Interventional MRI with sparse sampling: an application of compressed sensing

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INTRODUCTION

In interventional MRI (I-MRI), a sequence of MR images is reconstructed in order to guide a diagnostic or therapeutic procedure where an invasive device is inserted in the body. The need for near-real-time image updates places two distinct constraints on I-MRI reconstruction: 1) high frame rate (several frames per second, depending on the application [2,3]); 2) *causal* reconstruction of the image sequence (as opposed to other dynamic MRI applications, where the complete image sequence can be recovered after all the data are collected [1]). Several methods have been proposed, which take advantage of the temporal correlations in I-MRI to reduce *k*-space coverage, thus allowing a higher frame rate [4]. We present a compressed sensing (CS) method, which exploits the redundancy present in many I-MRI acquisitions for reduced-encoding image reconstruction.

METHODS

The CS theory states that a signal $\boldsymbol{x}$ of length N can be recovered stably from a set of M linear measurements $\boldsymbol{d}=\boldsymbol{\Phi x}$ (with $M<N$) as long as $\boldsymbol{x}$ is sufficiently sparse in a known representation and $\boldsymbol{\Phi}$ satisfies a certain "restricted isometry" property with respect to that representation [5]. Recovery is performed effectively via l_1-norm minimization [1]. Denoting $\boldsymbol{d_n}=\boldsymbol{\Phi_n x_n}$ as the measurements acquired for the nth frame (e.g., a reduced set of phase-encoding lines), we propose to estimate a good (sparse) representation for $\boldsymbol{x_n}$ based on $\{\boldsymbol{d_1},\ldots,\boldsymbol{d_n}\}$. Specifically, assuming $\boldsymbol{x_1}$ is a reference image acquired with full resolution (e.g., before the intervention), we can model subsequent images as $\boldsymbol{x_n}=\boldsymbol{T_n x_1}+\boldsymbol{y_n}$, where $\boldsymbol{T_n}$ is a transformation (rotation, translation) designed to account for, e.g., respiratory motion, and $\boldsymbol{y_n}$ is a sparse image which captures the motion of the interventional device and the errors in the modeling by $\boldsymbol{T_n}$. By acquiring the center of *k*-space at every frame, and assuming most of the signal energy is due to anatomical features, we can accurately estimate the current shift and rotation matrix $\boldsymbol{T_n}$ by estimating the *k*-space rotation and phase shift between $\boldsymbol{d_1}$ and $\boldsymbol{d_n}$. Then, $\boldsymbol{y_n}$ will be a sparse vector which can be effectively recovered by solving the convex optimization problem

$$\min \|\boldsymbol{y_n}\|_1+\alpha\|\boldsymbol{D}(\boldsymbol{T_n x_1}+\boldsymbol{y_n})\|_1 \quad \text{such that} \quad \|\boldsymbol{\Phi_n}(\boldsymbol{T_n x_1}+\boldsymbol{y_n})-\boldsymbol{d_n}\|_2<\varepsilon \qquad (1)$$

where $\boldsymbol{D}$ takes finite differences in the spatial domain, the term $\alpha\|\boldsymbol{D}(\boldsymbol{T_n x_1}+\boldsymbol{y_n})\|_1$ is included to reduce noise in the reconstruction, and ε is often set according to the noise level [6]. Note that for $\alpha=0$, from a Bayesian interpretation of (1), $\boldsymbol{T_n x_1}$ provides the mean for the prior distribution of x_n.

RESULTS

Reduced-encoding acquisition with varying sampling patterns was simulated from a set of fully sampled I-MRI data. Bulk motion was estimated with good accuracy from the center of *k*-space (e.g., *15x15 k*-space samples). We compared several randomized sampling patterns (previously studied in the CS literature [5,6,7]), as well as low-frequency phase-encoding lines. Figure 1 shows an example of CS-based reconstruction and frame-by-frame errors for different reconstruction methods. Table 1 shows mean errors for different sampling strategies and reconstruction methods.

	Zero-Padding	Keyhole	CS
32 RP	X	X	0.150
PE: 16 LF + 16 HF	0.130	0.094	0.086
PE: 24 LF	0.109	0.101	0.090
PE: 32 LF	0.085	0.088	0.080

Table 1. Mean relative errors for different sampling strategies and reconstruction methods. "PE" refers to phase encodes, "LF" are acquired at low-frequencies whereas "HF" are chosen uniformly at random; "RP" substitutes the phase encoding step for an inner product with a random i.i.d. Gaussian vector (frequency encodes are always assumed). Note that, despite the good properties of randomized sampling for CS [6], in this case the improved SNR obtained by sampling the center of *k*-space outweighs the CS-related benefits of random sampling. One aspect not included in this analysis is computational complexity: although CS reconstruction is computationally more demanding than other methods, efficient solution of (1) is an active area of research showing promising results [6].

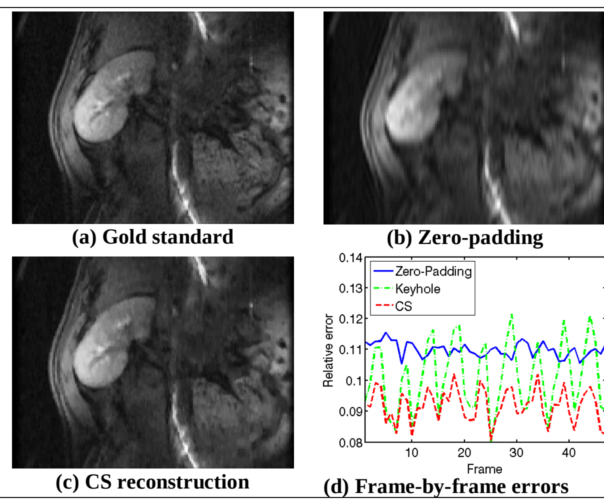

Figure 1. Results obtained from 24 low-frequency phase-encoding lines. (a) Original frame (fully encoded) in the dataset; (b) Zero-padding reconstruction; (c) CS reconstruction using the proposed method; (d) Plot of the relative errors for the different frames using zero-padding reconstruction, keyhole and CS.

CONCLUSION

CS provides a promising method for I-MRI reconstruction. In this work, we have tailored the CS reconstruction to take advantage of the sparsity present in I-MRI. Preliminary results compare favorably with alternative reconstruction methods.

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