Advanced Angiographic Imaging Techniques: Non-Cartesian

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Dynamic Contrast Enhanced MRA

Challenge

Need high spatial resolution to resolve vessels, but also need a high temporal resolution to separate arterial and venous phases.

Increased frame rates can be provided by:

- Parallel Imaging
- Partial Fourier
- Keyhole
- View Sharing
- Non Cartesian Acquisitions
- Compressed Sensing / HYPR

Background: Cartesian

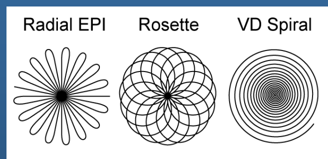
Cartesian Imaging

- Used by nearly all clinical MRI pulse sequences
- Very robust to gradient errors
- Image Reconstruction is Easy
- Parallel Imaging is Easy
- Anisotropic FOV is Easy

Drawbacks

- Sensitive to flow/motion
- Slow
- Uniform Undersampling -> Coherent Aliasing Artifact

Background: Non-Cartesian



Non-Cartesian Imaging

- Offers unique benefits for a subset of applications
- Sensitive to Gradient Errors
  - Gradient Delays
  - Eddy Currents
  - Concomitant Gradients
- Image Reconstruction More Difficult

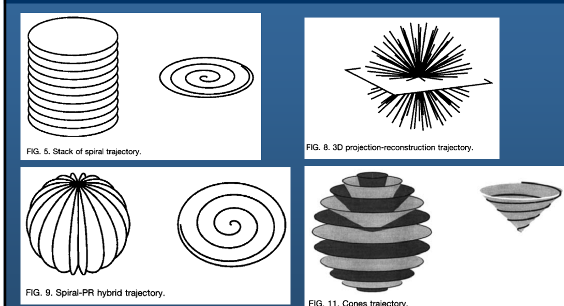


FIG. 5. Stack of spiral trajectory.

FIG. 8. 3D projection-reconstruction trajectory.

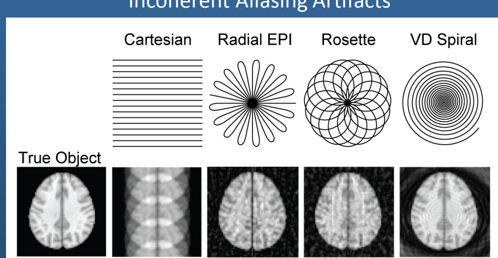
FIG. 9. Spiral-PR hybrid trajectory.

FIG. 11. Cones trajectory.

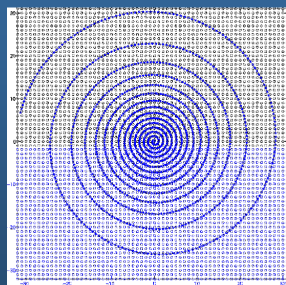
Figures From: P. Irarrazabal and D.Nishimura
MRM 1995; Vol. 33 p.656

Background: Non-Cartesian

Incoherent Aliasing Artifacts

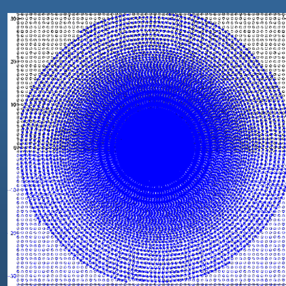


Background: Gridding



[1] O'Sullivan et al. IEEE Trans. Med. Imaging 1985, 4(4):200-207
[1] Jackson et al. IEEE Trans. Med. Imaging 1991, 10(3):473-478

Background: Gridding



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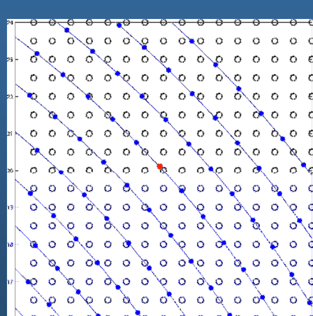
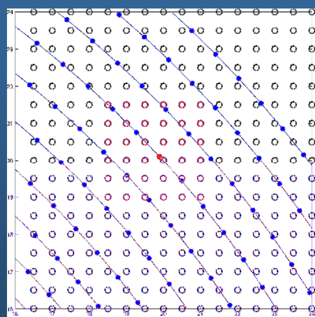
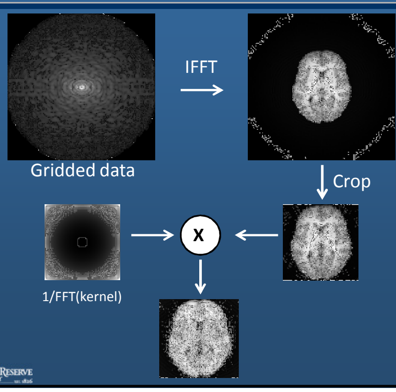
Gridding Example



Gridding Example



Gridding Example



Background: Gridding/NUFFT Software

Jeff Fessler's Image Reconstruction Toolbox:
http://www.eecs.umich.edu/~fessler/code/index.html
Matlab-based implementations of NUFFT and much more

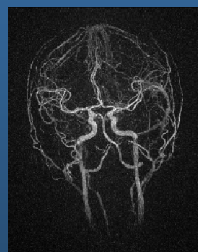
NFFT: *http://www-user.tu-chemnitz.de/~potts/nfft/*
Implementations of various Non-uniform FFTs in C (Linux-based)

Jim Pipe has some stuff here: http://www.ismrm.org/mri_unbound/

Dynamic CE-MRA

Reduce aliasing artifacts via:

- 3D projection reconstruction acquisition (VIPR[1])
  - incoherent aliasing artifacts
- Acquire multiple radial lines in a single shot
- Pre-contrast subtraction
  - removes aliasing of the background tissue
  - vessel images are sparse (< 5% non-zero)

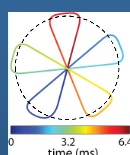


2560 projections
3D MIP

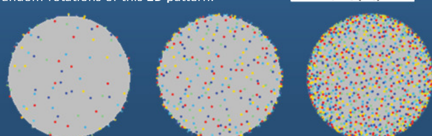
[1] Barger et al. MRM 48:297-305 (2002)

Dynamic CE-MRA: Methods

Implemented a 2D radial EPI sequence:



3D spherical k-space is progressively filled in by pseudo-random rotations of this 2D pattern:

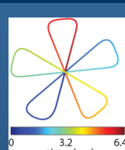


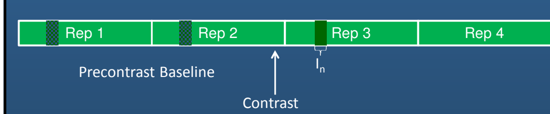
16 shots 64 shots 256 shots

Methods:

Acquisition

- 3T Siemens System with 12-channel head coil
- 3D FLASH, FA= 20 degrees
- TR= 8.68 ms for 1.0 mm isotropic resolution
- TR= 10 ms for 0.8 mm isotropic resolution
- 5 radial lines per shot
- 4096 unique shots repeated 4 times (~2.5 mins)





Use all data to obtain coil sensitivities and field map

Methods:

Contrast
Single dose (0.1 mmol/kg) of gadolinium-based contrast agent.
Injection rate: 3 mL/s

Reconstruction Approaches:

1.) CG-SENSE[1]: initialize each frame with the previous timeframe

2.) CG-SENSE with BM4D[2] denoising: Lee et al. Proc. ISMRM 2012, #2257
initializes each frame with zeros

In both cases: time-segmented reconstruction[3] for field map correction

[1] Pruessmann et al. Mag Reson Med 2001; 46: 638-651
[2] Maggioni et al. IEEE Trans. Image Process. 2012 (In Press)
[3] Noll et al. IEEE Trans Med Imaging 1991; 10(4):629-637

CG-SENSE

MR signal formation can be written as a system of linear equations:

$$y = Ax$$

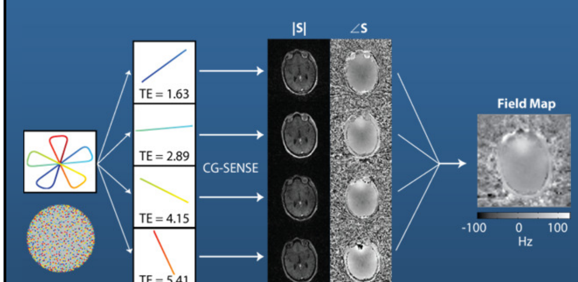
For multi-coil MRI data

$$\begin{bmatrix} y_1 \\ \vdots \\ y_N \end{bmatrix} = \begin{bmatrix} EC_1 \\ \vdots \\ EC_N \end{bmatrix} x$$

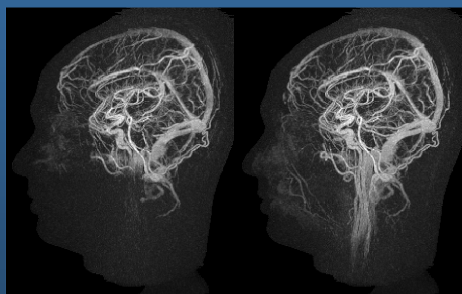
K-space data (y); Encoding Matrix (E); Coil Sensitivies (C); image (x)

Use the conjugate gradient algorithm to solve

Field Map Estimation



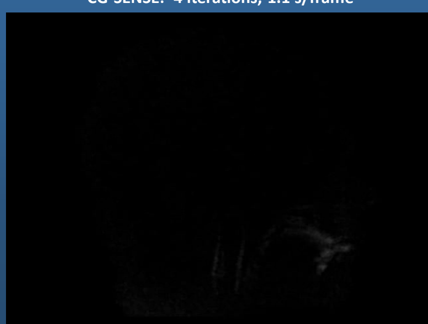
Fieldmap Correction



Uncorrected Corrected

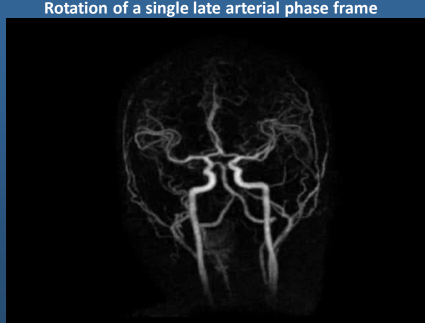
Results: Dynamic CE-MRA: 1 mm

CG-SENSE: 4 iterations, 1.1 s/frame



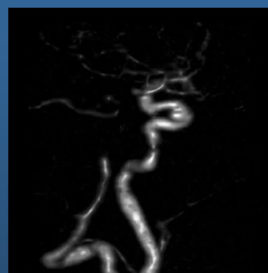
Results: Dynamic CE-MRA: 1 mm

Rotation of a single late arterial phase frame



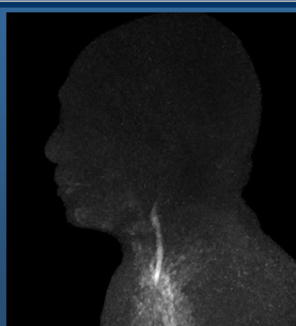
Case 1: LICA aneurysm

2D x-ray DSA

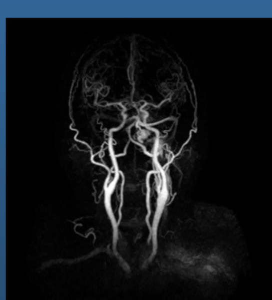


MRA: volume rendering

Case 2: AVM



Case 2: AVM



Localized MIP

A

P

Compressed Sensing

The theory of compressed sensing is a relatively recent development:

E. Candes et. al. IEEE Trans. Information Theory 2006; 52:489-509
D. Donoho. IEEE Trans. Information Theory 2006; 52:1289-1306

Early work in applying CS to MRI was performed by :
M. Lustig et al. Magn. Reson. Med. 2007; 58:1182-1195

Three key components required:

- Transform sparsity
- Incoherent aliasing artifacts in the transform domain
- Nonlinear image reconstruction that promotes sparsity

CG-SENSE + Denoising

Adluru et al. JMRI 2012; 32:1217-1227 proposed a reconstruction approach which employed Non-local Means (NLM) denoising to remove incoherent aliasing artifacts.

Lee et. al. Proc. ISMRM 2012 #2257 proposed alternating CG-SENSE iterations with application of the BM4D[1] denoising algorithm.

[1] Maggioni et al. IEEE Trans. Image Process. 2012 (In Press)

CG-SENSE + Denoising

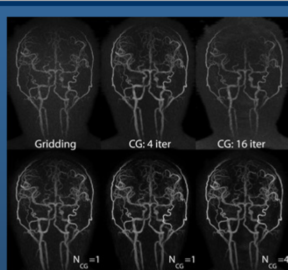
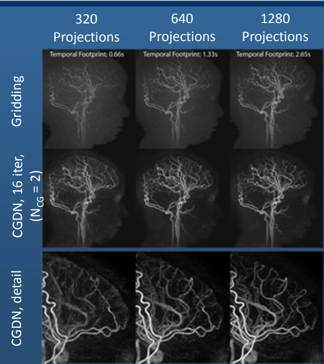


Fig.1: Coronal MIPs for various reconstructions of a late arterial phase frame using 640 projections (1.33 seconds of data).

CG-SENSE + Denoising



Results: 32 channel coil, 0.8 mm

CG-SENSE + Denoising: 2 sec / frame every 0.5 s
Each frame initialized with zeros

Projection Ordering

Goal:

sample uniformly, regardless of time scale

e.g. Short time scale used for individual frames, but long time scale used when estimating coil sensitivities and field map.

Existing approach:

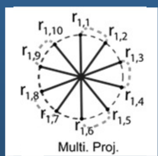
When only one projection is acquired per TR, the 3D golden angle approach of Chan et al. (MRM 2009) can be used.

No known algorithm for cases with multiple-projections per TR

Projection Ordering: Multi-projection

Proposed approach:

Treat the end points of the projections as charged particles on the surface of a sphere. Treat each shot as a rigid body.



$$\vec{F}_{i,k} \propto \sum_{\substack{s=1\\ s\neq i}}^{N_s} \sum_{p=1}^{N_p} \frac{\vec{r}_{i,k} - \vec{r}_{s,p}}{\left|\vec{r}_{i,k} - \vec{r}_{s,p}\right|^3}$$

$$\vec{\tau}_{i,k} = \vec{r}_{i,k} \times \vec{F}_{i,k}$$

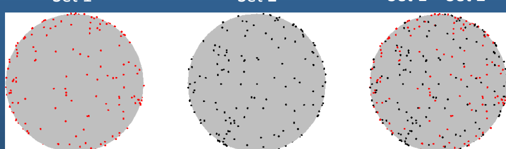
$$\vec{\tau}_i = \sum_{k=1}^{N_p} \vec{\tau}_{i,k}$$

$$\vec{u}_i = \vec{\tau}_i / \left|\vec{\tau}_i\right| \qquad \varphi_i = \alpha \left|\vec{\tau}_i\right|$$

Projection Ordering: Multiclass

Initialize with Random Points

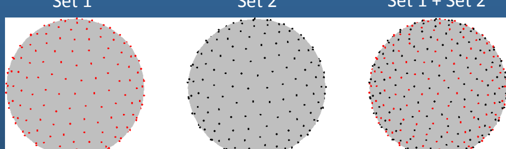
Set 1 Set 2 Set 1 + Set 2



Projection Ordering: Multiclass

Weighted toward subsets

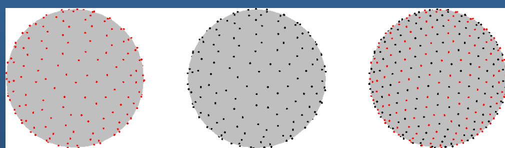
Set 1 Set 2 Set 1 + Set 2



Projection Ordering: Multiclass

Weighted toward full set

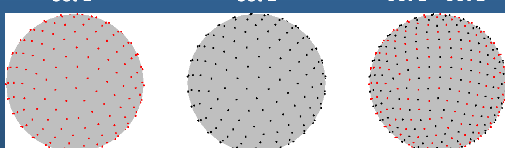
Set 1 Set 2 Set 1 + Set 2



Projection Ordering: Multiclass

Intermediate weighting

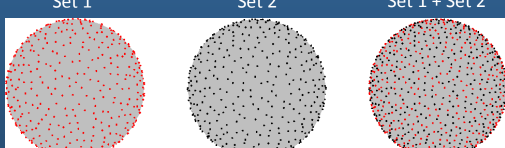
Set 1 Set 2 Set 1 + Set 2



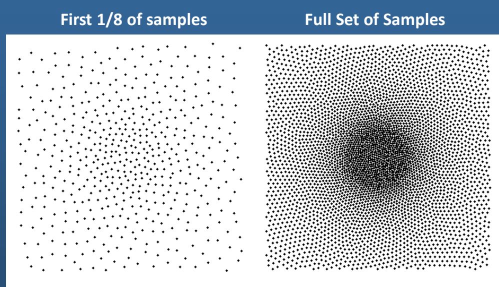
Projection Ordering: Multiclass

Multi-projection case has fewer degrees of freedom so uniformity is not as good as the case when all charges are allowed to move independently

Set 1 Set 2 Set 1 + Set 2



Projection Ordering: 3D Cartesian Example



Conclusions

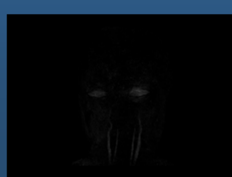
Summary

• Time-resolved 3D acquisition at 0.8 – 1 mm isotropic resolution with temporal resolution of ~1 s / frame

• Reconstruction at acceleration factors > 100.

• Iterative reconstruction is computationally intensive

• Field maps and coil sensitivities can be obtained from the same dataset



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