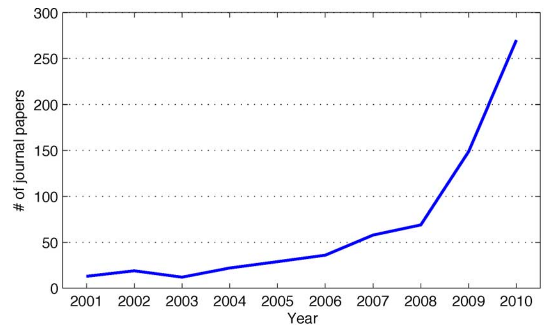
Guest Editorial
Compressive Sensing for Biomedical Imaging

WHILE it is common knowledge that most images can be greatly compressed, compressive sensing (CS) theory has established that such compression can be done during the data acquisition process and then the uncompressed image can be recovered through a computationally tractable optimization procedure such as L1-norm minimization [1]–[4], or greedy algorithms [5]. In the field of biomedical imaging, CS is exciting for several reasons. First, it allows accurate recovery of an image from far fewer measurements than the number of unknowns, and does not require close match between the sampling pattern and characteristic image structures. Also, CS techniques can often efficiently deliver practical results in terms of increased imaging speed, reduced radiation dose, enhanced image quality, and other benefits. Given its transformative potential for system design, algorithm development, and preclinical and clinical applications, CS has recently become a hot topic in biomedical imaging [6].

Some of the key ideas and methods of CS were introduced and applied to biomedical imaging well before the advent of modern CS theory. While not an imaging method *per se*, an early observation of the ability of ℓ_1 regularization to produce sparse signals was in geophysics [7]. Early sparsity-based imaging methods employed variations on reweighted least-squares [8] to solve the associated nonlinear recovery problem. Theoretical results and algorithms for spectrum-blind sampling in imaging [9]–[11] introduced the possibility of perfect image recovery from highly undersampled Fourier data subject to object sparsity. Combining random sampling and an efficient nonlinear sparse reconstruction algorithm led to a compressive sensing method for Fourier imaging, including MRI and tomography [12].

As shown in Fig. 1, CS has seen impressive successes and fast growth over the past ten years, including applications in medical imaging. Applications of CS to MRI have been the earliest, most numerous, and most diverse, owing to the tremendous flexibility in designing the acquisition process and the pressing need that MRI has, as a slow acquisition modality, to reduce the sampling requirements. Representative works, classified by subtopic/application include the following: static MRI [13], dynamic MRI [14]–[16], parallel MRI [17]–[19], MR spectroscopic and parametric imaging [20]–[22], diffusion tensor imaging [23], flow imaging [24], optimized acquisition [25]–[27], CS reconstruction algorithms [28]–[30], and image quality evaluation [31], [32]. Optical imaging modalities rank next in level of activity, covering bioluminescence [33], [34], optoacoustics [35], [36], fluorescence molecular tomography [37], [38], and diffusion optical tomography [39]–[41]. CT is drawing an increasing number of CS applications [42]–[45], while CS in ultrasound [46]–[48] is only beginning to be explored. Applications of CS in PET or SPECT [49] have been relatively few, perhaps because the acquisition in these modalities has fewer degrees of freedom, and these modalities are usually photon-limited rather than sampling-limited.



(a)

Subject Area	*Count*	*Percent*
Electrical Engineering	254	32.2
Applied Physics	72	9.1
Materials Science	64	8.1
Applied Mathematics	64	8.1
Medical Imaging	57	7.2
Optics	52	6.9
Information Systems	50	6.3
Instrumentation	40	5.1
Geochemistry and Geophysics	34	4.3
Artificial Intelligence	32	4.1

(b)

Fig. 1. Bibliographic analysis of the CS field. (a) The total numbers of journal papers for each of the past 10 years, and (b) the total numbers of journal papers in each of the top 10 application areas. The data were extracted using the ISI Web of Knowledge (http://pcs.isiknowledge.com) on February 28, 2010, with the topic search rule "Compressive Sensing" OR "Compressed Sensing" OR "Compressive Sampling."

The latest methodological developments include dictionary learning that promises to sparsify an image adaptively, and has a great potential to maximize the use of prior knowledge [50]. Inspiring progress is being made in the area of low-rank matrix recovery [51], [68]–[71], where low-rank structure replaces or augments sparsity, and reconstruction algorithms analogous to CS are already being applied to biomedical imaging [52]–[54].

This special issue reports cutting-edge results on CS for biomedical imaging, and elaborate the methodologies behind such case studies. Clearly, CS has important and immediate applications in CT, MRI, PET, SPECT, ultrasound and optical imaging. Needless to say, this volume can only show tips of the iceberg.

The paper by Çukur *et al.* [55] offers an optimized trade-off between image contrast and scan efficiency for MRI. The proposed technique first corrects the signal decay in high-frequency

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data and then employs a sparsity-based nonlinear reconstruction to improve the image quality. The technique is successfully demonstrated for noncontrast-enhanced flow-independent angiography of the lower extremities.

The paper by Ravishankar and Bresler [56] proposes a scheme for adaptively learning the sparsifying transform (dictionary) and simultaneously reconstructing the image from highly undersampled k-space data. Overlapping image patches are used, and the dictionary is adapted to the particular image instance for much higher under-sampling rates. The proposed alternating algorithm learns the sparsifying dictionary to remove aliasing and noise in one step, and subsequently fill in the k-space data in the other step.

The paper by Lingala *et al.* [57] introduces an algorithm to perform dynamic MRI from under-sampled k-t space data. The data-dependent KL transform is incorporated in the algorithm for a range of imaging problems in the form of regularized matrix recovery. Both temporal basis functions and spatial weights are determined from measured data to provide high image quality.

The paper by X. Ye *et al.* [58] presents a fast algorithm for TV-based partially parallel MRI reconstruction. A variable splitting method helps reduce the computational cost. The Barzilai–Borwein step size selection technique is adopted for accelerated convergence. Experimental results demonstrate that the proposed algorithm requires much fewer iterations and less computational time than recently developed operator splitting and Bregman splitting methods.

The paper by Montefusco *et al.* [59] deals with high-resolution volumetric MRI from reduced frequency acquisition sequences. The main contribution is to integrate the spatio-temporal correlation, gradient sparsity and other constraints. A penalized forward–backward splitting approach leads to a convergent iterative two-step procedure.

The paper by K. Lee *et al.* [60] presents a statistical method for functional MRI. Recent studies indicate that independent component analysis (ICA) does not guarantee independence of simultaneous activity patterns in the brain, and sparsity of the signals is more promising. The proposed data-driven sparse generalized linear model promises to facilitate studies on synchronous and functionally organized neural hemodynamics.

The paper by Akçakaya *et al.* [61] develops a Bayesian least squares-Gaussian scale mixture (BLS-GSM) method. It utilizes dependencies of wavelet coefficients. A major limitation of coronary MRI is the long acquisition time and constraints on respiratory and cardiac motions. With fully-sampled k-space datasets from seven healthy subjects, a comparative study demonstrates that BLS-GSM allows acceleration of coronary MRI.

The paper by Michailovich *et al.* [62] represents another CS application in the MRI field. This work shortens the acquisition time of high angular resolution diffusion imaging (HARDI). It was shown that the number of diffusion encoding gradients could be significantly minimized utilizing the spherical ridgelet transformation, and the sparsity constraints in the diffusion domain be combined with additional constraints in the spatial domain. Then, an efficient algorithm was developed, and produced encouraging experimental results.

The paper by Xu *et al.* [63] formulates a statistical interior tomography (SIT) approach empowered by CS. With projection data modeled by the Poisson distribution, an objective function with a TV term is formulated in the framework of maximization of a posteriori probability (MAP). An alternating minimization method optimizes the objective function with an initial image from the direct inversion of the truncated Hilbert transform. The results demonstrate that SIT has better resolution and less bias than its deterministic counterpart in the case of low count data.

The paper by O. Lee *et al.* [64] improves diffuse optical tomography (DOT). While popular nonlinear iterative methods are computationally expensive, this paper treats DOT as a joint sparse recovery problem and proposes a noniterative and exact inversion algorithm that achieves the L_0 optimality as the rank of measurement matches the unknown sparsity level. The algorithm is based on the recently discovered generalized MUSIC criterion, which exploits the advantages of both CS and the MUSIC algorithm from array signal processing.

The paper by Baritaux *et al.* [65] proposes a method based on the (2,1)-mixed-norm penalization for fluorescence diffuse optical tomography (FDOT). It isolates few anatomical regions where fluorescent probes exist and regularizes in the selected anatomical regions. In the variational framework, a practical method is formulated and applied to synthetic and experimental data.

The paper by H. Lee *et al.* [66] studies the connectivity of brain networks. The sparse linear regression model with an L1-norm penalty is used to estimate the brain connectivity from a small set of noisy measurements. As an example, with 97 regions of interest from FDG-PET real datasets for the autism spectrum disorder children and the pediatric control subjects, the proposed method is shown to identify consistently the brain networks that characterize significant group differences in network connectivity.

Finally, we note that we received 30 submissions and only accepted 12 papers of very high quality. By reviewing recent papers in this field and the manuscripts submitted to this special issue, we are motivated to point out the following topics for future research.

First, theoretical research can be performed in the context biomedical imaging applications. Biomedical images have some generic but powerful properties such as sparsity, regularity, nonnegativity, similarity, and high dimensionality. Medical imaging processes and the associated inverse problems often share common characteristics such as line integral or Fourier measurements, ill-posedness of the inverse problem, Gaussian or Poisson noise statistics, etc. Computational schemes may be developed to address these properties and constraints systematically and efficiently. A challenging problem is to extend matrix completion theory to tensor completion [68], [69]. Also, there are opportunities for algorithmic development. An interesting possibility is to improve dictionary learning techniques, and combine reconstruction, segmentation, registration, and database algorithms so that domain knowledge can be maximally utilized. Furthermore, speed is a major issue for CS algorithms to be practically useful. While the amount of raw data is greatly reduced, computational time is unfortunately increased. Thus, high-performance computing platforms and infrastructure will become more involved. Last but not the least, any CS algorithm must be rigorously evaluated and validated before its clinical or preclinical applications [67]. Although it may be technically tedious, it is invaluable and necessary to conduct numerical and human observer studies with representative datasets, using the reproducible research and open access approaches.

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