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Data-driven Models and Approaches for Imaging

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Abstract: Data-driven techniques are becoming popular in imaging. There is growing interest in learning signal models for various applications. We describe recent research that developed efficient, scalable, and effective data-driven models and methodologies for imaging and image processing. Efficient sparsifying transform learning methods have been proposed, often incorporating various properties such as union-of-transforms, rotation invariance, etc. Transform learning-based approaches achieve high-quality results for X-ray computed tomography (CT) or magnetic resonance image (MRI) reconstruction from limited data. We also discuss recent work on efficient methods for synthesis dictionary learning, including in combination with low-rank models. Newly proposed dictionary-based algorithms provide promising results for dynamic MRI reconstruction from limited measurements.

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1. Introduction

Various models and properties of signals and images have been explored in recent years including sparsity, low-rank, tensor models, etc. Such models are particularly useful in inverse problems in imaging and image processing. In particular, data-driven techniques are becoming increasingly popular in a variety of applications. For example, while natural signals and images are known to be sparse in some transform domains (e.g., wavelet, finite differences, or discrete cosine transform) or dictionaries, the data-driven adaptation of such dictionaries [1, 2] and sparsifying transform [3–6] models leads to much better or sparser representations of data and such learned models have been shown to provide promising performance in applications [7–11]. In the following section, we briefly present some of the recent data-driven approaches for imaging along with some results illustrating their performance.

2. Overview of Recent Data-Driven Methods for Imaging

2.1. Sparsifying Transform Learning and Its Applications

The sparsifying transform model assumes that signals or image patches are sparse in some sense in a transform domain. The goal of transform learning is to learn such transformation operators from data [3]. Often various properties are assumed for the transforms such as well-conditioning [3], double sparsity [4], union of transforms property [6], rotation (and flip) invariance [8], etc., or the transforms are learned and applied in an online manner [9,12]. Transform learning algorithms typically alternate between updating the sparsifying transform and finding the transform domain sparse approximations of data. Importantly, the latter step typically involves simple thresholding, while the transform update is also often performed efficiently [5, 6]. Various convergence guarantees have been established for the alternating transform learning algorithms [5,6].

Transform learning-based methods have shown promising performance in applications such as image and video denoising [6, 9], and image reconstruction in magnetic resonance imaging (MRI) [13, 14] and computed tomography (CT) [10]. In MRI and CT, they achieve high quality reconstructions from limited data or low-dose data (in CT). The reduction in measurement count for MRI could enable lower image scan times. The transforms can be adapted based on training data [10], or directly from the imaging measurements themselves [13, 14]. In particular, in the transform-blind compressed sensing technique [7,13,14], the sparsifying transform and image are jointly estimated from limited measurements such as undersampled k-space data in MRI. Here, as an example, we consider the reference brain image in Fig. 1, and simulate retrospective (Cartesian) undersampling of its k-space. Fig. 1 shows some blind compressed sensing MRI reconstructions and reconstruction errors (magnitude of the difference between the magnitudes of the reconstructed and reference images) obtained using the adaptive DLMRI [7], UTMRI [14] and UNITE-MRI [14] methods. While the dictionary learning-based DLMRI method provided significant improvements over the prior non-adaptive (with wavelets and total variation sparsity) image reconstruction method [15], the recent efficient transform learning-based UTMRI (with a single square sparsifying transform) and UNITE-MRI (with a union of 16 square

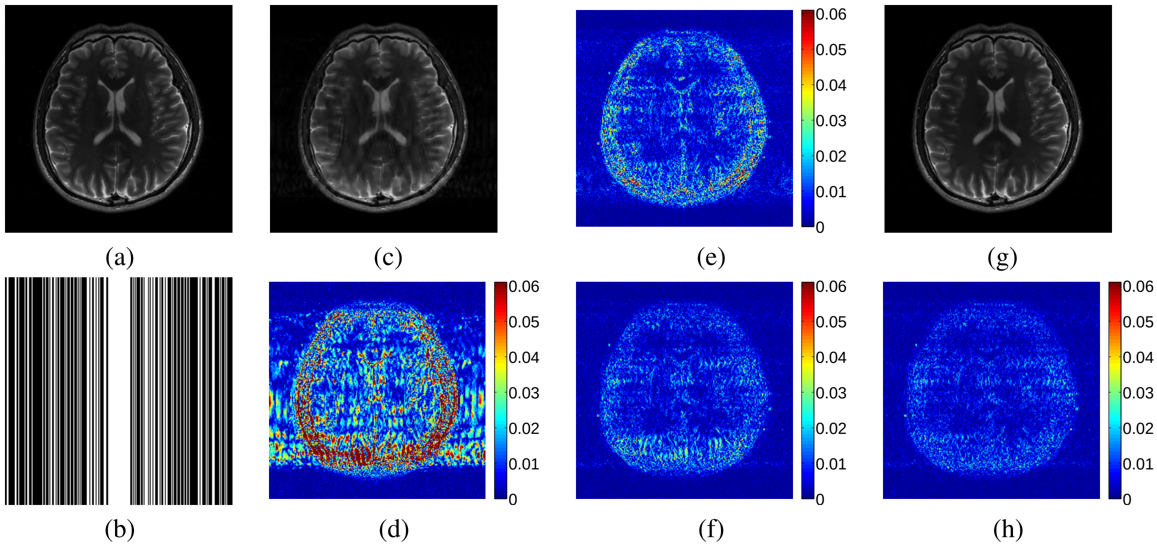

Fig. 1. Transform-blind compressed sensing MRI results [14] (magnitudes of complex-valued images are displayed): (a) 256×256 reference image; (b) k-space sampling mask with Cartesian sampling and 2.5x undersampling; (c) Sparse MRI reconstruction [15] (PSNR = 31.6 dB, runtime of 100 sec); reconstruction errors for (d) Sparse MRI, (e) DLMRI [7] (PSNR = 39.2 dB, runtime of 2186 sec), (f) UTMRI [14] (PSNR = 42.5 dB, runtime of 125 sec), and (h) UNITE-MRI [14] (PSNR = 44.3 dB, runtime of 611 sec); and (g) the UNITE-MRI reconstruction.

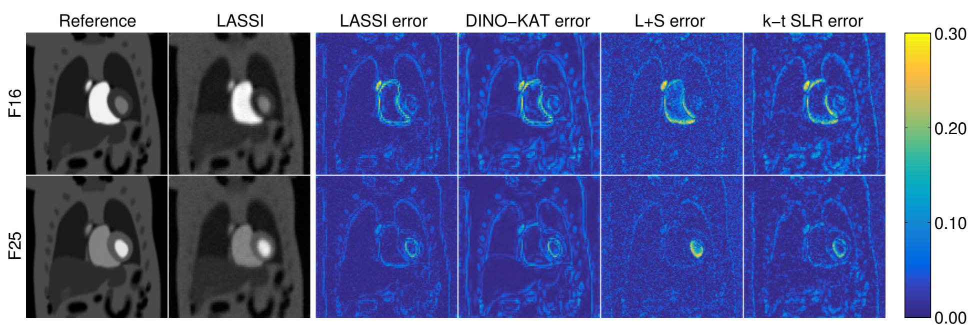

Fig. 2. LASSI [11] reconstructions and error maps (clipped for viewing) for the LASSI, DINO-KAT dMRI [11], L+S [17], and k-t SLR [18] methods shown for frames of the PINCAT data [18], for pseudo-radial sampling and 9x (k-t space) undersampling. The reference frames are also shown.

transforms) methods achieved even better quality image reconstructions (less artifacts), but with substantially lower reconstruction times (see Fig. 1). In the context of undersampling of k-space in MRI, recent work [16] has shown the benefits of learning undersampling patterns from training data to minimize reconstruction errors.

2.2. *Efficient Dictionary Learning and Extensions*

Unlike the sparsifying transform model, the synthesis dictionary model suggests that the signal or image patch can be approximated by a linear combination of a few atoms or columns of a dictionary. While many algorithms exist for dictionary learning [1,2], recent works [11,19] investigated efficient dictionary learning schemes, especially for inverse problems. For example, the LASSI and DINO-KAT [11] methods provide promising performance for dynamic MRI reconstruction from limited k-t space data. In the LASSI model, the underlying dynamic image sequence is treated as the sum of a low-rank component and a component whose spatiotemporal patches are sparse in a learned dictionary (learned based on imaging measurements themselves) domain. Fig. 2 shows example LASSI reconstructions [11] of some representative frames of the PINCAT data [18] for nine fold (retrospective) undersampling of k-t space with pseudo-radial sampling. The reconstruction error maps are shown for the LASSI, DINO-KAT dMRI [11], L+S [17], and k-t SLR [18] methods, which show that LASSI achieves fewer artifacts and smaller distortions than the others.

3. Conclusions

We briefly discussed data-driven approaches for imaging, especially inverse problems. The adaptive signal modeling and image reconstruction techniques were shown to provide high quality results in limited data setups. With growing interest in machine learning approaches to imaging, we expect many more innovations in this field in the future.

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