Institut des sciences du vivant Frédéric Joliot

Perfecting Brain Scans: New Horizons

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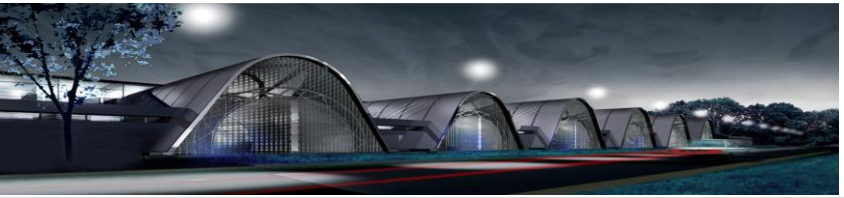
cea

FORTH
FOUNDATION FOR RESEARCH AND TECHNOLOGY - HELLAS

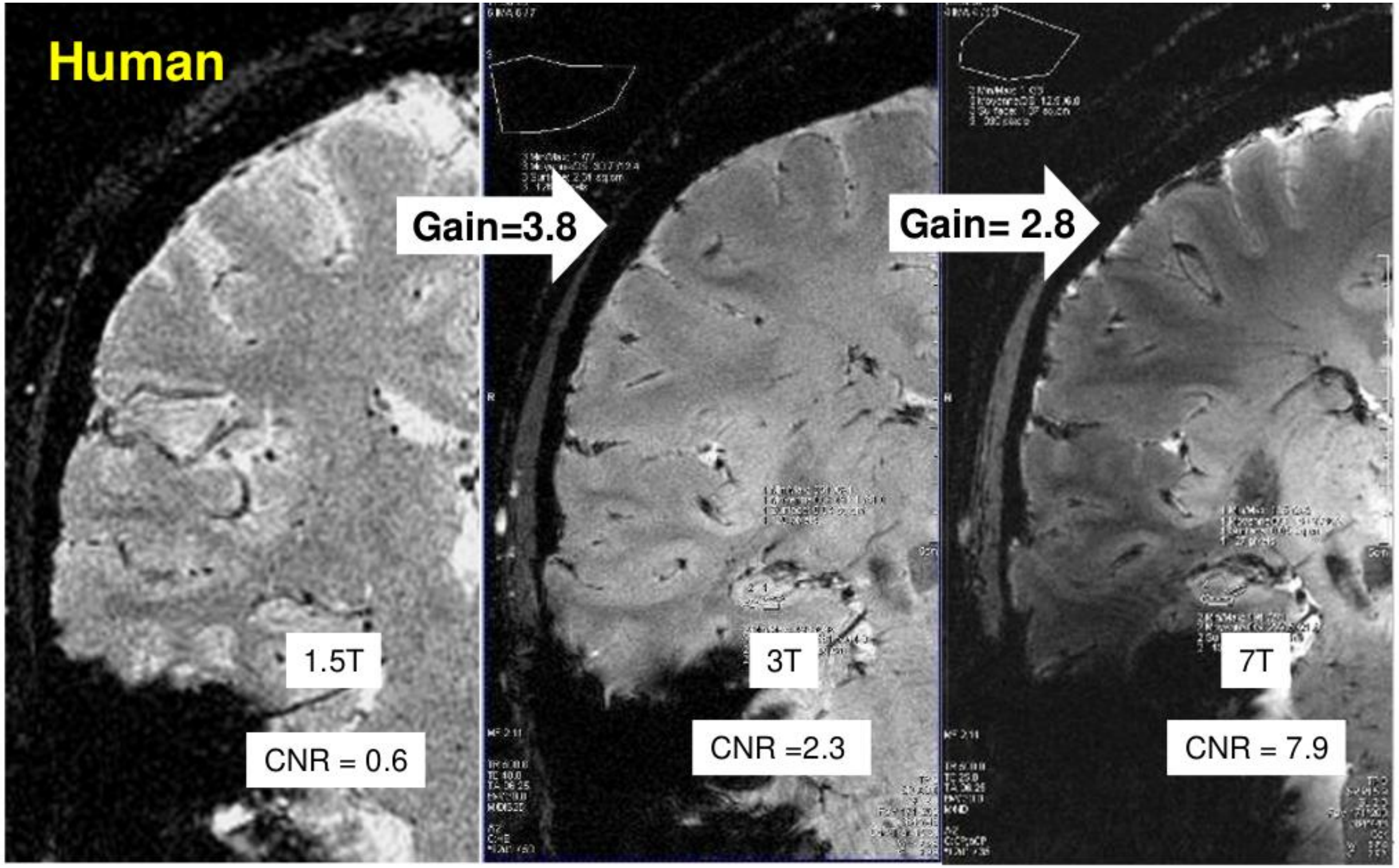
13 FORTH Retreat
July 15-16 2022, Heraklion, Crete

NeuroSpin Inria MIND université PARIS-SACLAY

NeuroSpin: A unique facility for Brain Imaging

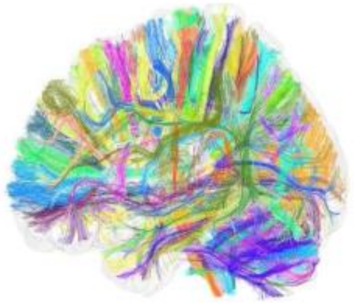


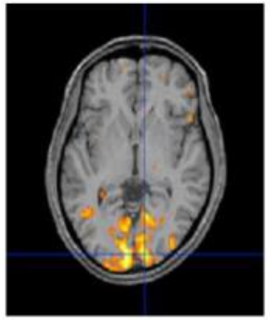
Why Ultra-High Field MRI?

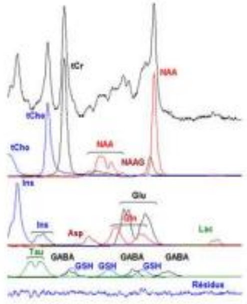


Comparison of CNR (Contrast to noise) of the T2* contrast in MRI

Gain also for :

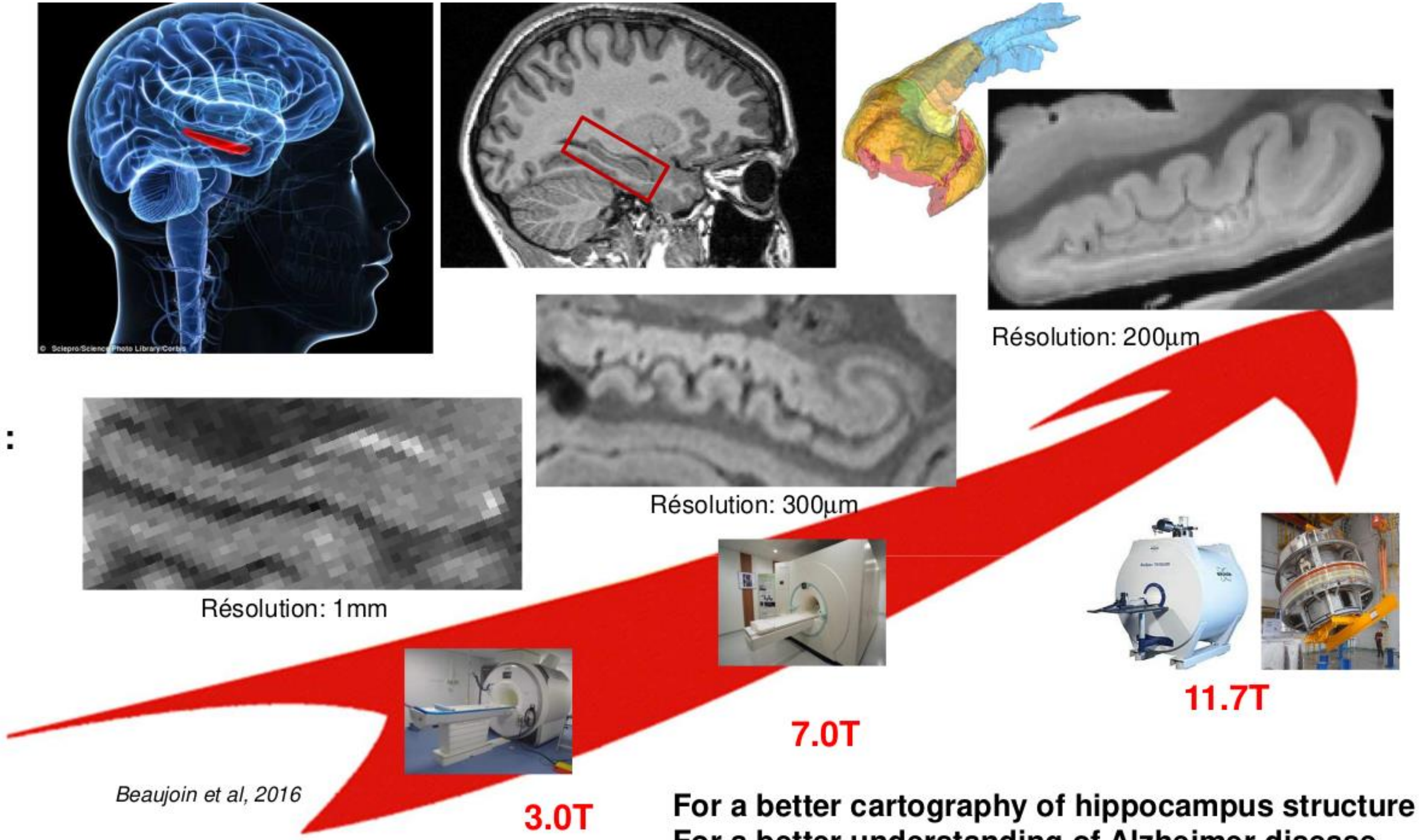






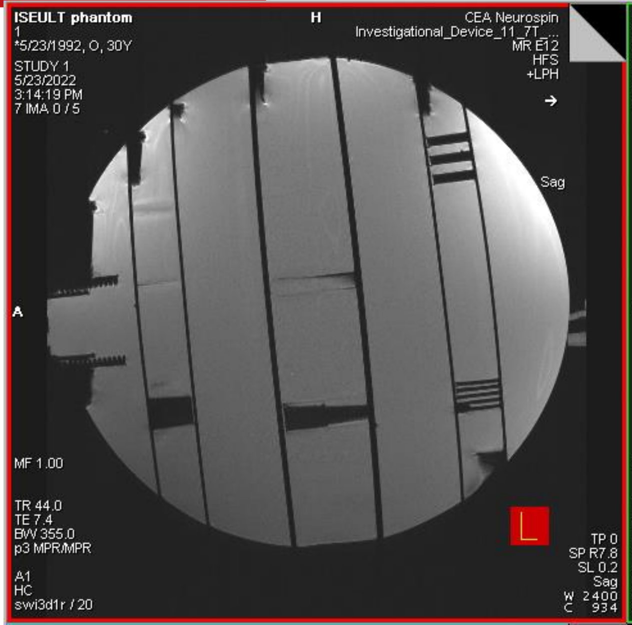
Why Ultra-High Field MRI?

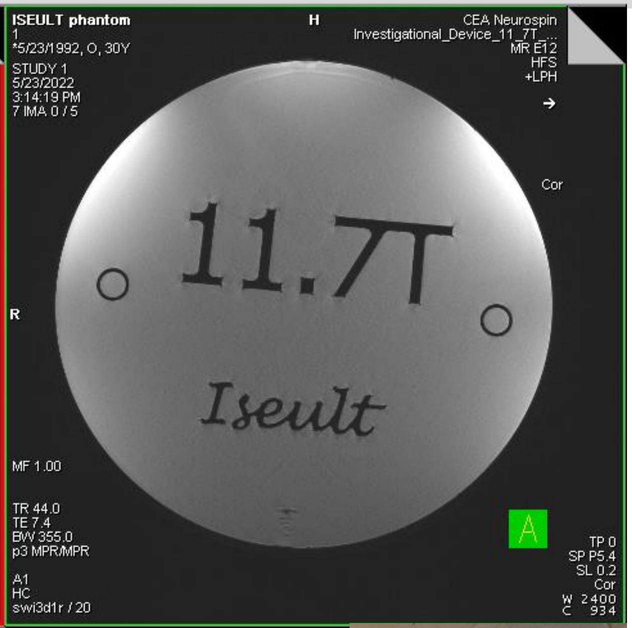
Human hyppocampus :
***in vivo* at 3T, 7T**
***post-mortem* at 11.7T**

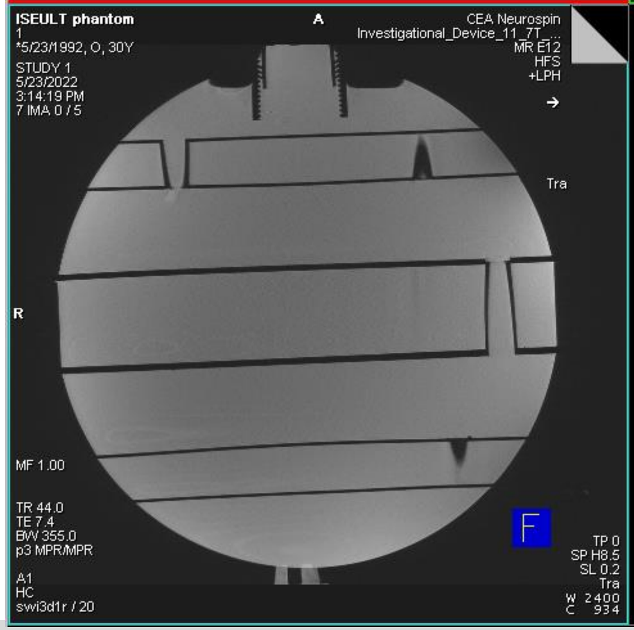


For a better cartography of hippocampus structure
For a better understanding of Alzheimer disease, ...

Ultra High Resolution Phantom Imaging at 11.7 T

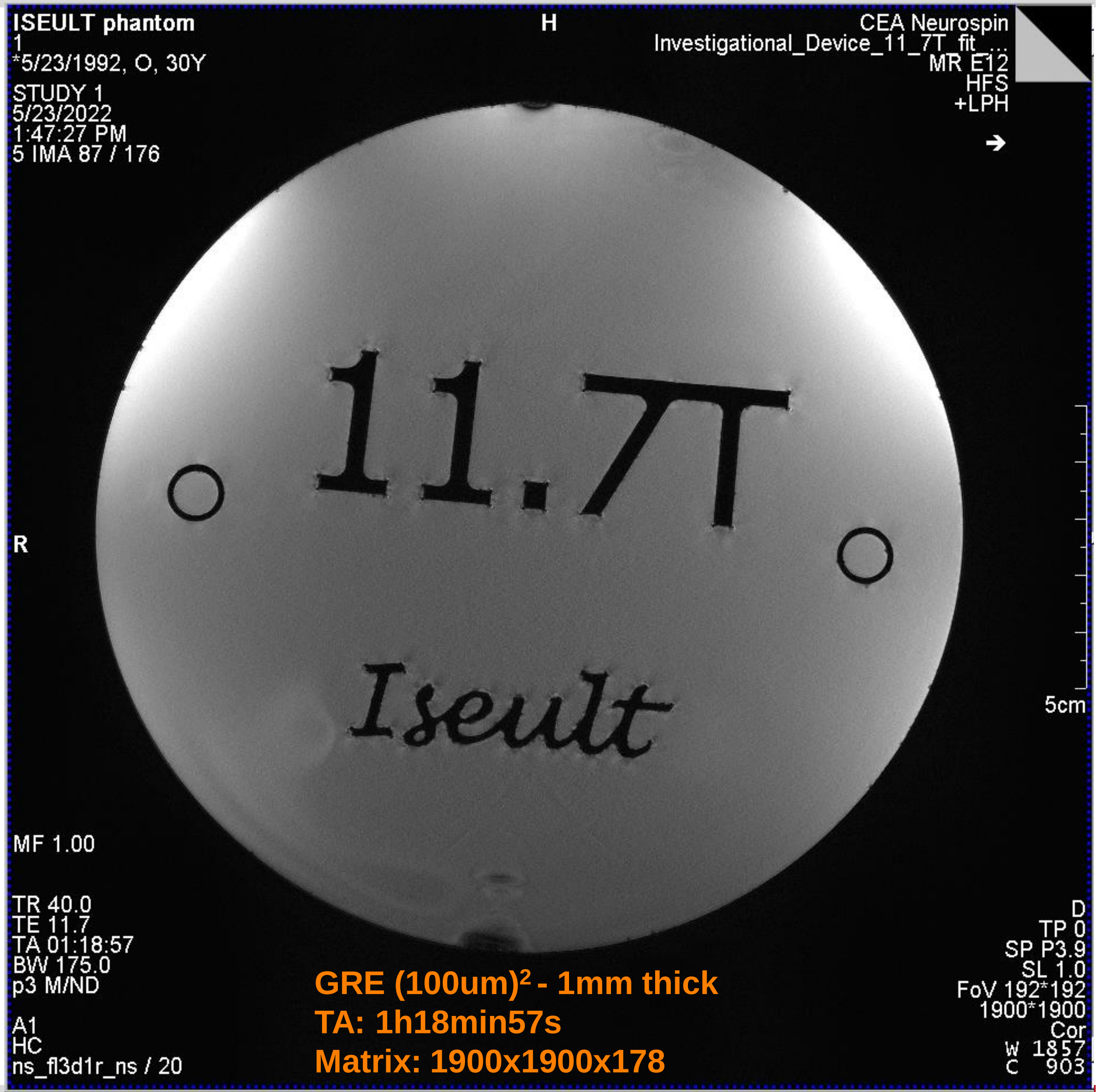






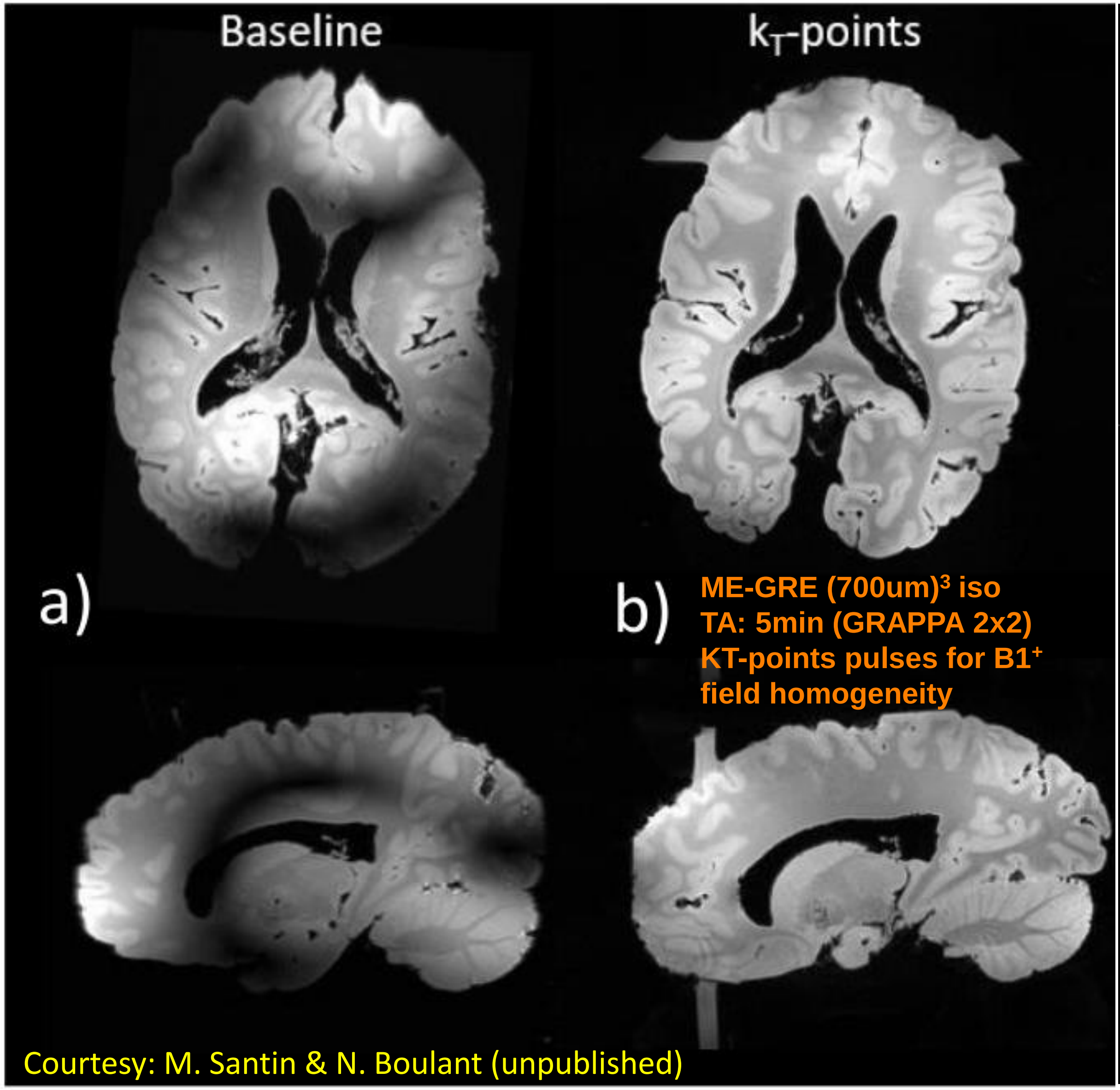
GRE (200um)^3 isotropic
TA: 3h35min2s
Matrix: 940x940x832

Courtesy: N. Boulant & A. Vignaud

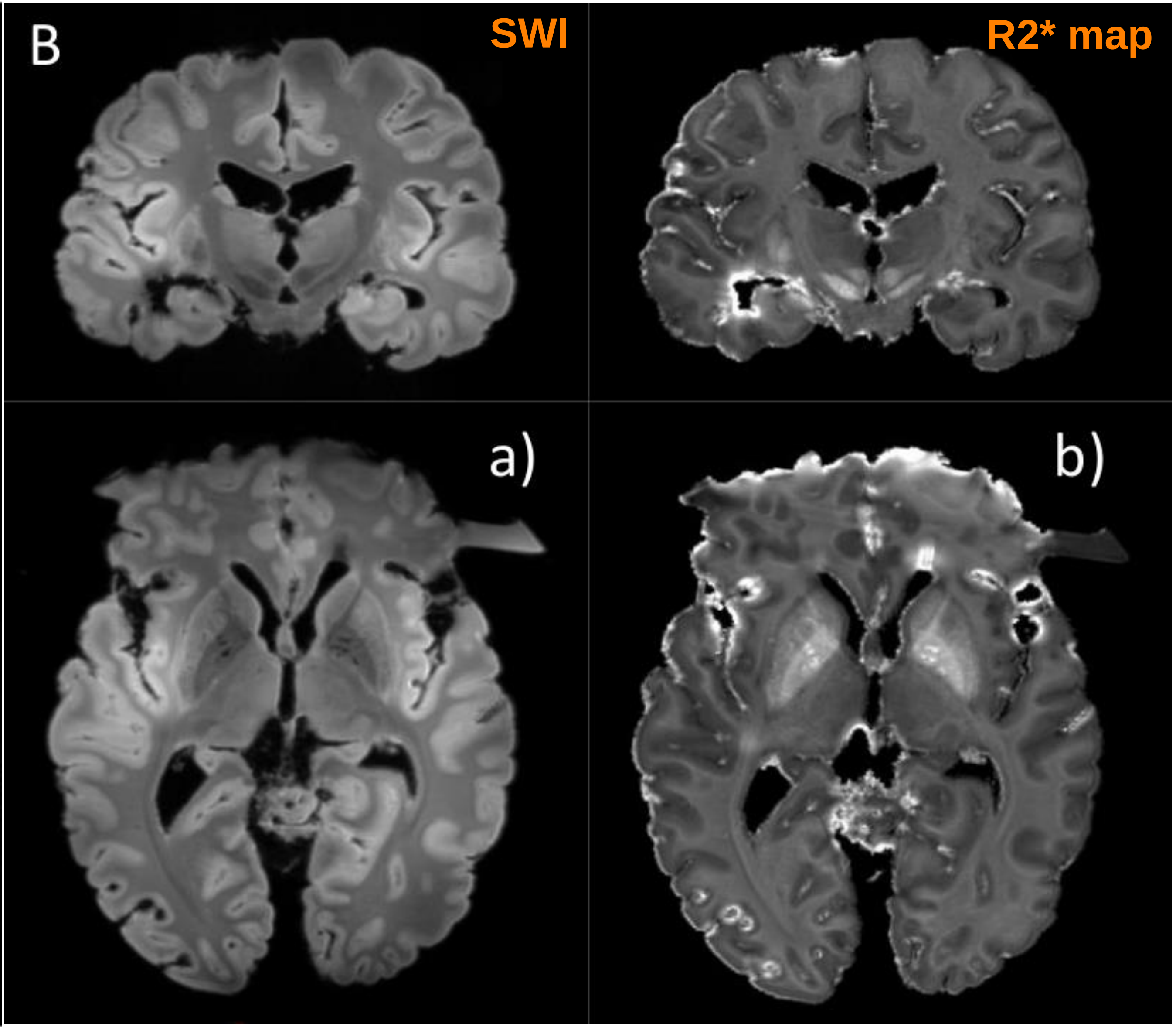


GRE (100um)^2 - 1mm thick
TA: 1h18min57s
Matrix: 1900x1900x178

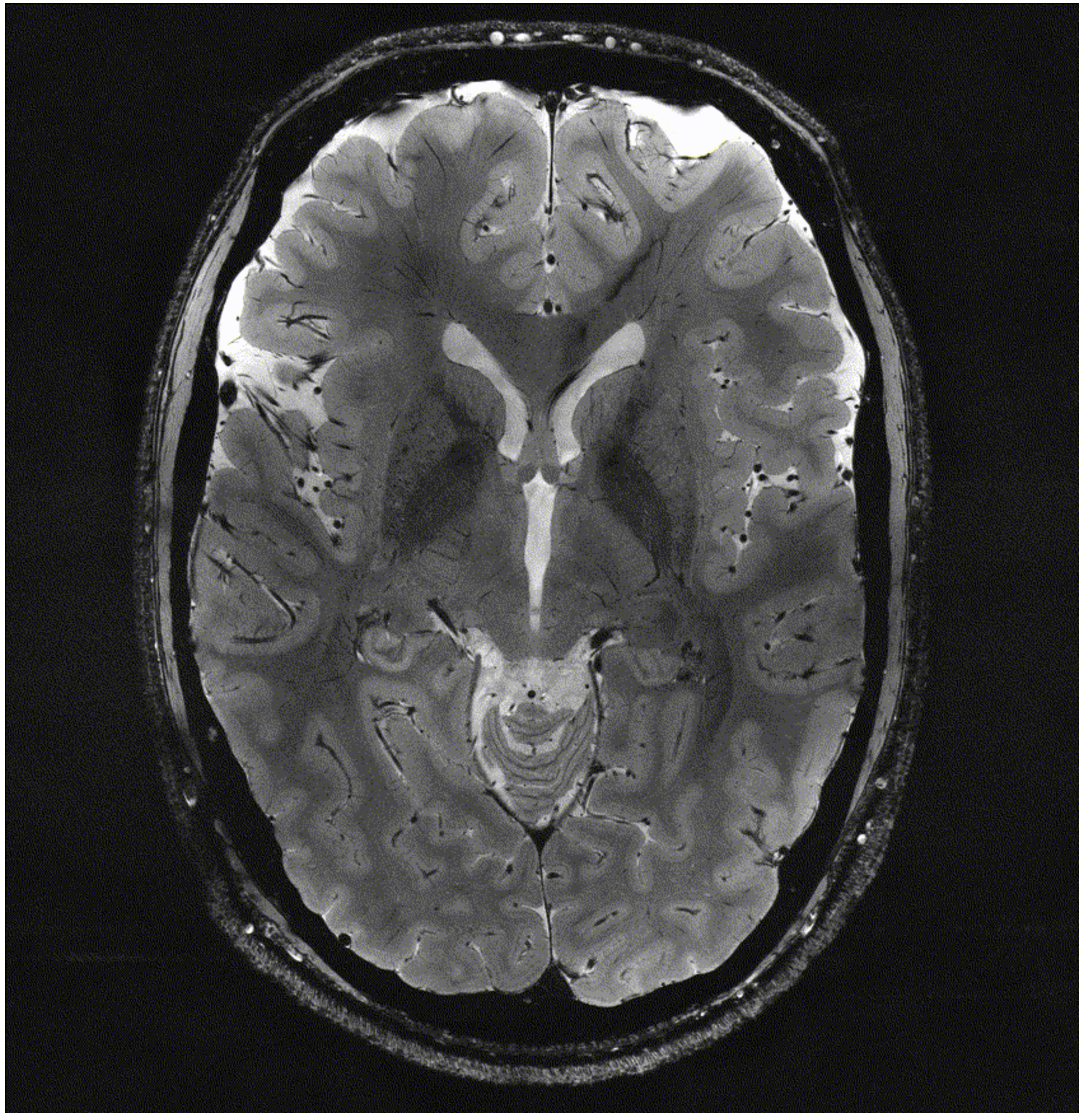
First HR Ex-Vivo Human Brain Imaging at 11.7 T



ME-GRE (700um)^3 iso
TA: 5min (GRAPPA 2x2)
KT-points pulses for $B1^+$ field homogeneity



High Resolution Imaging



Acquisition Time of 50 minutes!

2D T2*w axial, 7T scanner, 120 x 120 x 600 μm^3
Matrix size: 1690 x 1744, 21 slices, 2 averages

32-channel receiver coil, Motion correction,

Full sampling

How can we accelerate this?

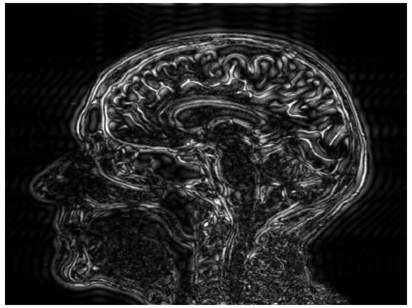
J. Z et al., Eur. Radiol., 2010, 20(4):915-922

Sampling in MRI

Spectral frequency

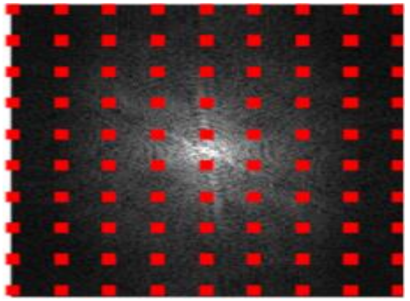
K-space

iDFT

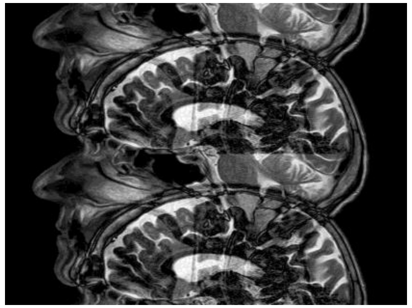


Sampling in MRI

K-space



iDFT



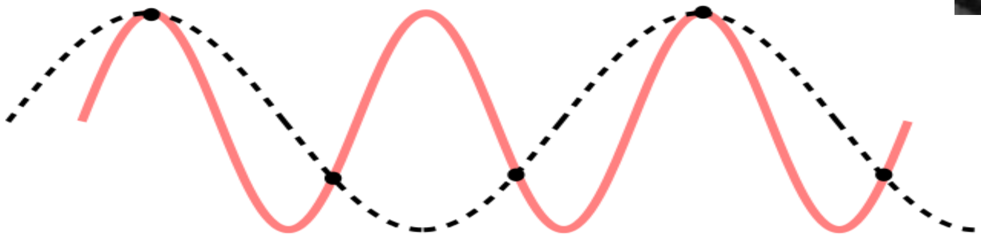
Nyquist-Shannon theory

$\uparrow$ resolution $\Rightarrow$ $\uparrow$ #samples

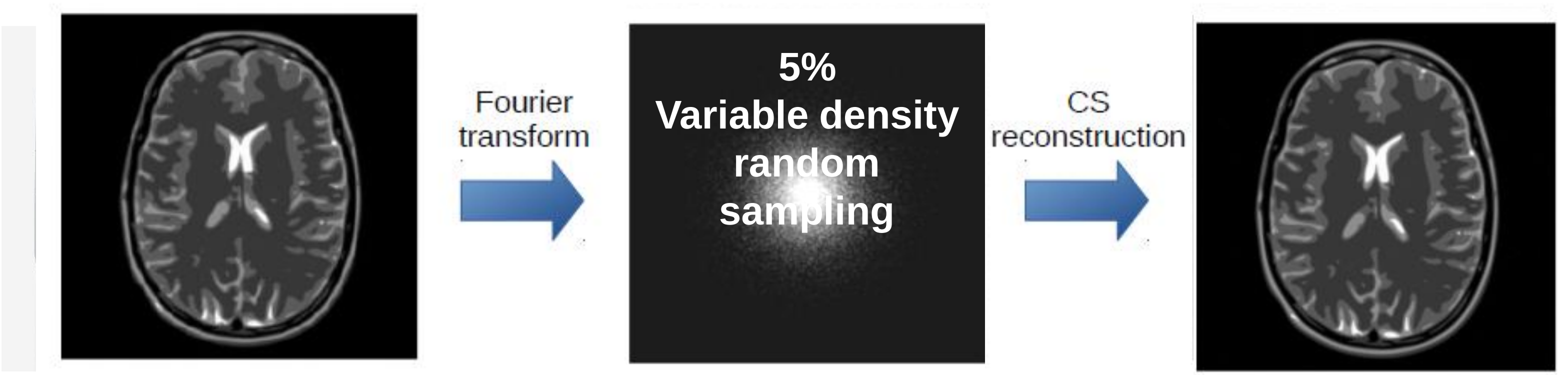
Long acquisition times

The sampling frequency should be at least twice the highest frequency contained in the signal

Harry Nyquist

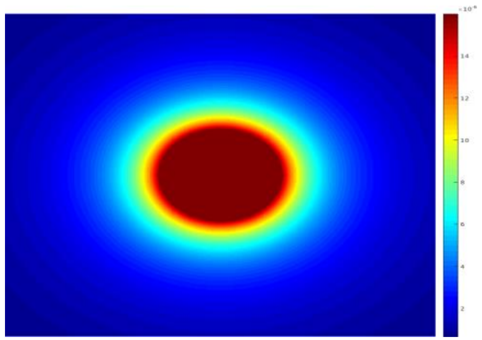


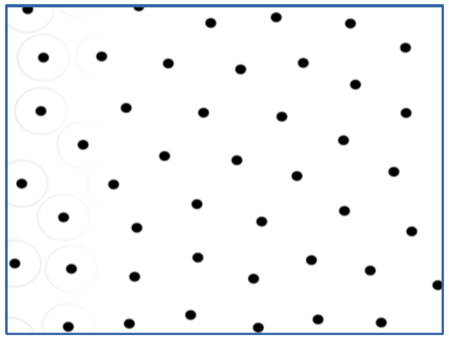
Compressed Sensing in MRI



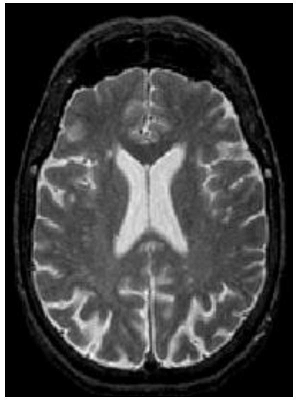
Under-sampling with guarantees of image recovery if these two criteria are fulfilled :

i. **Variable-density sampling**
ii. **Locally uniform coverage**

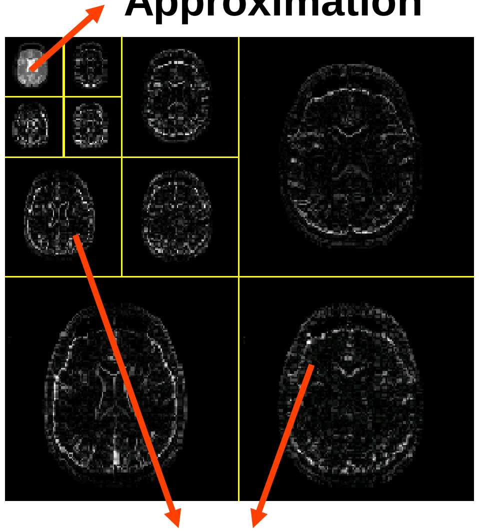




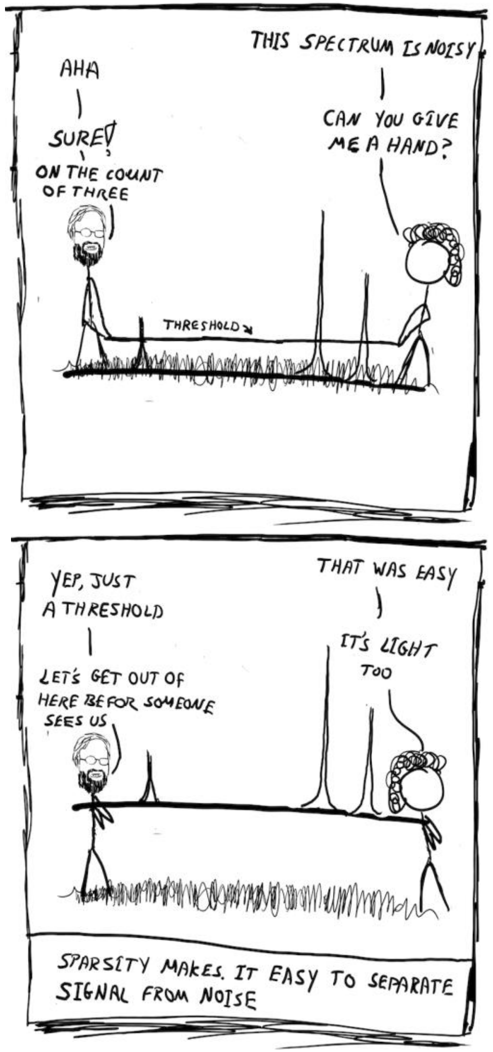
MR Images are sparse in Wavelet Domain



Approximation



Detail → SPARSE



Can be recovered by sparsity constraints

Candes et al. 2006. Communications on Pure and Applied Mathematics ; Lustig et al. 2007. MRM;
Puy et al, IEEE SPL 2011; Chauffert et al, SIAM IS 2014; Boyer et al. 2016. SIAM IS;
Adcock et al. *Breaking the coherence barrier: A new theory for compressed sensing*. Forum of Mathematics, Sigma 2017. Vol. 5.

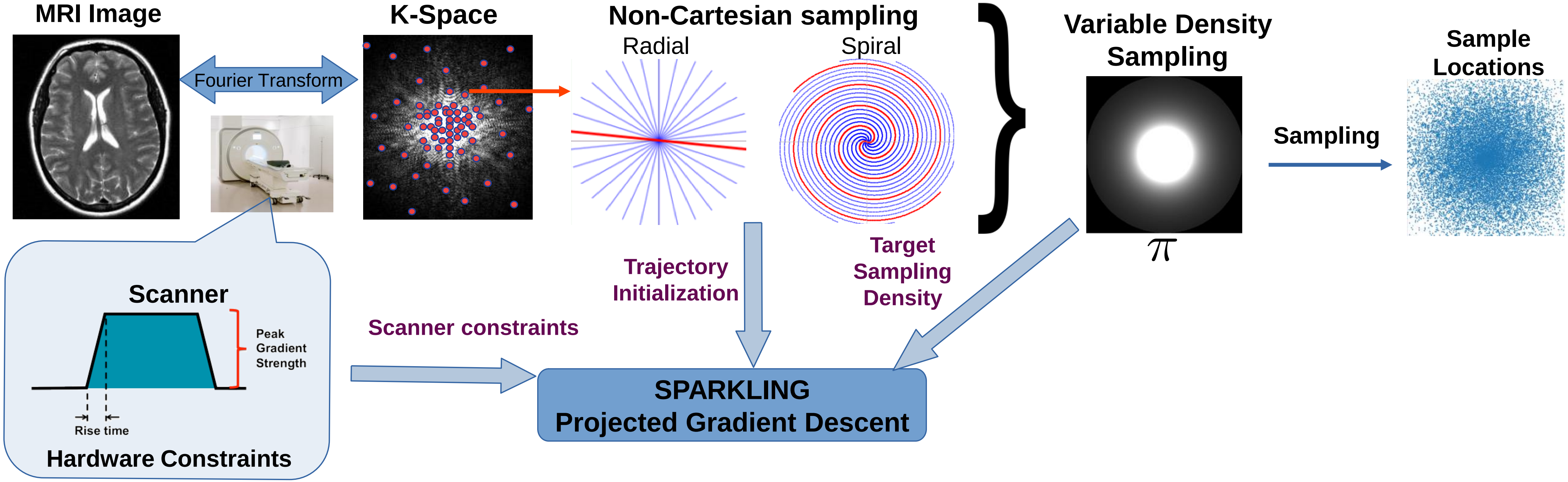
SPARKLING: Spreading Projection Algorithm for rapid K-space sampLING

- Lazarus et al, *SPARKLING: variable-density k-space filling curves for accelerated T_2 *-weighted MRI.* Magnetic Resonance in Medicine, 2019

- Chaithya G R et al, *Optimizing full 3D SPARKLING trajectories for high-resolution Magnetic Resonance Imaging. IEEE Transactions on Medical Imaging* 2022

- Daval-Frérot et al, Iterative staticΔ B0 field map estimation for off-resonance correction in non-Cartesian susceptibility weighted imaging, *Magnetic Resonance in Medicine* 2022

SPARKLING



$$\widehat{\mathbf{K}} = \arg\ \min_{\mathbf{K}\in\mathcal{Q}_N} F_N(\mathbf{K}) = [F_N^a(\mathbf{K}) - F_N^r(\mathbf{K})]$$

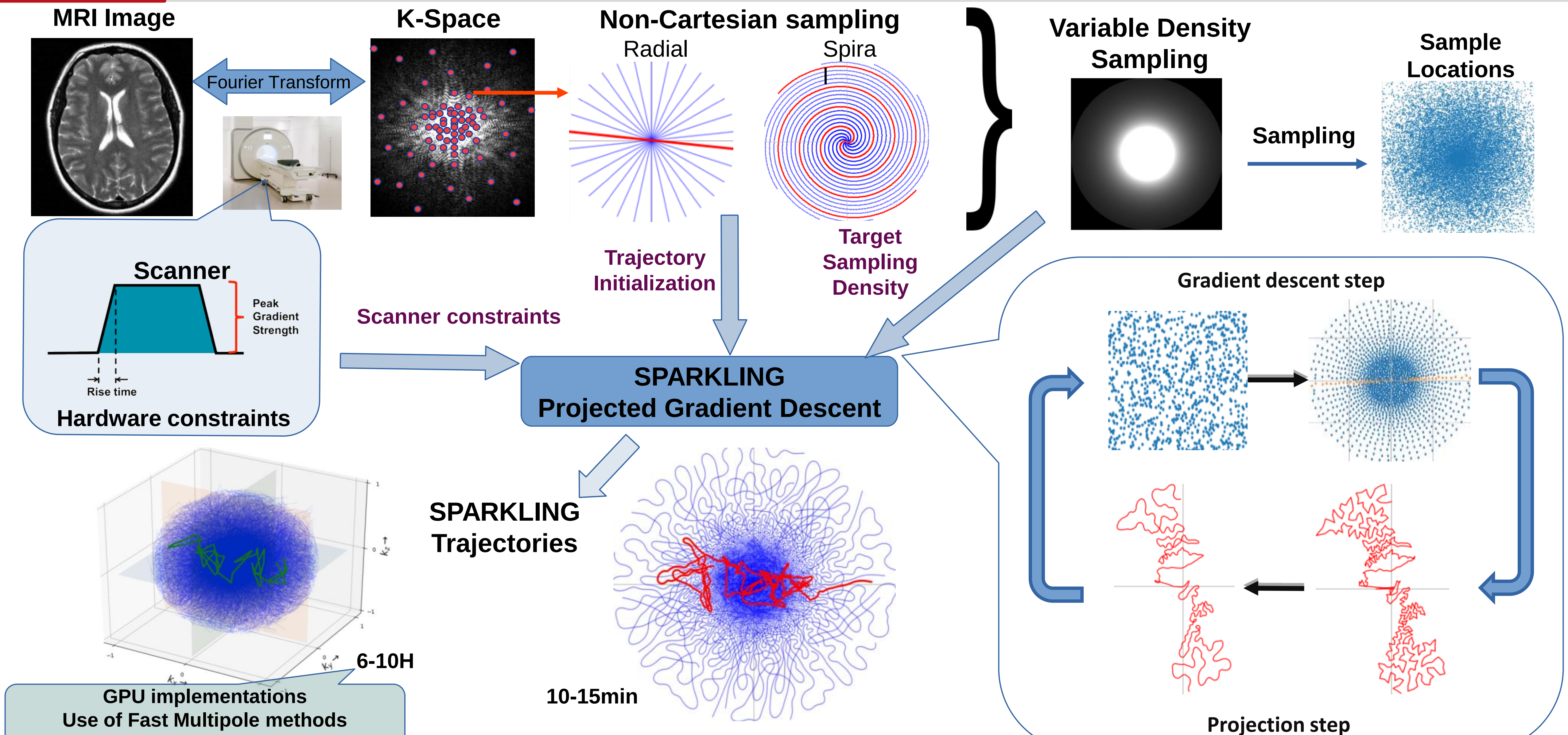
$$F_N^a(\mathbf{K}) = \frac{1}{N}\sum_{n=1}^{N}\int_{\Omega} H(x-\mathbf{K}[n])\pi(x)\,dx \qquad F_N^r(\mathbf{K}) = \frac{1}{2N^2}\sum_{n,m=1}^{N} H(\mathbf{K}[n]-\mathbf{K}[m])$$

Attraction term: follow the target sampling density

Repulsion term: locally uniform density

Boyer et al, SIAM IS 2016; Chauffert et al, Construct Approx 2017

SPARKLING, cont’d

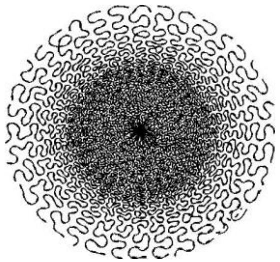


Lazarus et al, MRM 2019; Chaithya et al, *IEEE* TMI 2022

Applications of SPARKLING

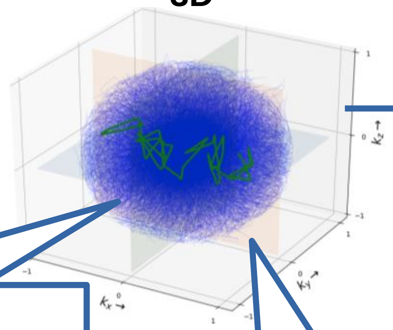
C. Lazarus

2D

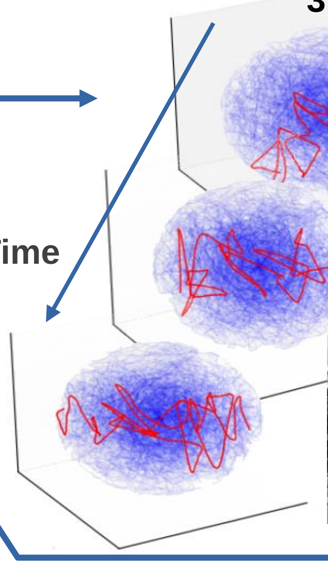


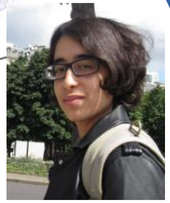
Chaithya G R

3D



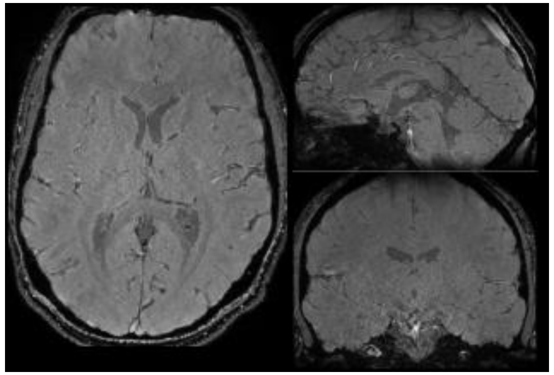
3D + Time



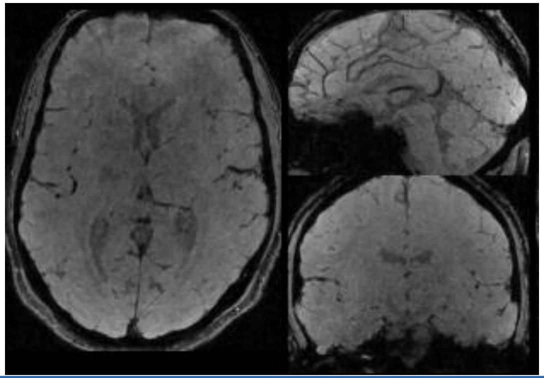


Z. Amor

Cartesian p4
Scan Time: 15min 13s



SPARKLING
Scan Time: 3min



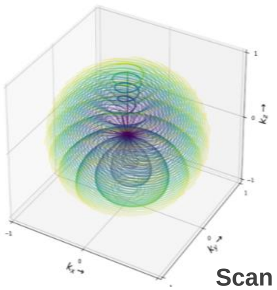
T2* GRE: SWI

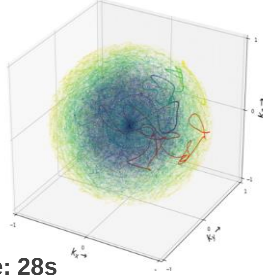
Sodium Imaging

TPI

Baptista et al, *ISMRM* 2022

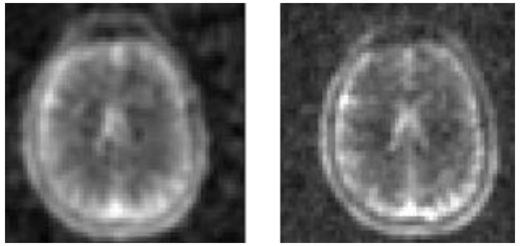
SPARKLING

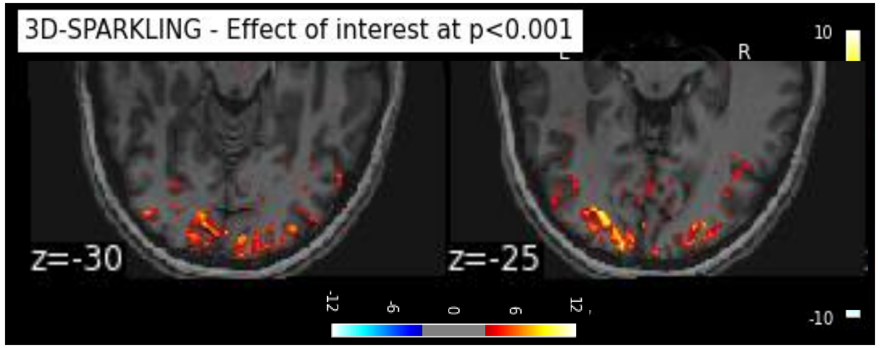


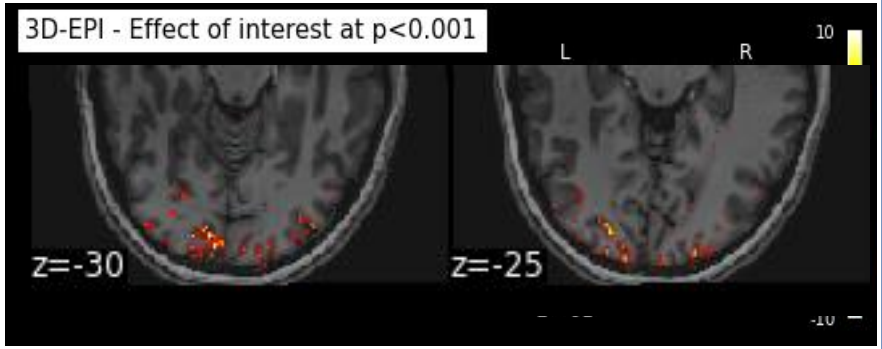


Scan Time: 28s

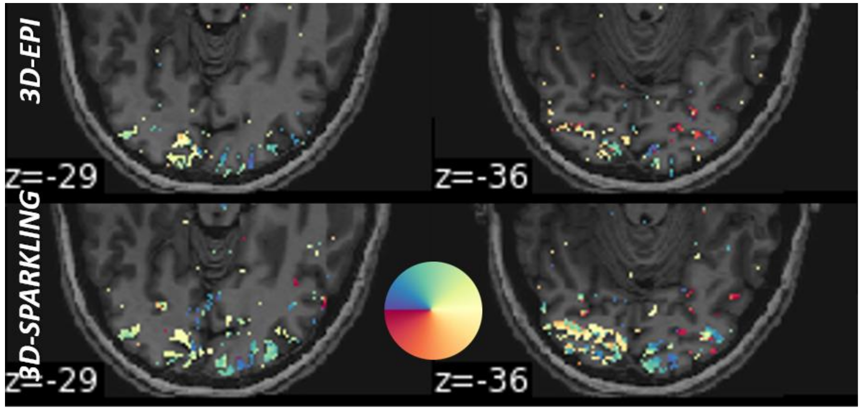
R. Baptista



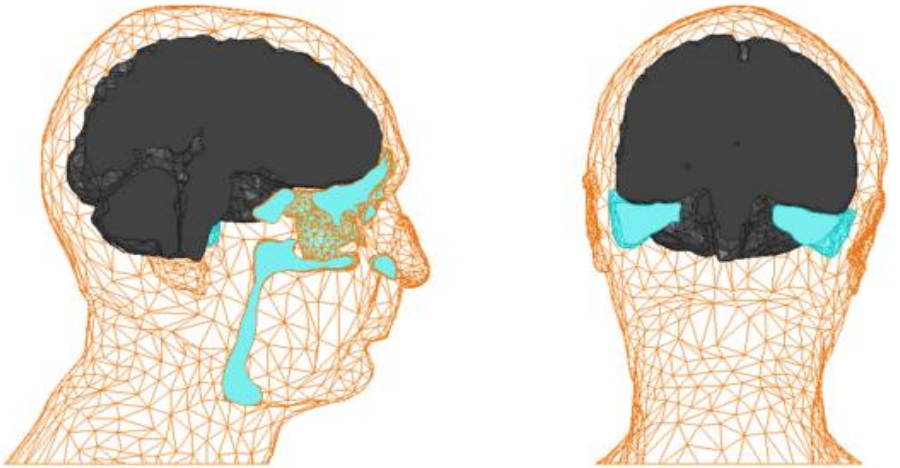




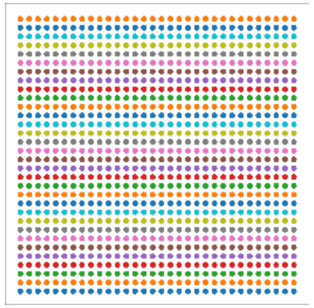
fMRI Amor et al, *ISMRM* 2022



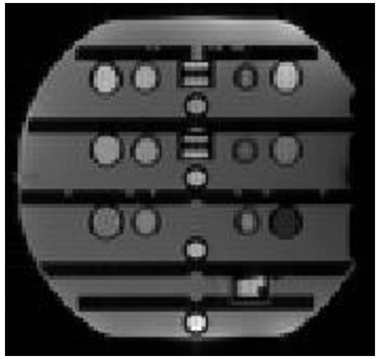
Spatial inhomogeneities of B_0 & Off-resonance effects

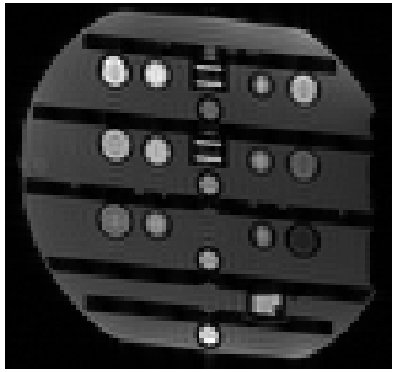


Cartesian example

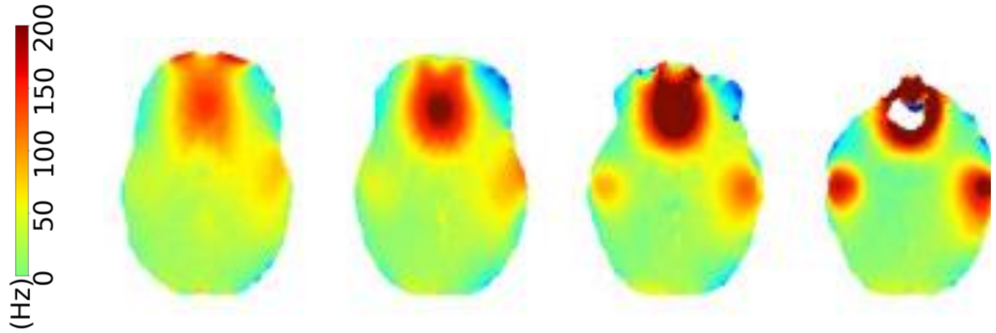


Line by line
Cartesian trajectory

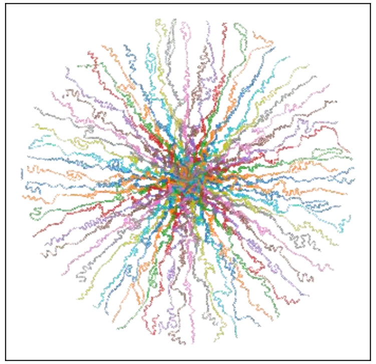




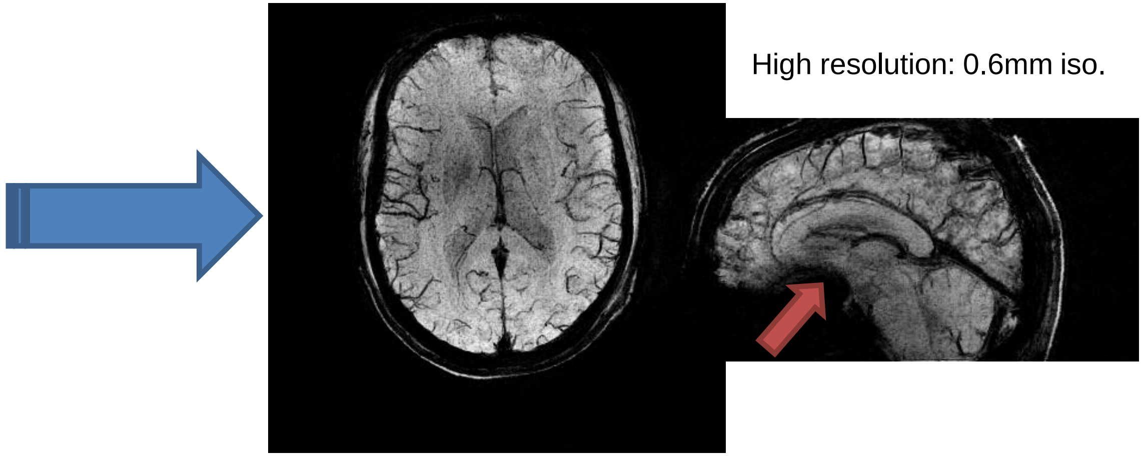
+ ΔB_0



field maps



3D SPARKLING



High resolution: 0.6mm iso.

Meneses et al. ***Static field shimming in the human brain for ultra-high field MRI : conceptual limits and development of a novel hardware prototype*.**

Correcting the ΔB_0 Effects using an External Fieldmap

NIST 3T Cylindrical Stack-of-Sparklings
0.6mm iso, FOV 230mm, AF=10, OS=2

Fourier model

$$s(\mathbf{t}) = \int f(r)\, e^{-i2\pi(k(\mathbf{t})\cdot r)} dr$$

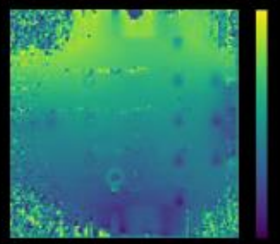
- $s(t)$ is the acquired signal at time t
- $f(r)$ is the image at position r

Extended Fourier model

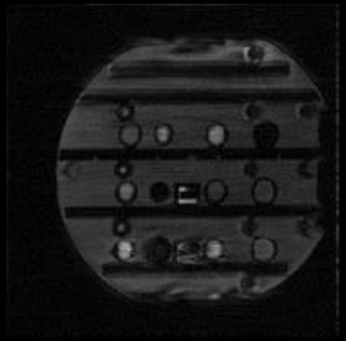
$$s(\mathbf{t}) = \int f(r) e^{-i\omega(r)\mathbf{t}} e^{-i2\pi(k(\mathbf{t})\cdot r)} dr$$

- $\omega(r)$ is the resonance frequency offset caused by B_0 inhomogeneities at position r and time t

$$\omega(r) = 2\pi \Delta B_0(r)$$



ΔB_0 field map

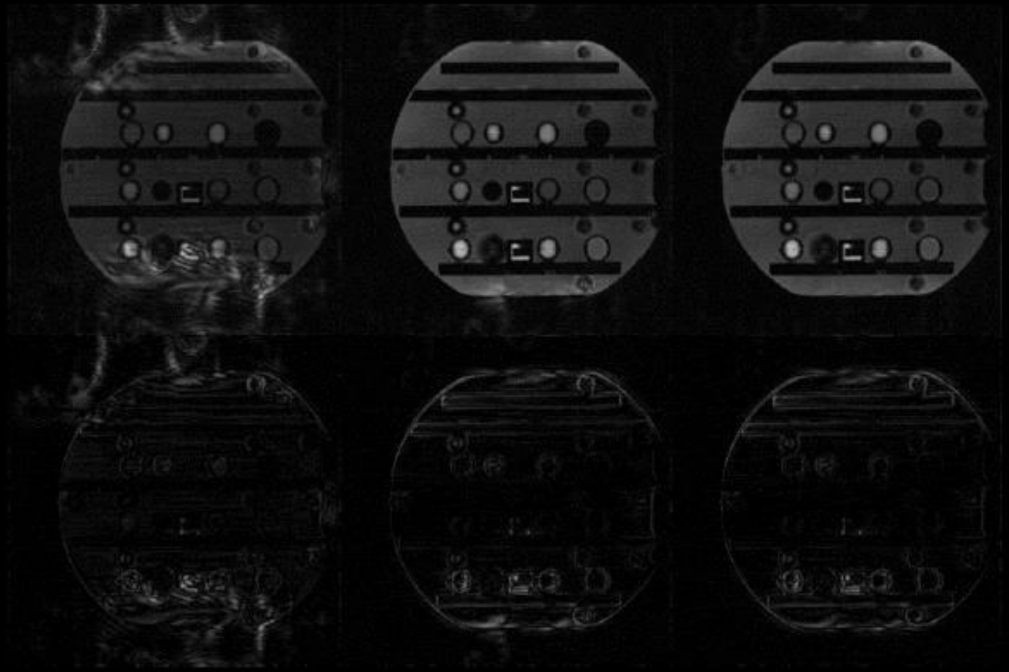


Original

(1) Corrected magnitudes & (2) Differences to the original

(1)

(2)

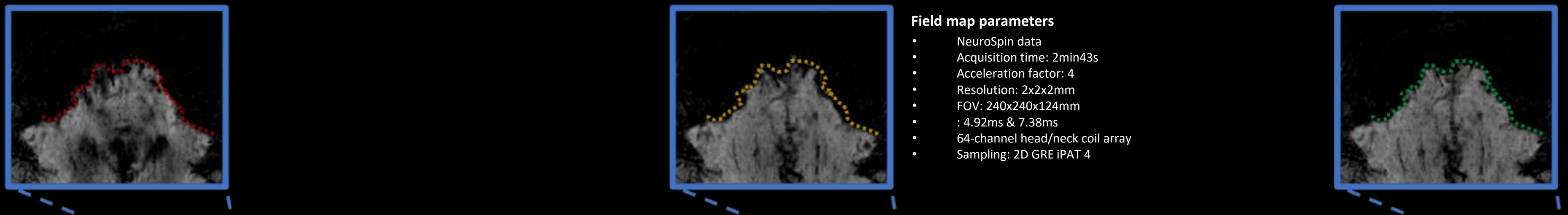


L=5 L=7 L=9

Number of interpolators

Source: [1] Man, L C, John M. Pauly and A. Macovski (1997). In *Magnetic Resonance in Medicine.*

Correction of B0 inhomogeneities: External vs Internal



Field map parameters

- NeuroSpin data
- Acquisition time: 2min43s
- Acceleration factor: 4
- Resolution: 2x2x2mm
- FOV: 240x240x124mm
- : 4.92ms & 7.38ms
- 64-channel head/neck coil array
- Sampling: 2D GRE iPAT 4

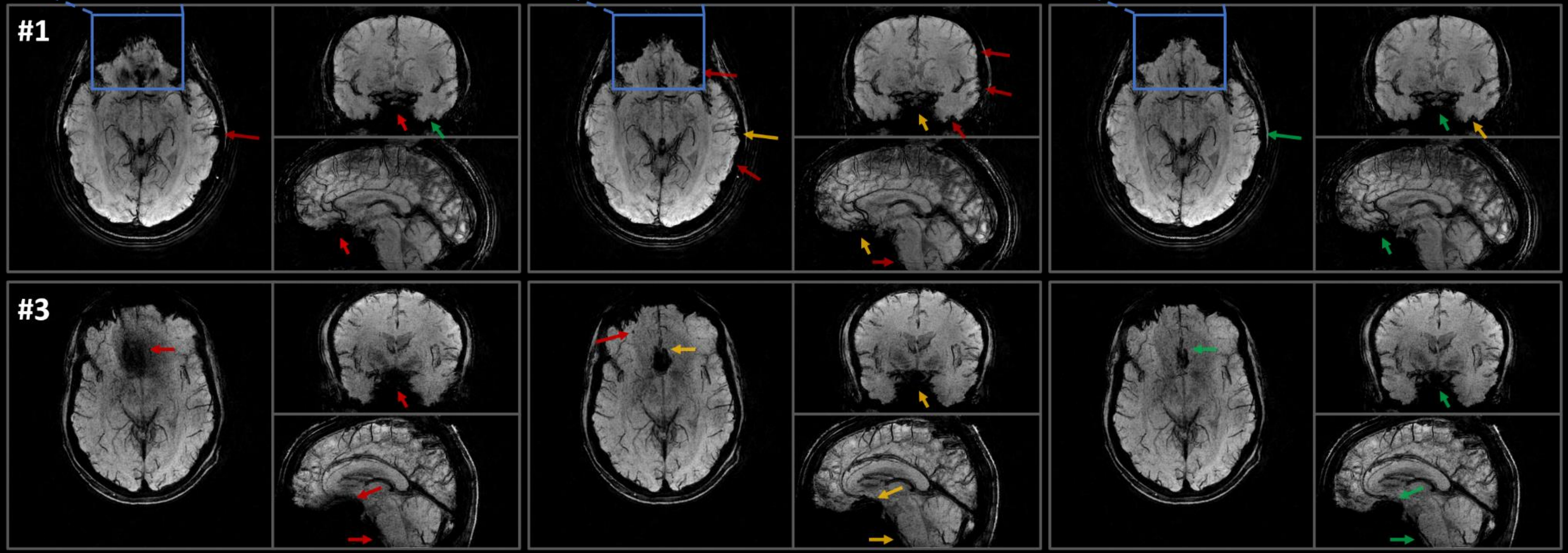
Field map parameters

- NeuroSpin data
- Acquisition time: 2min30s
- Acceleration factor: 20
- Resolution: 0.6x0.6x0.6mm
- FOV: 240x240x124mm
- : 20ms
- 64-channel head/neck coil array
- Sampling: Full 3D SPARKLING (C20D3)

G Daval-Frérot

AF=10

AF=20



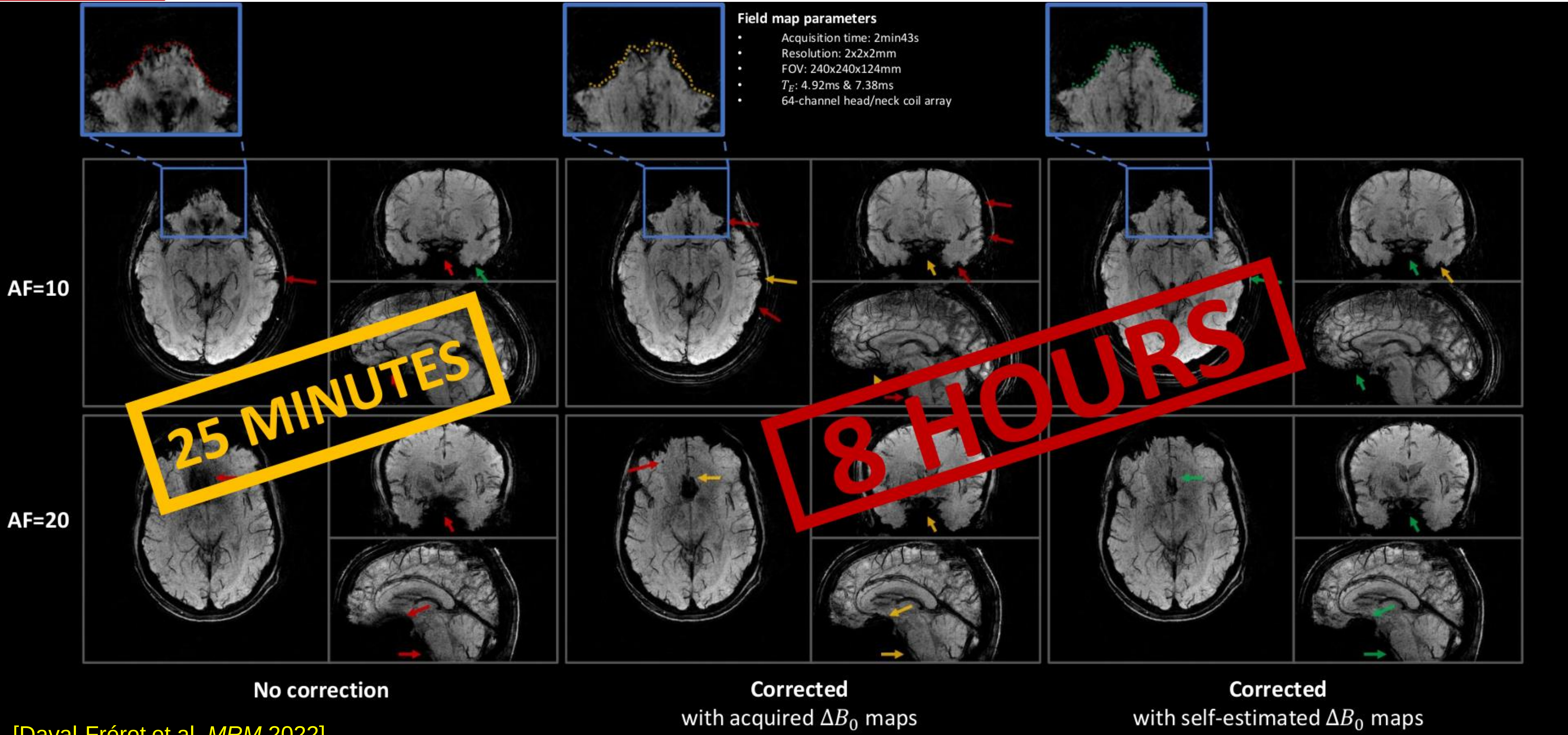
No correction

Corrected
with acquired maps

Corrected
with self-estimated maps

[Daval-Frérot et al, *MRM* 2022]

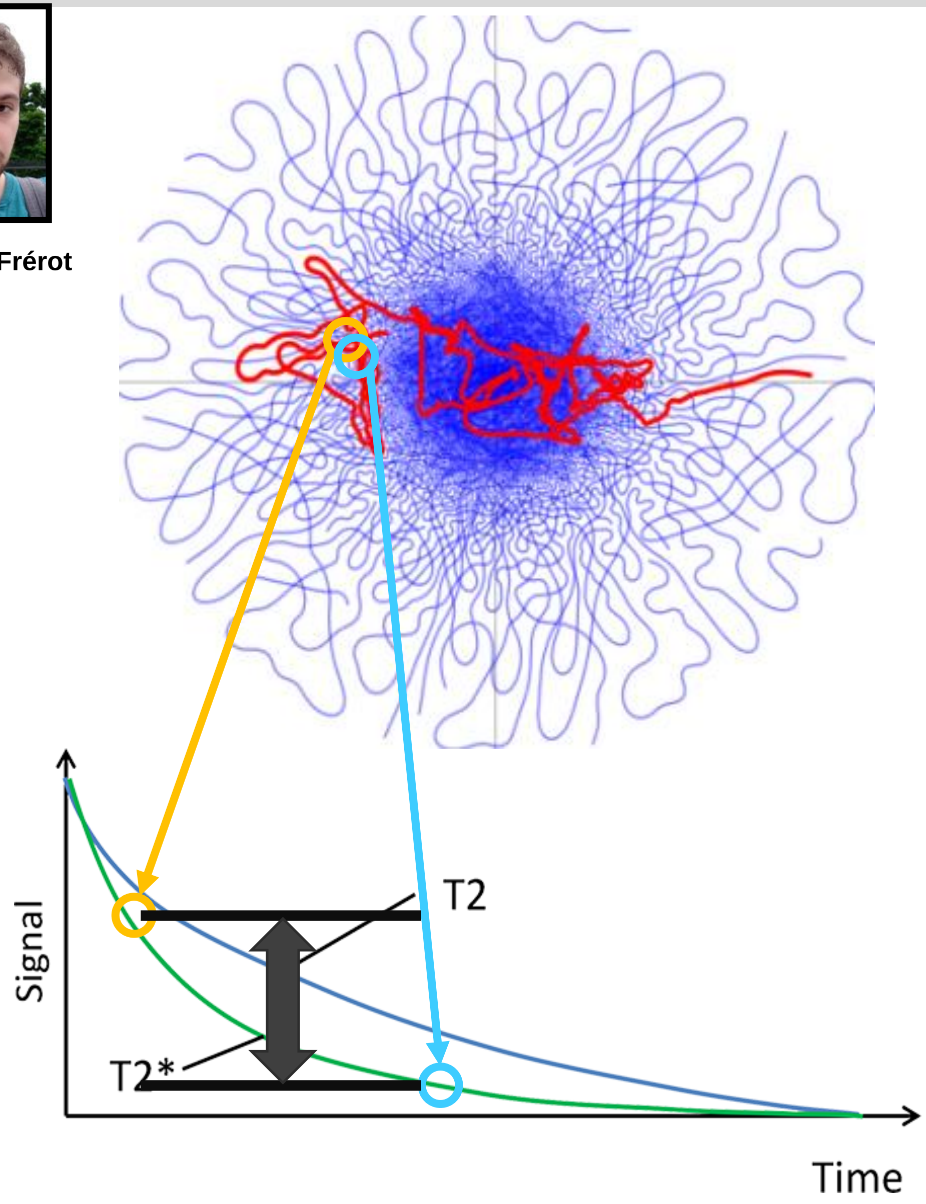
Correction of B0 inhomogeneities: External vs Internal



[Daval-Frérot et al, *MRM* 2022]

Off-resonance artifacts and signal decay


Chaithya G R G Daval-Frérot



Fourier model

$$s(t) = \int f(r)\, e^{-i2\pi(k(t)\cdot r)} dr$$

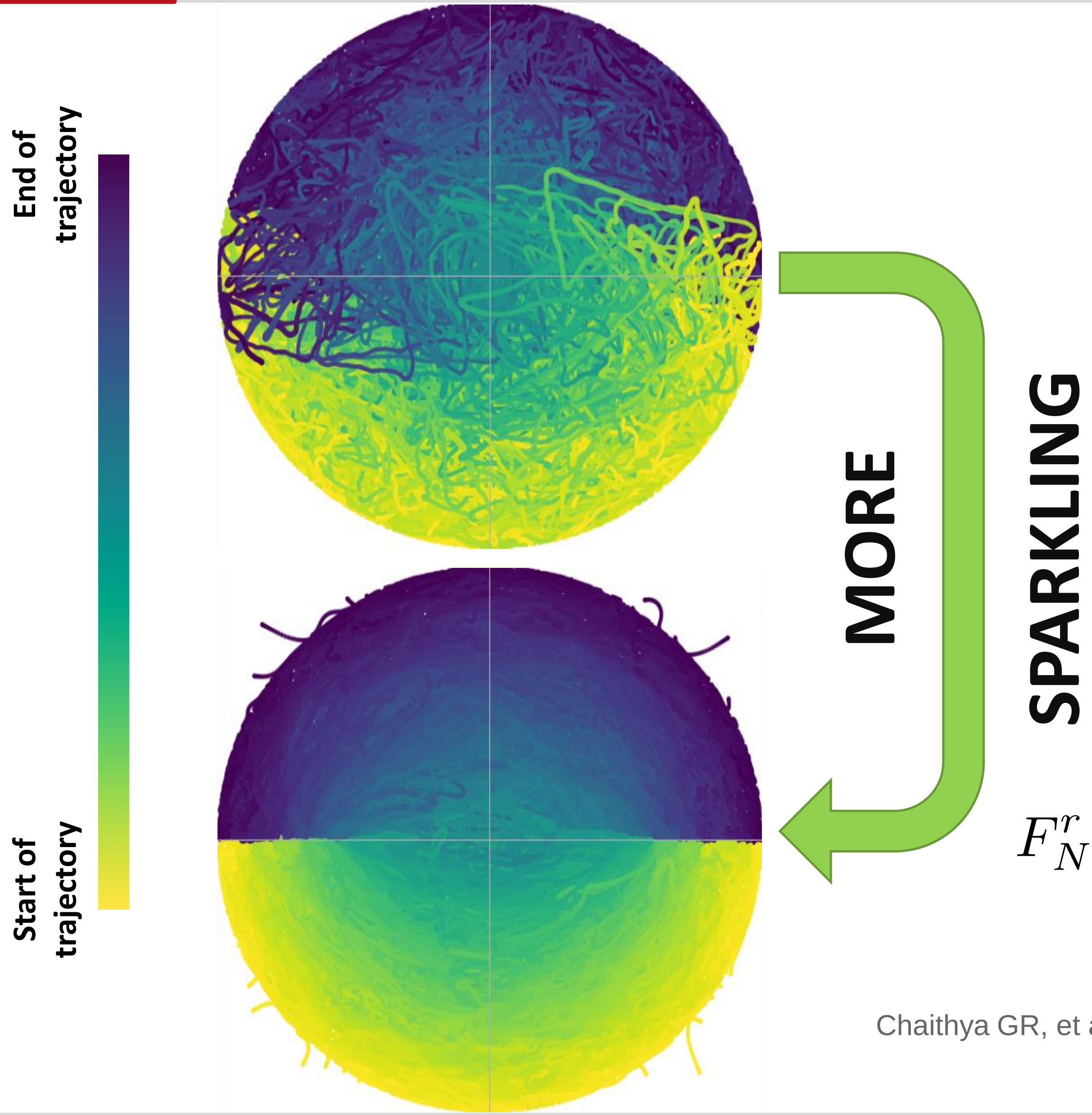
- $s(t)$ is the acquired signal at time t
- $f(r)$ is the image at position r

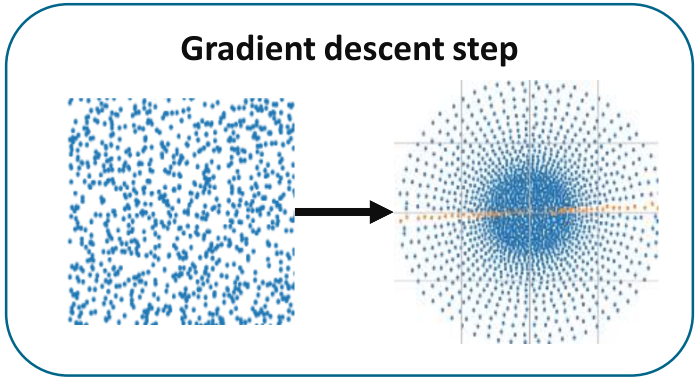
Extended Fourier model

$$s(t) = \int f(r) e^{-(\alpha(r)+i\omega(r))t} e^{-i2\pi(k(t)\cdot r)} dr$$

- $\alpha(r)$ is the signal decay at position r
- $\omega(r)$ is the off-resonance frequency at position r

Minimizing Off-resonance Effects (MORE) SPARKLING





Attraction term

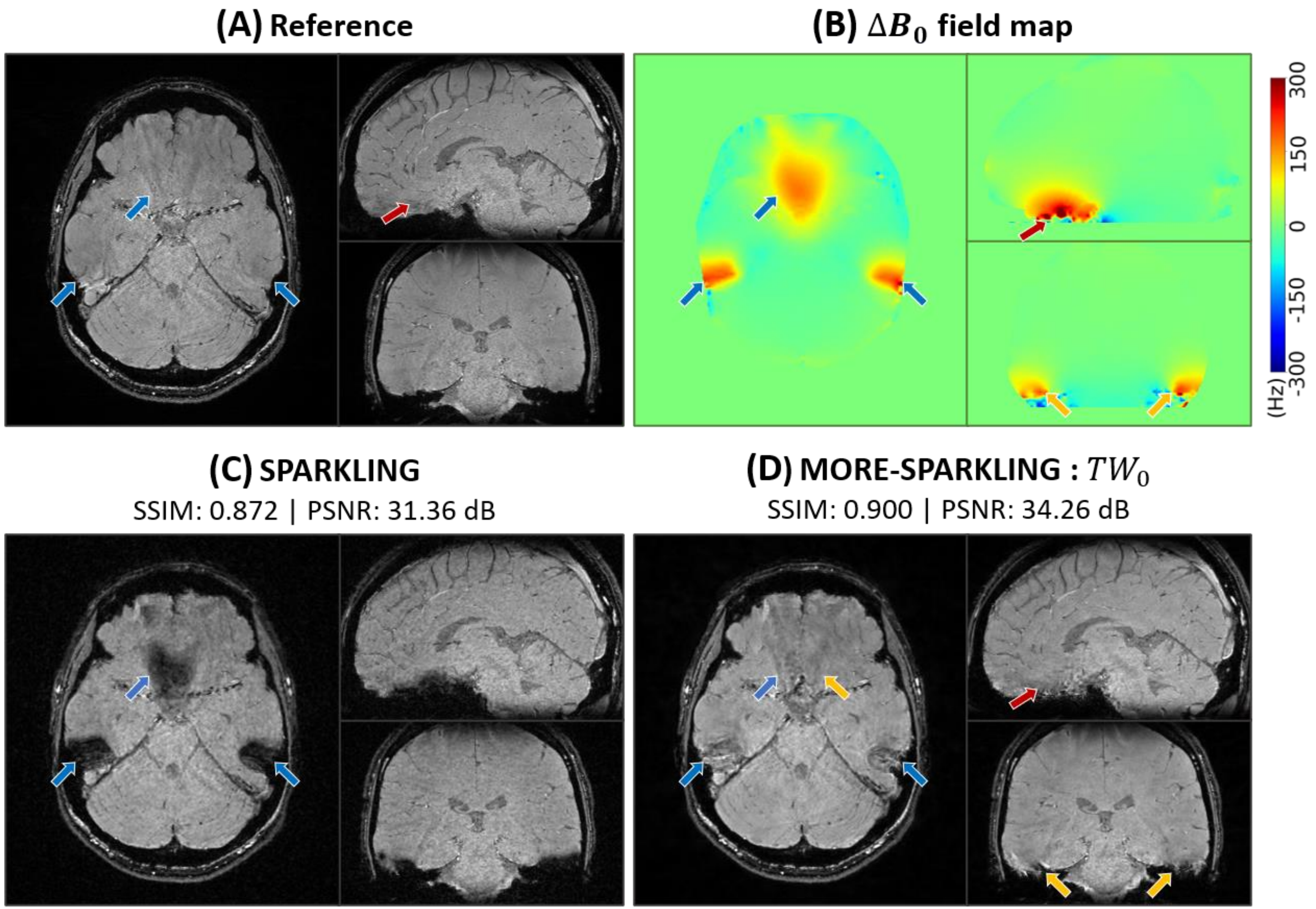
$$F_N^a(\mathbf{K}) = \frac{1}{N}\sum_{n=1}^{N}\int_{\Omega} H(x - \mathbf{K}[n])\pi(x)\,dx$$

Repulsion term

$$F_N^r(\mathbf{K}) = \frac{1}{2N^2}\sum_{n,m1=1}^{N} H(\mathbf{K}[n] - \mathbf{K}[m])\, e^{\frac{|t_n - t_m|\tau}{N}}$$

Chaithya GR, et al, *ISMRM* 2022 (EU Patent App. 22305592.2. 2022)

MORE SPARKLING: In vivo Results



Acquisition parameters

- 3T Prisma
- Healthy volunteer
- Acquisition time: 2min30s
- Acceleration factor: 20
- Resolution: 0.6x0.6x0.6mm
- FOV: 240x240x124mm
- & : 20ms & 37ms
- 64-channel head/neck coil array
- Trajectory: Full-3D Stack-of-SPARKLING

Reconstruction parameters

- Pre-computed density compensation |
- Iterative calibrationless reconstruction
- Soft thresholding regularization

Chaithya GR, et al, *ISMRM* 2022 (EU Patent App. 22305592.2. 2022)

Interim Summary

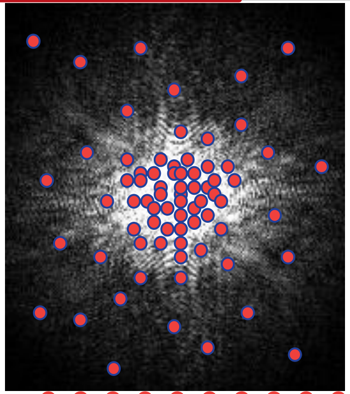
- **3D SPARKLING**
  - 3D SPARKLING achieves isotropic high resolution in short scan time (2’30”@600µm iso)
  - Works at 3T and 7T
  - Discrepancy between retrospective and prospective results due to off-resonance effects
  - Internal estimation of static B0 inhomogeneities
  - Off-resonance effects correction during image reconstruction too computational demanding
  - MORE SPARKLING (temporal weighting) to counteract off-resonance effects
  - Application to both anatomical, metabolic and functional imaging (BOLD fMRI)

- **Perspectives**
  - Embedded motion estimation and correction
  - Quantitative susceptibility mapping
  - Diffusion-weighted MRI
  - Neurodegenerative diseases (Parkinson’s syndromes)
  - Neonatal imaging

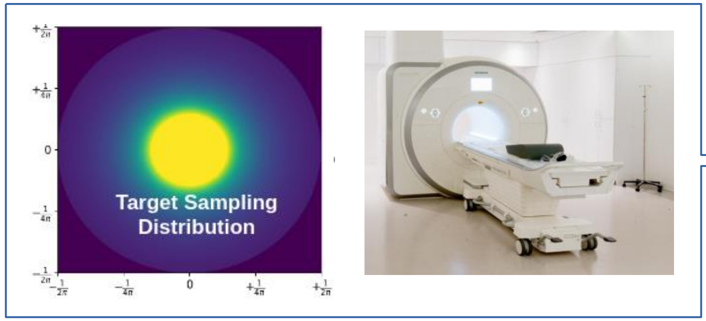
Unrolled neural networks for non-Cartesian MR image reconstruction

- Muckley et al, Results of the 2020 fastMRI challenge for machine learning mr image reconstruction, *IEEE Transactions on Medical Imaging*, 2021

- Ramzi et al, NC-PDNet: a Density-Compensated Unrolled Network for 2D and 3D non-Cartesian MRI Reconstruction, *IEEE Transactions on Medical Imaging* 2022

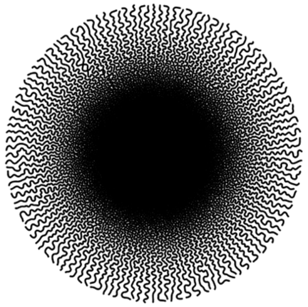


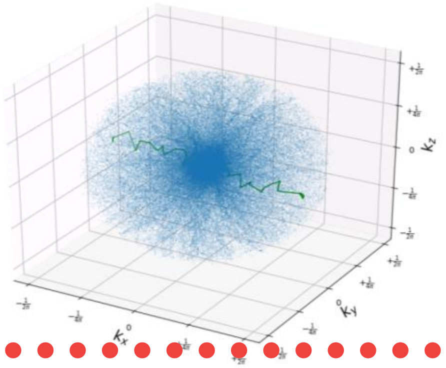
How to efficiently sample k-space data under Hardware constraints?



SPARKLING

Lazarus et al, MRM 2019

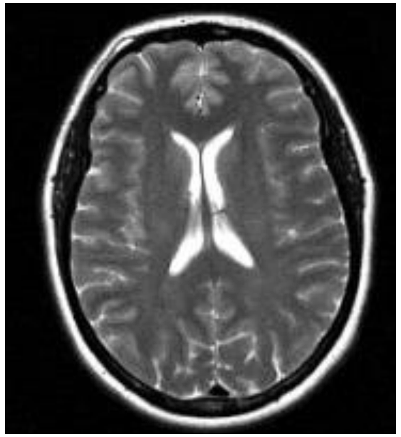




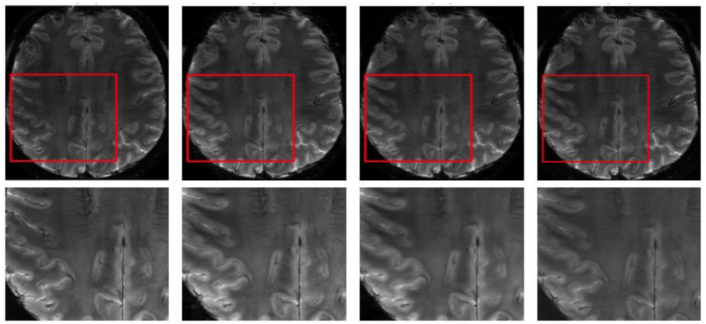
Acquisition Time

Nonlinear Reconstruction

How to efficiently reconstruct from under-sampled data?



Recon Time



Cartesian Reference | Self Calibrating | L1-ESPIRiT | OSCAR Calibrationless

pysap-mri

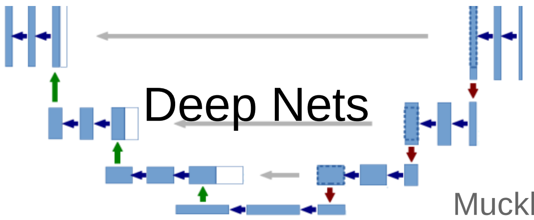
CS Reconstruction

Farrens et al, *Astro & Comput* 2020
El Gueddari et al, *ISMRM WS* 2020
El Gueddari et al, *J Imaging* 2021

K-Space Data

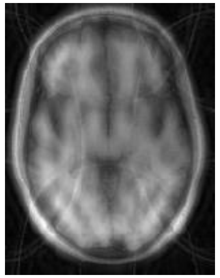
Recon Time

Deep Nets



Muckley, et al, *IEEE TMI* 2021

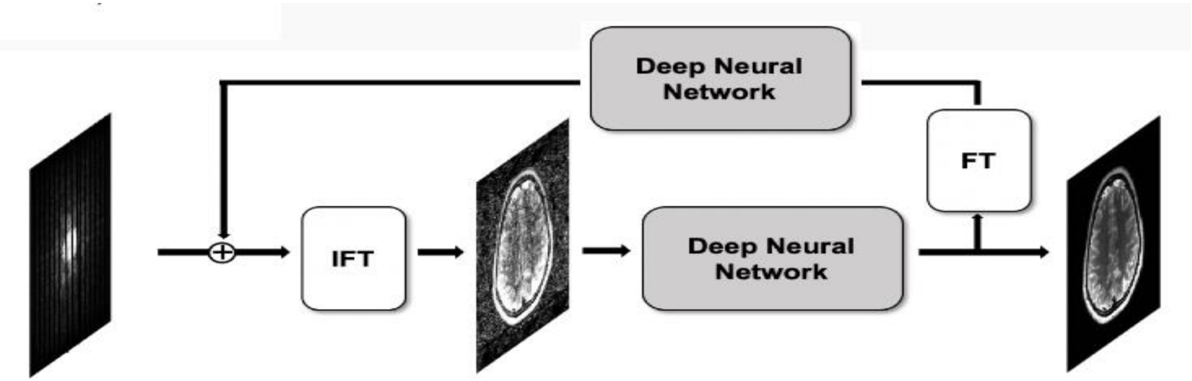
Ramzi et al, *IEEE TMI* 2022

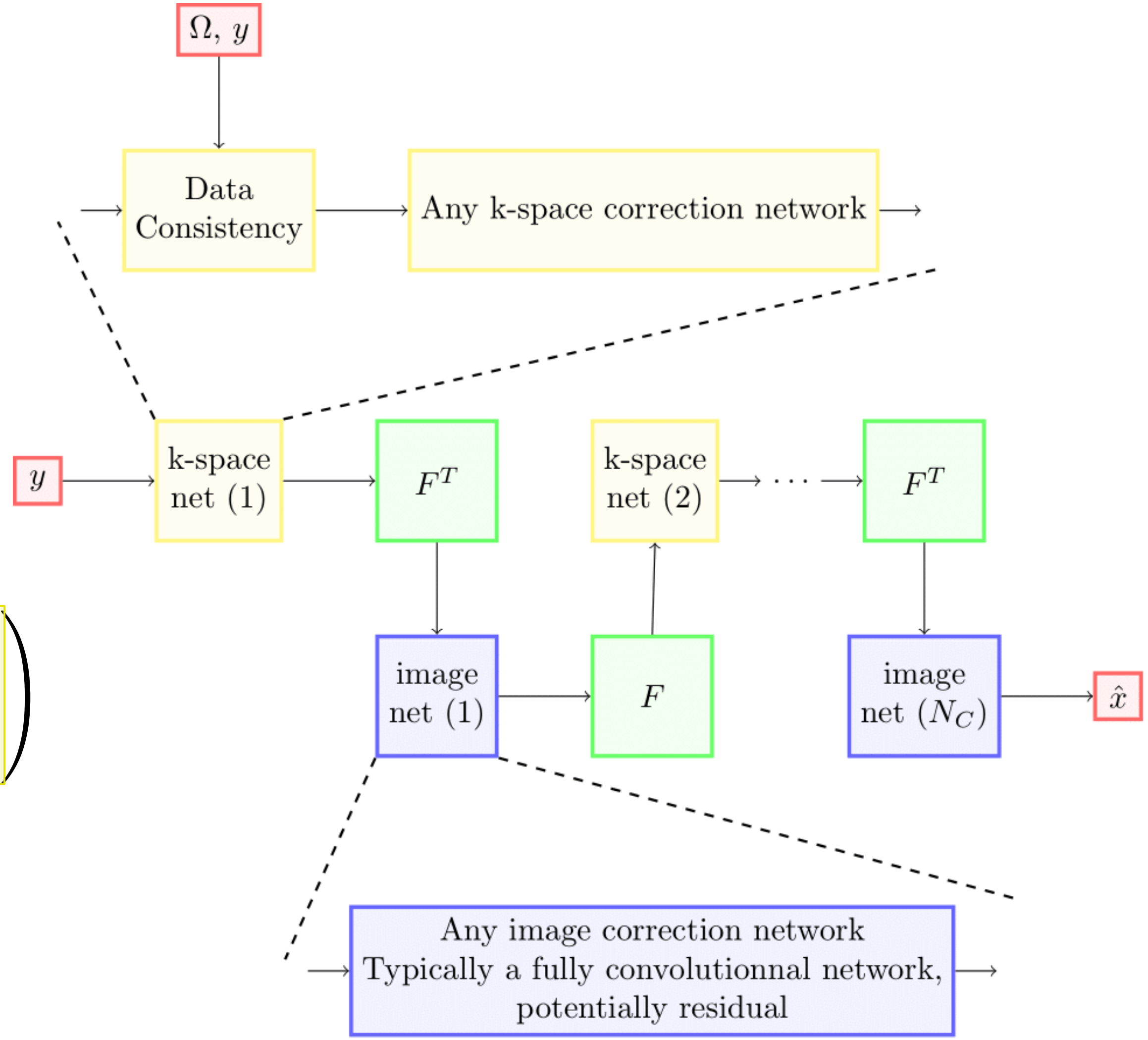


Gridded Reconstruction

Cross-Domain Learning in a Nutshell

Z. Ramzi





- **Key intuitive idea:** Alternate the corrections between image domain and k-space
- **Tool**: unrolling optimization algorithms

$$\mathbf{x}_{n+1} = \mathbf{x}_n - \tau_n \left(\sum_{\ell=1}^{L} \mathbf{F}_\Omega \mathbf{S}_\ell \right)^H \left(\sum_{\ell=1}^{L} \mathbf{F}_\Omega \mathbf{S}_\ell \mathbf{x}_n - \mathbf{y}_\ell \right)$$

$$\mathbf{x}_{n+1} = \mathrm{prox}_{\tau_n \mathcal{R}}(\mathbf{x}_{n+1})$$

Adler and Ötkem, *IEEE TMI* 2018

Ramzi et al, App. Sci 2020, *ISMRM* 2020

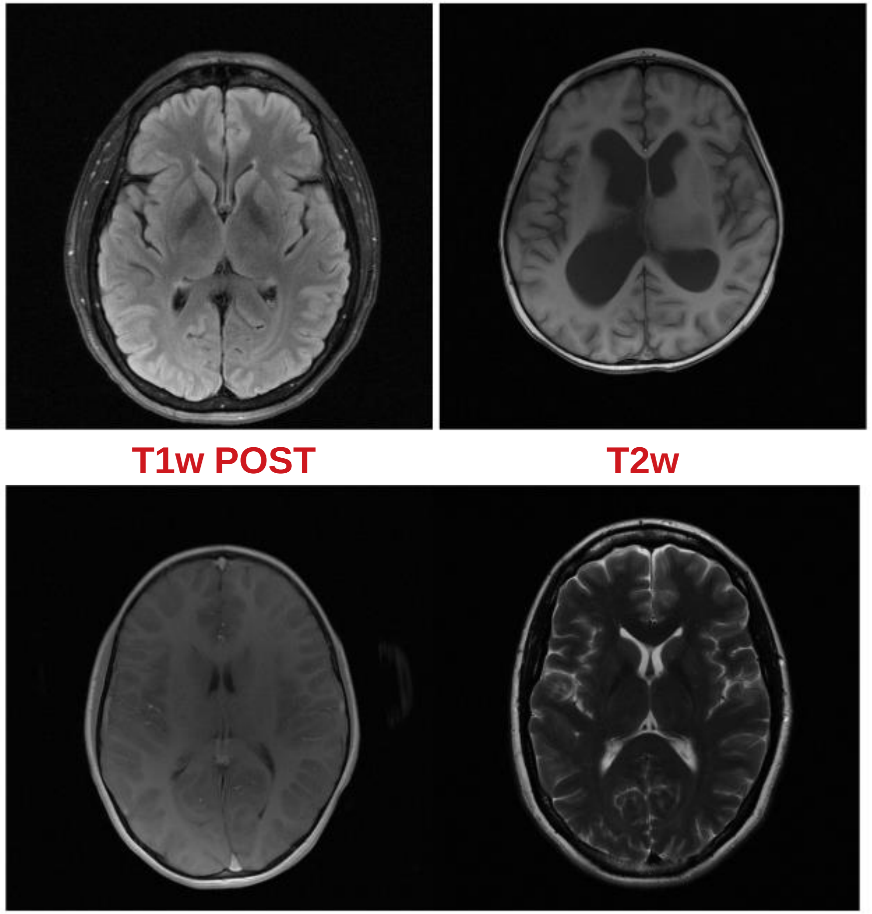
The 2020 FastMRI Challenge

FACEBOOK AI · NYU Langone Health

- **Objectives:**
  - → Run an international challenge to benchmark the deep learning solutions for MR brain image reconstruction
  - → Acquisition setup that fits the clinical realm (multi-coil acquisition, multiple imaging contrasts)
  - → Larger training set with a total of 6,970 brain scans (approx. 1.5 TB of raw k-space data, 3001 scans at 1.5T)

Ground Truth

FLAIR | T1w | T1w POST | T2w



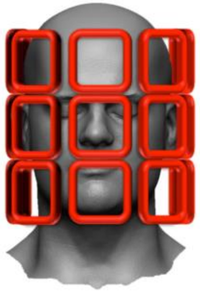


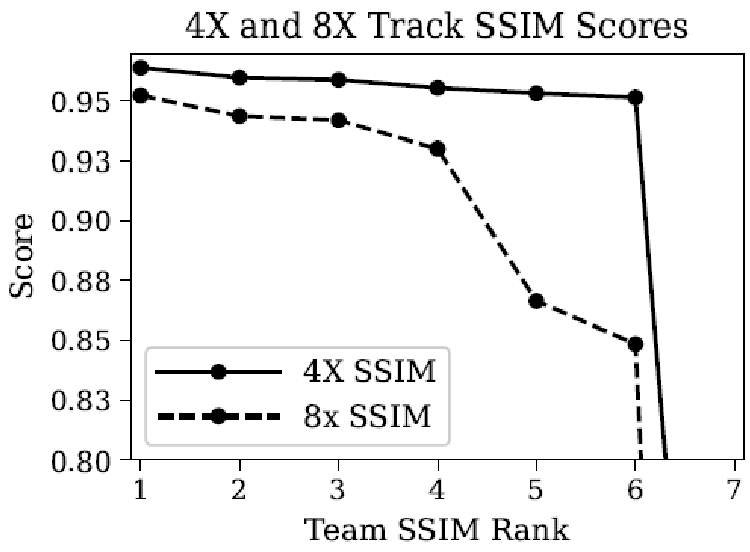
Table 1: Summary of Siemens data for 4X/8X tracks.

Split	T1	T1POST	T2	FLAIR	Total
Siemens/Main Tracks					
train	498	949	2,678	344	4,469
val	169	287	815	107	1,378
test (4X)	33	54	170	24	281
test (8X)	32	68	152	25	277
challenge (4X)	26	67	192	18	303
challenge (8X)	24	65	159	14	262
Transfer Track (4X, all challenge)					
GE	22	29	83	77	211
Philips	18	0	50	50	118

Quantitative Challenge Results

Table 2: Summary of SSIM scores by contrast.

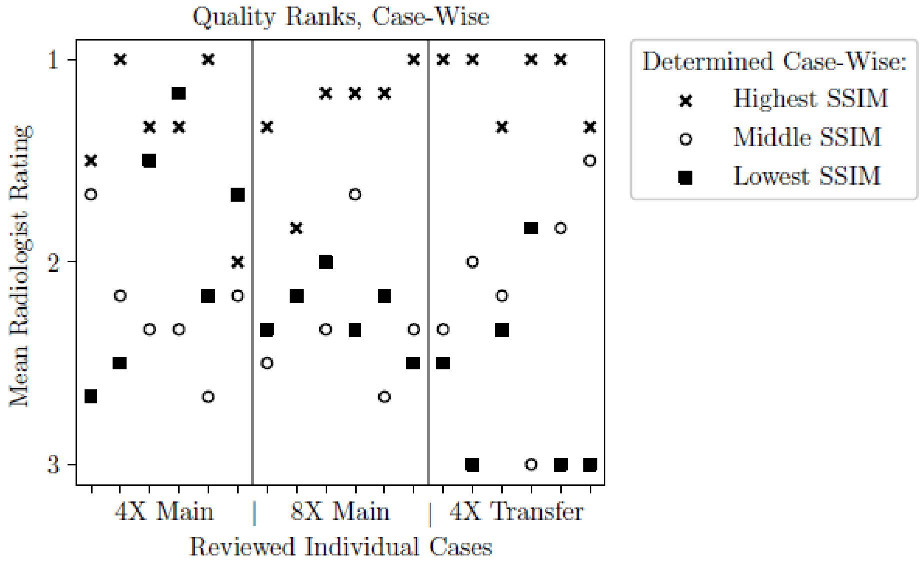
Team	AVG	T1	T1POST	T2	FLAIR
4X Track					
AIRS Medical	**0.964**	**0.967**	**0.969**	**0.965**	**0.930**
ATB	0.960	0.964	0.965	0.961	0.924
Nspin	0.959	0.963	0.965	0.960	0.920
8X Track					
AIRS Medical	**0.952**	**0.953**	**0.969**	**0.951**	**0.918**
ATB	0.944	0.943	0.954	0.943	0.905
Nspin	0.942	0.940	0.953	0.942	0.898



Muckley, et al, *IEEE TMI* 2021

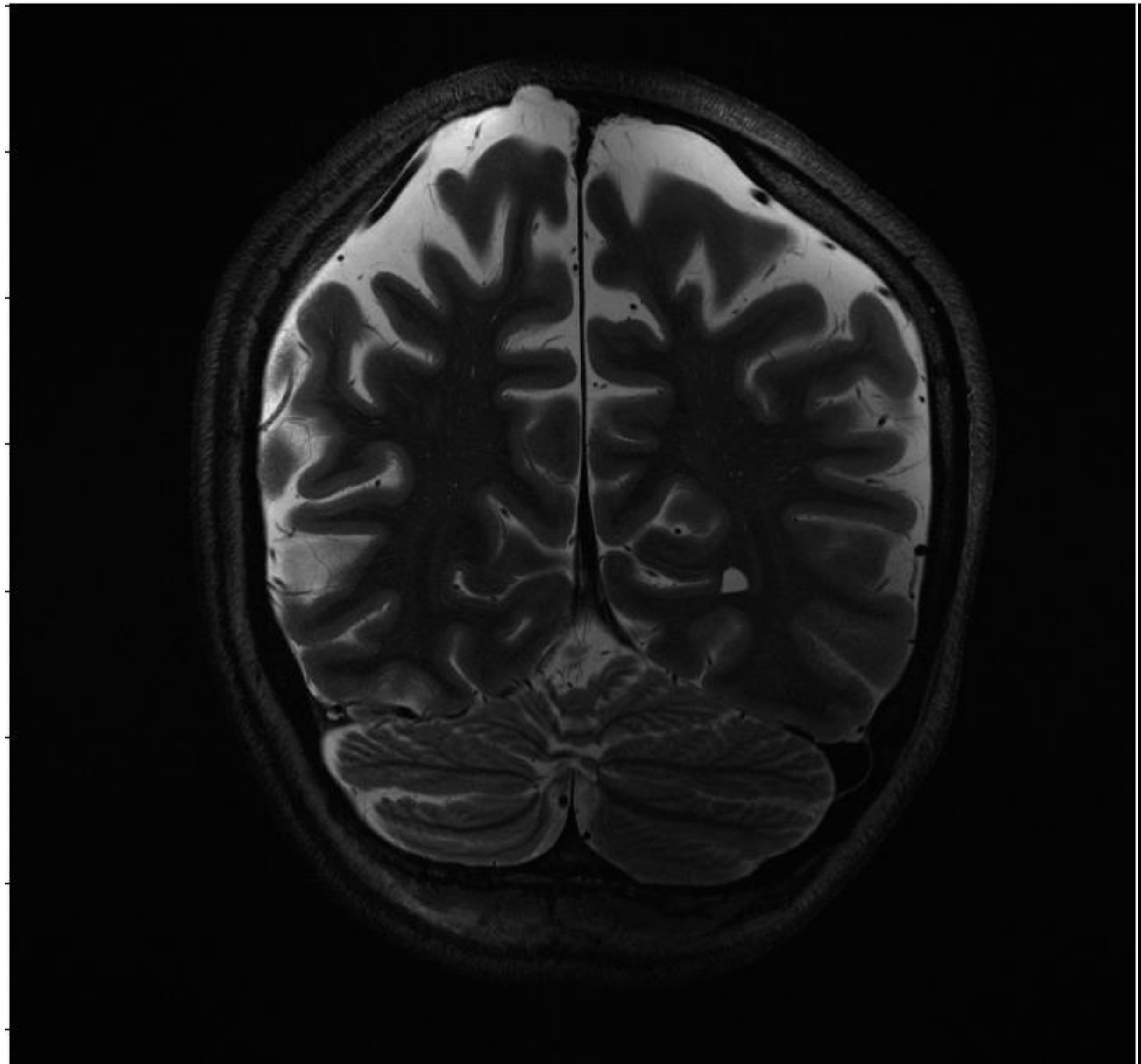
Table 3: Summary of quality ranks and Likert scores (lower is better).

Team	Rank	Artifacts	Sharpness	CNR
4X Track				
AIRS Medical	**1.36**	**1.53**	**1.53**	**1.53**
Nspin	1.94	1.81	1.72	1.75
ATB	2.22	1.75	1.97	1.86
8X Track				
AIRS Medical	**1.28**	**1.67**	**1.89**	**1.94**
Nspin	2.25	1.86	2.72	2.28
ATB	2.28	1.92	2.56	2.42



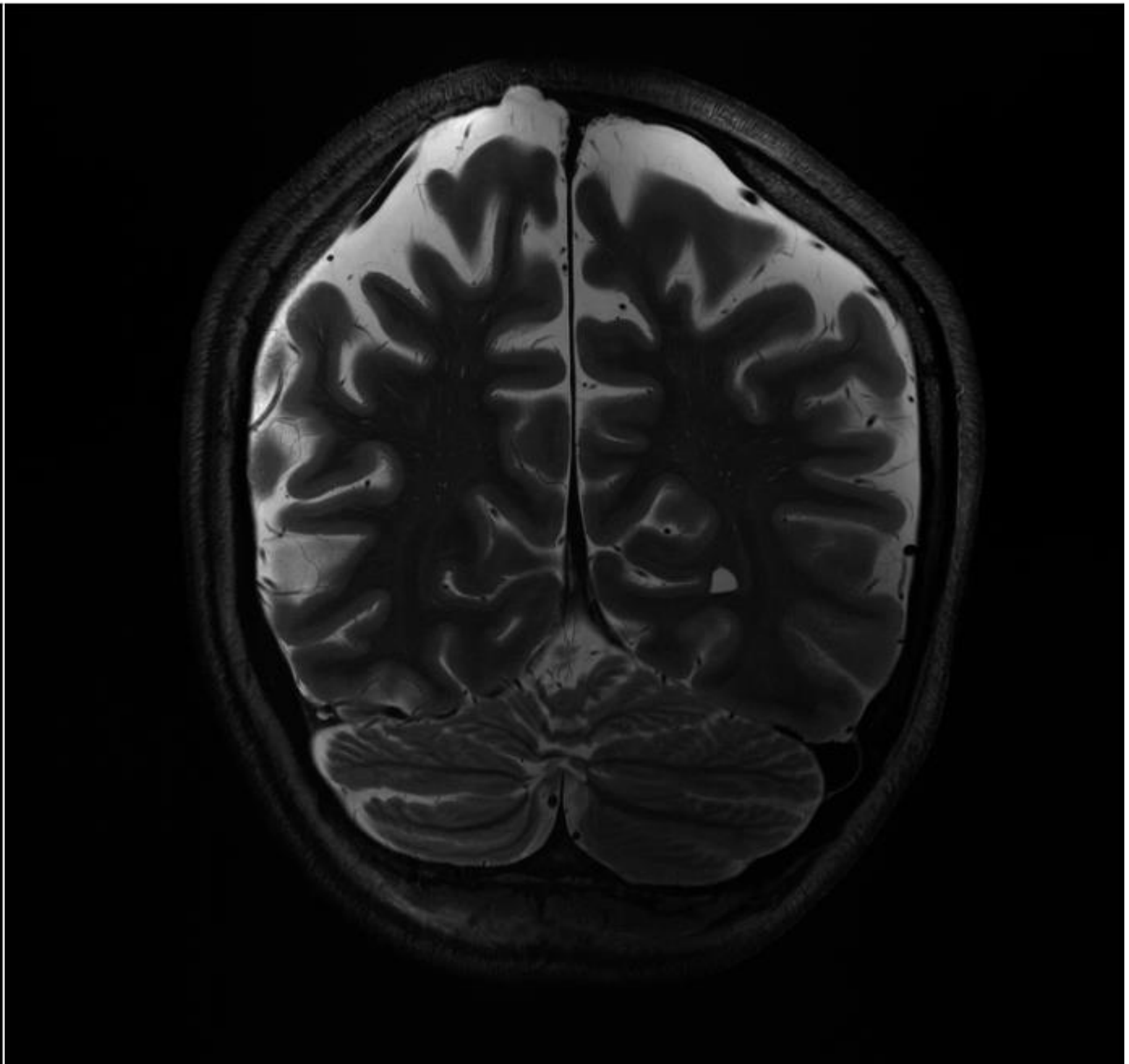
https://nips.cc/Conferences/2020/ScheduleMultitrack?event=16140 (fastMRI keynote)

Transfer at 7T on high resolution image (AF=2)



Ground truth, T2, GRAPPA, 7T

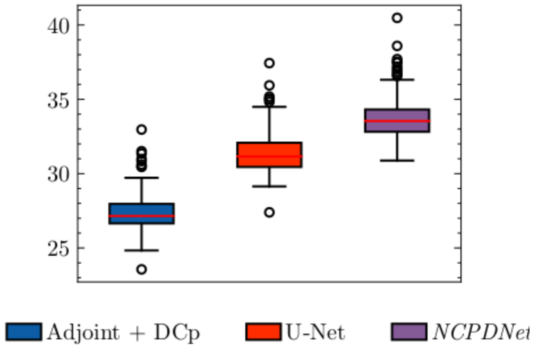
Ramzi et al, ISMRM 2021



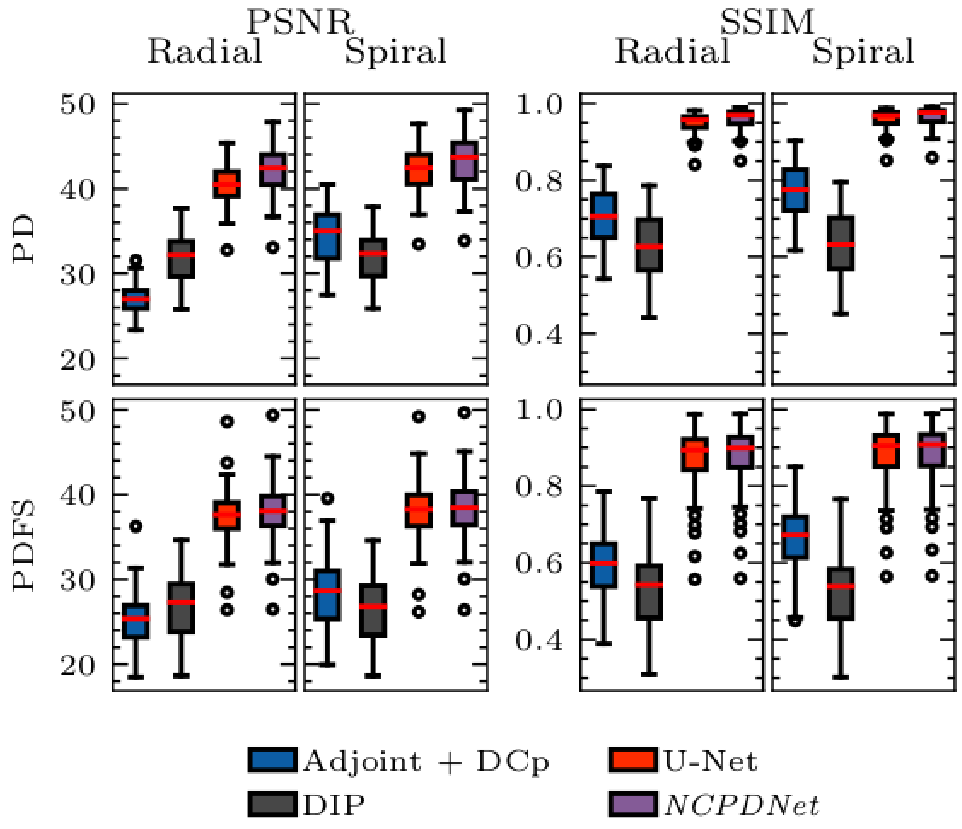
XPDNet recon, trained on R=4, lower res, no cerebellum

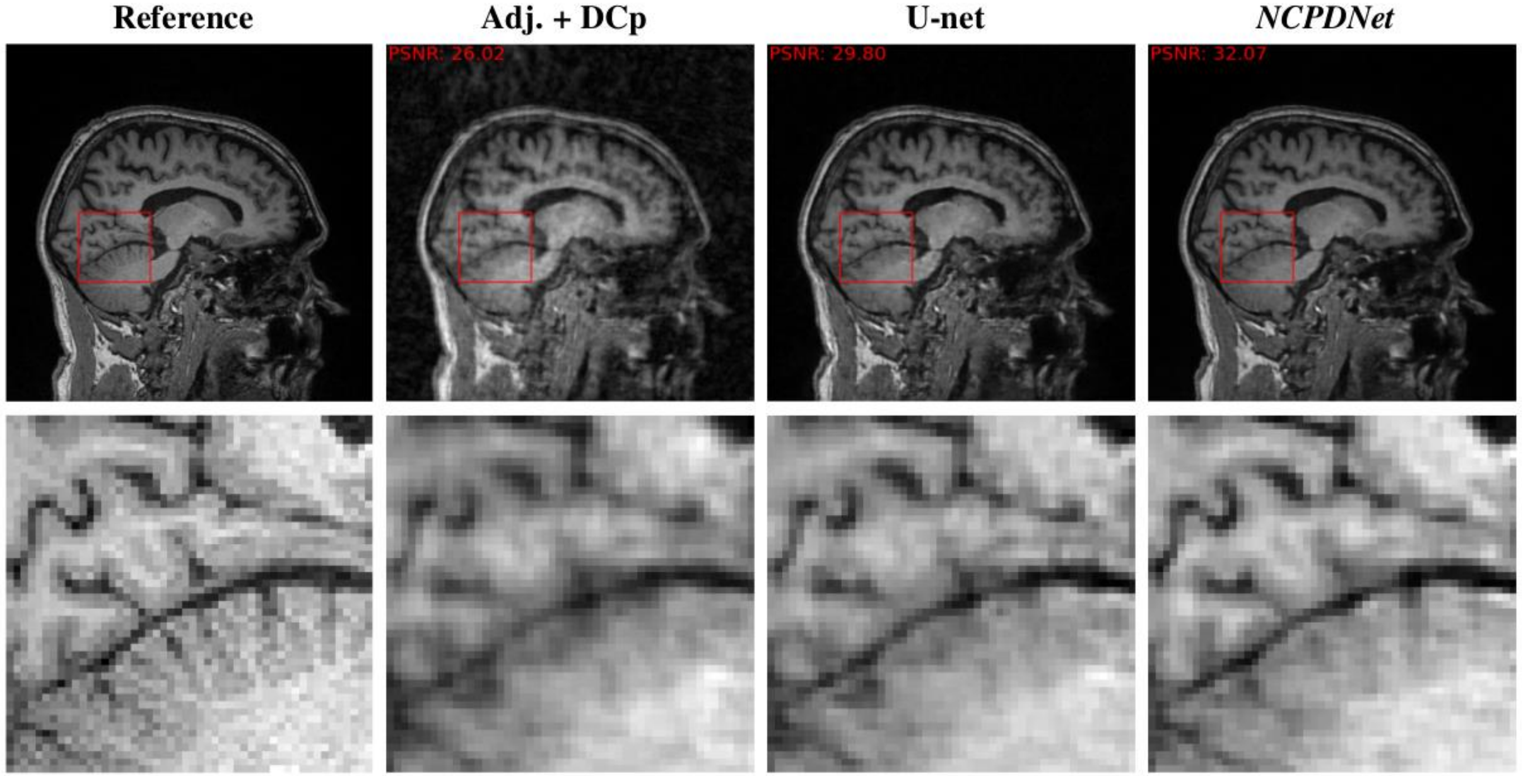
NC-PDNet Results

Model	Radial	Spiral	# Parameters
Adjoint + DCp	25.91 / 0.6486	31.36 / 0.7197	0
DIP	29.21 / 0.5834	29.19 / 0.5832	0
U-net on Adjoint + DCp	38.78 / 0.9106	40.02 / 0.9215	481k
NC-PDNet	**40.00 / 0.9191**	**40.68 / 0.9255**	163k



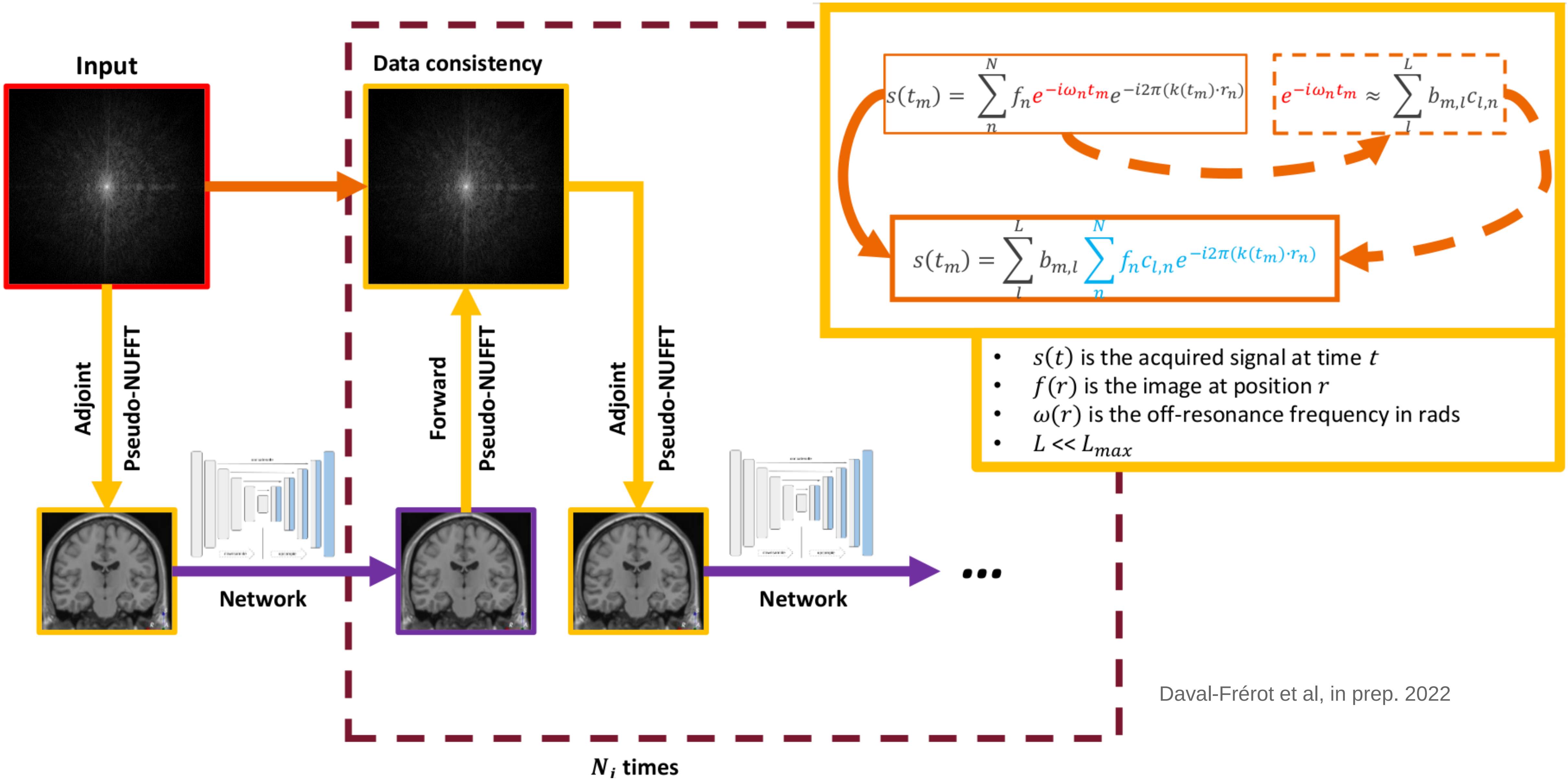

Z. Ramzi





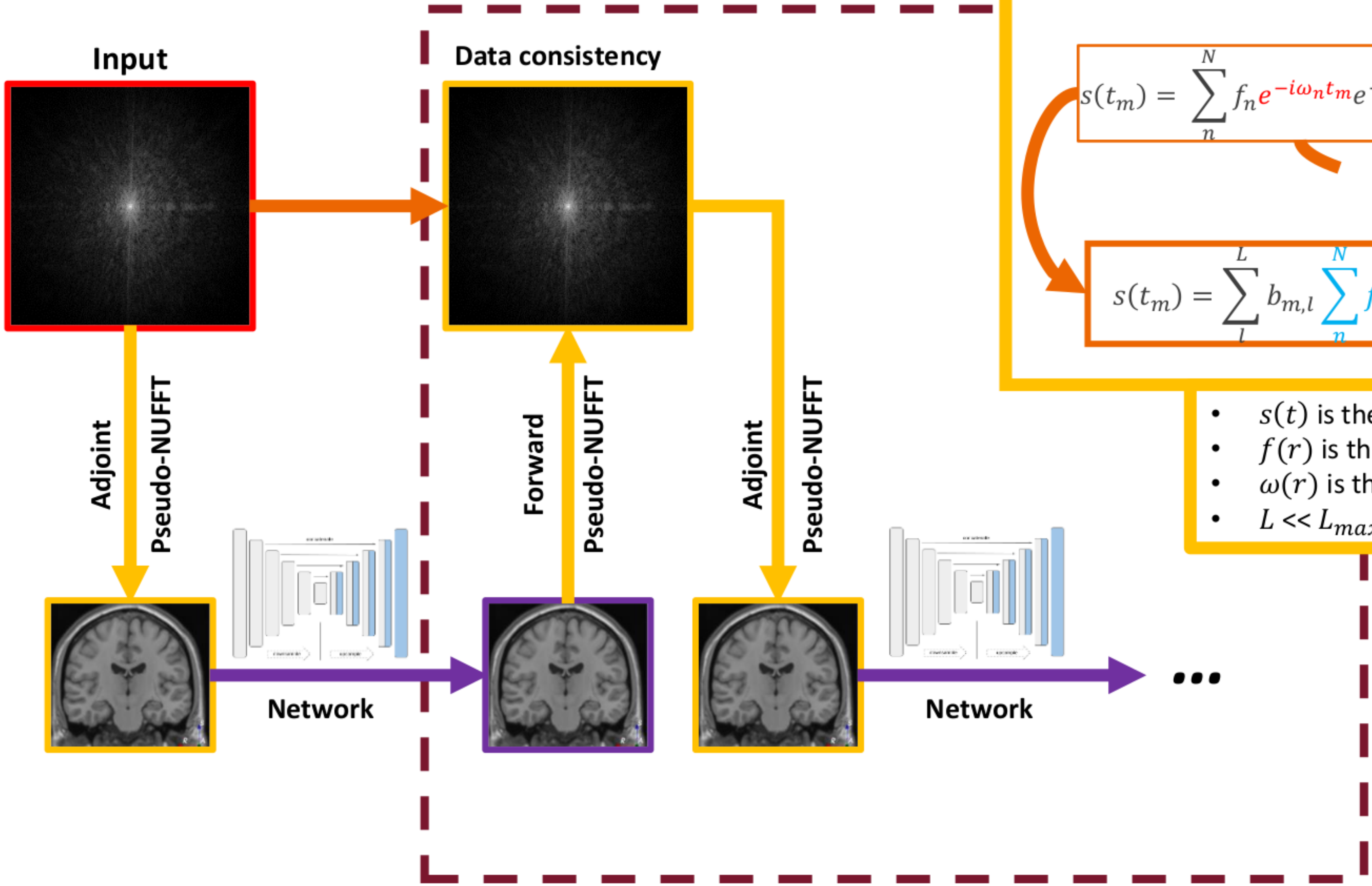
Ramzi et al, *IEEE TMI* 2022

Deep-learning – stacked ΔB0 PD-net architecture



Daval-Frérot et al, in prep. 2022

Deep-learning – stacked ΔB0 PD-net architecture



N_i times

$$s(t_m) = \sum_{n}^{N} f_n e^{-i\omega_n t_m} e^{-i2\pi(k(t_m)\cdot r_n)}$$

$$e^{-i\omega_n t_m} \approx \sum_{l}^{L} b_{m,l} c_{l,n}$$

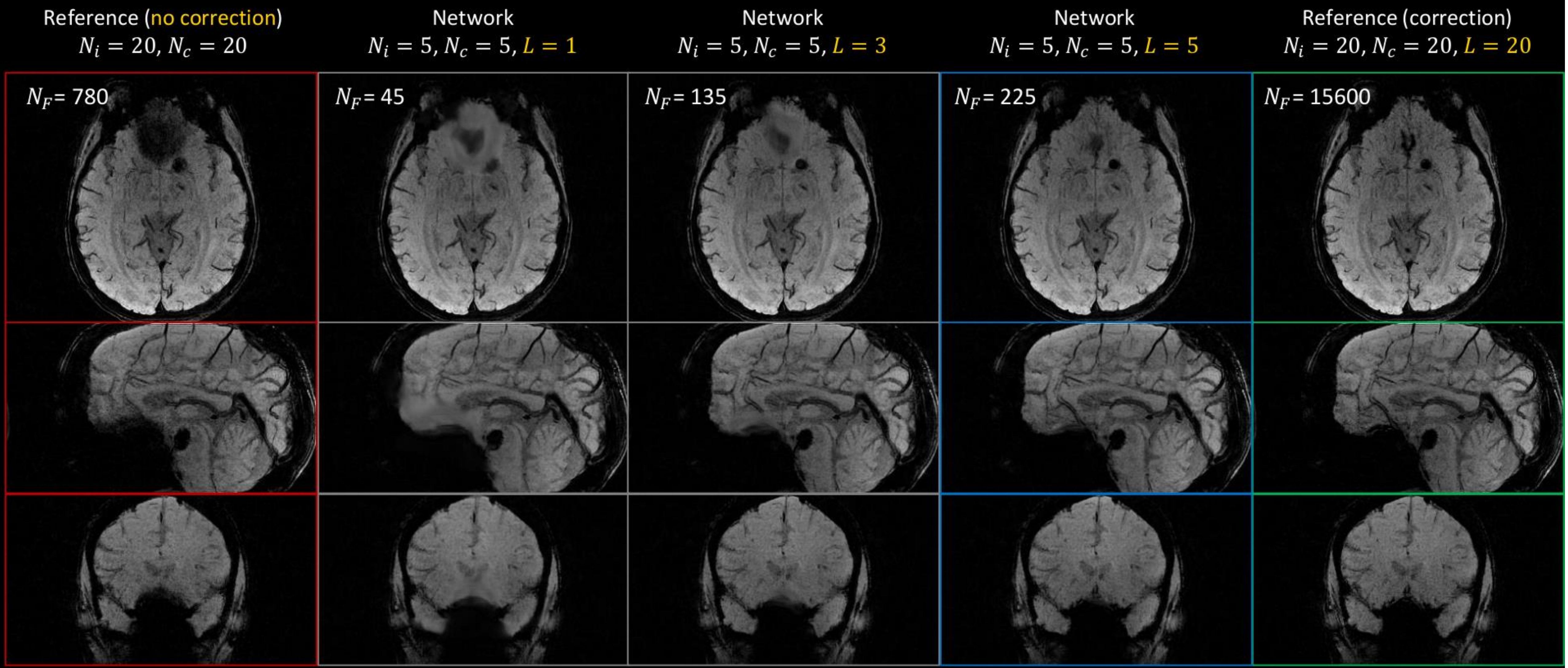
$$s(t_m) = \sum_{l}^{L} b_{m,l} \sum_{n}^{N} f_n c_{l,n} e^{-i2\pi(k(t_m)\cdot r_n)}$$

- $s(t)$ is the acquired signal at time t
- $f(r)$ is the image at position r
- $\omega(r)$ is the off-resonance frequency in rads
- $L << L_{max}$

How to accelerate ?

- Reduce NUFFT calls N_F
  - Reduce iterations N_i
  - Reduce channels N_c
  - Reduce interpolators L

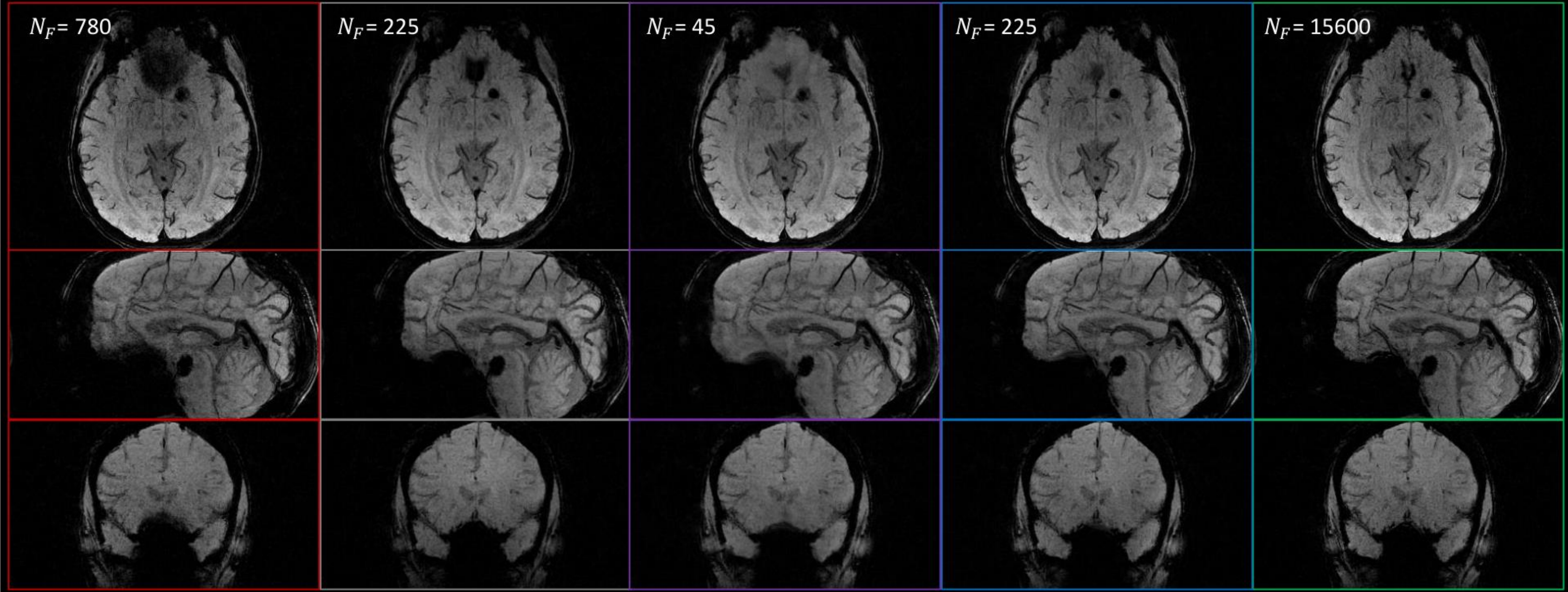
Deep-learning – Results



TEST SCORES	RMSE: 0.033 PSNR: 30.02 SSIM: 0.911	RMSE: 0.025 PSNR: 32.21 SSIM: 0.944	**RMSE: 0.022** **PSNR: 33.37** **SSIM: 0.951**

Deep-learning – Results

Reference (no correction)	Wavelets	Network (no correction)	Network	Reference (correction)
$N_i = 20, N_c = 20$	$N_i = 5, N_c = 5, L = 5$	$N_i = 5, N_c = 5$	$N_i = 5, N_c = 5, L = 5$	$N_i = 20, N_c = 20, L = 20$



TEST SCORES

	Wavelets	Network (no correction)	Network
RMSE	0.027	0.028	**0.022**
PSNR	31.78	31.26	**33.37**
SSIM	0.932	0.926	**0.951**

Summary

Deep learning is mature for MR image reconstruction in the supervised setting

- Improved image quality at lower computational cost during test phase
- Robustness to various imaging contrasts, SNR, field strengths
- Different network architectures learned for the AF4 and the AF8 tracks

Our XPDNet solution

- Ranked in 2nd position in the 2020 Brain fastMRI challenge, 1st in academia
- Benefits from the physics-based knowledge & the advances of DL (e.g. MWCNN)
- Works for non-Cartesian sampling, in 3D and has been extended to correct for off-resonance artifacts

Outlook

- Towards self-supervision in NC-PDNet
- 4D NC-PDNet for fMRI (model parallelism)

Conclusions & Perspectives

- **Shorter acquisition**
  - 3D SPARKLING available for T2* imaging at 3T & 7T scanners
  - SPARKLING for fMRI is promising
  - Preliminary validation in Sodium MR UTE MRI at 7Tesla (32-fold acceleration)
  - Next: SPARKLING for T1-w, T2-w and diffusion-weighted MRI (structural connectivity)

- **Faster image reconstruction**
  - NC-PDNet for 3D SWI: scalability to multi-coil imaging
  - Integrate $\Delta B0$ inhomogeneity correction within the image reconstruction network

- **Ongoing works:**
  - Hybrid approach for the joint learning of the non-Cartesian sampling trajectories and image reconstruction networks
  - SPARKLING for Quantitative Susceptibility Mapping (QSM):
    - Deep brain stimulation for Parkinson’s disease (Henri Mondor Hospital, Creteil)
  - Neonatal brain imaging in premature infants (Robert Debré hospital, Paris)

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Pierre-Antoine
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Kumari Pooja, *MSc*

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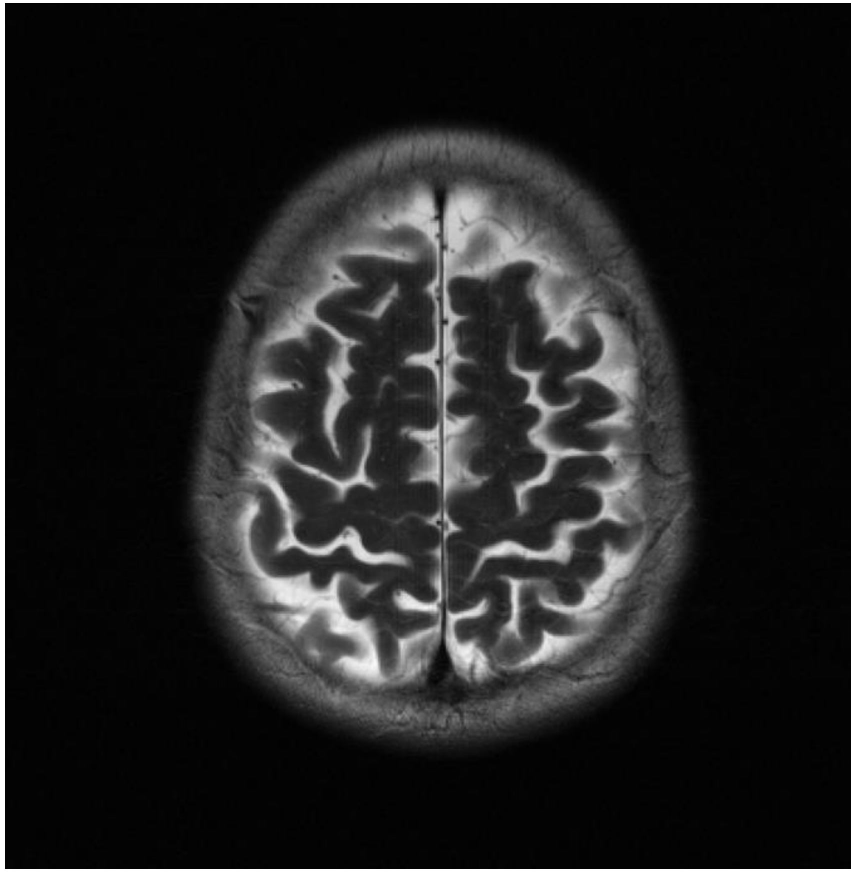
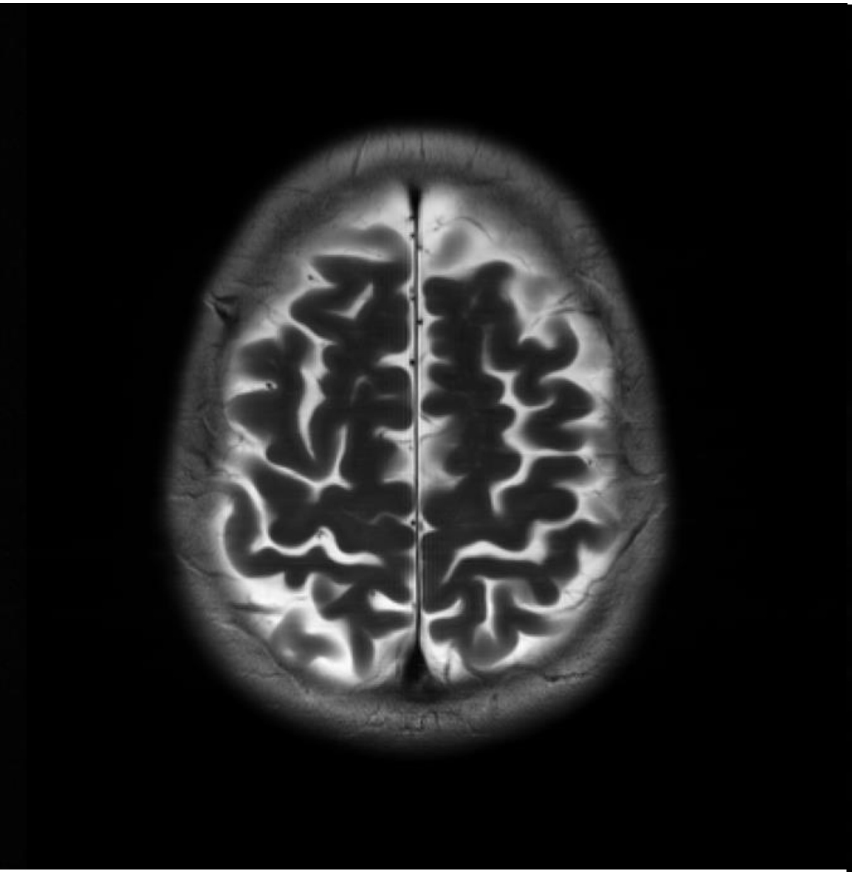
Thank you for your attention!

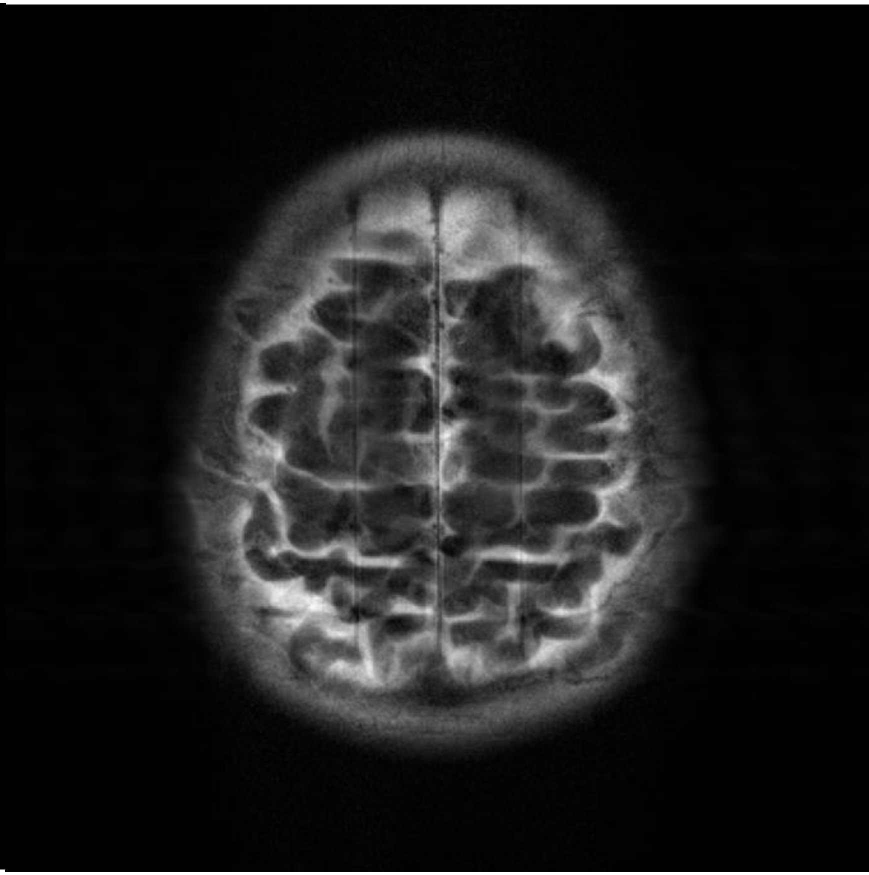
XPDNet vs GRAPPA Reconstruction on Validation fastMRI data

T2 contrast – 8X Track

Ground truth | **XPDNet** recon (PSNR=36.8dB/SSIM=0.96) | **GRAPPA** recon (PSNR=26.1dB/SSIM=0.77)







Recon time: 0.25 s/slice

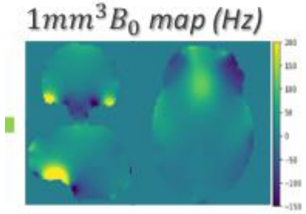
Recon time: 1. s/slice [TensorFlow]
1.7 s/slice [numpy]

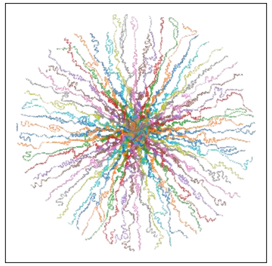
[Ramzi et al, *ISMRM* 2021]

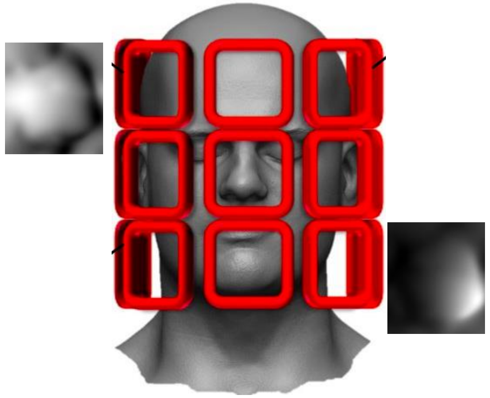
Compressed Sensing MR Image Reconstruction

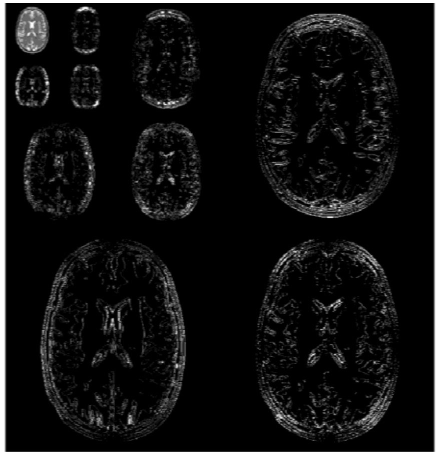
$$\widehat{\mathbf{x}} = \arg\min_{\mathbf{x}\in\mathbb{C}^{n\times n}} \sum_{\ell=1}^{L} \frac{1}{2}\left\|\mathbf{y}_\ell - \widetilde{\mathbf{F}}_\Omega \mathbf{S}_\ell \mathbf{x}\right\|_2^2 + \mathcal{R}(\Psi \mathbf{x})$$

Optimization algorithms
Forward-Backward
FISTA, POGM'
Condat-Vu, PDHG









$$\mathcal{R} = \|\cdot\|_1, \|\cdot\|_{2,1}, \ldots$$

MOD|OPT

PySAP
Python Sparse data Analysis Package

Farrens et al, Astrophysics & Computing, 2020.

https://github.com/CEA-COSMIC/pysap