Optimizing calibration kernels and sampling pattern for ESPIRiT based compressed sensing implementation in 3D MRI

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The new hope: Compressed Sensing or Compressive Sensing

E. Candès, J. Romberg, and T. Tao, "**Robust Uncertainty principles: Exact signal reconstruction from highly incomplete frequency information,**" IEEE Trans. Information Theory, 2006

D. Donoho, "**Compressed sensing,**" IEEE Trans. Information Theory, 2006

- It states that signals or images can be accurately reconstructed from far fewer measurements than traditional methods that satisfy Shannon-Nyquist theorem under certain conditions.
- It works on two principles, sparsity and incoherence.

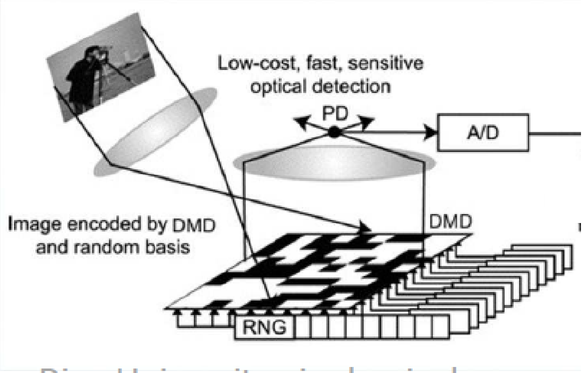
Courtesy: Mike Davies (University of Edinburgh)

Potential applications

Compressed Sensing provides a new way of thinking about signal acquisition.

Applications areas already include:

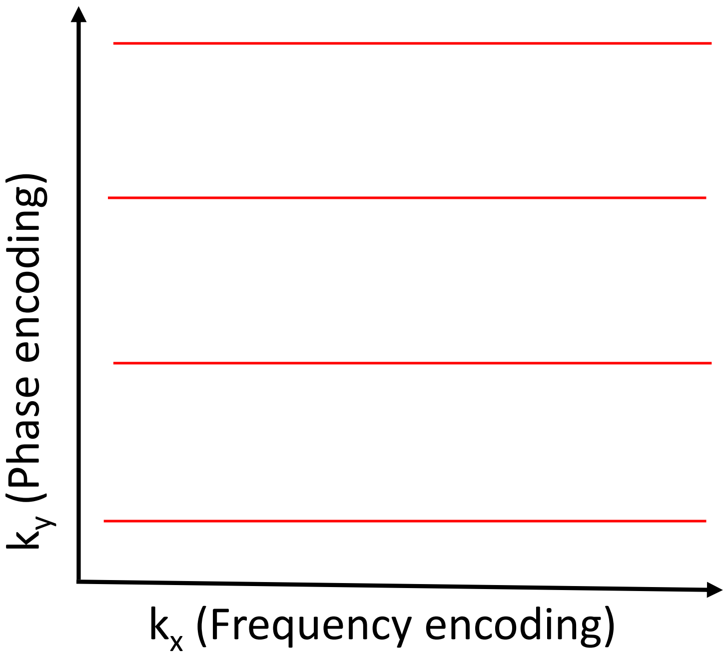
- Medical imaging
- Hyperspectral imaging
- Astronomical imaging
- Distributed sensing
- Radar sensing
- Geophysical (seismic) exploration
- High rate A/D conversion



Rice University single pixel camera

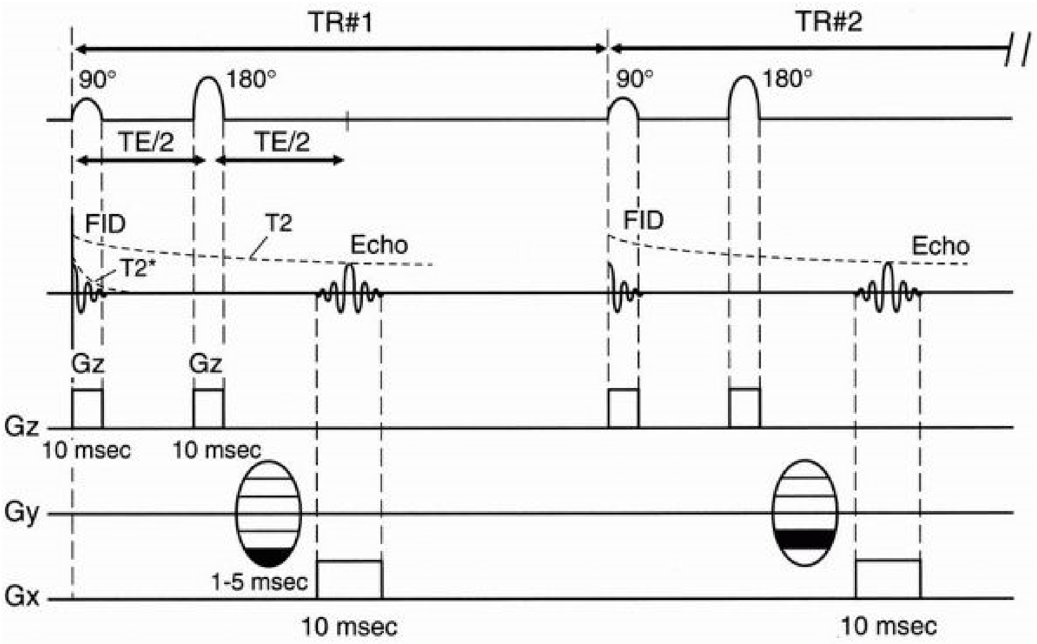
MRI data acquisition

k-space data



- The readout gradient G_x is on for the echo duration (i.e.) a line of k-space is acquired for each echo along the x direction.
- The phase encode gradient G_y varies for every repetition pulse which causes the shift in k-space along y direction.

Spin Echo Pulse sequence diagram



TE- Echo Time; TR – Repetition time

- Acquisition Time is proportional to the number of phase encodes (N_p) (i.e.) equal to the number of repetitions (TR's)

MR image acquisition: Challenges

- an inherently slow process.
- Complete measurements can be costly and time consuming.
- Currently, parallel imaging is used to speed up image acquisition.
- However, there is a great need for further acceleration in several MRI applications due to clinical time constraints (i.e. maximum permissible time inside an MRI scanner) and local motion (i.e. due to breathing, beating heart) as a result of the long data acquisition process. .
- **Compressed Sensing** is the answer to solve this problem as it has been shown to provide further acceleration in MR data acquisition.

Compressed Sensing (CS) in MRI (Sparse MRI)

Michael 'Miki' Lustig

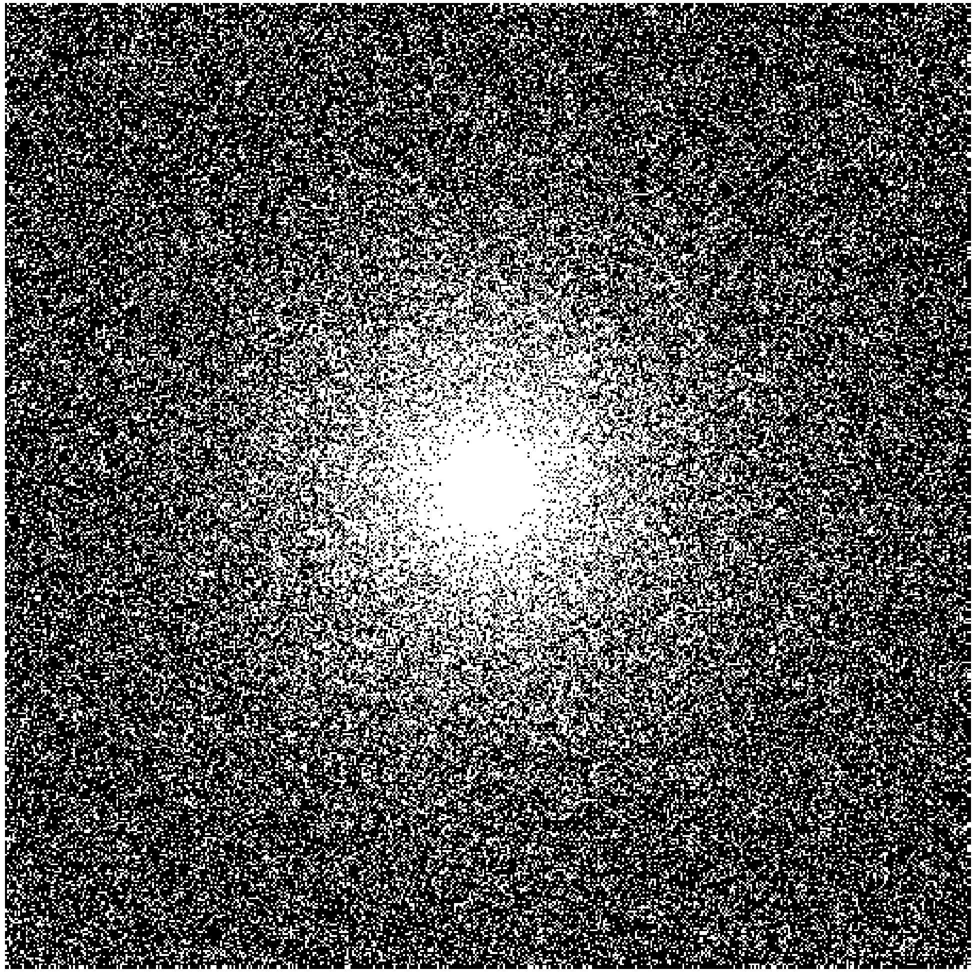
A successful application of CS has three requirements:

- Transform sparsity: The desired image should have a sparse representation in a known transform domain (i.e., it must be compressible by transform coding).
- Incoherence of undersampling artifacts: The artifacts in linear reconstruction caused by k-space undersampling should be incoherent (noise like) in the sparsifying transform domain.
- Nonlinear reconstruction: The image should be reconstructed by a nonlinear method that enforces both sparsity of the image representation and consistency of the reconstruction with the acquired samples.

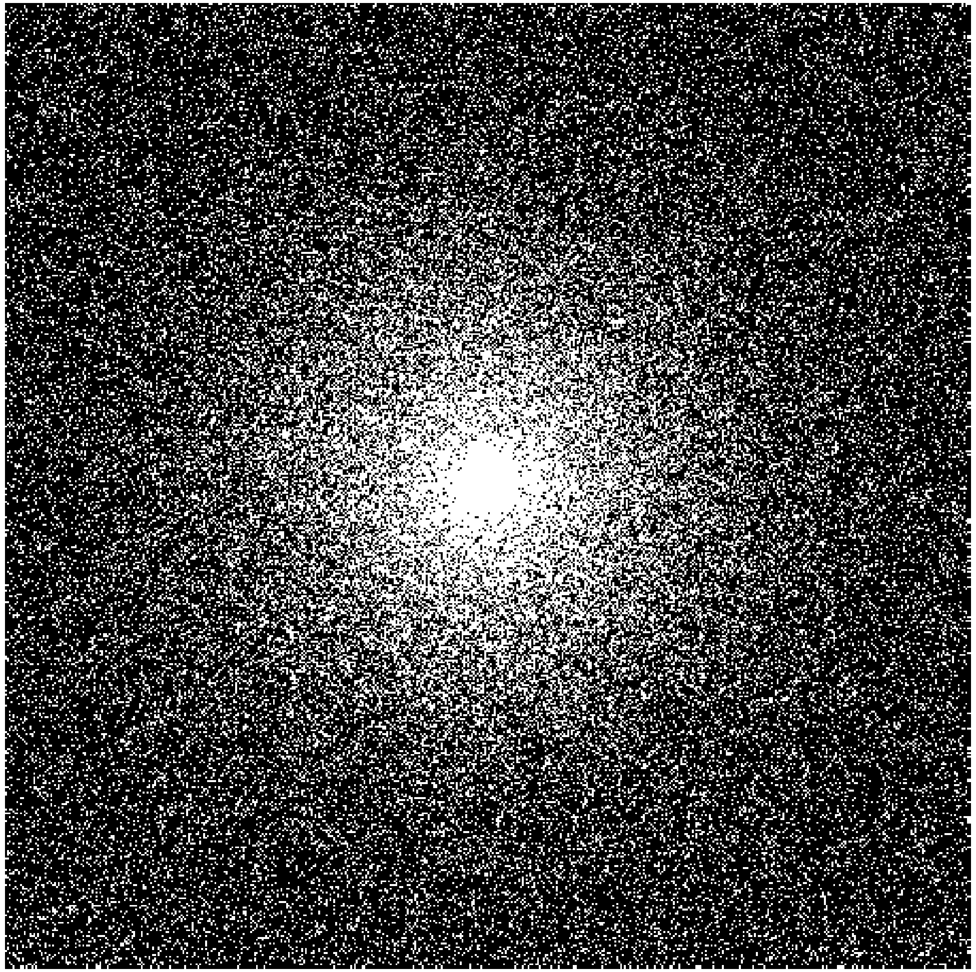
Lustig, M., Donoho, D. L., Santos, J. M., & Pauly, J. M. (2008). Compressed sensing MRI. *Ieee Signal Processing Magazine, 25*(2), 72-82. doi: Doi 10.1109/Msp.2007.914728

Compressed Sensing Example

Random Sampling Mask R=3

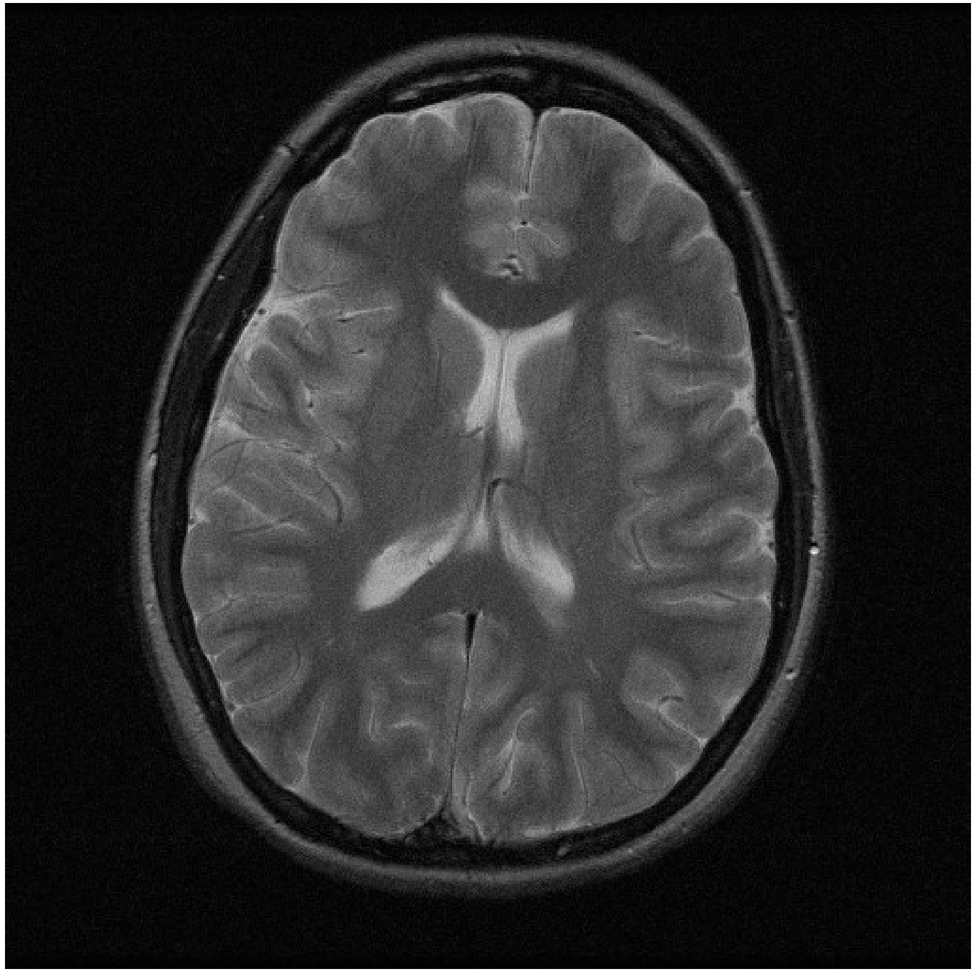


Random Sampling Mask R=4

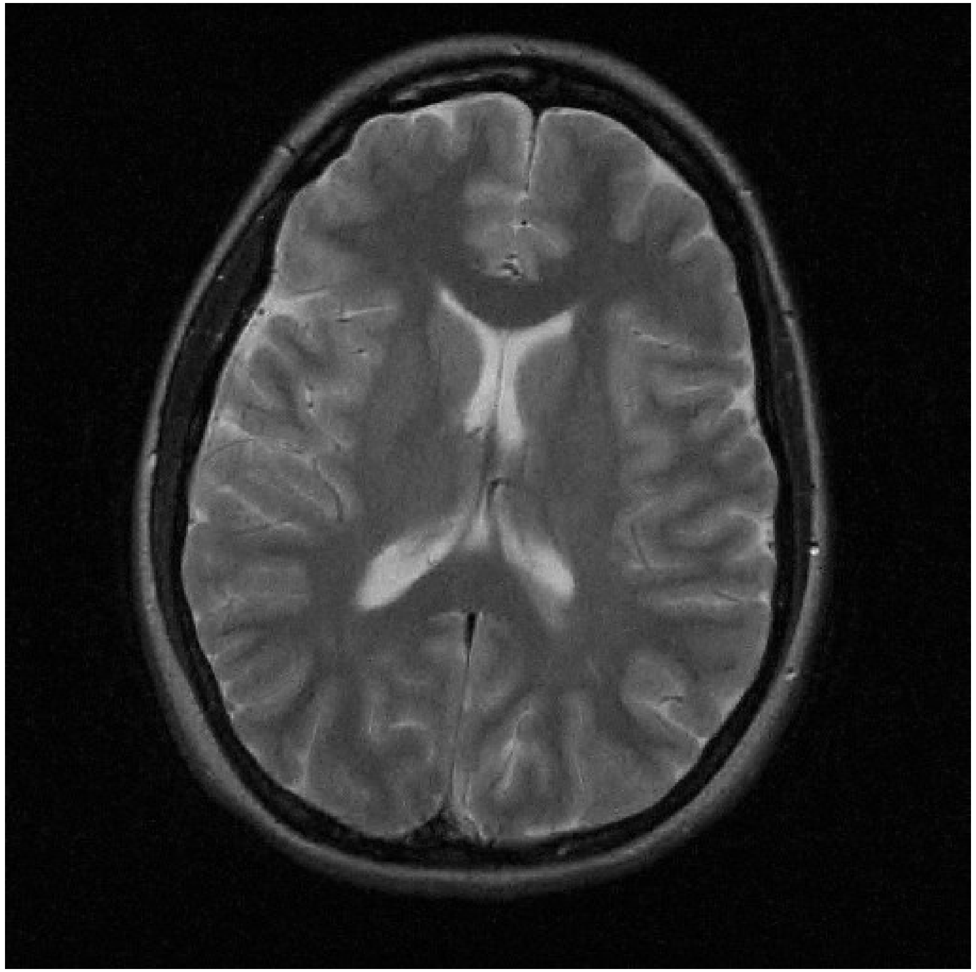


Compressed Sensing Example

Original Image

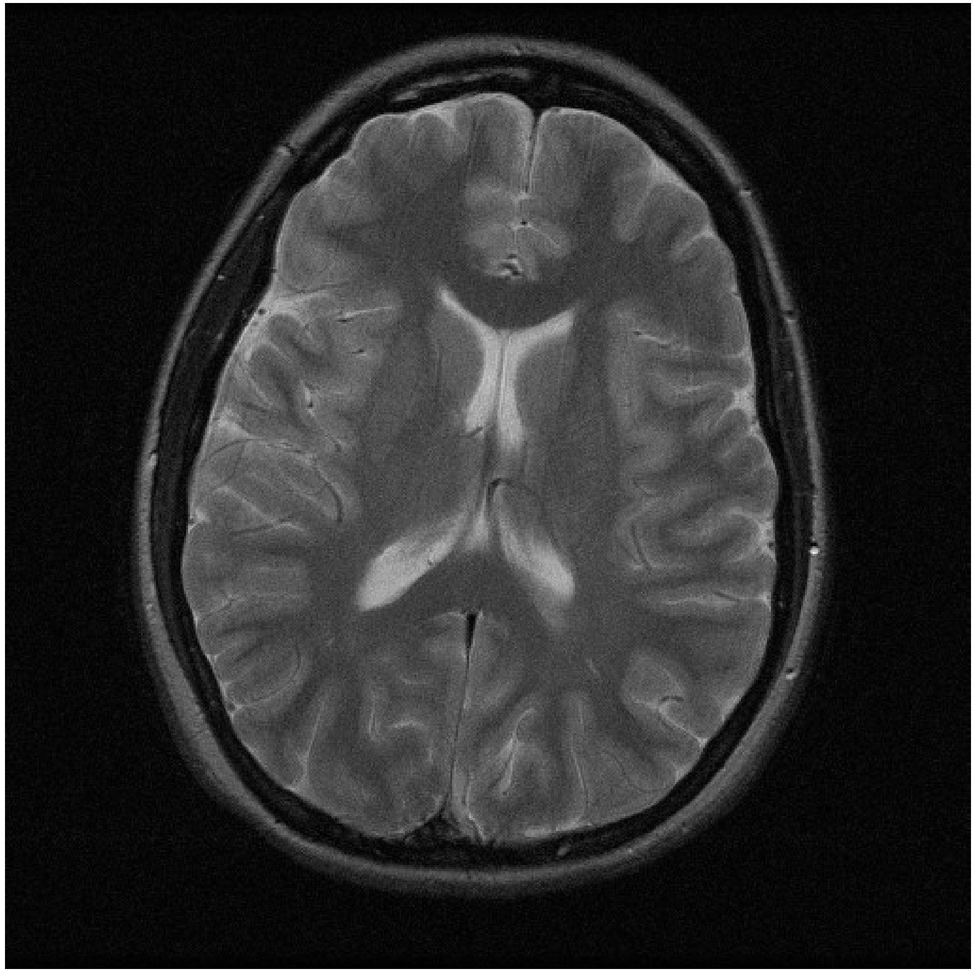


Compressed Sensing Reconstruction R=3

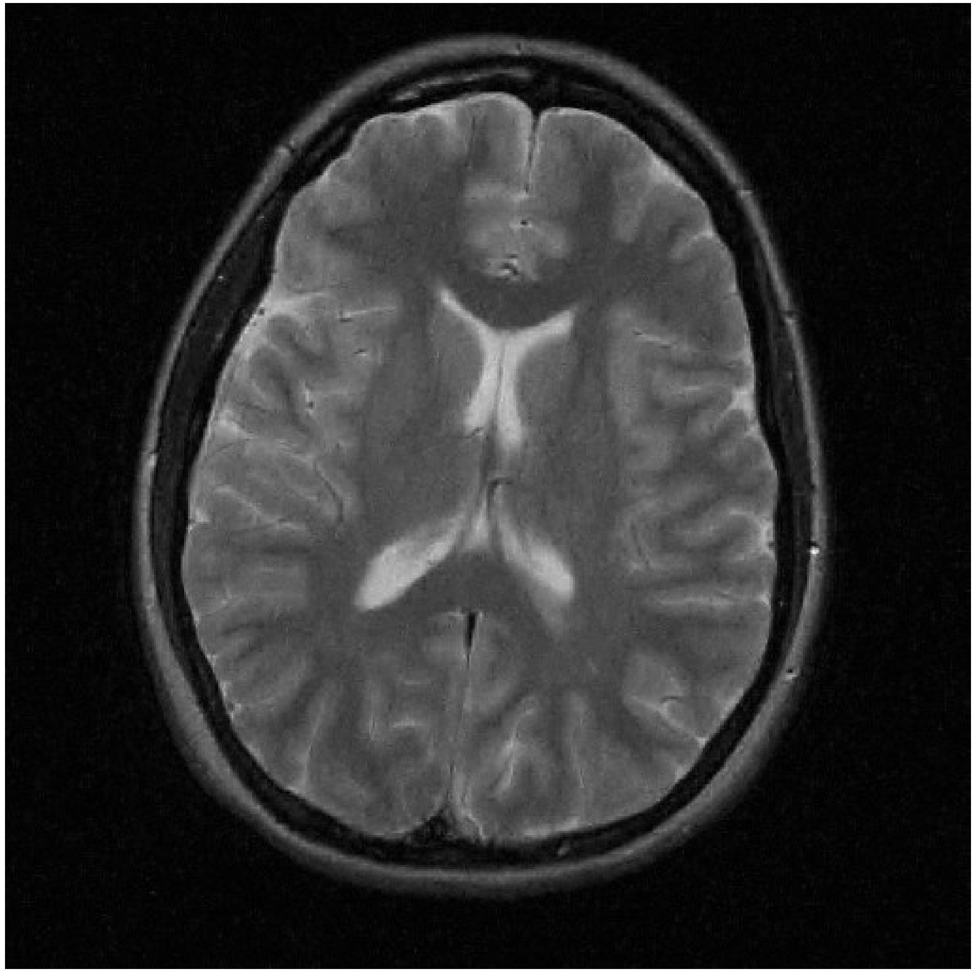


Compressed Sensing Example

Original Image

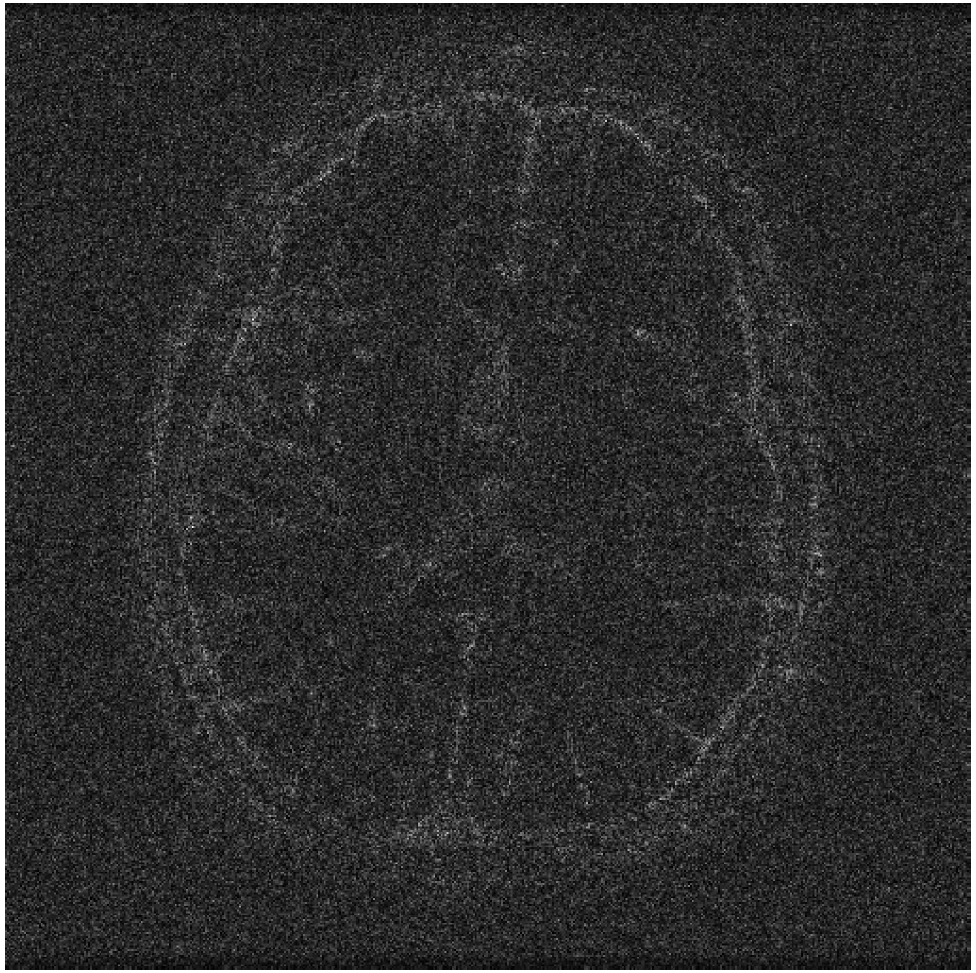


Compressed Sensing Reconstruction R=4

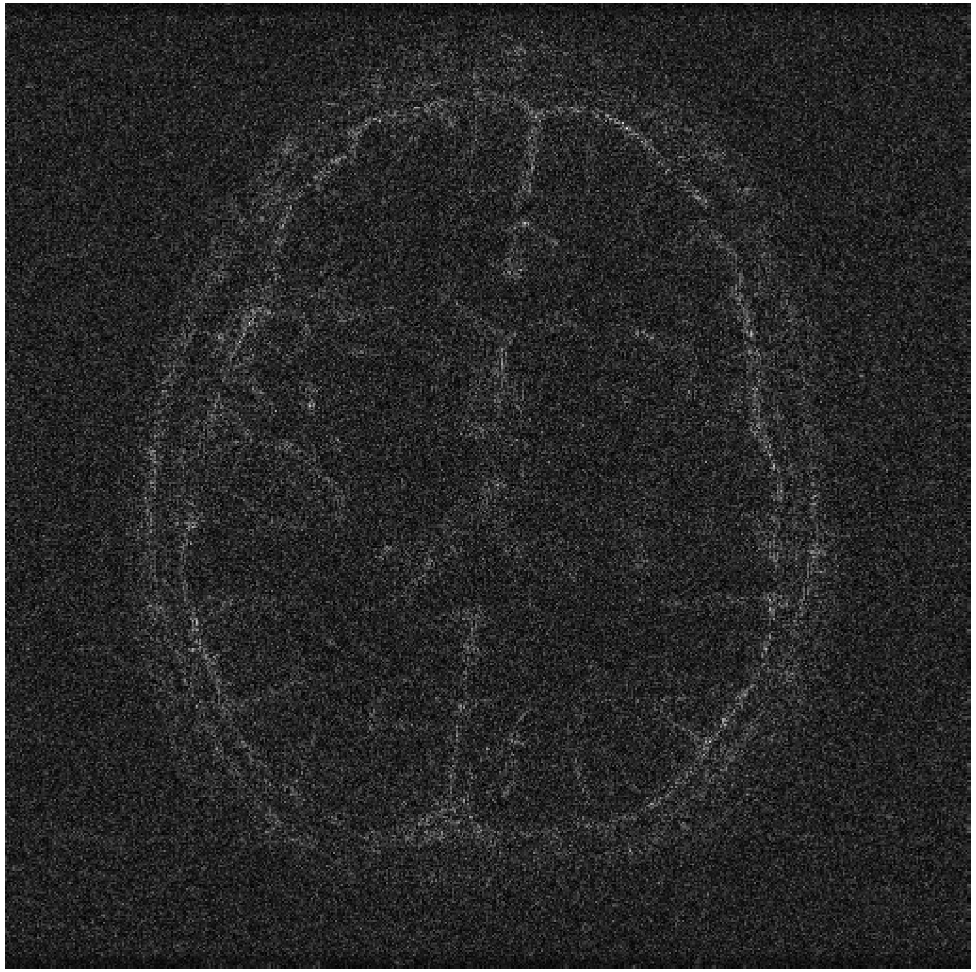


Compressed Sensing Example

Error R=3



Error R=4



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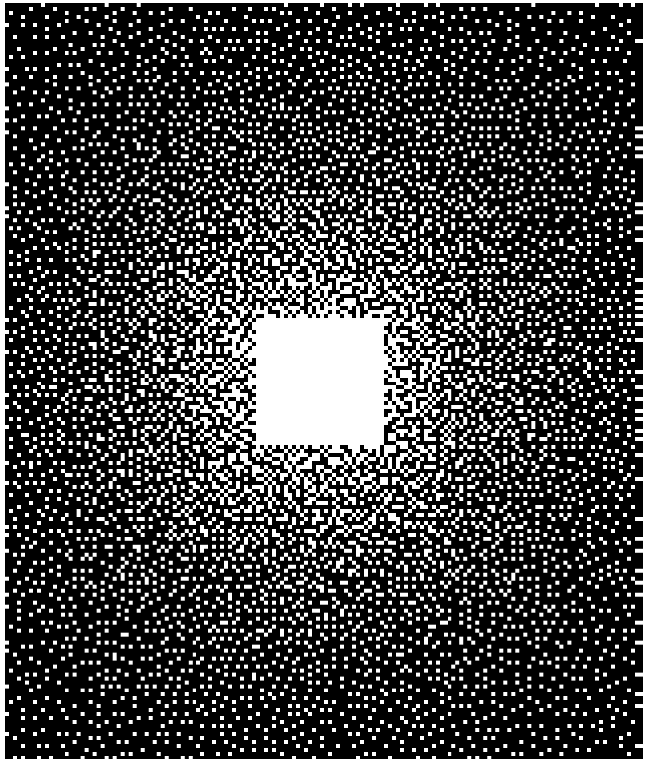
CS implementation in MRI Scanner: Challenges

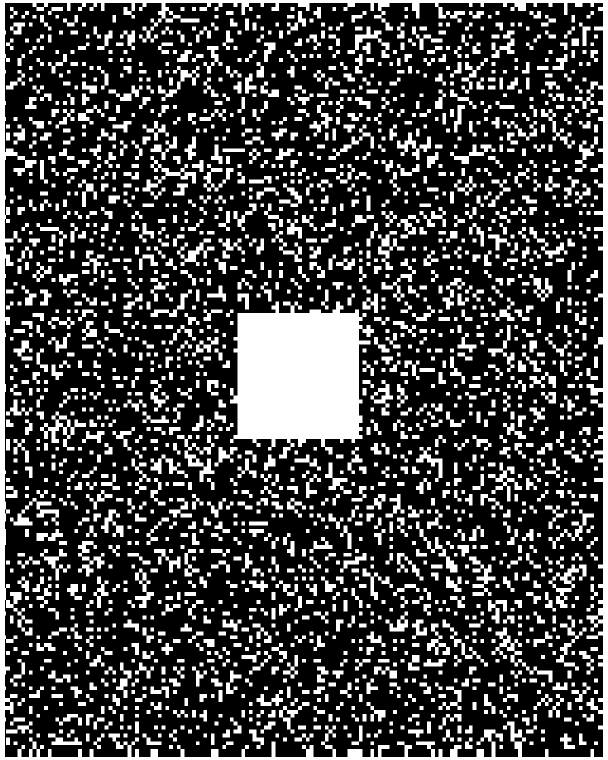
- CS works well for a random undersampling scheme that requires subsampling in both directions.
- It cannot be implemented in traditional 2D MRI because of the presence of only one phase encode direction. Subsampling the frequency encode or readout does not provide a reduction in scan time.
- However, it can be implemented in 3D MRI by exploiting the two phase encoding directions (generally k_y and k_z)
- We have successfully managed to implement this subsampling scheme by modifying a clinical 3D MRI sequence (efGRE3d). As a result 3d MRI datasets can be acquired at reduced scan times.
- It has been validated by custom built in-house phantom data so far. The next step is to collect real brain data from volunteers at reduced scan times and test the efficacy of CS reconstruction.

Effect of Sampling Mask

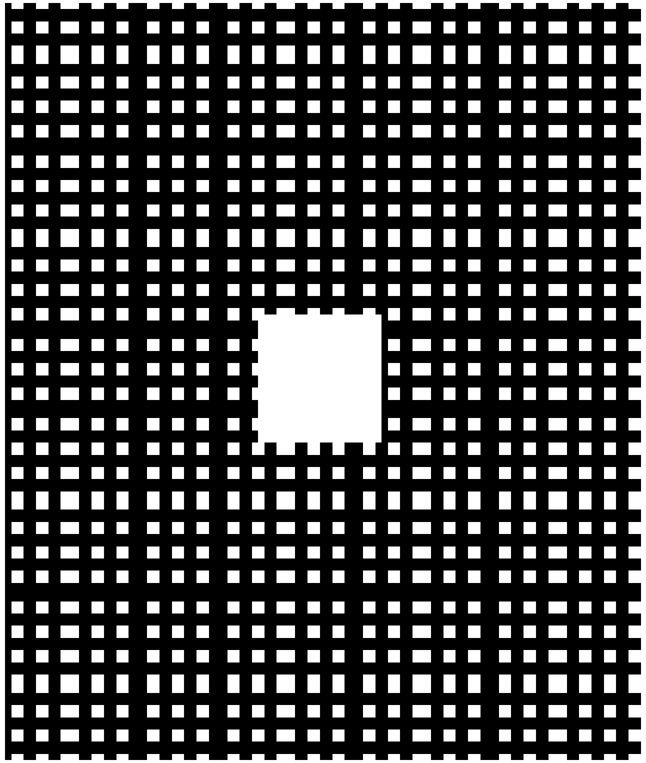
Poisson Disk Subsampling R=4



Random Subsampling R=4

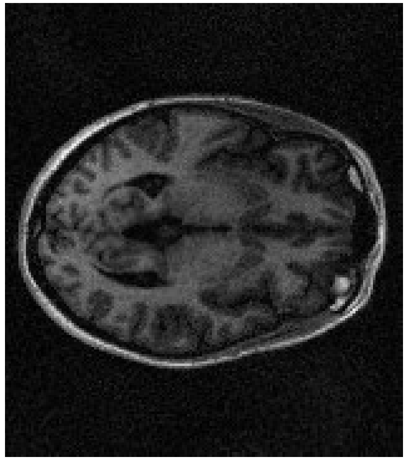


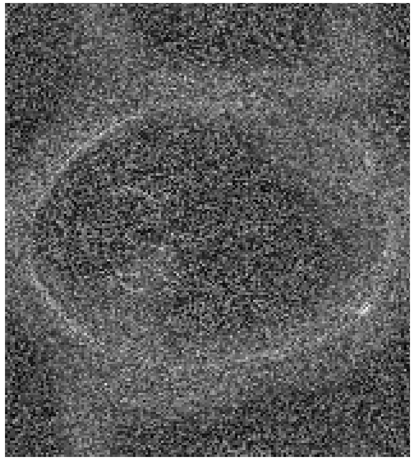
Uniform Subsampling R=4



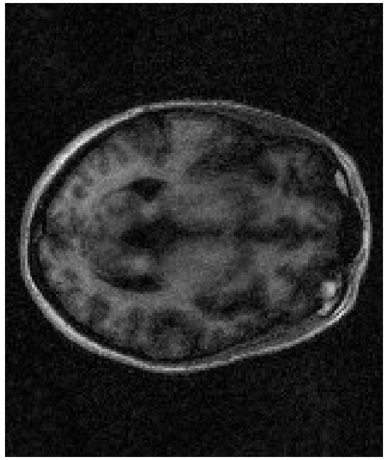
Effect of Sampling Mask

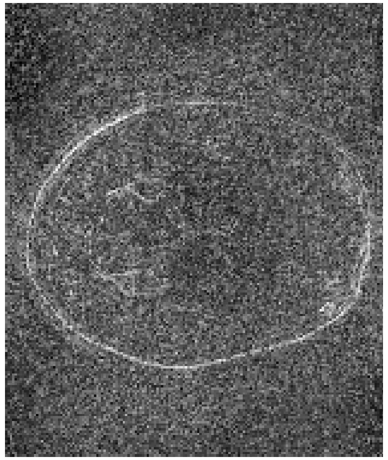
Poisson Disk Subsampling R=4



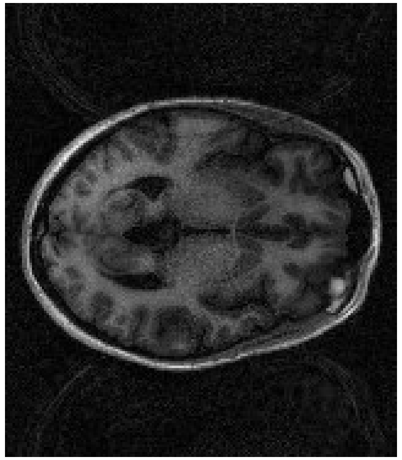


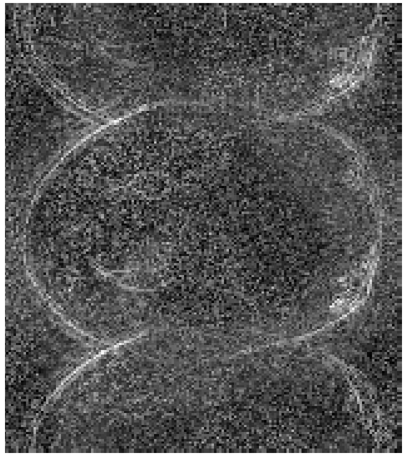
Random Subsampling R=4





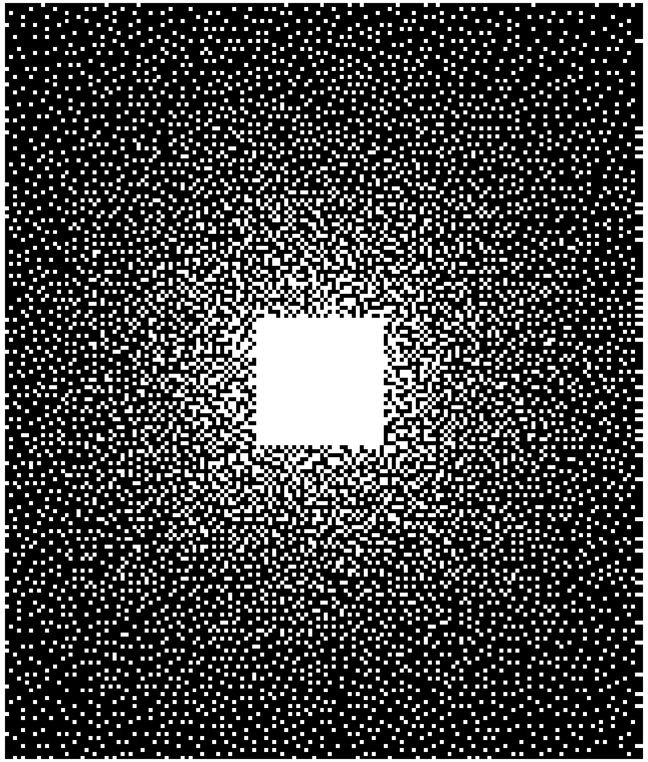
Uniform Subsampling R=4



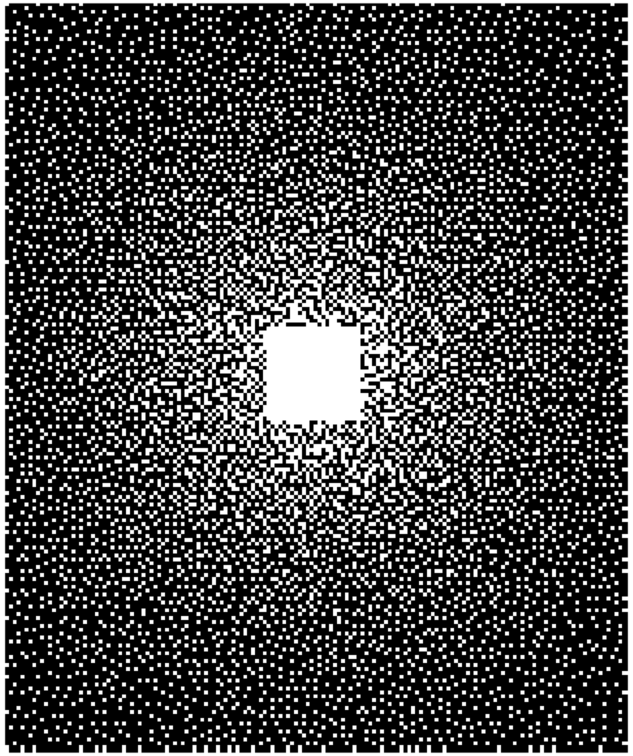


Effect of calibration size/central data

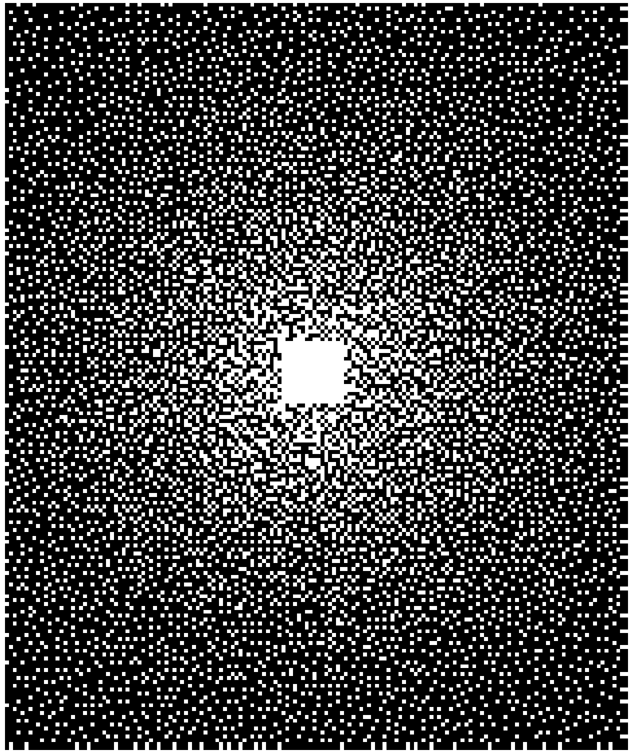
Poisson Disk R=4 32x32 centre



Poisson Disk R=4 24x24 centre

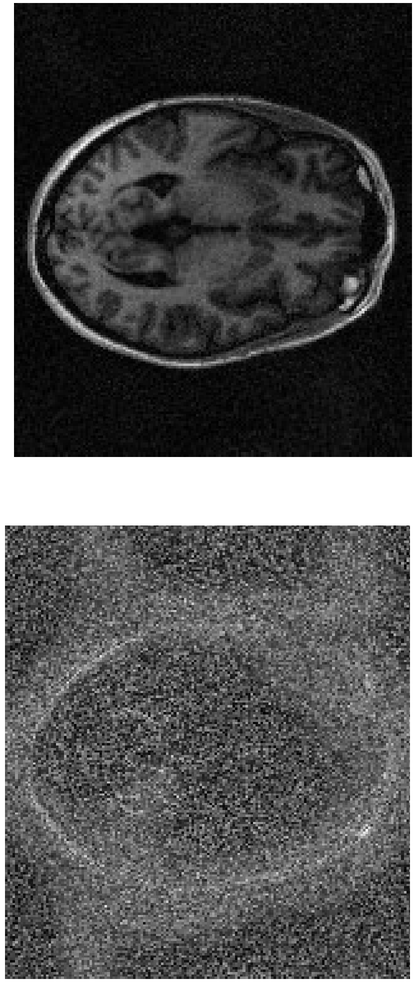


Poisson Disk R=4 16x16 centre

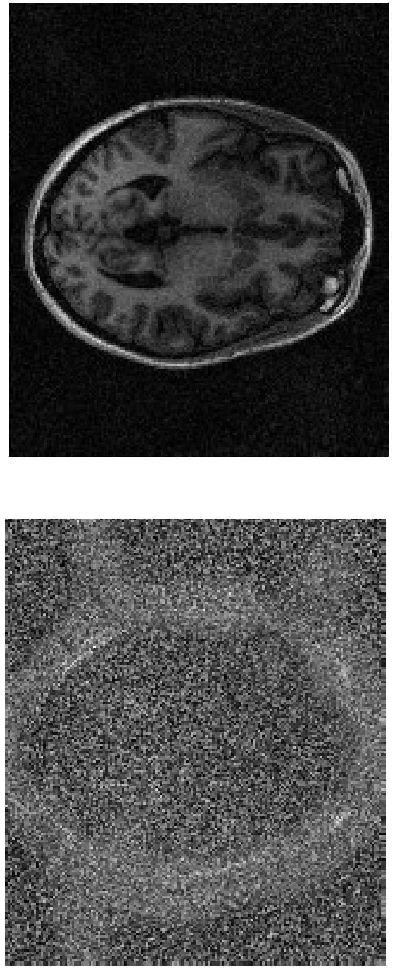


Effect of calibration size/ central data

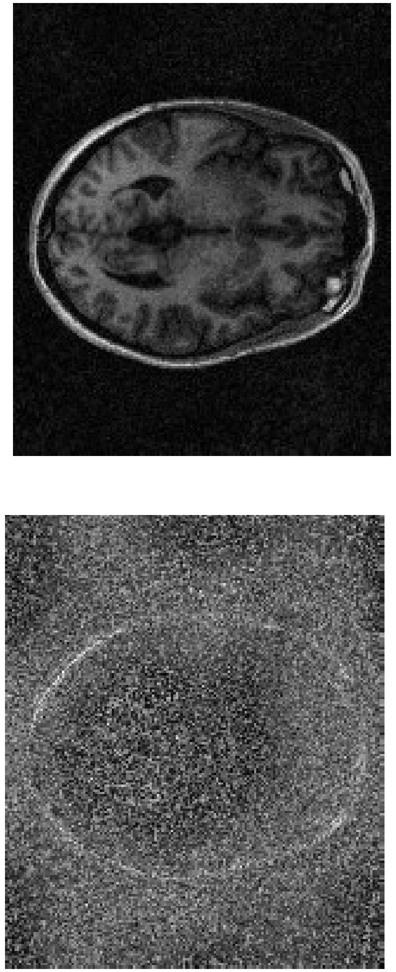
Poisson Disk R=4 32x32 centre



Poisson Disk R=4 24x24 centre



Poisson Disk R=4 16x16 centre



RMSE/ nRMSE values

Calibrat-ion size	Type of sampling mask	RMSE	nRMSE (%)	No. of samples	R
16x16	Poisson Disk	5.8933	20.98	7625	4.02
24x24	Poisson Disk	5.1622	17.65	7495	4.09
32x32	Poisson Disk	5.0043	16.78	7460	4.11
32x32	Random	7.2809	26.85	7576	4.05
32x32	Uniform	5.5393	18.59	7680	4.00

Discussion/ Open Questions??

- Does the performance of CS reconstruction depend on the contrast setting in the image??
- Can an intuitive subsampling scheme be designed according to the type of structure being imaged??
- Is there any other way to quantify reconstruction errors apart from RMSE and nRMSE values??
- Is it important to investigate the nature of the error rather than just look at error values??
- Can the performance of CS reconstructions improve if an efficient segmentation method is incorporated into the algorithm??

Acknowledgements

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- Prof Mike Davies (IDCOM, University of Edinburgh)
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