Accelerating Dynamic Contrast-Enhanced MRI Using Compressed Sensing

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Introduction

Compressed Sensing (CS) has emerged as an effective approach to fast magnetic resonance imaging [1-3]. By taking advantage of the signal sparsity in a transformed domain, an image can be reconstructed from k-space signals sampled below the Nyquist rate. In the CS imaging, sparsifying transform plays a key role in the reconstruction algorithm. In this study, we developed a dynamic CS imaging method that utilizes a temporal difference operator to enhance the image sparsity. The new method was assessed using simulated and *in vivo* dynamic MRI data where the temporal difference images are sparse by nature.

Methods

In the new method, a high-resolution reference image is acquired before or after contrast injection, and the dynamic data frames are undersampled using randomly selected phase encodings (with increased density weighting in the central k-space). The new method reconstructs the dynamic image using the following model: $I = I_{ref} + I_{diff}$, which has a corresponding k-space signal model $d_{diff} = d - d_{ref}$ [4]. Note that I_{diff} is spatially sparse because similar structures in both the dynamic and reference images will be removed . Using this model, the CS algorithm is applied to reconstruct I_{diff} by optimizing the following cost function:

$$\varepsilon(I_{diff}) = \left\| F * I_{diff} - d_{diff} \right\|^2 + \lambda_1 \left| W * I_{diff} \right|_1 + \lambda_2 * TV(I_{diff})$$

where F is the Fourier transform matrix, W is the sparsifying transform, e.g., the discrete wavelet transform. Subsequently, the dynamic image is reconstructed from I_{diff} and I_{ref}. The optimization was performed using the SparseMRI V0.2 program [1].
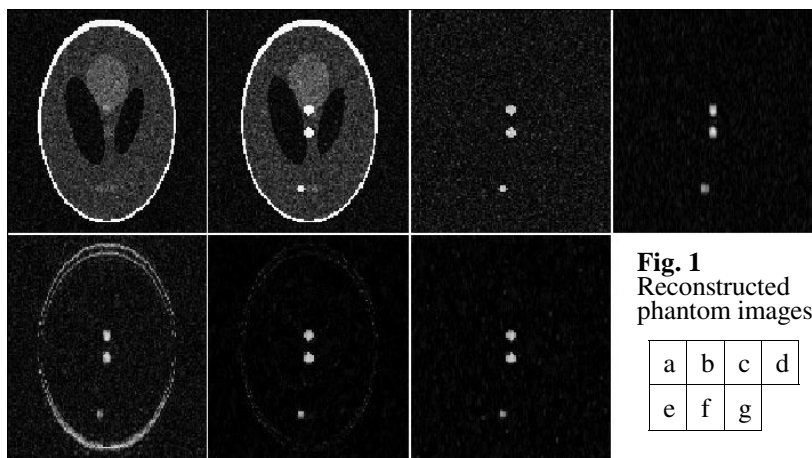

Fig. 1 Reconstructed phantom images.

a	b	c	d
e	f	g	

To test the proposed method, a simulated dynamic phantom dataset was generated using the phantom function and Fourier transform in Matlab (Mathworks, Natick, MA). In addition, the method was tested with *in vivo* dynamic mice tumor data collected on a SISCO 4.7 Tesla system using a rapid T1-weighted gradient echo sequence (matrix 512x128, FOV 24cm x 6cm, TR = 63 ms, TE = 4.3 ms, slice thickness = 2 mm, slices = 7, frames = 50). All processing were performed on a PC workstation with 1.86 GHz CPU and 1.25 GB memory.

Results

The results are shown in Fig. 1 and Fig. 2. In both figures, the images shown are: (a) reference image, (b) dynamic image, and (c) the difference image, all from 128 phase encodings; and the corresponding difference image reconstructed using: (d) Fourier transform, (e) Keyhole, (f) conventional CS (reference and dynamic image separately reconstructed, then subtracted), and (g) the proposed method. Images in (d-f) in both figures were reconstructed using 32 encodings, i.e., 25% of the total phase encoding lines. For better visualization, only the area around the mice's chest (128 x128) is show in Fig. 2. In both the phantom simulation and the *in vivo* experiment, the CS reconstructions show higher resolution than the Fourier and Keyhole images, as expected. In addition, the proposed method reconstructs images with reduced artifacts and noise than the conventional CS imaging.

Discussion

Compressed Sensing has proven to be an effective method for MR image reconstruction from undersampled k-space data. The proposed method took advantage of the temporal redundancy between dynamic image frames to obtain improved sparsity and reconstruction quality. Results show that it can form dynamic images with reduced artifacts and noise. Potential problems include sensitivity to inter-frame phase variation and automatic selection of regularization parameters.

Fig. 2 Reconstructed *in vivo* images:

a	b	c	d
e	f	g	

References

[1] M Lustig et al. MRM 2007 (in press).
[2] M Lustig et al. 14th ISMRM 2006, p 2420
[3] H. Jung et al. Phys. Med. Bio. 2007, pp. 145-148.
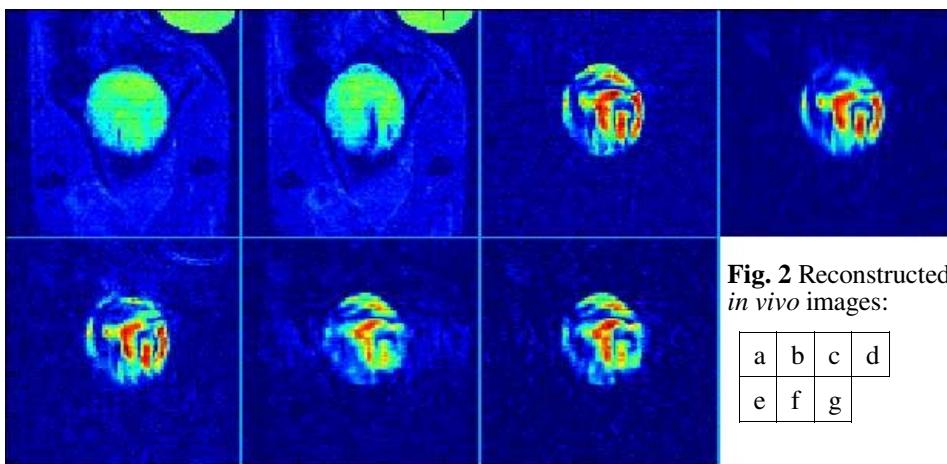[4] J. Hanson et al., MRM, 1996, 36, pp. 172-175.