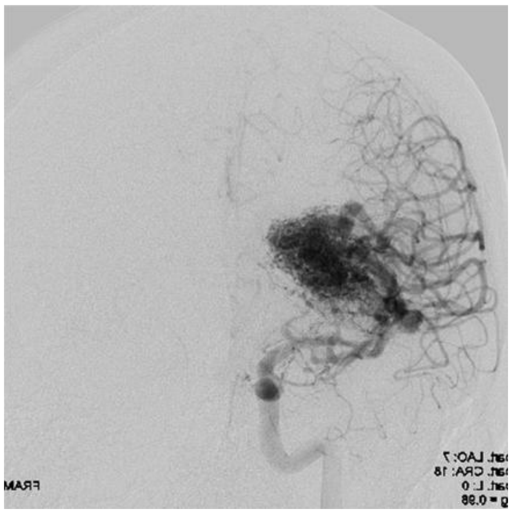
Application of Temporally Constrained Compressed Sensing for High Spatial and Temporal Resolution MRI

J. V. Velikina, K. M. Johnson, S. R. Kecskemeti,
C. A. Mistretta, P. A. Turski, A. A. Samsonov

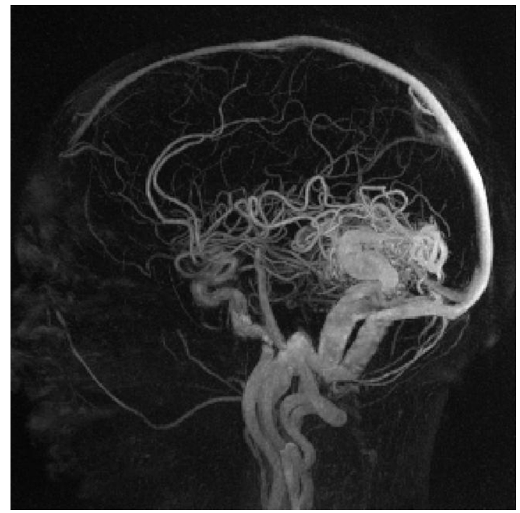
University of Wisconsin – Madison

Accelerated Imaging: Motivation

- MRI is slower compared to other imaging modalities



X-ray DSA:
0.4x0.4 mm
30 fps



2D SPGR, TR 4ms:
1.0x1.0 mm
1 fps

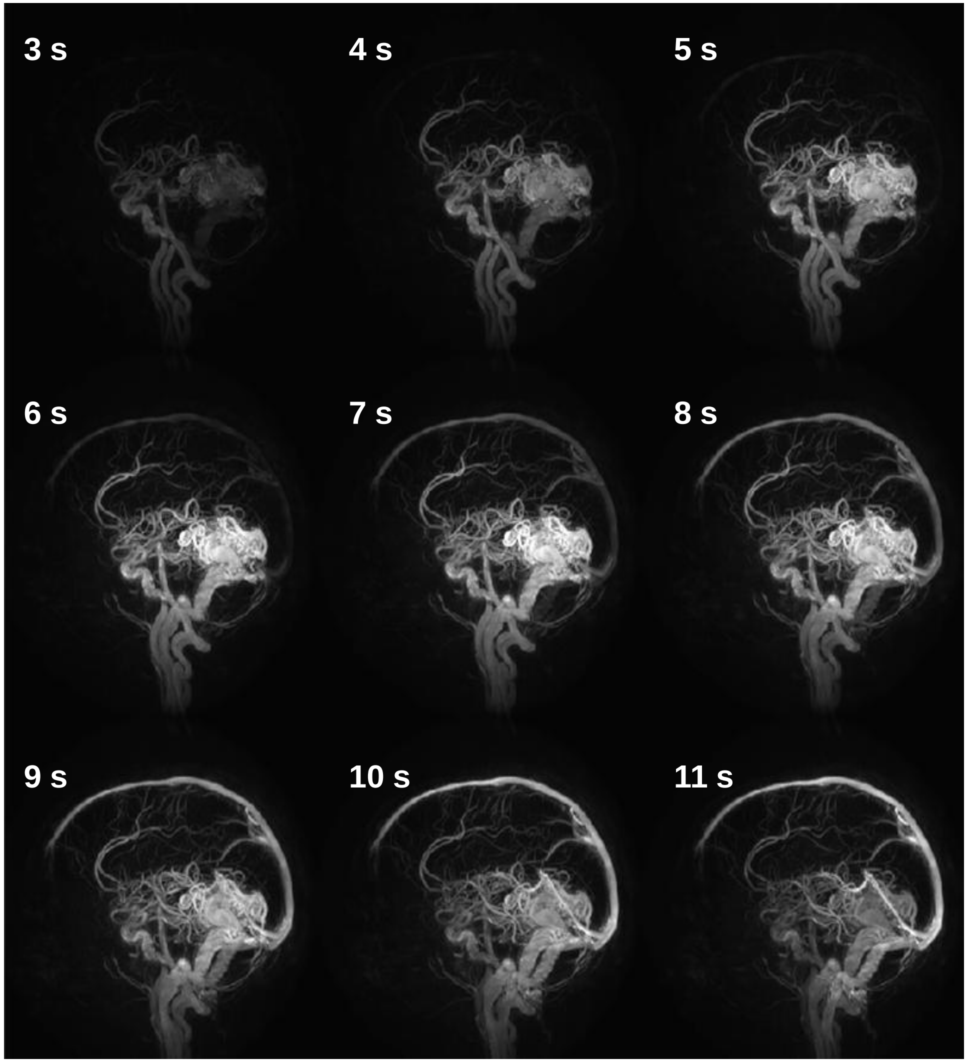
- In MRI data are acquired sequentially, so exam time is proportional to the number of samples

- Many MR applications have to be done within a limited scan time (breath hold, passage of contrast, etc.)

Dynamic Contrast-Enhanced Imaging

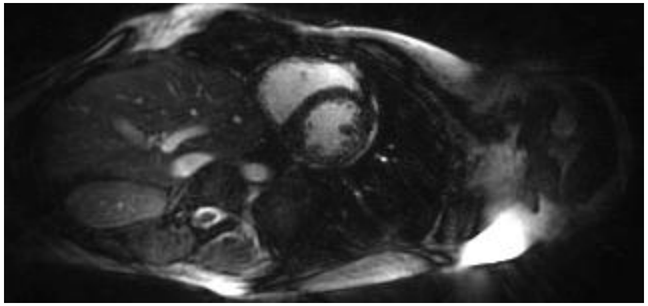
- Contrast uptake and wash-out in neuroangiography may take less than 10 s

- For some pathologies desired temporal resolution is 0.5-1s with sub-millimeter spatial resolution



Cardiac Imaging

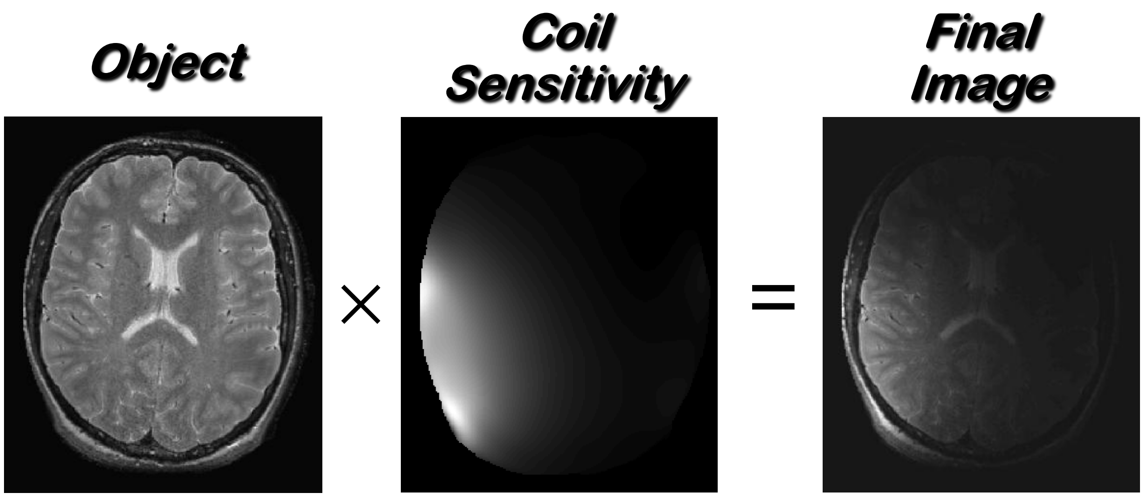
- In cardiac imaging a breath hold is often required to avoid respiratory motion (< 20 s)
- Desirable temporal resolution is 50 ms

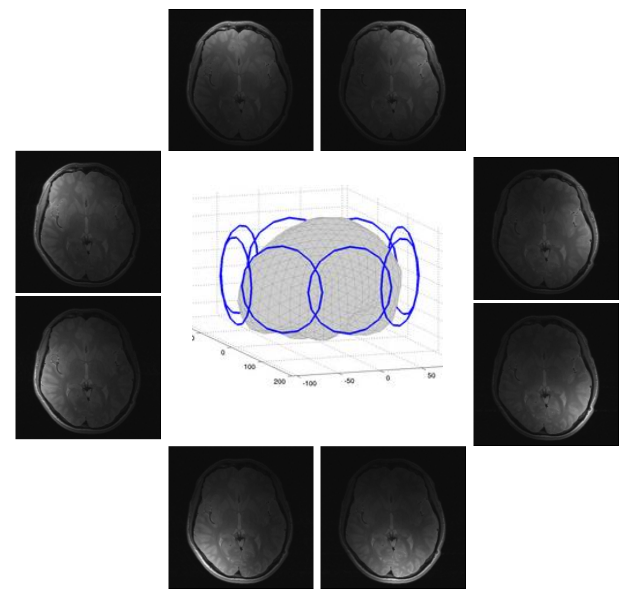


- Other considerations: patient discomfort, likelihood of motion, etc.

Acceleration mechanisms

- Novel acquisition strategies (non-Cartesian imaging, R = 2-4)
- Parallel imaging (R = 2-4)





- Advanced reconstruction algorithms – reconstruction from incomplete data

MRI Signal Modeling

$$s_\gamma(\mathbf{k}) = \int_{VOI} e^{i\mathbf{k}\cdot\mathbf{r}} c_\gamma(\mathbf{r}) f(\mathbf{r})\, d\mathbf{r}, \quad \gamma = 1, \ldots, N_C$$

$$\mathbf{s} = \mathbf{E}\mathbf{f}$$

Data Vector

Image Vector

The Encoding Matrix

- Incomplete data ➡ underdetermined problem
  - # of unknowns (pixels) > # of equations (measurements)
  - infinite number of solutions
  - need a way to pick a single solution

Prior Information

- Prior information about the underlying image can constrain reconstruction

$$Ef = s \text{ such that } f \text{ is } \ldots$$

- Can use different types of prior information:
  - theoretical assumptions (smoothness, sparsity)
  - image model (arterial input function, dependence on control variables)
  - image-specific assumptions (low resolution or time-averaged image)
- Prior information provides regularization of the underdetermined problem

Compressed Sensing

- CS uses sparsity model of prior info:

  $Ef = s$ s. t. f has smallest possible # of non-zero pixels

- Mathematically sparsity is measured with l_0 norm

$$\min_f \|f\|_0 \text{ s.t. } Ef = s$$

- l_0 norm is computationally challenging

- If *NxN* signal f is sparse (has only *K* non-zero entries), and *E* satisfies Restricted Isometry Principle, then solutions of l_0 and l_1 problems coincide and f can be reconstructed exactly from *O(K* log*N)* samples by solving

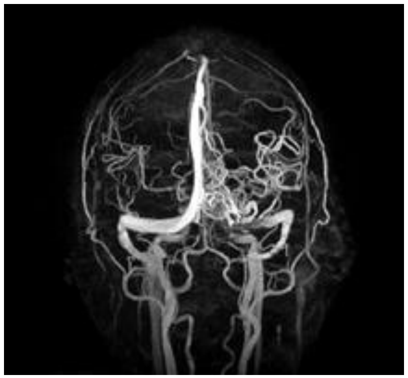
$$\min_f \|f\|_1 \text{ s.t. } Ef = s$$

Candes EJ et al, IEEE Trans. Inform. Theory, 52 (2004), 589-509.

Does CS Work in MRI?

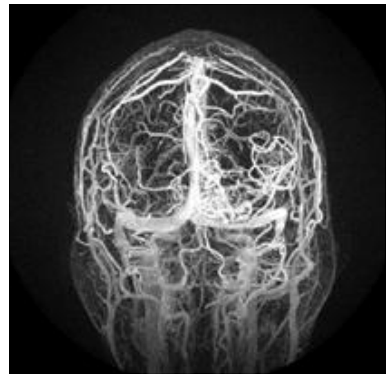
- CS seems a good match for MRI
  - many MRI images appear intrinsically sparse
  - random phase encodes or non-Cartesian acquisitions (radial, spiral) provide incoherent sampling
- Applications of CS in MR demonstrated good results with acceleration factors < 4-6.
- Higher accelerations typically lead to loss of resolution (blurry images, blocky artifacts)
- Acceleration factors have to correspond to the level of sparsity

Validity of Sparsity Assumption



Angio images should be sparse

Imaging imperfections →



Lack of sparsity

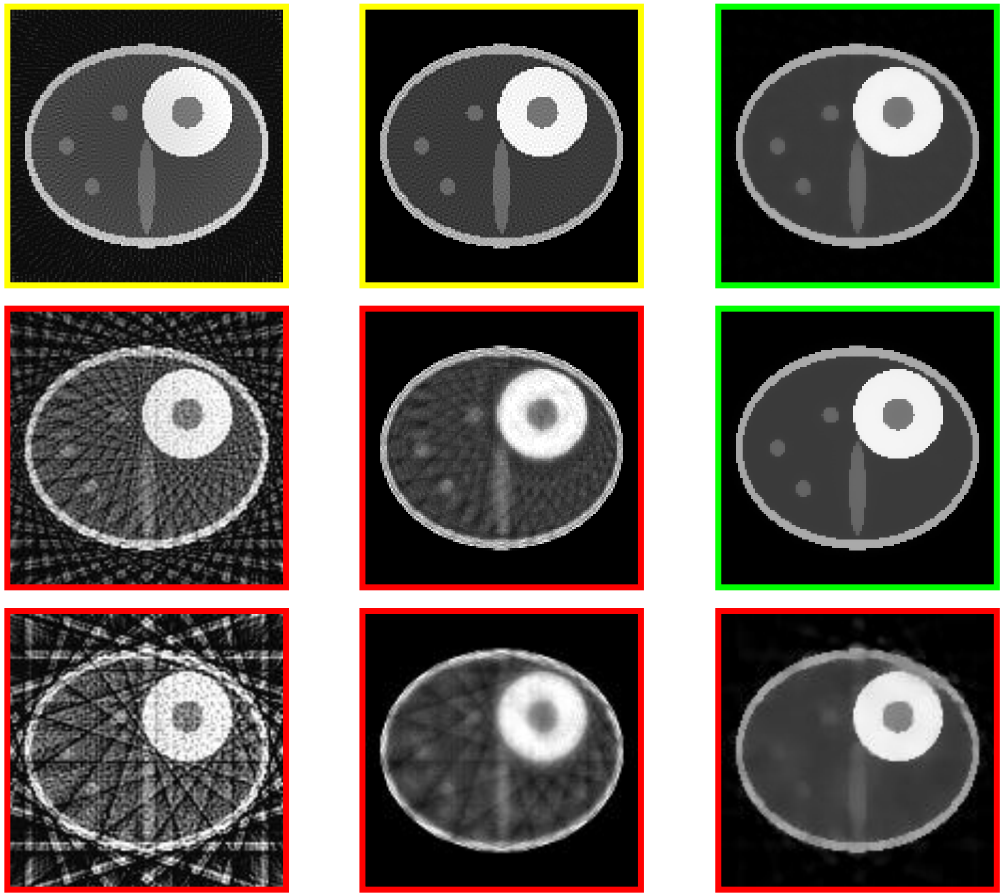
→ Limit on achievable acceleration factors

- A properly designed sparsifying transform and switching to unconstrained problem may improve reconstruction

$$\min_{f} \left(\|Ef - s\|_2^2 + \lambda \|\Phi f\|_1 \right)$$

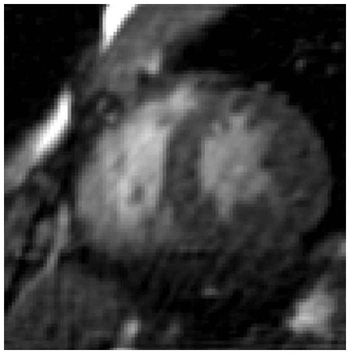
- Typically, Φ is a discrete gradient (TV) or a wavelet transform

Sparsity and Acceleration



Higher acceleration is possible with sparser representation

Sparsity and Acceleration


Gridding, R=4

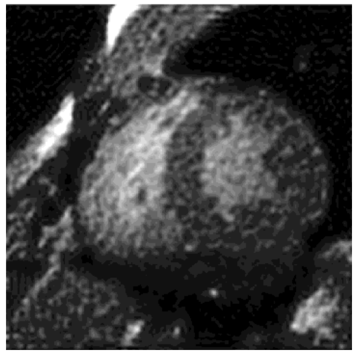
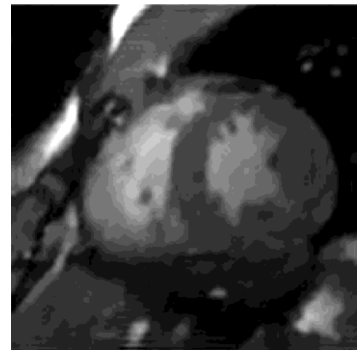
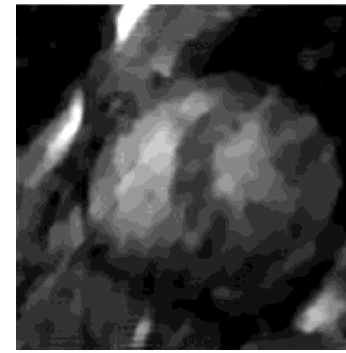
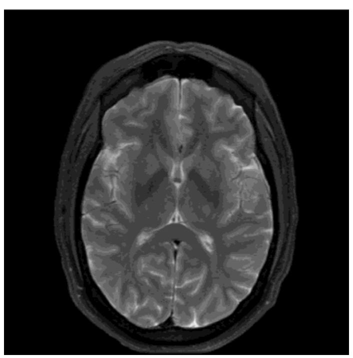
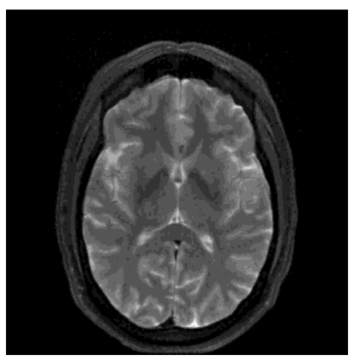


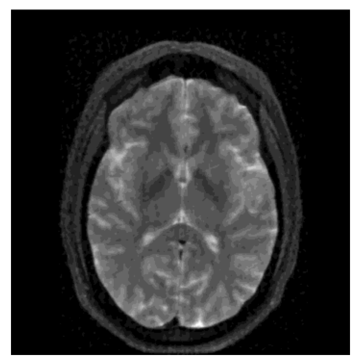
Image Norm Minimization, R=4

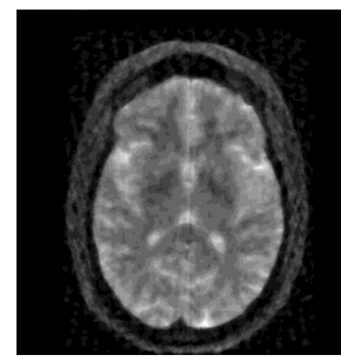

TV Minimization R=4


TV Minimization R=8


Original Image


TV, R=6

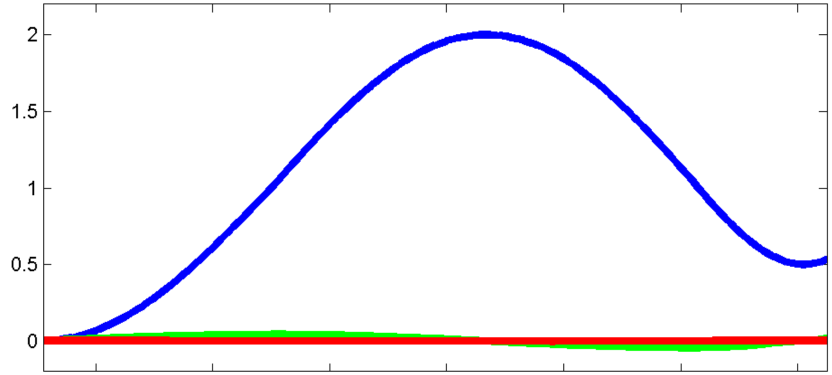

TV, R=8


TV, R=16

- If sparsity level is insufficient to support acceleration factors, reconstructed image is biased towards model assumptions

Temporally Constrained CS

- Sparsity may be enhanced by taking into account spatio-temporal correlations of an image series
- Prior information about dynamic contrast-enhanced image series – temporal waveform of each pixel is smoothly varying



- We regularize the problem with temporal constraint

$$\min_{\bar{\mathbf{f}}} \left(\left\| \bar{\mathbf{E}}\bar{\mathbf{f}} - \bar{\mathbf{s}} \right\|_2^2 + \lambda \left\| \Delta^2 \bar{\mathbf{f}} \right\|_{\ell_1/\ell_2} \right)$$

Samsonov AA, ISMRM 2005: 2311

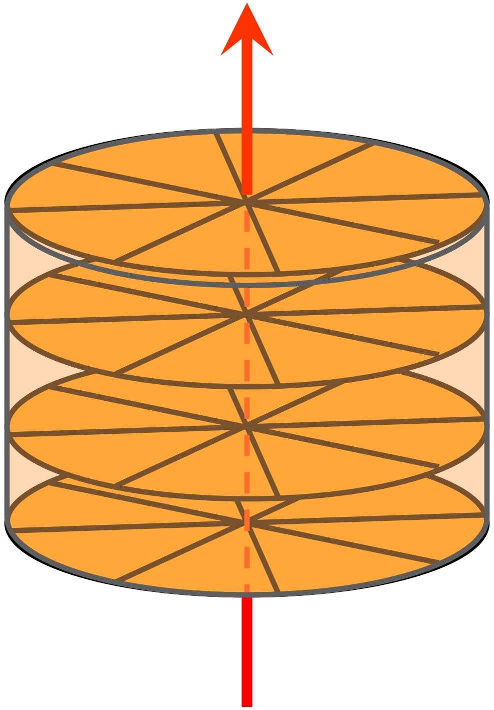
Adluru G et al, MRM, 57(2007):1027-1036.

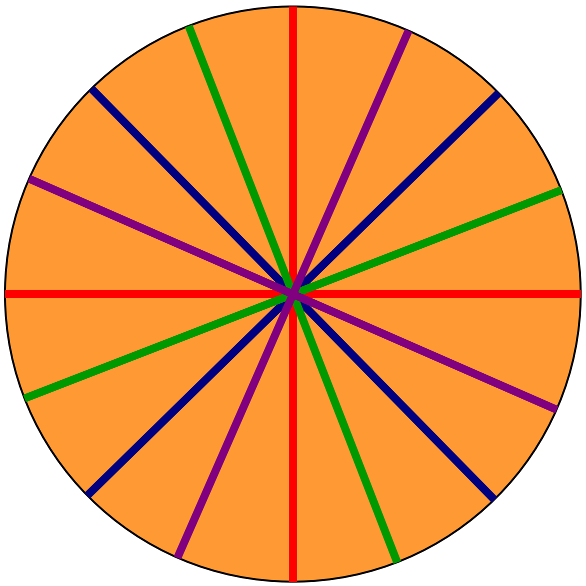
Jung H et al, MRM, 61 (2009), 103-116

Velikina et al. ISMRM 2010: 4876

Acquisition scheme

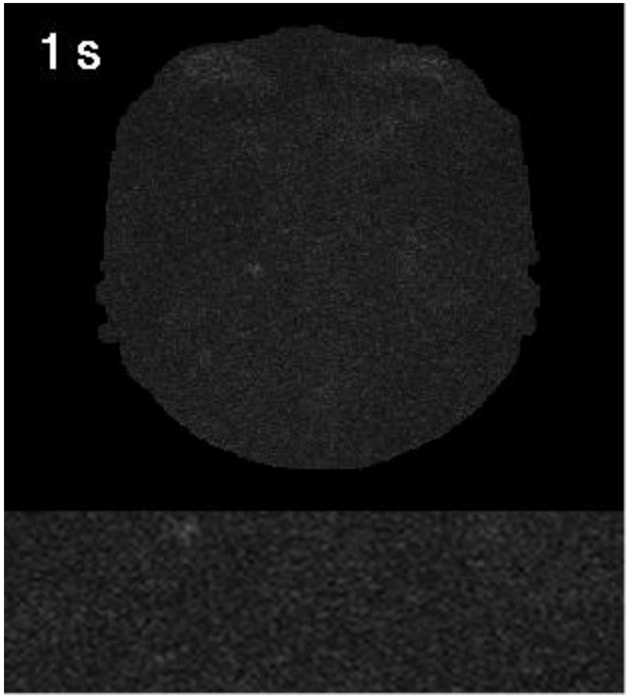
- The data are acquired using “stack-of-stars” radial sampling
- Projections in neighboring frames are interleaved to increase coverage and disperse artifacts





Aneurysm patient

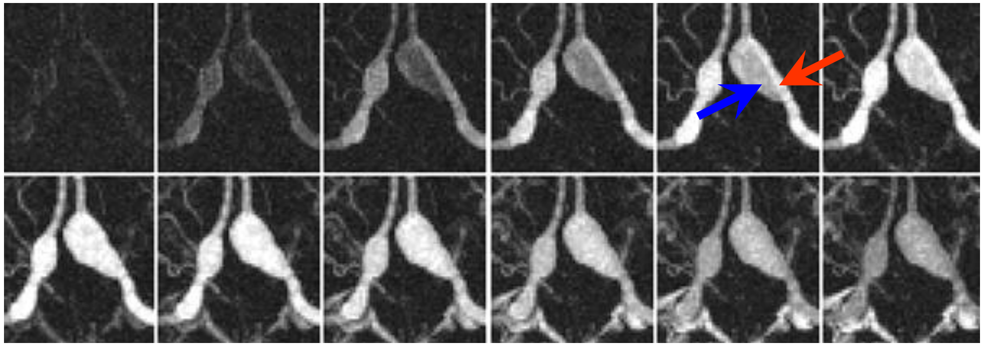
- 3.0 T GE Discovery^{TM} MR750, 8-channel head coil
  - 0.86x0.86x2 mm^3
  - 20 slices
  - 1.2 s / frame
  - 15 projections/frame

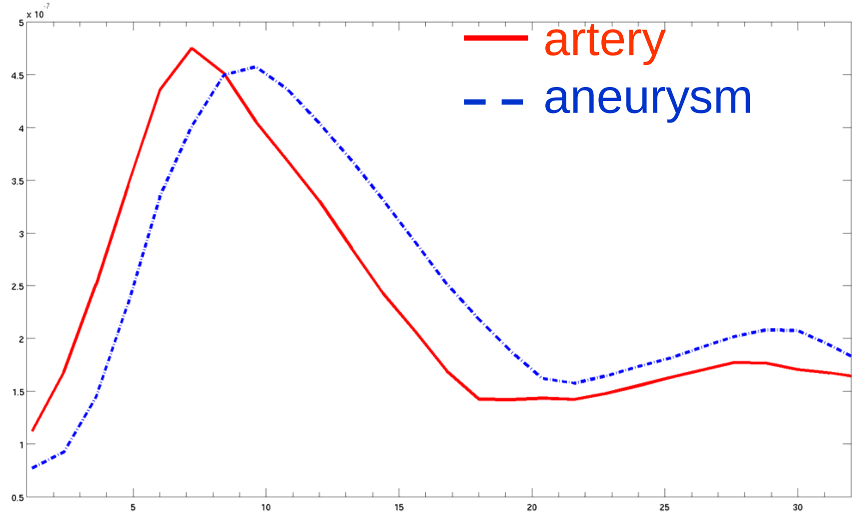


- R = 27
- TE/TR=1.5/4 ms
- FA=25^o,
- BW=125 kHz

Filling of Aneurysm

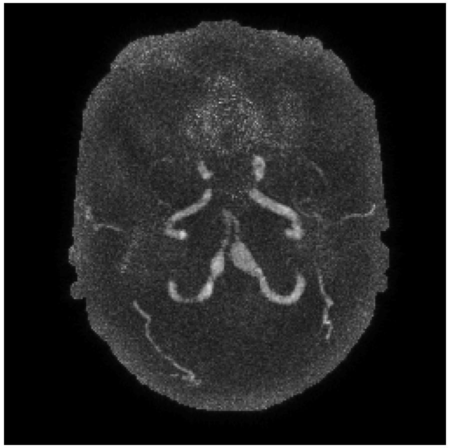
- Temporal resolution is sufficient to demonstrate delayed filling of aneurysm





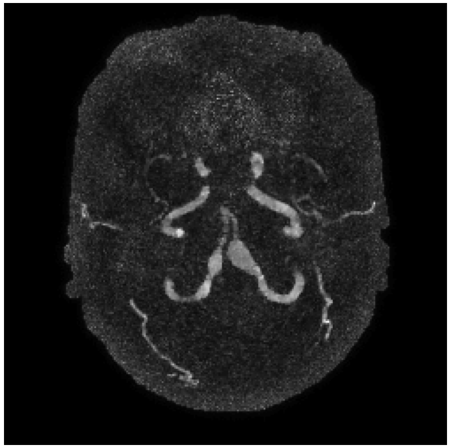
What about spatial constraints?

- At high acceleration factors, “standard CS” produces images of inferior quality

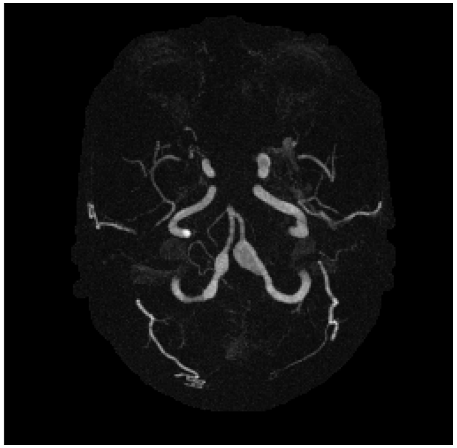


SENSE

Image norm minimization



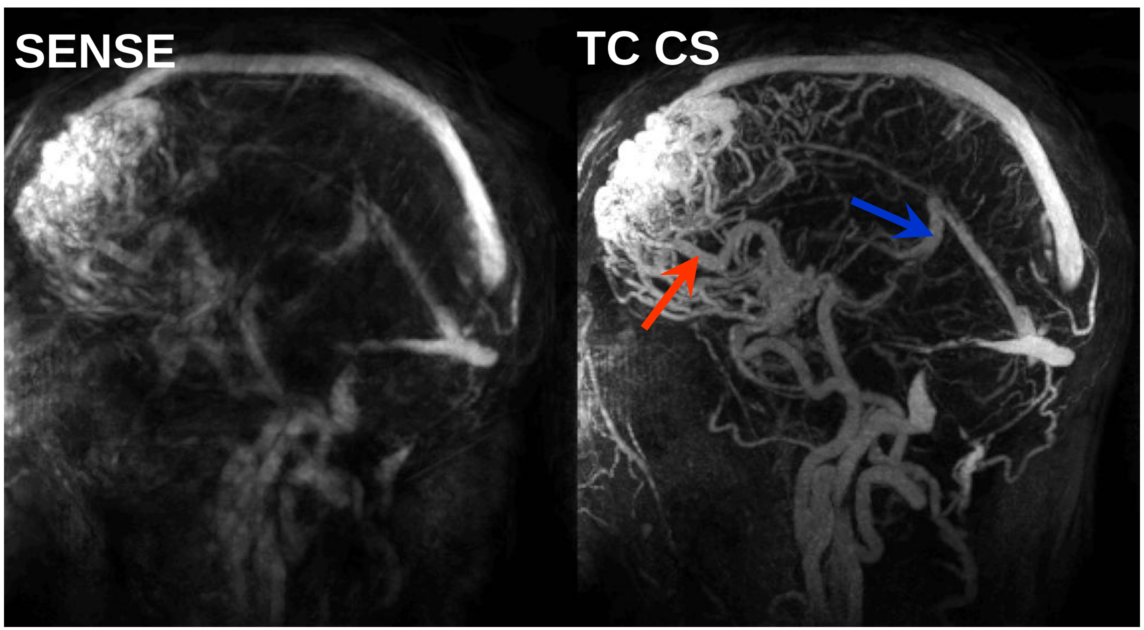
TV minimization



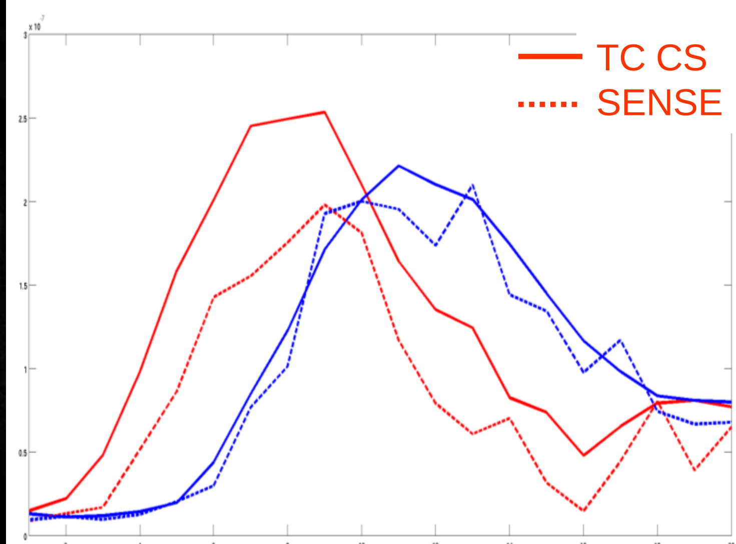
TC CS

AVM Patient

- 3.0 T GE Discovery™ MR750, 32-channel coil
  - $0.68 \times 0.68 \times 1.5\ mm^3$
  - 114 slices (57 acquired , GRAPPA with R=2)
  - 1.2 s / frame
  - 6 projections/frame, R = 84

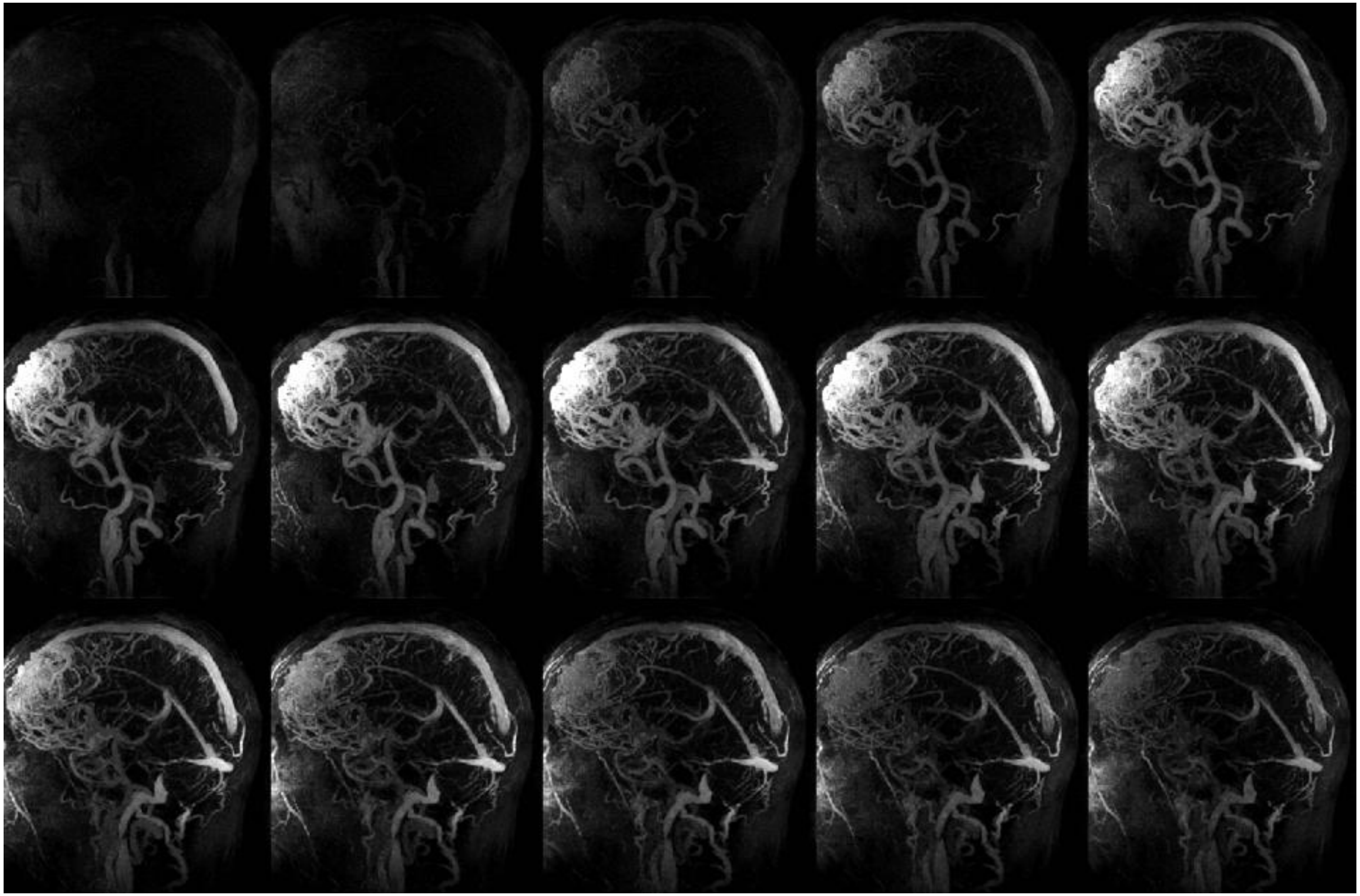


Limited MIPs



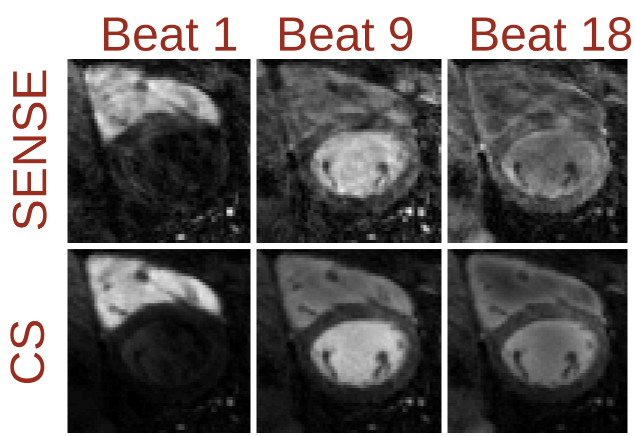
AVM patient

- TC CS provides good A/V separation and spatial resolution

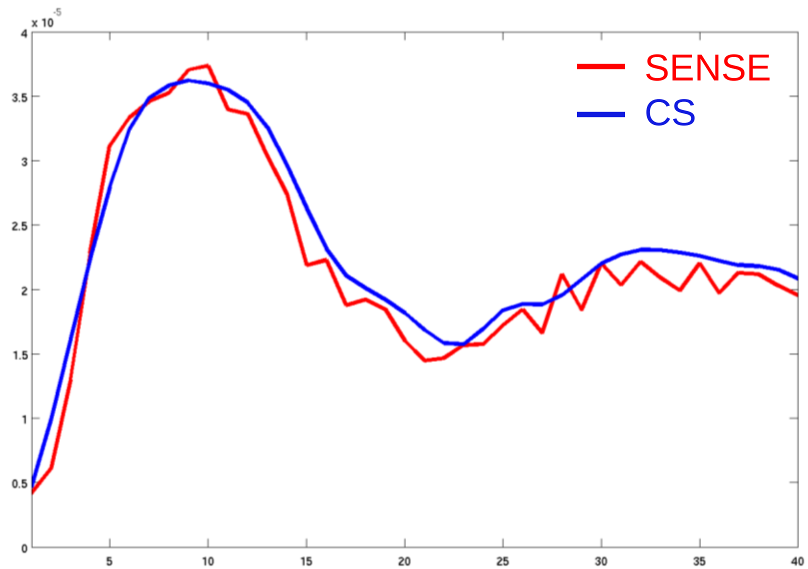


3D Cardiac Perfusion

- Imaging of entire left ventricle (FOV = 350 x 350 x 80 mm)
- High spatial resolution: 1.8 x 1.8 x 8 mm
- High temporal resolution: 174 ms
- Acceleration factor: 50 (8 projections per frame)
- Total exam time: 48 s (breath hold 10 s into exam, shallow breathing in the end)



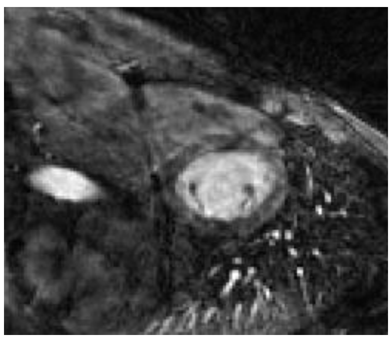
Perfusion measurements in left ventricle



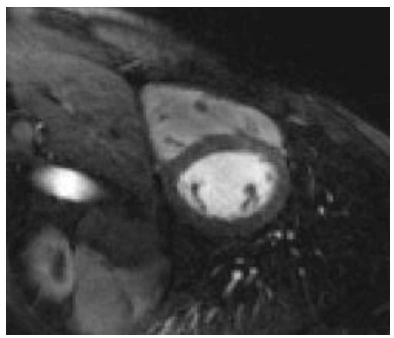
Why 2nd difference?

- Can we constrain 1st temporal difference instead?

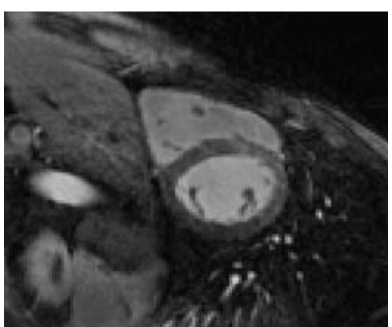
$$\min_{\bar{\mathbf{f}}} \left(\left\| \bar{\mathbf{E}}\bar{\mathbf{f}} - \bar{\mathbf{s}} \right\|_2^2 + \lambda \left\| \Delta^1 \bar{\mathbf{f}} \right\|_{\ell_1/\ell_2} \right)$$



SENSE

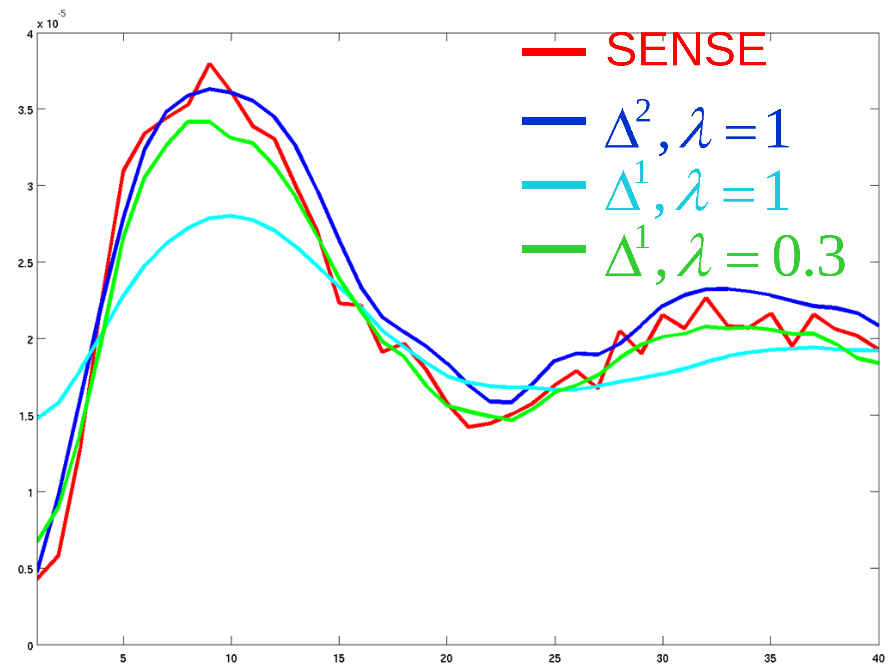


TC CS $\Delta^2, \lambda = 1$



TC CS $\Delta^1, \lambda = 1$

TC CS $\Delta^1, \lambda = 0.3$



Conclusions

- Sparsity is necessary for CS but spatial sparsity is usually limited in MRI, allowing only mild acceleration factors
- Sparsity can be achieved by exploiting inter-image dependencies in an image series
- Careful design is needed based on required acceleration and available sparsity
- 2^{nd} difference operator in temporal dimension is a novel way to sparsify image series
- The use of 2^{nd} difference operator allows acceleration factors 25-85 in contrast-enhanced applications to depict contrast dynamics
- The concept of regularization in temporal (or parametric) dimension was also shown feasible for acceleration of quantitative MRI techniques

Acknowledgements

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- We thank GE Healthcare for research support

- Thank you for your attention!