Compressed Sensing in Radar Signal Processing

Learn about the most recent theoretical and practical advances in radar signal processing using tools and techniques from compressive sensing. Providing a broad perspective that fully demonstrates the impact of these tools, the accessible and tutorial-like chapters cover topics such as clutter rejection, CFAR detection, adaptive beamforming, random arrays for radar, space–time adaptive processing, and MIMO radar. Each chapter includes coverage of theoretical principles, a detailed review of current knowledge, and discussion of key applications, and also highlights the potential benefits of using compressed sensing algorithms. A unified notation and numerous cross-references between chapters make it easy to explore different topics side by side. Written by leading experts from both academia and industry, this is the ideal text for researchers, graduate students, and industry professionals working in signal processing and radar.

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To my daughter Claudia: my light, my hope, my love – ADM

To my husband Shalomi and children Yonatan, Moriah, Tal, Noa, and Roei for their boundless love and for filling my life with endless happiness – YE

To my students and collaborators for their contributions to my work on radar – AH

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Introduction

Digital signal processing (DSP) is a revolutionary paradigm shift that enables processing of physical data in the digital domain, where design and implementation are considerably simplified. The success of DSP has driven the development of sensing and processing systems that are more robust, flexible, cheaper, and, consequently, more widely used than their analog counterparts. As a result of this success, the amount of data generated by sensing systems has grown considerably. Furthermore, in modern applications, signals of wider bandwidth are used in order to convey more information and to enable high resolution in the context of imaging. Unfortunately, in many important and emerging applications, the resulting sampling rate is so high that far too many samples need to be transmitted, stored, and processed. In addition, in applications involving very wideband inputs it is often very costly, and sometimes even physically impossible, to build devices capable of acquiring samples at the necessary rate. Thus, despite extraordinary advances in sampling theory and computational power, the acquisition and processing of signals in application areas such as radar, wideband communications, imaging, and medical imaging continue to pose a tremendous challenge.

Recent advances in compressed sensing (CS) and sampling theory provide a framework to acquire a wide class of analog signals at rates below the Nyquist rate, and to perform processing at this lower rate as well. Together with the theory, various prototypes have been developed that demonstrate the feasibility of sampling and processing signals at sub-Nyquist rates in a robust and cost-effective fashion. More specifically, CS is a framework that enables acquisition and recovery of sparse vectors from underdetermined linear systems. This research area has seen enormous growth over the past decade and has been explored in many areas of applied mathematics, computer science, statistics, and electrical engineering. At its core, CS enables recovery of sparse high-dimensional vectors from highly incomplete measurements using very efficient optimization algorithms. More specifically, consider a vector $\boldsymbol{x}$ of length n. The vector is said to be k-sparse if it has at most k nonzero components. More generally, CS results apply to signals that are sparse in an appropriate basis or overcomplete representation.

The main idea underlying CS is that the vector $\boldsymbol{x}$ can be recovered from measurements $\boldsymbol{y} = \boldsymbol{A}\boldsymbol{x}$, where $\boldsymbol{y}$ is of length $m \ll n$ as long as $\boldsymbol{A}$ satisfies certain mathematical properties that render it a suitable CS matrix. The number of measurements m can be chosen on the order of $k \log n$, which in general is much smaller than the length of the vector $\boldsymbol{x}$. A large body of work has been published on a variety of optimization algorithms that can recover $\boldsymbol{x}$ efficiently and robustly when $m \approx k \log n$. Loosely speaking, the theory of CS deals with conditions under which the recovery of information has vanishing or small errors. The mathematical framework of CS has inspired new acquisition methods and new signal processing applications in a large variety of areas, including image processing, analog to digital conversion, communication systems, and radar processing. In many of these examples the basic ideas underlying CS need to be extended to include, for example, continuous-time inputs, practical sampling methods, other forms of structure on the input, computational aspects, noise affects, different metrics for recovery performance, nonlinear acquisition methods, and more.

Two books devoted to this topic have been published recently, which focus on many of these aspects, as well as on the underlying mathematical results [1,2]. Their main emphasis is on the basic underlying theory and its generalizations, optimization methods, as well as applications primarily to image processing and analog-to-digital conversion. The latter is also covered in depth in [3].

Radar signal processing represents a fertile field for CS applications. By their very nature, radars collect data about surveillance volumes (search radars), targets (tracking radars), terrain and ground targets (imaging radars), or buried objects (radar tomography). From radar's early days in World War II, through the emergence of digital radar in the 1970s, to today's advanced systems, the amount of data a radar system has to handle has increased by orders of magnitude. While early digital radars had to contend with 10s and 100s of kbps, today's radars may be faced with data rates in the Gbps range or more, leading to demanding requirements in cost, hardware, data storage, and processing. The implications of applying CS to radar are potentially enormous: sampling rates could be lowered, the number of antenna elements in large arrays might be reduced and the computers required to handle the data may be downsized.

This book aims to present the latest theoretical and practical advances in radar signal processing using tools from CS. In particular, this book offers an up-to-date review of fundamental and practical aspects of sparse reconstruction in radar and remote sensing, demonstrating the potential benefits achievable with the CS paradigm. We take a wider scope than previous edited books on CS-based radars: we do not restrict ourselves to specific disciplines (such as earth observation as in [4]) or applications (such as urban sensing as in [5]), but discuss a variety of diverse application fields, including clutter rejection, constant false alarm rate (CFAR) processing, adaptive beamforming, random arrays for radar, space–time adaptive processing (STAP), multiple input multiple output (MIMO) systems, radar super-resolution, cognitive radar [6] applications involving sub-Nyquist sampling and spectrum sensing, radio frequency interference (RFI) suppression, and synthetic aperture radar (SAR).

The book is aimed at postgraduate students, PhD students, researchers, and engineers working on signal processing and its applications to radar systems, as well as researchers in other fields seeking an understanding of the potential applications of CS. To read and fully understand the content it is assumed that the reader has some background in probability theory and random processes, matrix theory, linear algebra, and optimization theory, as well as radar systems. The book is organized into eleven chapters broadly cathegorized into five areas: sub-Nyquist radar (Chapter 1); detection, clutter/interference mitigation, and CFAR techniques (Chapters 2–6); super-resolution and beamforming (Chapters 7 and 8); radar spectrum sensing/sharing (Chapters 9 and 10); radar imaging (Chapter 11). Each chapter is self-contained and typically covers three main aspects: fundamental theoretical principles, overview of the current state of the art, and emerging/future research directions. Some chapters are also complemented with analyses on real data. Since the chapters are independent, there is flexibility in selecting material both for university courses and short seminars.

In Chapter 1, the authors review several sub-Nyquist pulse-Doppler radar systems based on the Xampling framework. Contrary to other CS-based designs, their formulations directly address the reduced-rate analog sampling in space and time, avoid a prohibitive dictionary size, and are robust in the face of noise and clutter. The chapter begins by introducing temporal sub-Nyquist processing for estimating the target locations using less bandwidth than conventional systems. This paves the way to cognitive radars, which share their transmit spectrum with other communication services, thereby providing a robust solution for coexistence in spectrally crowded environments. Next, without impairing Doppler resolution, the authors reduce the dwell time by transmitting interleaved radar pulses in a scarce manner within a coherent processing interval or slow time. Then, they consider MIMO array radars and demonstrate spatial sub-Nyquist processing, which allows the use of few antenna elements without degradation in angular resolution. Finally, they demonstrate application of sub-Nyquist and cognitive radars to imaging systems such as SAR. For each setting, the authors present a state-of-the-art hardware prototype designed to demonstrate the real-time feasibility of sub-Nyquist radars.

Chapter 2 discusses the problem of clutter mitigation, which has posed challenges to radar designers and engineers since the early days of radar. Early techniques matured to current approaches like STAP, which use a coherently processed data cube to estimate clutter statistics and to perform adaptive filtering. This chapter examines CS techniques for the mitigation of structured interference, such as clutter. The author first introduces the relevant sensing model and describes results in uncompressed adaptive filtering. This paves the way to the development of models for measurement compression of the coherent data cube and of approaches to estimate and filter clutter from compressed measurements. The chapter includes recent results showing how clutter second-order statistics can be reliably estimated from compressed measurements if the clutter has well-controlled eigenspectrum. Additionally, the covariance of the interference can be incorporated into the CS estimation process to improve performance.

RFIs pose serious threats to the proper operations of ultra wideband (UWB) radar systems due to severely degrading their imaging and target detection capabilities. RFI mitigation is a challenging problem, since dynamic RFI sources utilize diverse modulation schemes, hence they are difficult to model precisely. Fortunately, RFI sources possess certain unique properties that can be exploited for their mitigation. In Chapter 3 the authors propose several sparse signal recovery methods for effective RFI mitigation. They first show that the RFI sources possess a low rank property and are sparse in the frequency domain, while in contrast the desired UWB radar echoes are sparse in the time domain. Therefore, robust principal component analysis (RPCA) can be used to simultaneously exploit these properties for effective RFI mitigation. RPCA, however, requires a fine tuning of a user parameter, which is dependent on the signal-to-interference ratio (SIR). This parameter tuning is not straightforward in practice due to the lack of prior knowledge on the RFI sources and on the desired UWB radar echoes. To avoid the user parameter tuning problem, the authors consider modeling the RFI sources within a pulse repetition interval (PRI) as a sum of sinusoids. The CLEAN algorithm can then be used with the Bayesian information criterion (BIC) to determine the number of sinusoids and to estimate their parameters. They show that CLEAN-BIC is user-parameter-free and can be used to remove dominant RFI sources effectively. However, since the sparse property of the UWB radar echoes are not utilized by CLEAN-BIC, the resulting SAR images appear noisy, especially for low SIR values. To take advantage of the merits of both RPCA and CLEAN-BIC algorithms, the authors consider using CLEAN-BIC to estimate SIR, and the estimated SIR value is then used to determine the user parameter for the RPCA algorithm. Finally, the algorithms are applied to both simulated and experimentally measured data for performance evaluation.

Chapter 4 is focused on target detection from a set of compressive radar measurements corrupted by additive white Gaussian noise. The complications in the calculation of false alarm and detection probabilities that are caused by the nonlinear nature of target recovery schemes in CS have impeded the application of such systems in practice. In this chapter, the authors aim to show how recent advances in the asymptotic analysis of CS recovery algorithms help to overcome this challenge. Fully adaptive and practical CS target detection schemes are provided together with a detailed analysis of their performance through extensive simulated and experimental data.

In Chapter 5, the authors present CFAR detectors for STAP random arrays. The problem is formulated as detection of sparse targets given space–time observations from thinned random arrays. The observations are corrupted by colored Gaussian noise of an unknown covariance matrix, but secondary data are available for estimating the covariance matrix. It is shown that the number of elements required to constrain the peak sidelobe level scales logarithmically with the array aperture, whereas the number of elements of a uniform linear array (ULA) scales linearly with the array aperture. New adaptive detectors are developed that cope with the high sidelobes of random arrays. Performance and complexity analysis demonstrate high performance at a reasonable computation cost with significantly fewer elements than a ULA.

In Chapter 6, sparse-based STAP methods are developed by exploiting the intrinsic sparsity of the clutter spatial-temporal power spectrum and of the space–time adaptive weight vectors. First, the signal model of received space–time data for an airborne phased array radar is introduced, and the intrinsic model sparsity for radar STAP is analyzed. Second, leveraging on the sparsity of clutter spatial-temporal power spectrum, a robust and fast iterative sparse recovery method is introduced. It can not only alleviate the effect of noise and dictionary mismatch but can also reduce the computational complexity via recursive inverse matrix calculation. Finally, based on the sparsity of space–time adaptive weight vectors, a fast STAP method based on projection approximation subspace tracking (PAST) with a sparse constraint is discussed. It provides a robust and stable estimation of the clutter subspace when a small set of training samples is available. Based on both the simulated and actual airborne phased array radar data, it is verified that the developed methods can provide satisfactory performance with a small training sample support in a practical complex nonhomogeneous environment.

Chapter 7 considers the use of CS techniques for the resolution of multiple targets. Estimating the relative angles, delays, and Doppler shifts from the received signals allows for the determination of the locations and velocities of objects. However, due to practical constraints, the probing signals have finite bandwidth B, the received signals are observed over a finite time interval of length T only, and in addition, a radar typically has only one or a few transmit and receive antennas. Those constraints fundamentally limit the resolution up to which objects can be localized: the delay and Doppler resolution is proportional to $1/B$ and $1/T$, and a radar with N_T transmit and N_R receive antennas can only achieve an angular resolution proportional to $1/(N_T N_R)$. The author shows that the continuous angle-delay-Doppler triplets and the corresponding attenuation factors can be resolved at much finer resolution, using ideas from CS. Specifically, provided the angle-delay-Doppler triplets are separated either by factors proportional to $1/(N_T N_R - 1)$ in angle, $1/B$ in delay, or $1/T$ in Doppler direction, they can be recovered at significantly smaller scale or higher resolution.

Traditional adaptive beamformers are very sensitive to model mismatch, especially when the training samples for adaptive beamformer design are contaminated by the desired signal. In Chapter 8, the authors propose a strategy to reconstruct a signal-free interference-plus-noise covariance matrix for adaptive beamformer design. Using the sparsity of sources, the interference covariance matrix can be reconstructed as a weighted sum of the tensor outer products of the interference steering vectors, and the corresponding parameters are estimated from a sparsity-constrained covariance matrix fitting problem. In contrast to classical CS and sparse reconstruction problems, the formulated sparsity-constrained covariance matrix fitting problem can be effectively solved by using the a priori information on array structure rather than using convex relaxation. Simulation results demonstrate that the proposed adaptive beamformer almost always provides near-optimal performance.

Chapter 9 deals with two-dimensional (2-D) spectrum sensing in the context of a cognitive radar to gather real-time space–frequency electromagnetic awareness. Assuming a sensor equipped with multiple receive antennas, a formal discrete-time sensing signal model is developed, and two signal processing techniques capable of recovering the space–frequency occupancy map via block sparsity exploitation are presented. The former relies on the iterative adaptive algorithm (IAA) and incorporates a BIC-based stage to foster block-sparsity in the recovery process. The latter resorts to the regularized maximum likelihood (RML) estimation paradigm, which automatically promotes block-sparsity in the 2-D profile evaluation. Some illustrative examples (both on simulated and real data) are provided to compare the different strategies and highlight the effectiveness of the developed approaches.

In Chapter 10, a cooperative spectrum-sharing scheme for a MIMO communication system and a sparse sensing-based MIMO radar is presented. Both the radar and the communication systems use transmit precoding. The radar transmit precoder, the radar subsampling scheme, and the communication transmit covariance matrix are jointly designed in order to maximize the radar SIR, while meeting certain communication rate and power constraints. The joint design is implemented at a control center, which is a node with which both systems share physical layer information, and which also performs data fusion for the radar. Efficient algorithms for solving the corresponding optimization problem are presented. The cooperative design significantly improves spectrum sharing performance, and the sparse sensing provides opportunities to control interference.

Chapter 11 discusses applications of CS to radar imaging problems with reference to SAR and inverse synthetic aperture radar (ISAR) sensors. The authors first provide the relevant mathematical expressions for CS and SAR necessary to formulate the problem of CS SAR imaging. Thereafter, they consider the case where unknown motion errors are present during the SAR acquisition process. Autofocusing, i.e., the blind compensation of the aforementioned errors, is discussed, and general CS solutions are presented. The chapter ends with a survey of CS methods for ISAR imaging of targets with unknown motion.

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Symbols

A unified notation is used throughout the book.

$\boldsymbol{z}$	column vector (lower case)
$\boldsymbol{Z}$	matrix (upper case)
z_i	ith element of $\boldsymbol{z}$
$Z_{i,l}$	(i,l)-th entry of $\boldsymbol{Z}$
$\boldsymbol{A}$	sensing matrix
$\boldsymbol{\Psi}$	sparsity matrix
$\boldsymbol{\Phi} = \boldsymbol{A}\boldsymbol{\Psi}$	product
$\boldsymbol{y}$	observed measurement vector
$\boldsymbol{x}$	original signal vector
k	sparsity
n	ambient dimension
m	number of measurements
$\\|\cdot\\|_p$	p-norm
$(\cdot)^T$	transpose operator
$(\cdot)^*$	conjugate operator
$(\cdot)^H$	conjugate transpose operator
$(\cdot)^\dagger$	pseudo inverse of the matrix argument
$\mathrm{tr}\,(\cdot)$	trace of the square matrix argument
$\mathrm{Rank}\,(\cdot)$	rank of the square matrix argument
$\lambda_{\max}(\cdot)$	maximum eigenvalue of the square matrix argument
$\lambda_{\min}(\cdot)$	minimum eigenvalue of the square matrix argument
$\mathrm{diag}(\boldsymbol{x})$	N-dimensional diagonal matrix whose ith diagonal element is x_i, $i = 1,\dots,N$, with $\boldsymbol{x} \in \mathbb{C}^N$
$\mathrm{Range}\,(\boldsymbol{A})$	range span of the column vectors of the matrix $\boldsymbol{A}$
$\boldsymbol{I}$	identity matrix (its size is determined from the context)
$\boldsymbol{0}$	matrix with zero entries (its size is determined from the context)
$\mathbb{R}^N$	set of N-dimensional vectors of real numbers
$\mathbb{C}^N$	set of N-dimensional vectors of complex numbers
$\mathbb{H}^N$	set of $N \times N$ Hermitian matrices
$\succeq$	for any $\boldsymbol{A} \in \mathbb{H}^N$, $\boldsymbol{A} \succeq \boldsymbol{0}$ means that $\boldsymbol{A}$ is a positive semidefinite matrix
$\succ$	for any $\boldsymbol{A} \in \mathbb{H}^N$, $\boldsymbol{A} \succ \boldsymbol{0}$ means that $\boldsymbol{A}$ is a positive definite matrix

T	standard notation for sets (uppercase letter)
$\|T\|$	cardinality of a set T
$\hat{\boldsymbol{x}}$	result of ℓ_1 minimization/recovery algorithm
$\text{supp}(\boldsymbol{x})$	support of vector $\boldsymbol{x}$
I	standard notation for subset of indices
$\boldsymbol{x}_T$	length-$\|T\|$ sub-vector containing the elements of $\boldsymbol{x}$ corresponding to the indices in T
$\boldsymbol{A}_T$	$m \times \|T\|$ sub-matrix containing the columns of the $m \times n$ matrix $\boldsymbol{A}$ indexed by T
j	imaginary unit
$\text{Re}(x)$	real part of the complex number x
$\text{Im}(x)$	imaginary part of the complex number x
$\|x\|$	modulus of the complex number x
$\arg(x)$	argument of the complex number x
$\mathbb{E}[\cdot]$	statistical expectation
$\odot$	Hadamard product
$\otimes$	Kronecker product
$\dot{y}, \frac{\partial y}{\partial x}, \frac{dy}{dx}$	first derivative of y with respect to variable x
$\ddot{y}, \frac{\partial^2 y}{\partial x^2}, \frac{d^2 y}{dx^2}$	second derivative of y with respect to variable x
$\mathbb{P}[\cdot]$	probability measure
$x(t)$	continuous time signal
$h(t)$	pulse shape
x_i	measurements of $x(t)$
$\delta_k = \delta_k(\boldsymbol{A})$	restricted isometry constant.

Statement of restricted isometry property (RIP): a matrix $\boldsymbol{A}$ satisfies the RIP of order K if

$$(1 - \delta_k)\|\boldsymbol{x}\|_2 \leq \|\boldsymbol{A}\boldsymbol{x}\|_2 \leq (1 + \delta_k)\|\boldsymbol{x}\|_2$$

for all $\boldsymbol{x}$ with $\|\boldsymbol{x}\|_0 \leq K$.