Multi-slice Compressed Sensing Imaging

M. Lustig[1], D. L. Donoho[2], and J. M. Pauly[1]

[1]Electrical Engineering, Stanford University, Stanford, CA, United States, [2]Statistics Department, Stanford University, Stanford, CA, United States

Introduction: Compressed sensing [1-2] (CS) is a promising way to exploit the implicit sparsity of MR images for undersampling k-space, and significantly reducing scan time [3-5]. The CS approach requires that the desired image have a sparse representation in a transform domain, that the aliasing artifacts in that transform domain be incoherent, and that a non-linear reconstruction be used to enforce both sparsity of the image representation and consistency with measurements.

Random under-sampling of k-space provides the required high degree of incoherence. Randomized schemes for spirals and Cartesian 3D sampling have been shown to be effective as the aliasing spreads uniformly in two dimensions [3-5]. However, most of the clinical scans today are Cartesian 2D sampling. The incoherency that can be achieved by undersampling such scans is limited to spreading the aliasing in 1D only.

Here, a new randomized sampling strategy is proposed for 2D Cartesian imaging. The multi-slice nature of the 2D acquisitions is used to improve the incoherence in the wavelet domain compared to a simple 2D scan, thus achieving better reconstructions and accelerations. We demonstrate an application for multi-slice fast spin-echo imaging.

Theory: The coefficient spread function (CSF) is a generalization of the point-spread function (PSF) to a transform domain. It measures the interference caused by a single transform coefficient to other coefficients due to undersampling. Formulas for calculating the CSF were given in [4-5]. The side-lobe heights in the CSF offer a measure of sampling incoherence.

In a conventional image domain analysis of 2D multi-slice imaging, the undersampling of one slice can not affect other slices, and aliasing from one slice can not spread to its neighbors. However, in the wavelet domain (of the y-z plane) the slices are no longer independent. Undersampling each slice differently in k-space causes leakage of aliasing to other slices and other wavelet scales thus improving the incoherency. This can be observed in the Coefficient Spread Function (CSF) analysis in Fig. 1.

Methods: We acquired a T2-weighted multi-slice k-space data of a brain of a healthy volunteer using a FSE sequence (256x192x32, res=0.82mm, slice=3mm, echo-train=15, TR/TE=4200/85ms). For each slice we acquired different sets of 80 phase-encodes chosen randomly from 192 possible phase encodes, for an acceleration factor of 2.4. The volumetric data was CS reconstructed with wavelets (Daubechies 4) as the sparsifying transform (applied in both the x-y and the y-z planes) using non-linear conjugate gradient [4-5]. The result was compared to CS reconstruction from a single slice and to a minimum-norm linear reconstruction.

Results: Using the multi-slice approach, the CS reconstruction is able to recover fine as well as coarse structures in the image, eliminating most of the aliasing artifacts. The 2D CS reconstruction still exhibits residual coarse scale aliasing. This is mainly because that coarse scale wavelets are generally less sparse, and because of the large side lobes in the coarse scale CSF.

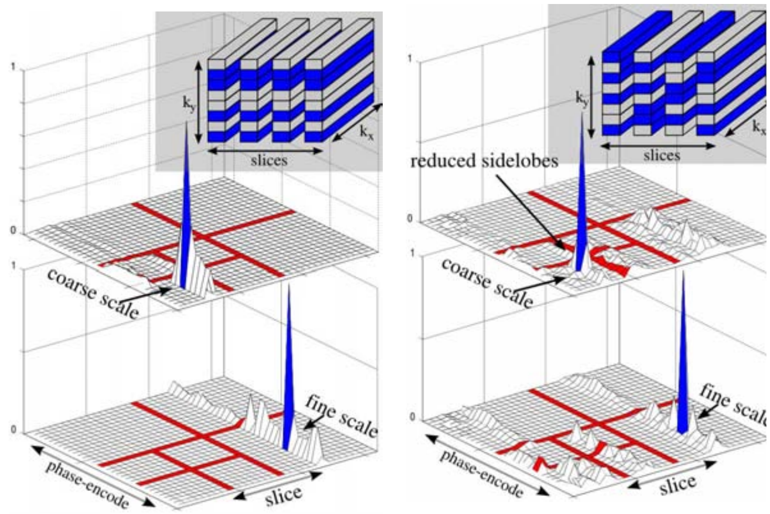
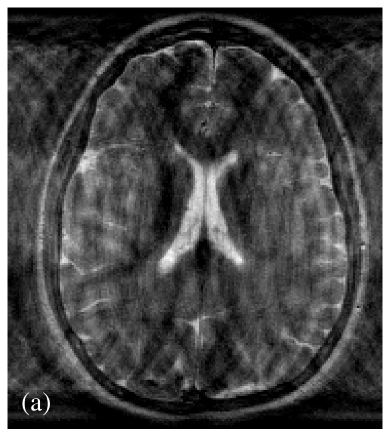


Figure 1: *Coefficient Spread Function analysis in the wavelet domain. Left: Random phase encode undersampling spreads the interference only in 1D and mostly within the same wavelet scale This causes the height of the sidelobes to be large. Right: Randomizing the phase-encodes differently for each slice spreads the interference between nearby slices and among different wavelet scales. This greatly reduces the interference, especially for the coarse-scale wavelet coefficients which are also generally less sparse.*



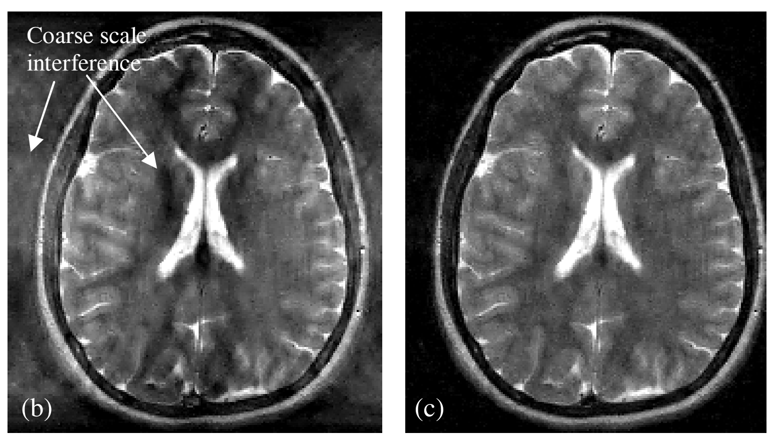


Figure 2: *Reconstruction from 1D random undersampling. (a) minimum-norm. (b) CS reconstruction of a single slice. (c) Multi-slice CS reconstruction.*

Discussion: Using the proposed multi-slice approach, we are able to get a better CS reconstruction from highly under-sampled data. This approach opens the possibility of using CS effectively in multi-slice sequences for accelerating acquisitions. These results also show the importance of the CSF analysis. Although we showed a Cartesian example, using these ideas for non-Cartesian multi-slice imaging is also possible. It is also important to mention that CS exploits sparsity, and therefore can be used along with methods like partial k-space and SENSE that exploit different redundancies.

References: [1] Candes et al, IEEE Tran Info Theo 52:489–509(2006) [2] Donoho DL, IEEE Tran Info Theo 52:1209-1306(2006) [3] Lustig et al, Proc ISMRM 2005:685 [4] Lustig et al, Proc ISMRM 2006:695 [5] Lustig et al, “Sparse MRI”, manuscript submitted to MRM