Applying compressed sensing in parallel MRI

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Introduction Applying compressed sensing (CS) [1,2] in MRI has recently attracted much attention, and initial investigation has shown that MR images can be reconstructed from a small subset of the k-space data in the single receiver coil case [3]. The use of multiple receiver coils is now standard in many imaging protocols. We consider the use of CS in recovering MR images from multi-coil datasets and compare the results to those of using a standard direct recovery method (SENSE).

Theory CS theory asserts that, with high probability, the sparse representation of a signal can be recovered from a linear measurement set that is much smaller than that normally needed to define the signal in full. K-space data acquired from different receiver coils are distinct linear combinations of the underlying image due to the distinct coil sensitivity distributions. Thus incorporating measurements from multiple receiver coils allows a higher acceleration factor to be achieved. Image reconstruction can be performed via solving the following convex optimization (adopting the same norm notation as in [1]):

$$\arg\min_x \|y-\Phi x\|_2 + \lambda\|\Psi x\|_1 \ , y = \begin{bmatrix} y_1 \\ y_2 \\ \cdots \\ y_M \end{bmatrix}, \ \Phi = \begin{bmatrix} diag(h)\cdot W \cdot diag(c_1) \\ diag(h)\cdot W \cdot diag(c_2) \\ \cdots\cdots \\ diag(h)\cdot W \cdot diag(c_M) \end{bmatrix} \tag{1}$$

where y_i, c_i, x and h are the stacked column vectors of the partial k-space data acquired from the ith coil, the coil sensitivity of the ith coil, the image to be recovered, and the k-space sampling mask used, respectively. We treat the measurement matrix Φ as a collection of coil sensitivity weighted Fourier matrices (W is the full Fourier encoding matrix) and Ψ is a suitable sparsifying transform. λ is a small constant that controls the data fidelity. Knowledge of the object support region can also be incorporated by masking x with a binary support mask.

Method A T1-weighted 3D brain scan was performed using the SPGR sequence on a GE 1.5T scanner equipped with an 8-channel head coil (128×256×128, TR/TE = 23/10ms, flip angle = 15º). Axial plane (in which under-sampling in both directions is feasible) reconstructions at an acceleration factor of 8 were performed using both CS and 2D SENSE. The sparsifying transform used was the Debauchies-4 wavelet and non-linear conjugate gradient was used to solve (1) [3].

Results Comparing the reconstruction results of using 2D SENSE and compressed sensing (Figure 1), it is seen that the former is corrupted by a high level of noise, whereas the CS reconstruction obviously suffers less from reconstruction noise while being subject to blurring and slight loss of image contrast. Our reconstruction results also showed that applying CS in 2D pMRI also achieves better results than the conventional SENSE approach at high acceleration factors.

Discussion CS reconstruction of MR images using data from multiple receiver coils is limited by two factors: firstly, MR images in practice do not have coefficients which are exactly zeros in the wavelet domain, violating the ideal CS assumption; secondly, the matrix Φ in Eq.(1) is not as mutually incoherent with Ψ as a Fourier matrix [2], and thus data acquired from multiple coils cannot fully compensate for the k-space under-sampling.

Although Φ is of large scale in practice, it (as well as its transpose) can be efficiently implemented using the FFT. The results (128×128) presented took only 100 iterations (about 1 minute) using a Matlab implementation.

Conclusion Initial investigation of applying compressed sensing in parallel MR imaging has led to some promising results and led to better results than the conventional direct recovery at high acceleration factors.

Reference

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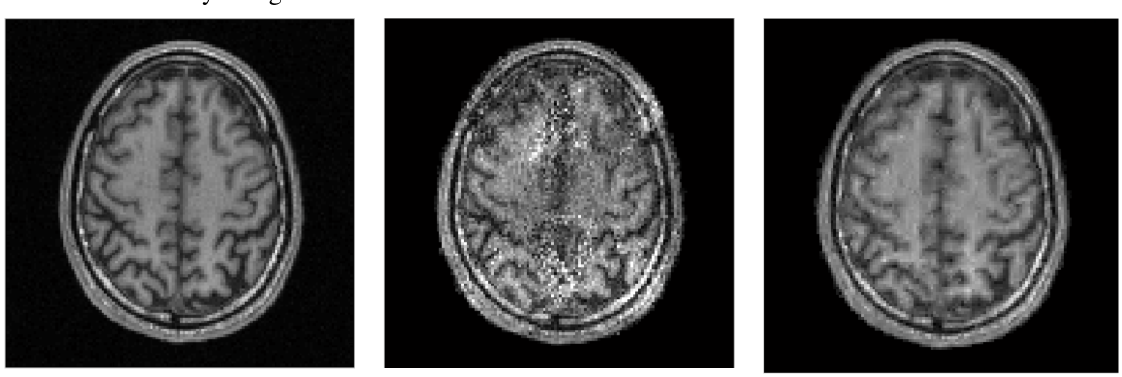

(a) (b) (c)

Figure 1: Reconstruction with (a) full dataset and at acceleration factor of 8 using (b) 2D SENSE (c) CS reconstruction.