. "Accelerated stochastic gradient method for composite regularization". In: *International Conference on Artificial Intelligence and Statistics*. 1086–1094.

[194] Zhu, L., E. Liu, and J. H. Mcclellan. 2015. "Seismic data denoising through multiscale and sparsity-promoting dictionary learning". *Geophysics*. 80(6): WD45–WD57.

[195] Zhu, X. X. and R. Bamler. 2014. "Superresolving SAR Tomography for Multidimensional Imaging of Urban Areas: Compressive sensing-based TomoSAR inversion". *IEEE Signal Processing Magazine*. 31(4): 51–58.

Full text available at: http://dx.doi.org/10.1561/2000000103

[196] Zhu, X. X. and R. Bamler. 2010. "Tomographic SAR Inversion by L_1 -Norm Regularization- The Compressive Sensing Approach". *IEEE Transactions on Geoscience and Remote Sensing*. 48(10): 3839–3846.

[197] Zhuge, X. and A. G. Yarovoy. 2012. "Study on Two-Dimensional Sparse MIMO UWB Arrays for High Resolution Near-Field Imaging". *IEEE Transactions on Antennas and Propagation*. 60(9): 4173–4182.

[198] Zou, H. and T. Hastie. 2005. "Regularization and variable selection via the elastic net". *Journal of the Royal Statistical Society*. 67(2): 301–320.