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Computational MRI: Compressive Sensing and Beyond

The process of forming images from measured data using computational algorithms is referred to as *computational imaging*. Rapid advances in computational hardware and signal processing algorithms have resulted in a flurry of activity in computational imaging in several application areas, including medicine, biology, remote sensing, and seismic imaging. Medical imaging has witnessed extensive research in computational imaging, beginning with computed tomography (CT), which relies on algorithms to construct a 3D volume from X-ray measurements taken from X-ray projections at different angles; this work received the 1979 Nobel Prize in Medicine. Most of the current medical-imaging modalities [e.g., magnetic resonance imaging (MRI), CT, positron emission tomography] employ computational imaging in one form or another.

Advances in computational MRI were primarily driven in the last decade by parallel image acquisition using multiple receiver coils and compressed sensing (CS). The ability of these approaches to break the classical Nyquist sampling limit has been exploited to considerably reduce the acquisition time in static imaging applications and to significantly improve the spatial and temporal resolution in dynamic imaging applications. Extensive research in this area has facilitated developments of efficient transforms, novel regularization priors, smart acquisition strategies, fast optimization algorithms, and computational toolboxes. The recent U.S. Food and Drug Administration approval of CS products for clinical scans makes MRI one of the main benefactors of CS algorithms.

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In this issue

While the application of CS-based algorithms in medical imaging is maturing, the recent research in this area has initiated a new computational way of thinking. The main focus of this special issue of *IEEE Signal Processing Magazine (SPM)* is on recent developments in computational MRI. These developments are pushing the frontier of computational imaging beyond CS. Similar to CS, most of these algorithms rely on image representation in one form or another. However, the common recent thread is the departure from handcrafted image representations (e.g., sparse wavelet model) to learning-based image representations. These learned representations are seamlessly combined with clever measurement strategies to significantly advance the state of the art in a number of areas. Several exciting applications including significantly improved spatial and temporal resolution, a considerable reduction in scan time, measurement of biophysical parameters directly from highly undersampled data, and direct measurement of very high-dimensional data are reviewed in this special issue of *SPM*.

This issue describes key ideas underlying the computational approaches used in MRI. These approaches range from CS algorithms that rely on fixed transforms or dictionaries, to adaptive or shallow-learning algorithms that adapt the image representation to the data (e.g., low-rank and dictionary-based methods), to recent deep-learning methods that learn a highly nonlinear representation from exemplar data. The articles provide insight into the capabilities of the current algorithms, their limitations, and their utility in challenging MRI problems. While the focus of this special issue is on medical imaging and in particular MRI, most of the problems, and hence solutions, are easily translatable to signal recovery applications in other areas.

Overview

The 11 articles in this issue represent three broad categories. Each article explains its specific problem setting and the applications where the problem occurs, the various solution approaches (algorithms), and experimental comparisons (either from existing work or new ones).

Model-based reconstruction in MRI using fixed transforms

The first article, "Mathematical Models for Magnetic Resonance Imaging Reconstruction," by Doneva, is an overview of MRI acquisition schemes from a computational perspective. Doneva discusses the various challenges stemming from the nonideal nature of the acquisition. She also provides a brief overview of the various model-based reconstruction algorithms introduced to overcome these challenges.

In his article, "Optimization Methods for Magnetic Resonance Image Reconstruction," Fessler covers the model-based algorithms from an optimization theory perspective in greater detail. Specifically, he poses the image reconstruction algorithm as an optimization algorithm and reviews various regularization penalties or priors designed to exploit specific image properties, including sparsity and data-adaptive regularizers. The article also reviews computationally efficient algorithms to solve the aforementioned optimization problems.

Shallow-learning methods that adapt the transform or representation to the data

The article "Transform Learning for Magnetic Resonance Image Reconstruction" by Wen et al. provides an overview of learning-based methods in MRI. These methods range from those that use fixed transforms/models, to shallow-learning methods that adapt the transform to the image content, to deep-learning methods.

The next article, "Structured Low-Rank Algorithms," by Jacob, Mani, and Ye reviews advances in recovering images by lifting their Fourier data to a structured matrix. The low-rank nature of these matrices is used to recover them from undersampled measurements. The authors also discuss the ability of the framework to exploit image properties that are difficult to capture by image-domain methods, including continuous-domain sparsity, exponential time profiles, phase relations, and manifold structure of images, as well as connection to deep-learning methods.

In "Linear Predictability in Magnetic Resonance Imaging Reconstruction," Haldar and Setsompop provide a historical review of linear prediction-based methods used in MRI, including the earliest methods in computational MRI; Fourier domain parallel MRI algorithms; and recent methods that can exploit limited spatial support, phase constraints, and sparsity. The authors also provide interesting examples of highly accelerated imaging by combining multiple constraints.

Christodoulou and Lingala next present "Accelerated Dynamic Magnetic Resonance Imaging Using Learned Representations," a unified view of learning algorithms to dynamic MRI, designed to overcome challenges including motion, while capitalizing on opportunities including pseudo-repetitive motion and temporal correlations. These algorithms range from blind CS, low-rank reconstruction methods, higher-order multidynamic methods, explicit motion-estimation and compensated-recovery methods, and manifold regularized-recovery methods.

In the next article, "Computational MRI With Physics-Based Constraints," Tamir et al. introduce physics-based models in MRI. These models are used as constraints for CS reconstruction and quantitative imaging. The article focuses on spin density and relaxation effects. The authors also discuss approaches to selecting user-controllable scan parameters based on the physical model. Several multicontrast imaging and quantitative mapping examples are presented.

In their article, "Plug-and-Play Methods for Magnetic Resonance Imaging," Ahmad et al. review plug and play (PnP) methods, where an off-the-shelf denoising subroutine is used as a regularization prior in image reconstruction problems. The authors describe how the PnP method can be interpreted as a solution to an equilibrium equation, allowing convergence analysis from the equilibrium perspective. The article demonstrates applications of PnP methods in MRI applications.

Deep-learning algorithms for MRI

The next article, "Compressed Sensing: From Research to Clinical Practice With Deep Neural Networks," by Sandino et al., reviews the challenges with the classical model-based algorithms using fixed transforms in the clinical perspective. It then demonstrates how these challenges can be overcome in a step-by-step fashion using a deep-learning-based reconstruction framework by applying unrolled neural networks.

In their article, "Deep-Learning Methods for Parallel Magnetic Resonance Image Reconstruction," Knoll et al. review recent advances in deep learning applied to reconstructing highly undersampled MR images using neural networks. The article reviews image-domain-based techniques that introduce deep regularizers and describes Fourier domain methods that use neural network-based interpolation strategies.

Finally, in "Deep Magnetic Resonance Image Reconstruction," Liang et al. provide an overview of deep-learning-based algorithms in MR inverse problems. The authors present two general classes of approaches: 1) algorithms that rely on a model-based framework with deep-learned priors, which are unrolled, and 2) deep architectures that do not rely on loop unrolling. They also discuss signal processing approaches to maximizing the potential, and they point out open problems.

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Guest Editors

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necessary. "Some main estimation techniques are maximum a posteriori probability estimation, MMSE estimation, and least square estimation," Ngo explains. "Depending on the requirements of implementation complexity, quality of estimation, and pilot sequences, as well as the side information the APs have, a suitable estimator will be chosen."

Since cell-free massive MIMO is a new technology, many open issues remain, and a variety of research questions must be addressed before the system can be rolled out into real-world settings. "The project's next steps include proposing and developing a complete, useful, and practical cell-free massive MIMO system that includes signal processing schemes, channel estimation, pilot assignment schemes, power controls, and AP selection schemes," Ngo says. After that, he plans to build several testbeds to verify the benefits of cell-free massive MIMO, as well as validate the proposed signal processing techniques.

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