13.22 Which 1980's and 1990's super-resolution reconstruction ideas would prove useful when 2011's compressed sensing reconstruction is used for MR sparse angiography?

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Introduction:
With the availability of efficient algorithms for non-linear optimizations there has been an explosion of interest in applying compressive sensing (CS) techniques [1, 2]. A key idea behind MR sparse angiography is the gathering of reduced k-space data sets. This concept traces back to super-resolution reconstruction (SR) algorithms [3, 4] designed to improve upon techniques of earlier partial Fourier transform reconstructions [5]. We discuss some of the processes and validation techniques from super-resolution reconstruction that can be adapted to compressed sensing reconstruction.

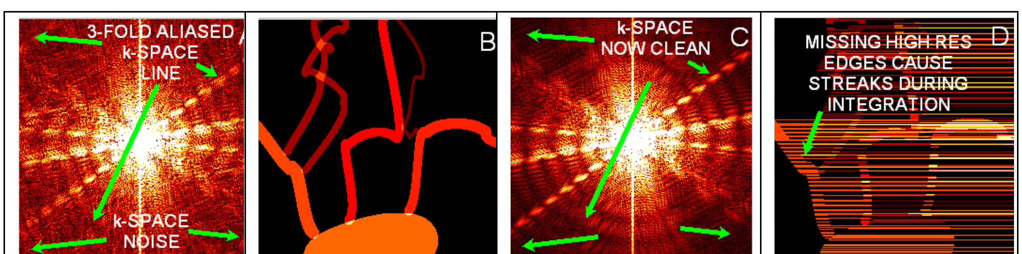
Discussion 1: *Use of accurately simulated data is a key to validation and fine tuning of reconstruction algorithms.*
CS algorithms have been validated on simulated frequency domain data (Fig. A) generated by discrete Fourier transforming (DFT) a sampled, real-number (magnitude), Shepp-Logan phantom image (Fig. B) [1]. However, frequency domain data generated in this manner do not reflect the true characteristics of MRI *k*-space data in many ways: (1) High frequency components are distorted through signal aliasing (c.f. Fig. C); (2) Experimental noise is incorrectly modeled since MRI reconstructions have Gaussian white noise characteristics in both real and imaginary components of the image which are modified by the operation to produce the magnitude image; (3) The frequency peak value is centred in *k*-space, which does not model the presence of experimental distortions which lead to 'image phasing' issues; and (4) the centre peak is included as a sparse sample. Validating CS algorithms on simulated data calculated in k-space provides a better match to experimental MRI scenarios. The CS reconstruction algorithm by Lustig et al [2] attempts to handle phase issues by using information from a limited data set associated with the centre of k-space (a low-resolution image). The SR approach of modeling the hermitian and anti-hermitian components of all of the available data set [3, 6] may provide a better solution.

Discussion 2: *Use of algorithms that accurately match the data characteristics.*
We propose using a data model suggested in SR paper [6] that treats MRI images as a sum of quasi box-car data blocks of differing intensities; a *k*-space data model involving a sum of sinc functions *sin Ak / Ak*. Multiplying the experimentally gathered *k*-space data by *k* then permits a simplified reconstruction involving only sinusoidal *k*-space components; edges in the image domain. This reconstruction approach truly matches the compressed sensing criterion that the data be sparse in one domain. The actual success of this approach can prove problematic (Fig. D c.f. [6]) since image reconstruction requires digital integration of 'very sharp' edges which typically 'fall between' the sampled values of the image when this model truly matches the data characteristics. In the talk we demonstrate moving the SR solutions into CS.

Discussion 3: *Which 'gold standard' image is correct for validation*?
Smith et al. [7] proposed all reconstructions be subject to initial validation via '*DFT matching*', i.e. no image pixel should differ from a low resolution image by more than 8% of the largest intensity jump in an image row or column; a Gibbs phenomena based success criterion. In [3, 5] SR reconstructions often had higher spatial resolutions than the ideal reconstruction from the original k-space data set. To overcome validation issues in this situation, proposals have been made for frequency domain mean square error metrics [3] or (better) automated visual difference predictors [8] that determine whether the human eye would notice differences between images from various reconstruction algorithms.

Conclusion:
We outlined issues raised during investigation of super-resolution image reconstruction techniques that have not been resolved with current compressed sensing algorithms. In the talk, we show results from addressing such issues in the new CS context.

References:
[1] E. Candes and J. Romberg, Software available at www.l1-magic.org. Accessed 31 May 2011.
[2] M. Lustig et al., Magnetic Resonance in Medicine #58: 1182 – 1195, 2007.
[3] M. R. Smith et al., IEEE Transactions on Medical Imaging, #5:3, 132 - 139, 1986.
[4] Z-P. Liang et al., Reviews of Magnetic Resonance in Medicine, #4, 67-185, 1992.
[5] G. McGibney et al., Magnetic Resonance in Medicine, 3#9, 51 - 59, 1993.
[6] M. R. Smith and S.T. Nichols, Magnetic Resonance Imaging, # 8, pp. 173 - 183, 1990.
[7] M. R. Smith and S. T. Nichols, Proceedings of 10th Annual Meeting Society of MRM, San Francisco, #2, 749, 1991.
[8] M. R. Smith et al., Invited talk at MR Signal Processing Workshop, Beckman Institute, Illinois, Oct. 1996.



A) Aliasing and other issues means that k-space information generated from a DFT of an angiographic phantom image (B) does not match the experimentally gathered k-space data (C) whose reconstruction will exhibit truncation artifacts. Direct digital integration of SR edge reconstructions (D) generated using the proposed approach involving multiplying the k- Space data by *k* could appear unstable when 'too successful' with images with many sharp edges [c.f. SR results in 6]