Image reconstruction from 3D non-Cartesian data employing a combined conjugate gradient and denoising algorithm

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Introduction

3D radial acquisitions (e.g. VIPR [1]) are attractive for applications where k-space is highly undersampled due to the incoherent aliasing artifacts produced. This makes these trajectories suitable for use with compressed sensing (CS) reconstructions [2]. CS MRI typically formulates the reconstruction as an inverse problem where the cost function to be minimized has both a data fidelity term and a sparsity promoting penalty term based on the L_1 norm. In contrast enhanced MR angiography (CE-MRA) with precontrast subtraction, the vessel images are sparse and the L_1 norm can be applied directly in the image domain. An alternative reconstruction approach proposed by Adluru et. al. [3], uses an iterative projection onto convex sets (POCS) framework. In this case, the image estimate is alternately: 1.) projected onto a data fidelity term and 2) denoised using the non-local means (NLM) algorithm. In this work we propose a CG-POCS algorithm suitable for combined CS and parallel imaging reconstruction of images from undersamled 3D non-Cartesian data. The proposed conjugate gradient and denoising (CGDN) algorithm requires very few iterations and does not require the tuning of any regularization parameters.

Methods

CGDN is a simple CS reconstruction approach. It was inspired by the work of Adluru et al. [3], but differs in a few respects: 1.) The Cartesian data in Adluru et. al. was undersampled along two dimensions, and used separate 2D spatial denoising and 1D temporal denoising. In contrast, 3D radial data is undersampled in all three spatial dimensions, so 3D spatial denoising was performed. Temporal denoising was omitted to reduce computation time and memory requirements. 2.) For the denoising step, we chose a recently proposed non-local transform domain filter, BM4D [4], which in our initial results has proved superior to NLM for denoising MR angiograms. 3.) We use a modified CG-POCS algorithm [5] where all of the POCS relaxation parameters were set to 1 for simplicity (i.e. no relaxation). In this case, the proposed reconstruction algorithm has two simple alternating steps:

1.) Perform N_{CG} iterations of CG-SENSE (as in [6], incorporating density compensation weights) to produce an image estimate.
2.) Denoise the resulting image estimate and use it as the new initial guess in step 1.

The image estimate was initialized with zeros. No regularization was used during CG-SENSE and denoising was performed separately on the real and imaginary components. An estimate of the noise standard deviation (required by BM4D) was determined from a background region. All other parameters of the BM4D algorithm were set to the defaults tabulated under "Hard Thresholding" in Table 1 of [5].

A volunteer was scanned on a 3T Siemens Verio system with a 12-channel head coil after undergoing informed consent in accordance with local IRB regulations. A (1 mm)^3 isotropic CE-MRA scan of the head was performed using a previously published multi-echo 3D radial acquisition with pseudorandom projection ordering [7]. All acquisition parameters were identical to those listed in the previous work.

Reconstructions of a single late arterial phase CE-MRA time frame (after baseline subtraction) were performed using either 1.1, 2.2 or 4.4 s of data (640,1280 or 2560 radial projections, respectively). These correspond to accelerations factors R~= 150, 75 and 38 relative to Nyquist. The reconstructions were performed using 16 total CG iterations with N_{CG} = 1,2,4, or 8 iterations between each denoising step. For comparison, gridding and CG-SENSE without denoising were also performed.

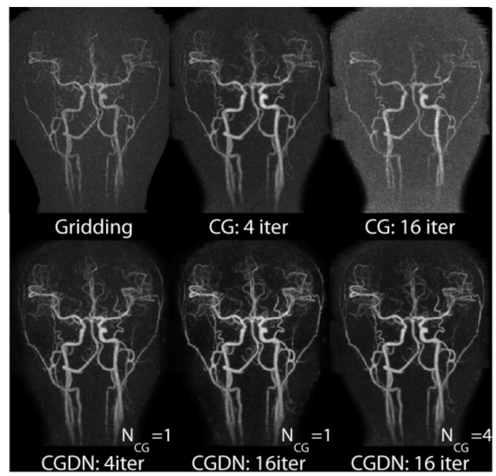

Fig. 1: Coronal MIPs for various reconstructions of a late arterial phase frame using 1280 projections.

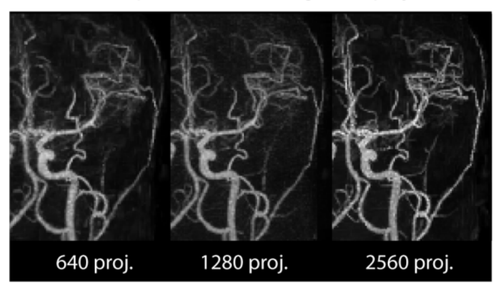

Fig. 2: CGDN reconstruction at varying number of projections. The larger vessels are clearly seen in all cases, although details of the smaller vessels become less clear with fewer projections.

Results and Discussion

The top row of Fig. 1 demonstrates that CG-SENSE reconstruction improves upon a simple gridding reconstruction in early iterations, but rapdily becomes unstable. The bottom row of Fig. 1 demonstrates a clear improvement when denoising is used. Only minor reduction in image quality results if the denoising is only applied after every 4 CG iterations (bottom right vs. bottom middle images). Fig. 2 shows a detail view of CGDN MIPs for 640, 1280 and 2560 projections. GraDeS is also able to reconstruct highly undersampled 3D CE-MRA data [7], but requires initialization with the result from a previous time frame. Here it is demonstrated with as little as 1-4 s of data (R~=40 to 150), the CGDN approach can reconstruct each CE-MRA time frame independently. When no data sharing occurs across frames, this leads to a clearly defined temporal resolution for the resulting timeseries. This is in contrast to the GraDeS approach where there is a tradeoff between the number of iterations and the apparent rate of contrast enhancement. Further improvement should be possible by also incorporating denoising along the temporal dimension.

References: 1. Barger et al. MRM 2002;48(2):297. 2. Lustig et al. MRM 2007 Dec;58(6):1182. 3. Adluru et al. JMRI 2010;32:1217. 4. Maggioni et al. IEEE Trans. Image Process. 2011 (In Press, http://www.cs.tut.fi/~foi/GCF-BM3D/). 5. Teramoto and Arai. Proc. ICASSP 1996 p.2702. 6. Pruessmann et al. MRM 2001;46(4):638. 7. Lee et. al. Proc. ISMRM 2011 p. 360.

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