

REFERENCES FOR COMPRESSED SENSING

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1. INTRODUCTION

This document attempts to collect bibliographical information for topics related to compressed sensing. This is intended to make it easy to quote references when writing articles on this or related topics. The references have been collected by careful study of a lot of original papers and reviews on the subject. Effort has been put in finding out original sources for each concept. At the same time, the authors make no warranty related to correctness of the data in this document.

TABLE 1. Review and survey papers

Book	Reference
Sparse and redundant representations, from theory to applications	Elad [67]
A wavelet tour of signal processing, the sparse way	Mallat [105]
Sparse image and signal processing: wavelets, curvelets, morphological diversity	Starck et al. [125]
Compressed Sensing: Theory and Applications	Eldar and Kutyniok [71]
A Mathematical Introduction to Compressive Sensing	Foucart and Rauhut [81]

TABLE 2. Review and survey papers

Concept	References
Structured compressed sensing	Duarte and Eldar [59]
Algorithms for sparse approximation	Tropp and Wright [139]
Dictionaries	Rubinstein et al. [117]
Dictionary learning	Tosic and Frossard [131]

1.1. Reviews and surveys on specific areas.

- Tropp and Wright [139] surveys variety of computational methods for solving linear inverse problems.

2. SPARSE REPRESENTATIONS

TABLE 3. Sparse representations

Concept	References
Dictionary	Mallat and Zhang [106]
Spark	Donoho and Elad [55]
Spark-Uniqueness Theorem	Donoho and Elad [55]
Compressible signals	Cohen et al. [41]
Mutual coherence	Donoho and Elad [55]
Coherence	Donoho and Elad [55], Donoho and Huo [56], Tropp [132], Gribonval and Nielsen [85]
Spark-Coherence relation	Donoho and Elad [55]
Coherence-Uniqueness	Donoho and Elad [55], Tropp [132], Gribonval and Nielsen [85]
Minimum l_1 is sparsest	Donoho [54]
Babel function	Tropp [132, 136]
Cumulative coherence function	Tropp [132, 136]

2.1. Surveys, Reviews, Books.

- (1) Mallat [105] A wavelet tour of signal processing: the sparse way
- (2) Elad [67] Sparse and redundant representations

2.2. Foundation papers.

- (1) Chen et al. [39] Atomic decomposition by basis pursuit
- (2) Donoho [54] For most large underdetermined systems of linear equations the minimal l_1 -norm solution is also the sparsest solution

2.3. Dictionary analysis.

- (1) Chen et al. [39] Atomic decomposition by basis pursuit
- (2) Elad and Bruckstein [68] A generalized uncertainty principle and sparse representation in pairs of bases
- (3) Donoho and Huo [56] Uncertainty principles and ideal atomic decomposition
- (4) Donoho and Elad [55] Optimally sparse representation in general (nonorthogonal) dictionaries via l_1 minimization
- (5) Tropp [132] Greed is good: Algorithmic results for sparse approximation

2.4. Sparse modeling.

- (1) Bruckstein et al. [26] From sparse solutions of systems of equations to sparse modeling of signals and images from CS perspective.

TABLE 4. Sparse modeling of real-life data

Concept	References
Sparse modeling	Bruckstein et al. [26]
Image modeling	Bruckstein et al. [26]

3. COMPRESSED SENSING

TABLE 5. Compressed sensing

Concept	References
Compressed Sensing	Donoho [53], Baraniuk [14], Candès [30], Candès and Wakin [35], Candes and Tao [34]
Restricted Isometry Property	Candès [30]
Null space property	Foucart and Gribonval [80]
Mutual coherence	Candes and Romberg [28]
Uniform Instance Optimality	Candès [30]
Universal sensors	
Johnson Lindenstrauss lemma	Dasgupta and Gupta [45]
Multiplicative noise	Herman and Strohmer [90], Chi et al. [40]
Noise folding	Arias-Castro and Eldar [9]
Coherence-RIP relation	Cai et al. [27]
Mutual-Coherence-RIP relation	Rudelson and Vershynin [120]

3.1. Surveys, Reviews, Books, Tutorials.

- (1) Candès and Tao [33] Decoding by linear programming
- (2) Candès [30] Compressive sampling
- (3) Donoho [53] Compressed sensing
- (4) Baraniuk [14] Compressive sensing [lecture notes]
- (5) Candès and Wakin [35] An introduction to compressive sampling
- (6) Baraniuk et al. [13] An introduction to compressive sensing
- (7) Eldar and Kutyniok [71] Compressed sensing: theory and applications
- (8) Foucart and Rauhut [81] A mathematical introduction to compressive sensing

3.2. Orthogonal systems.

- (1) Candès and Romberg [28] Sparsity and incoherence in compressive sampling

3.3. Noiseless recovery.

- (1) Candès and Tao [34] Near-optimal signal recovery from random projections: Universal encoding strategies?

3.4. Measurement noise.

- (1) Candès et al. [36] Stable signal recovery from incomplete and inaccurate measurements
- (2) Haupt and Nowak [87] Signal reconstruction from noisy random projections

3.5. Signal noise.

- (1) Arias-Castro and Eldar [9] Noise folding in compressed sensing

3.6. K-term approximation.

- (1) Cohen et al. [41] Compressed sensing and best k -term approximation

3.7. Perturbation and sensitivity analysis.

- (1) Herman and Strohmer [90] General deviants: An analysis of perturbations in compressed sensing
- (2) Chi et al. [40] Sensitivity to basis mismatch in compressed sensing

3.8. Analog compressed sensing.

- (1) Eldar [69] Analog compressed sensing
- (2) Eldar [70] Compressed sensing of analog signals in shift-invariant spaces

3.9. Blind compressed sensing.

- (1) Gleichman and Eldar [83] Blind compressed sensing

4. SENSING MATRICES AND DICTIONARIES

TABLE 6. Analytical dictionaries, frames, sensing matrices

Concept	References
Grassmannian frames	Strohmer and Heath [127]
Equiangular tight frames	Strohmer and Heath [127]
Deterministic constructions	DeVore [51]

4.1. **Surveys, Reviews, Books.**

- (1) Elad [67] Sparse and redundant representations
- (2) Rubinstein et al. [117] Dictionaries for sparse representation modeling

4.2. **Coherence.**

- (1) Candes and Romberg [28] Sparsity and incoherence in compressive sampling
- (2) Tropp [137] On the conditioning of random subdictionaries

4.3. **Babel function.**

- (1) Tropp [132] Greed is good: Algorithmic results for sparse approximation
- (2) Gribonval et al. [86] Atoms of all channels, unite! Average case analysis of multi-channel sparse recovery using greedy algorithms

4.4. **ERC: Exact reconstruction coefficient.**

- (1) TROPP [133] Just relax: convex programming methods for subset selection and sparse approximation
- (2) Tropp [134] Topics in sparse approximation

4.5. **NSP: Null space property.**

- (1) Foucart and Gribonval [80] Real versus complex null space properties for sparse vector recovery

4.6. **UUP: Uniform uncertainty principle.**

- (1) Candes and Tao [34] Near-optimal signal recovery from random projections: Universal encoding strategies?
- (2) Needell and Vershynin [114] Uniform uncertainty principle and signal recovery via regularized orthogonal matching pursuit

4.7. **ERP: Exact reconstruction principle.**

- (1) Candes and Tao [34] Near-optimal signal recovery from random projections: Universal encoding strategies?.

4.8. **RIP: Restricted isometry property.**

- (1) Candès [31] The restricted isometry property and its implications for compressed sensing
- (2) Davenport and Wakin [46] Analysis of orthogonal matching pursuit using the restricted isometry property
- (3) Bandeira et al. [12] Certifying the restricted isometry property is hard

4.9. JL Lemma.

- (1) Dasgupta and Gupta [45] An elementary proof of the Johnson-Lindenstrauss lemma

4.10. Random matrices.

- (1) Candes and Tao [34] Near-optimal signal recovery from random projections: Universal encoding strategies?.
- (2) Tropp [137] On the conditioning of random subdictionaries

4.11. Gaussian random matrices.

- (1) Candes and Tao [34] Near-optimal signal recovery from random projections: Universal encoding strategies?.
- (2) Rudelson and Vershynin [120] On sparse reconstruction from Fourier and Gaussian measurements

4.12. Rademacher random matrices.

- (1) Candes and Tao [34] Near-optimal signal recovery from random projections: Universal encoding strategies?.

4.13. Fourier random matrices.

- (1) Candes and Tao [34] Near-optimal signal recovery from random projections: Universal encoding strategies?
- (2) Rudelson and Vershynin [120] On sparse reconstruction from Fourier and Gaussian measurements

4.14. Deterministic constructions of sensing matrices.

- (1) DeVore [51] Deterministic constructions of compressed sensing matrices

4.15. Two ortho bases.**4.16. Union of bases.**

- (1) Gribonval and Nielsen [85] Sparse representations in unions of bases

4.17. Grassmannian frames.

- (1) Strohmer and Heath [127] Grassmannian frames with applications to coding and communication

4.18. Structured sensing matrices.

- (1) Haupt et al. [88] Toeplitz compressed sensing matrices with applications to sparse channel estimation
- (2) Rauhut et al. [116] Restricted isometries for partial random circulant matrices

5. SPARSE RECOVERY ALGORITHMS

5.1. Surveys, Reviews, Books.

- (1) Elad [67] Sparse and redundant representations
- (2) Tropp and Wright [139] Computational methods for sparse solution of linear inverse problems

TABLE 7. Greedy algorithms

Concept	References
Orthogonal Matching Pursuit	Mallat and Zhang [106], Pati et al. [115], Tropp [132]
OMP AWGN Coherence Guarantee	Ben-Haim et al. [17]
OMP RIP analysis	Davenport and Wakin [46]
OMP RIP analysis with noise	Zhang [149]
CoSaMP	Needell and Tropp [113]
CoSaMP for redundant dictionaries	Davenport et al. [48, 49]
Iterative thresholding for sparse approximation	Blumensath and Davies [22]
Iterative Hard Thresholding for CS	Blumensath and Davies [23]
Subspace pursuit	Dai and Milenkovic [43]
Stagewise OMP	Donoho et al. [58]
Regularized OMP	Needell and Vershynin [114]

TABLE 8. Convex relaxation algorithms

Concept	References
Convex Optimization	Boyd and Vandenberghe [24]
Basis pursuit	Chen et al. [39]
Efficient solvers for BP, BPIC, BPDN	Tropp and Wright [139]
Dantzig selector	Candes and Tao [29]
BP coherence guarantee	Donoho et al. [57]
BPIC coherence performance guarantee	Candes et al. [36]
BPDN coherence performance guarantee	Ben-Haim et al. [17]
BP random sparse signal recovery coherence guarantee	Tropp [137]
BP mutual coherence recovery guarantee	Candes and Romberg [28]

5.2. **Sparse representation formulations.** Given a signal $x \in \mathbb{C}^N$ which is known to have a sparse representation in a dictionary \mathcal{D} , the exact-sparse recovery problem is:

$$\hat{\alpha} = \arg \min_{\alpha \in \mathbb{C}^D} \|\alpha\|_0 \text{ subject to } x = \mathcal{D}\alpha. \quad (\text{P}_0)$$

When $x \in \mathbb{C}^N$ doesn't have a sparse representation in \mathcal{D} , a K -sparse approximation of x in \mathcal{D} can be obtained by solving the following problem:

$$\hat{\alpha} = \arg \min_{\alpha \in \mathbb{C}^D} \|x - \mathcal{D}\alpha\|_2 \text{ subject to } \|\alpha\|_0 \leq K. \quad (\text{P}_0^K)$$

Here x is modeled as $x = \mathcal{D}\alpha + e$ where α denotes a sparse representation of x and e denotes the approximation error.

A different way to formulate the approximation problem is to provide an upper bound to the acceptable approximation error $\|e\|_2 \leq \epsilon$ and try to find sparsest possible representation within this approximation error bound as

$$\hat{\alpha} = \arg \min_{\alpha \in \mathbb{C}^D} \|\alpha\|_0 \text{ subject to } \|x - \mathcal{D}\alpha\|_2 \leq \epsilon. \quad (\text{P}_0^\epsilon)$$

5.3. CS formulations. In the context of compressed sensing, for simplicity, we assume the sparsifying dictionary to be the Dirac basis (i.e. $\mathcal{D} = I$ and $N = D$). Further, we assume signal x to be K -sparse in \mathbb{C}^N . With the sensing matrix Φ and the measurement vector y , the CS sparse recovery problem in the absence of measurement noise (i.e. $y = \Phi x$) is stated as:

$$\hat{x} = \arg \min_{x \in \mathbb{C}^N} \|x\|_0 \text{ subject to } y = \Phi x. \quad (\text{CS}_0)$$

In the presence of measurement noise (i.e. $y = \Phi x + e$), the recovery problem takes the form of

$$\hat{x} = \arg \min_{x \in \mathbb{C}^N} \|y - \Phi x\|_2 \text{ subject to } \|x\|_0 \leq K. \quad (\text{CS}_0^K)$$

when a bound on sparsity is provided, or alternatively:

$$\hat{x} = \arg \min_{x \in \mathbb{C}^N} \|x\|_0 \text{ subject to } \|y - \Phi x\|_2 \leq \epsilon. \quad (\text{CS}_0^\epsilon)$$

when a bound on the measurement noise is provided.

5.4. Basis pursuit formulations. Basis Pursuit (BP) [39] suggests the convex relaxation of (P_0) by replacing l_0 -“norm” with l_1 -norm.

$$\hat{\alpha} = \arg \min_{\alpha \in \mathbb{C}^D} \|\alpha\|_1 \text{ subject to } x = \mathcal{D}\alpha. \quad (\text{P}_1)$$

For real signals, it can be implemented as a linear program. For complex signals, it can be implemented as a second order cone program.

In the presence of approximation error (P_0^ϵ) , where $x = \mathcal{D}\alpha + e$ with α being a K -sparse approximate representation of x in \mathcal{D} we can formulate corresponding l_1 -minimization problem as:

$$\hat{\alpha} = \arg \min_{\alpha \in \mathbb{C}^D} \|\alpha\|_1 \text{ subject to } \|x - \mathcal{D}\alpha\|_2 \leq \epsilon \quad (\text{P}_1^\epsilon)$$

where $\epsilon \geq \|e\|_2$ provides an upper bound on the approximation error. This version is known as **basis pursuit with inequality constraints (BPIC)**. The dual problem constructed using Lagrange multipliers is

$$\hat{\alpha} = \arg \min_{\alpha \in \mathbb{C}^D} \|\alpha\|_1 + \lambda \|x - \mathcal{D}\alpha\|_2^2. \quad (\text{P}_1^\lambda)$$

This is known as **basis pursuit denoising (BPDN)**. With appropriate choice of λ , the two problems BPIC and BPDN are equivalent. This formulation attempts to minimize the l_1 -norm subject to a penalty term over the approximation error. The Lagrangian constant λ controls how large the penalty due to approximation error will be.

TABLE 9. Concepts related to greedy algorithms

Concept	References
Greedy selection ratio	Tropp [132]

TABLE 10. Stochastic noise modeling

Concept	References
Complexity based regularization	Haupt and Nowak [87]
Bayesian estimation	Ji et al. [93]

5.5. Thresholding.

- (1) Ben-Haim et al. [17] Coherence-based performance guarantees for estimating a sparse vector under random noise

5.6. BP, BPDN, BPIC: Basis pursuit.

- (1) Chen et al. [39] Atomic decomposition by basis pursuit
- (2) Candes and Romberg [32] Practical signal recovery from random projections
- (3) Tropp [132] Greed is good: Algorithmic results for sparse approximation
- (4) TROPP [133] Just relax: convex programming methods for subset selection and sparse approximation
- (5) Tropp [134] Topics in sparse approximation
- (6) Candes and Tao [33] Decoding by linear programming
- (7) Donoho et al. [57] Stable recovery of sparse overcomplete representations in the presence of noise
- (8) Tropp [136] Just relax: Convex programming methods for identifying sparse signals in noise
- (9) Donoho [54] For most large underdetermined systems of linear equations the minimal l_1 -norm solution is also the sparsest solution
- (10) van den Berg and Friedlander [143] Probing the Pareto frontier for basis pursuit solutions
- (11) Cai et al. [27] On Recovery of Sparse Signals via l_1 Minimization
- (12) Tropp [137] On the conditioning of random subdictionaries
- (13) Rudelson and Vershynin [120] On sparse reconstruction from Fourier and Gaussian measurements
- (14) Ben-Haim et al. [17] Coherence-based performance guarantees for estimating a sparse vector under random noise
- (15) Elad [67] Sparse and redundant representations

5.7. MP: Matching pursuit.

- (1) Mallat and Zhang [106] Matching pursuits with time-frequency dictionaries

5.8. OMP: Orthogonal matching pursuit.

- (1) Pati et al. [115] Orthogonal matching pursuit: Recursive function approximation with applications to wavelet decomposition
- (2) Tropp [132] Greed is good: Algorithmic results for sparse approximation
- (3) Tropp [134] Topics in sparse approximation
- (4) Donoho et al. [57] Stable recovery of sparse overcomplete representations in the presence of noise

- (5) Tropp and Gilbert [138] Signal recovery from random measurements via orthogonal matching pursuit
- (6) Elad [67] Sparse and redundant representations
- (7) Ben-Haim et al. [17] Coherence-based performance guarantees for estimating a sparse vector under random noise
- (8) Davenport and Wakin [46] Analysis of orthogonal matching pursuit using the restricted isometry property
- (9) Mo and Shen [111] A remark on the restricted isometry property in orthogonal matching pursuit
- (10) Zhang [149] Sparse recovery with orthogonal matching pursuit under RIP

5.8.1. *Davenport and Wakin [46] Analysis of orthogonal matching pursuit using the restricted isometry property.*

Overview

This paper focuses on the solution of (\mathbf{P}_0) or (\mathbf{CS}_0) using OMP algorithm. It provides an analysis of OMP in this setting using the restricted isometry property of the sensing matrix (or dictionary) Φ . The analysis is performed for real signals.

Main results

If Φ supports RIP of order $K + 1$ with $\delta_{K+1} < \frac{1}{2\sqrt{K+1}}$ then OMP can recover K -sparse signals.

Suggested directions and open issues

Doubts

Other ideas

- RIP based analysis is performed only for real signals. There are couple of lemmas developed around RIP in real case. The rest of the analysis depends on these lemmas. Hence, the results are only for the real case. One of these lemmas is about preservation of inner product under RIP. If this lemma can be generalized for the complex case, then we will be able to get the guarantees of OMP recovery for the complex case too.

5.9. **ROMP: Regularized orthogonal matching pursuit.**

- (1) Needell and Vershynin [114] Uniform uncertainty principle and signal recovery via regularized orthogonal matching pursuit

5.10. **STOMP: Stagewise orthogonal matching pursuit.**

- (1) Donoho et al. [58] Sparse solution of underdetermined systems of linear equations by stagewise orthogonal matching pursuit

5.11. CoSaMP: Compressive sampling matching pursuit.

- (1) Needell and Tropp [113] CoSaMP: Iterative signal recovery from incomplete and inaccurate samples
- (2) Davenport et al. [48] CoSaMP with redundant dictionaries
- (3) Davenport et al. [49] Signal space CoSaMP for sparse recovery with redundant dictionaries

5.12. SP: Subspace pursuit.

- (1) Dai and Milenkovic [43] Subspace pursuit for compressive sensing signal reconstruction

5.13. Iterative thresholding.

- (1) Haupt and Nowak [87] Signal reconstruction from noisy random projections
- (2) Blumensath and Davies [22] Iterative thresholding for sparse approximations
- (3) Blumensath and Davies [23] Iterative hard thresholding for compressed sensing
- (4) Blumensath and Davies [21] Normalized iterative hard thresholding: Guaranteed stability and performance
- (5) Foucart [78] Hard thresholding pursuit: an algorithm for compressive sensing
- (6) Foucart [79] Recovering jointly sparse vectors via hard thresholding pursuit
- (7) Blumensath [20] Accelerated iterative hard thresholding

5.14. LARS, IRLS, LASSO: Least angle regression, Iteratively reweighted least squares.

- (1) Efron et al. [66] Least angle regression
- (2) Elad [67] Sparse and redundant representations

5.15. FOCUSS. This is a Shrinkage algorithm.

- (1) Gorodnitsky and Rao [84] Sparse signal reconstruction from limited data using FOCUSS: A re-weighted minimum norm algorithm

5.16. Bayesian.

- (1) Ji et al. [93] Bayesian compressive sensing

5.17. Block coordinated relaxation.

- (1) Sardy et al. [122] Block coordinate relaxation methods for nonparametric wavelet denoising

5.18. Dantzig selector.

- (1) Candes and Tao [29] The Dantzig selector: statistical estimation when p is much larger than n
- (2) Elad [67] Sparse and redundant representations

5.19. L1-Homotopy.

- (1) Asif and Romberg [11] Sparse Recovery of Streaming Signals Using L1-Homotopy

5.20. Combinatorial algorithms.

5.21. **Average case analysis.** This section lists papers which focus on average case analysis of different sparse recovery algorithms.

- (1) Elad [\[67\]](#) Sparse and redundant representations

6. JOINT RECOVERY

TABLE 11. Terms related to joint recovery

Concept	References
Signal matrix	Tropp et al. [141]
Coefficient matrix	Tropp et al. [141]
Row support	Tropp et al. [141]
Joint sparsity models	Duarte et al. [61]
Infinite measurement vectors (IMV)	Mishali and Eldar [108]
Single measurement vectors (SMV)	Cotter et al. [42], Mishali and Eldar [108]
Multiple measurement vectors (MMV)	Cotter et al. [42], Mishali and Eldar [108]

6.1. Surveys, Reviews, Books.

- (1) Duarte and Eldar [59] Structured compressed sensing: From theory to applications

6.2. MMV: Multiple measurement vector problems.

- (1) Cotter et al. [42] Sparse solutions to linear inverse problems with multiple measurement vectors

TABLE 12. MMV algorithms

Concept	References
MP for MMV	Cotter et al. [42]
FOCUSS for MMV	Cotter et al. [42]
BP for MMV	Chen and Huo [38]
OMP for MMV	Chen and Huo [38]
Simultaneous OMP	Tropp et al. [141]
Thresholded Landweber algorithm	[77]
Reduce MMV and Boost (ReMBo)	Mishali and Eldar [108]
Xampling	[109]

6.3. Thresholding.

- (1) Gribonval et al. [86] Atoms of all channels, unite! Average case analysis of multi-channel sparse recovery using greedy algorithms

6.4. M-FOCUSS.

6.5. Basis pursuit variants mixed norm minimization.

- (1) Tropp [135] Algorithms for simultaneous sparse approximation. Part II: Convex relaxation
- (2) Chen and Huo [38] Theoretical results on sparse representations of multiple-measurement vectors
- (3) Eldar and Rauhut [73] Average case analysis of multichannel sparse recovery using convex relaxation

6.6. S-MP: Matching pursuit, weak matching pursuit.

- (1) Lutoborski and Temlyakov [100] Vector greedy algorithms
- (2) Temlyakov [130] A remark on simultaneous greedy approximation
- (3) Leviatan and Temlyakov [96] Simultaneous greedy approximation in Banach spaces
- (4) Leviatan and Temlyakov [97] Simultaneous approximation by greedy algorithms

6.7. S-OMP, OMPMMV: Simultaneous Orthogonal matching pursuit.

- (1) Tropp et al. [140] Simultaneous sparse approximation via greedy pursuit
- (2) Tropp et al. [141] Algorithms for simultaneous sparse approximation. Part I: Greedy pursuit
- (3) Chen and Huo [38] Theoretical results on sparse representations of multiple-measurement vectors
- (4) Gribonval et al. [86] Atoms of all channels, unite! Average case analysis of multi-channel sparse recovery using greedy algorithms
- (5) Ding et al. [52] Performance of orthogonal matching pursuit for multiple measurement vectors

6.8. CoSaMP : Compressive Sampling Matching Pursuit.**6.9. ReMBo: Reduce MMV and Boost.**

- (1) Mishali and Eldar [108] Reduce and boost: Recovering arbitrary sets of jointly sparse vectors

6.10. Fast thresholded Landweber algorithms.

- (1) Fornasier and Rauhut [77] Recovery algorithms for vector-valued data with joint sparsity constraints

6.11. Rank aware and MUSIC based algorithms.

- (1) Davies and Eldar [50] Rank awareness in joint sparse recovery
- (2) Lee et al. [95] Subspace methods for joint sparse recovery
- (3) Kim et al. [94] Compressive MUSIC: Revisiting the link between compressive sensing and array signal processing

6.12. Multiple hypothesis testing.

- (1) Tang and Nehorai [129] Performance analysis for sparse support recovery

6.13. Distributed compressive sensing.

- (1) Duarte et al. [60] Distributed compressed sensing of jointly sparse signals
- (2) Duarte et al. [61] Joint sparsity models for distributed compressed sensing
- (3) Duarte et al. [62] Universal distributed sensing via random projections
- (4) Duarte et al. [64] Performance limits for jointly sparse signals via graphical models
- (5) Baron et al. [16] Distributed compressive sensing

6.14. Adaptive algorithms.

- (1) Amel and Feuer [8] Adaptive Identification and Recovery of Jointly Sparse Vectors

6.15. **Average case analysis.** This section lists papers which are focused on the average case analysis of various joint recovery algorithms.

- (1) Gribonval et al. [86] Atoms of all channels, unite! Average case analysis of multi-channel sparse recovery using greedy algorithms
- (2) Eldar and Rauhut [73] Average case analysis of multichannel sparse recovery using convex relaxation

7. STRUCTURED SIGNALS

TABLE 13. Structured compressed sensing

Concept	References
Structured compressed sensing	Duarte and Eldar [59]
Distributed compressed sensing	Duarte et al. [60]
Model based compressive sensing	Baraniuk et al. [15]
Universal distributed sensing via random projections	[62]
Analog compressed sensing	[69]
Compressed sensing of analog signals in shift invariant subspaces	[70]

7.1. Surveys, Reviews, Books.

- (1) Duarte and Eldar [59] Structured compressed sensing: From theory to applications

TABLE 14. Analysis of MMV algorithms

Concept	References
Average case analysis of multichannel sparse recovery using convex relaxation	Eldar and Rauhut [73]
Performance limits for jointly sparse signals via graphical models	Duarte et al. [64]
Rank awareness in joint sparse recovery	Davies and Eldar [50]
Robust recovery of signals from a structured union of subspaces	[72]

7.2. Block sparse signals.

- (1) Eldar et al. [74] Block-sparse signals: Uncertainty relations and efficient recovery

7.3. Union of subspaces.

- (1) Eldar and Mishali [72] Robust recovery of signals from a structured union of subspaces

7.4. Model based compressive sensing.

- (1) Baraniuk et al. [15] Model-based compressive sensing

8. DETECTION, CLASSIFICATION, ESTIMATION, FILTERING CLUSTERING

8.1. **Compressed detection.**

- (1) Davenport et al. [47] Signal processing with compressive measurements

8.2. **Compressed estimation.**

- (1) Davenport et al. [47] Signal processing with compressive measurements

8.3. **Compressed classification.**

- (1) Davenport et al. [47] Signal processing with compressive measurements

8.4. **Compressed linear filtering.**

- (1) Davenport et al. [47] Signal processing with compressive measurements

9. DICTIONARY LEARNING

TABLE 15. Dictionary Learning

Concept	References
Reviews and tutorials	Tosic and Frossard [131]
Method of Optimal Directions (MOD)	Engan et al. [75]
K-SVD	Aharon et al. [4]
Non-negative variant of K-SVD	Aharon et al. [5]
Analysis K-SVD for analysis sparse models	Rubinstein et al. [119]
Simultaneous Codeword Optimization (SimCo)	Dai et al. [44]
Parametric dictionary design	Yaghoobi et al. [147]
Multiscale representations	Sallee and Olshausen [121], Mairal et al. [101]
Uniqueness guarantee for dictionary learning	Aharon et al. [6]
Supervised dictionary learning	Mairal et al. [102]
Online dictionary learning	Mairal et al. [103]

9.1. Surveys, Reviews, Books.

- (1) Elad [67] Sparse and redundant representations
- (2) Rubinstein et al. [117] Dictionaries for sparse representation modeling
- (3) Tosic and Frossard [131] Dictionary learning

9.2. Uniqueness.

- (1) Aharon et al. [6] On the uniqueness of overcomplete dictionaries, and a practical way to retrieve them

9.3. MOD: Method of optimal directions.

- (1) Engan et al. [75] Method of optimal directions for frame design

9.4. k-SVD: k-Singular Value Decomposition.

- (1) Aharon et al. [5] K-SVD and its non-negative variant for dictionary design
- (2) Aharon et al. [4] K-SVD: An Algorithm for Designing Overcomplete Dictionaries for Sparse Representation
- (3) Rubinstein et al. [119] Analysis K-SVD: A dictionary-learning algorithm for the analysis sparse model

9.5. SIMCO: Simultaneous codeword optimization.

- (1) Dai et al. [44] Simultaneous codeword optimization (simco) for dictionary update and learning

9.6. Dictionary learning from compressive measurements.

- (1) Duarte-Carvajalino and Sapiro [65] Learning to sense sparse signals: Simultaneous sensing matrix and sparsifying dictionary optimization
- (2) Aghagolzadeh and Radha [3] Compressive dictionary learning for image recovery

9.7. Supervised dictionary learning.

- (1) Mairal et al. [102] Supervised dictionary learning

9.8. Online dictionary learning.

- (1) Mairal et al. [103] Online dictionary learning for sparse coding
- (2) Aghagolzadeh and Radha [2] COLD: Compressive Online Learning of Dictionaries

9.9. Multiscale dictionary learning.

- (1) Sallee and Olshausen [121] Learning sparse multiscale image representations

9.10. Other dictionary learning algorithms.

- (1) Yaghoobi et al. [147] Parametric dictionary design for sparse coding
- (2) Rubinstein et al. [118] Double sparsity: Learning sparse dictionaries for sparse signal approximation
- (3) Spielman et al. [124] Exact recovery of sparsely-used dictionaries

10. MISCELLANEOUS ITEMS

TABLE 16. Real vs. complex

Concept	References
Null space property	Foucart and Gribonval [80]

In the following there are other references for the general literature in these areas. These works don't consider the sparse model or compressed sensing framework.

10.1. **Signal processing.**

- (1) Mitra [110] Digital signal processing: a computer-based approach

10.2. **Detection and estimation.**

- (1) Van Trees [144] Detection, estimation, and modulation theory

10.3. **Statistical signal processing.**10.4. **Machine learning.**10.5. **Pattern recognition.**10.6. **Data clustering.**

- (1) Likas et al. [98] The global k-means clustering algorithm

11. SIGNAL PROCESSING APPLICATIONS

11.1. Surveys, Reviews, Books.

- (1) Elad [67] Sparse and redundant representations
- (2) Starck et al. [125] Sparse image and signal processing: wavelets, curvelets, morphological diversity

11.2. Phase retrieval.

- (1) Moravec et al. [112] Compressed Sensing phase retrieval
- (2) Chan et al. [37] Terahertz imaging with compressed sensing and phase retrieval

11.3. Superresolution.

- (1) Malioutov et al. [104] A sparse signal reconstruction perspective for source localization with sensor arrays

11.4. Source localization.

- (1) Malioutov et al. [104] A sparse signal reconstruction perspective for source localization with sensor arrays

11.5. Sensor array processing.

- (1) Malioutov et al. [104] A sparse signal reconstruction perspective for source localization with sensor arrays

11.6. Direction of arrival.

- (1) Malioutov et al. [104] A sparse signal reconstruction perspective for source localization with sensor arrays
- (2) Tang and Nehorai [129] Performance analysis for sparse support recovery

12. IMAGE PROCESSING APPLICATIONS

12.1. **Surveys, Reviews, Books.**

- (1) Elad [67] Sparse and redundant representations
- (2) Starck et al. [125] Sparse image and signal processing: wavelets, curvelets, morphological diversity

12.2. **Imaging systems.**

- (1) Chan et al. [37] Terahertz imaging with compressed sensing and phase retrieval
- (2) Duarte et al. [63] Single-pixel imaging via compressive sampling

12.3. **Image compression of facial images.**

- (1) Elad [67] Sparse and redundant representations

12.4. **Image deblurring.**

- (1) Elad [67] Sparse and redundant representations

12.5. **Image denoising.**

- (1) Elad [67] Sparse and redundant representations

12.6. **Image inpainting.**

- (1) Elad [67] Sparse and redundant representations

12.7. **Image separation.**

- (1) Elad [67] Sparse and redundant representations

12.8. **Image scaling up.**

- (1) Elad [67] Sparse and redundant representations

12.9. **Image restoration.**

- (1) Mairal et al. [101] Learning multiscale sparse representations for image and video restoration

12.10. **Image blind source separation.**

- Abolghasemi et al. [1] Blind separation of image sources via adaptive dictionary learning

12.11. **Face recognition.**

- (1) Wright et al. [146] Robust face recognition via sparse representation
- (2) Yang et al. [148] Towards a robust face recognition system using compressive sensing
- (3) Shi et al. [123] Is face recognition really a compressive sensing problem?

12.12. **MRI: Magnetic resonance imaging.**

- (1) Lustig et al. [99] Compressed sensing MRI
- (2) Gamper et al. [82] Compressed sensing in dynamic MRI

13. RADAR, SONAR, ETC.

13.1. Radar.

- (1) Herman and Strohmer [\[89\]](#) High-resolution radar via compressed sensing

14. HARDWARE

14.1. **Analog to digital converter.**

- (1) Mishali et al. [\[109\]](#) Xampling: Analog to digital at sub-Nyquist rates

15. MATHEMATICS

TABLE 17. Linear algebra

Concept	References
Gersgorin circle theorem	Brakken-Thal [25] Varga [145]

15.1. Algebra.

- (1) Artin [10] Algebra

15.2. Linear algebra and matrix analysis.

- (1) Hoffman and Kunze [91] Linear algebra, 2nd edition
- (2) Feingold et al. [76] Block diagonally dominant matrices and generalizations of the Gerschgorin circle theorem
- (3) Horn [92] The Hadamard product
- (4) Varga [145] Gershgorin and his circles
- (5) Strang [126] Linear algebra and its applications
- (6) Million [107] The Hadamard product
- (7) Brakken-Thal [25] Gershgorins theorem for estimating eigenvalues
- (8) Styan [128] Hadamard products and multivariate statistical analysis

15.3. Real analysis.

- (1) Aliprantis and Burkinshaw [7] Principles of real analysis

15.4. Probability, Statistics, Estimation, Detection, Classification.

- (1) Bernardo and Smith [19] Bayesian theory

15.5. Optimization.

- (1) Boyd and Vandenberghe [24] Convex optimization

16. DATA SETS AND SOFTWARE

TABLE 18. Data sets

Concept	References
All top sequence	Herman and Strohmer [89]

- (1) Berg et al. [18] Sparco: A testing framework for sparse reconstruction
- (2) van den Berg and Friedlander [142] SPGL1: A solver for large-scale sparse reconstruction

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