Moving the best parts of 1985's constrained sensing reconstruction to 2011's compressed sensing reconstruction M. Smith, Electrical and Computer Engineering, Radiology, Hotchkiss Brain Institute University of Calgary

Financial support from NSERC, Analog Devices and University of Calgary

Acknowledgements: Ethan MacDonald, Philippe Gauderon, Hongmei Zhu, Richard Frayne and Emily Marasco

### Topic to discuss

- Is MRI CS being validated the wrong way?
- Novel MRI approach for use with CS
- Impact of CS reconstruction using wrong simulated data
- Other things to try from constrained sensing reconstruction (super-resolution)

### CS validation approach demonstrated in L1-Magic software package



### CS validation approach that best mimics true MRI data



### Are these validation approaches really different?







Generate angiographic 256 x 256 phantom using techniques similar to Shepp-Logan phantom generation.
Evidence of k-space aliasing of data
Evidence of k-space 'mud' (noise from aliasing)



#### Aliasing fairly easy to 'fix' by generating kspace data from higher-resolution image



K-SPACE

6

- (mainly) outside of truncated area(ARROWS).Need to go to at least 1024 x 1024 resolution
- or calculate directly (analytically) in k-space

#### k-space offset can only be modeled via k-space data manipulation



REAL COMPONENT OF IMAGE WITH PHASE-SHIFT



Modeling of k-space data by ANY algorithm works best when complexity such as this is removed from the data set IMAGINARY COMPONENT OF IMAGE WITH PHASE-SHIFT



### Approach to solve k-space data offset using ideas from SR reconstruction

• Lustig et al. (MRM #58, 1182-95, 2007) used SMALL PARTof k-space (centre) to identify offset



• Smith et al. (IEEE TMI, #5:3, 132-9, 1986) suggest using ALL AVAILABLE DATA for phase correction

Hermitian data set  $S(n)_{H} = (S(n) + S(-n)^{*})/2$ anti-Hermitian data set  $S(n)_{AH} = (S(n) - S(-n)^{*})/2$ 

- Super reconstruction is performed on both data sets independently before images are recombined.
- Problem to overcome approach only demonstrated during 1D super resolution reconstruction. MATCHES some of Lustig's proposed symmetric CS sampling schemes,



#### MRI white noise MUST be added to k-space data



Henkleman, Med. Phys. 1985
McGibney, Med. Phys. 1993
Gudbjartsson , M.R.M. 1995
Image noise is
1.Quasi – gaussian on large
intensity object
2.Mixed characteristics on lower
intensity object
3.Rician on background



### Incorrect modeling of noise is a common problem seen in literature

- Generate DSC CBF
   concentration curves
- Add gaussian noise (NO!)
- Deconvolve and Analyse

#### **CORRECT MODEL**

- Generate DSC CBF concentration curves
- (1) Transform to Intensity space,
- (2) Add gaussian noise;
- (3) Transform back
- Deconvolve and Analyse
- Smith et al., MRM 2001.



#### Applying CS to wrong data set? My novel approach

- You need the data sparse in one domain to get CS to work
- Use (1D) simulation of box-car is not sparse
- Using the edges of the box-car is sparse



## Problems to solve with validating algorithms this sort of data

• How can you generate 'EDGE' k-space data experimentally?



ANSWER: Multiple original k-space data of NON-EDGE image by k.
 Important to avoid aliasing in original k-space data



## Problems to overcome when using 'edge' k-space data

- Multiplication by k enhances high frequency noise components
  - Especially true for 'wide' image components which are 'narrow' in frequency domain
  - SOLUTION: Fit wide and narrow separately?
- In super-resolution image reconstruction using TERA (Smith, 1990) only needed a few data points in edge k-space to recognize edges since 'sinusoids' are easy to model.

### Modeling the data edges can work 'too well' with phantoms

- Frequency components have form
   A cos (2 ∏F (k-1) / N) + j B sin (2 ∏F (k-1) / N)
  - Problem if F is NOT an integer as image edges fall between sample points so numerical integration fails

MISSING HIGH RES

EDGES CAUSE STREAKS DURING

INTEGRATION

 Solution with super-resolution reconstruction was its inherent ability to zoom data x 16 or more times PLUS ability to apply DFT matching and pole pulling to control image instabilities in reliable fashion

M. R. Smith and S. T. Nichols, Proceedings of 10th Annual Meeting Society of MRM, San Francisco, #2, 749, 1991

### Where are we at in trying these SR ideas with CS reconstruction?

- 'Correct' validation versus 'Incorrect' validation examined for L1MAGIC software completed
  - Working on Lustig re-validation different from L1magic
- Components
  - Experimentally gather limited k-space (on a 256 x 256)
  - Apply L1-magic
  - Generate CS-image (256 x 256)
- Validation
  - Compare CS-image to what you would have got if you had gathered all the 256 x 256 k —space data

### This is the INCORRECT validation procedure for constrained imaging



IMAGES FROM L1MAGIC SOFTWARE PACKAGE



Validation is wrong as we are not simulating the correct k-space data

- Components
  - Experimentally gather limited k-space (on a 256 x 256)
  - Apply L1-magic (or other reconstruction algorithm)
  - Generate CS-image (256 x 256)
- If we tune our CS algorithms for the wrong sort of simulated data then the algorithm may not be correctly tuned for the true experimental data.
  - If we tune our algorithms for the correct experimental data, what will be reviewer's comments?

Differences in the k-space data that will be sparsely sampled during CS validation



# So what happens if we use the correct data in CS reconstruction

- It will either work to bring back the 'gold standard' image or it will not work
  - Is the truncated image the correct 'gold standard' image?
  - Reviewers often insist on 'exact and unrealistic' phantoms which means 'good' algorithms that work well experimentally are discarded
- If the L1MAGIC algorithm does not work on 'real' kspace data (truncated with offsets causing image phase shifts) then we must investigate whether
  - Minor tuning of algorithm required
  - Major tuning of algorithm required

#### Differences in phantom images Which 'gold standard' acceptable to reviewers?



#### CS applied to truncated data



#### If the k-space data is fermi-filtered, does the CS reconstruction improve?



#### Lots of possible future directions

- DEFINE 'DOES THE RECONSTRUCTION IMPROVE?'
  - K-space difference metrics and Visual Difference Predictors
- STRANGE IMAGES; MISSING DATA REINTRODUCED, NOT MISSING NOISE.
  - Determine image then move back (FFT) into frequency domain. Now add back gaussian random noise on the new points of k-space data before IFFT.
- REVALIDATE LUSTIG'S CS RECONSTRUCTION APPROACH.
- BO AND GRADIENT ISSUES MEANS THAT THE PEAK OF K-SPACE DATA IS NOT CENTRED AT (0, 0) UNLIKE THE IDEAL PHANTOM.
  - Solution from super-resolution -- Reconstruct Hermitian and Anti-Hermitian components of image and recombine.
- INVESTIGATE ISSUES OF 'EDGE GENERATION' RECONSTRUCTION
  - Issues involving multiplying experimental k-space data by k
- OVERLAP BETWEEN SPARSE SAMPLING AND SUPER-RESOLUTION
  - Can they be usefully combined?

#### Conclusion

- Much may be transferred from early attempts to reduce kspace data requirement started with partial Fourier transforms (late '70s) and super-resolution (SR) algorithms (late '80's).
- Current constrained sensing (CS) algorithms are being incorrectly validated (i.e. assumed to be working correctly) using Shepp-Logan like phantoms.
- Have suggested a number of solutions and new approaches that could be moved from SR to CS.
- Initial investigations under way already show that current CS algorithms need to be modified to correctly handle the 'true' characteristics of experimental k-space