Computational MRI in the deep learning era

Philippe Ciuciu, Ph.D.

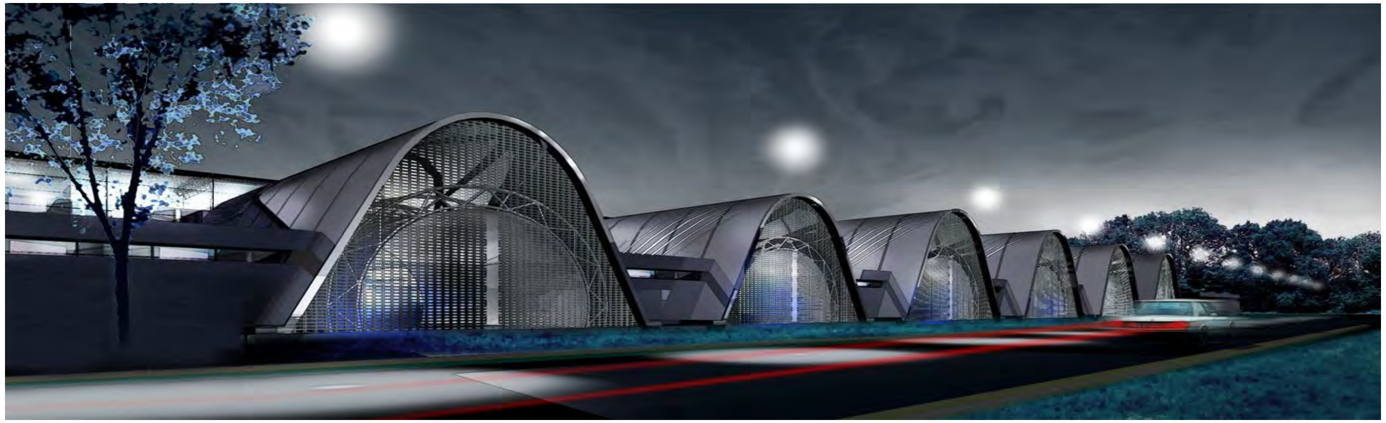
Inria-CEA MIND team

AI for HPC@Exascale

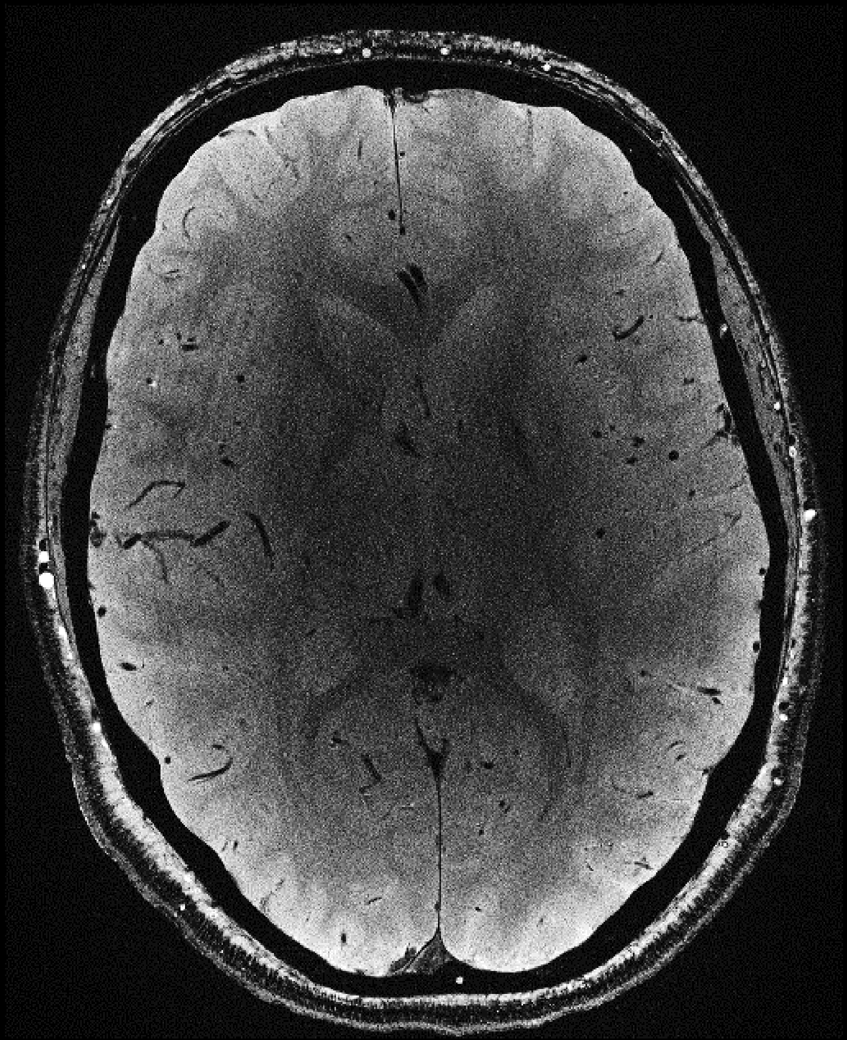
Paris, Oct 3rd 2024

NeuroSpin: A unique facility for Brain Imaging

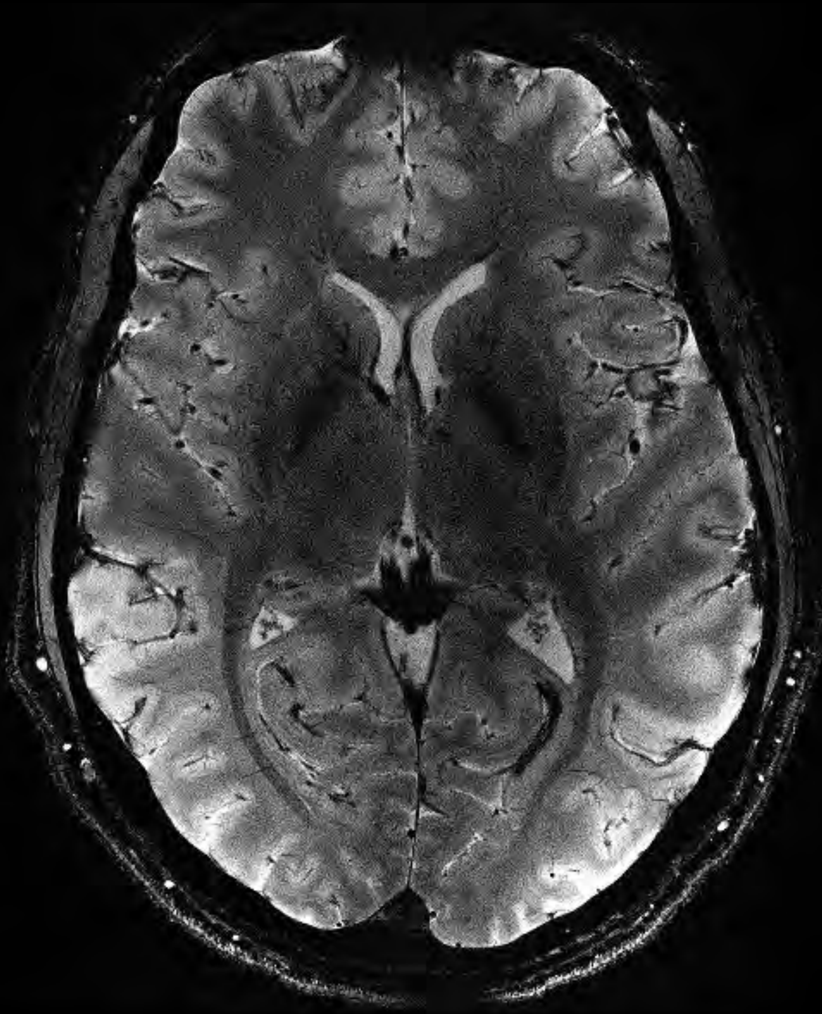
NeuroSpin



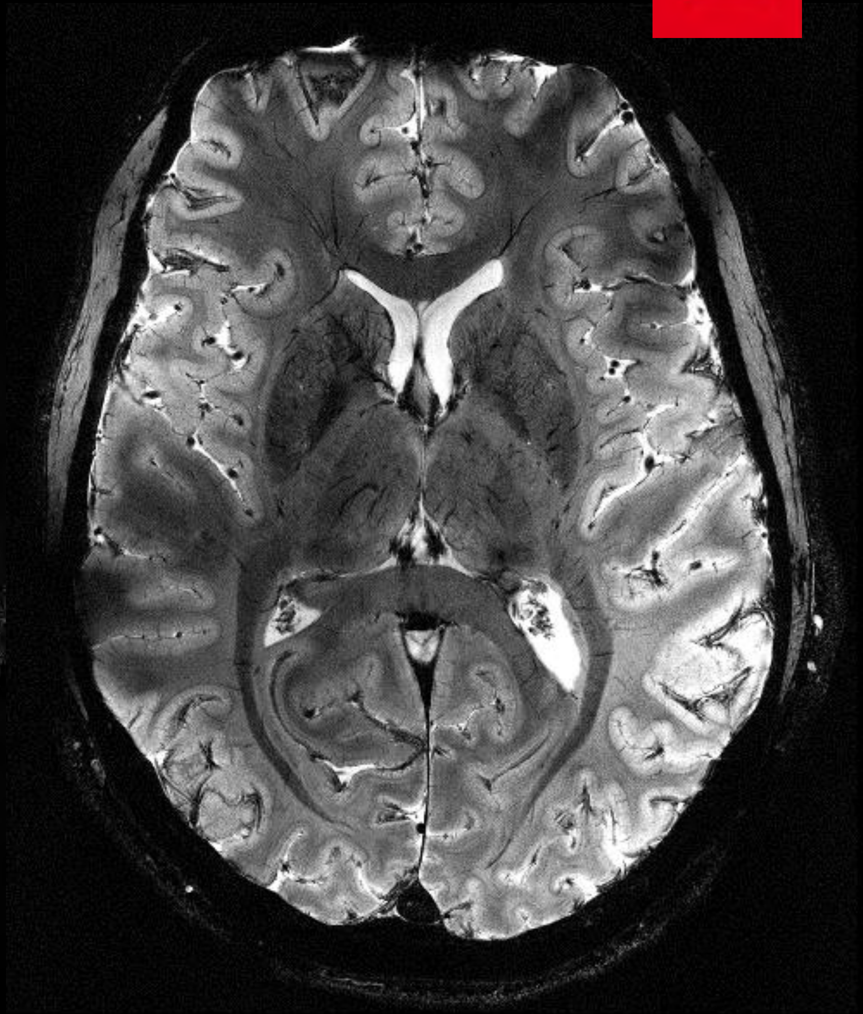
Probe the human brain singularity at unprecedented scale using outstanding scanners



3T

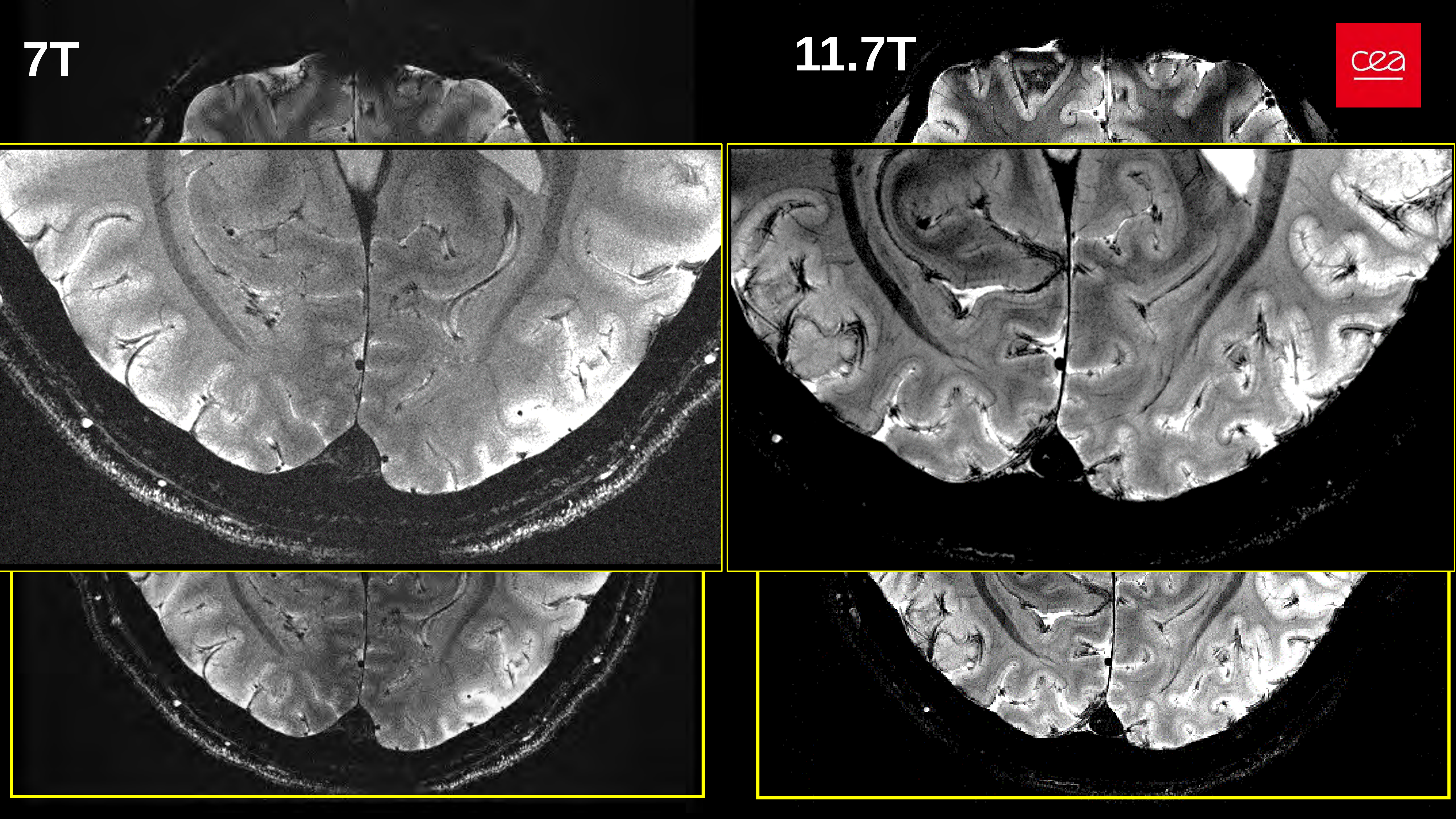


7T



11.7T

Spatial resolution = 0.2 × 0.2 × 1.0 mm^3, Acquisition Time = 4 min 20 s


7T
11.7T

Scientific & General Public Communication

Mauconduit et al. Proc Intl Soc Magn Reson Med 2024

Boulant et al. Nat Methods in press
https://doi.org/10.21203/rs.3.rs-3931535/v1

The CEA decided to maintain an embargo over this study till the end of the clinical investigation. Then they launched their communication plan…

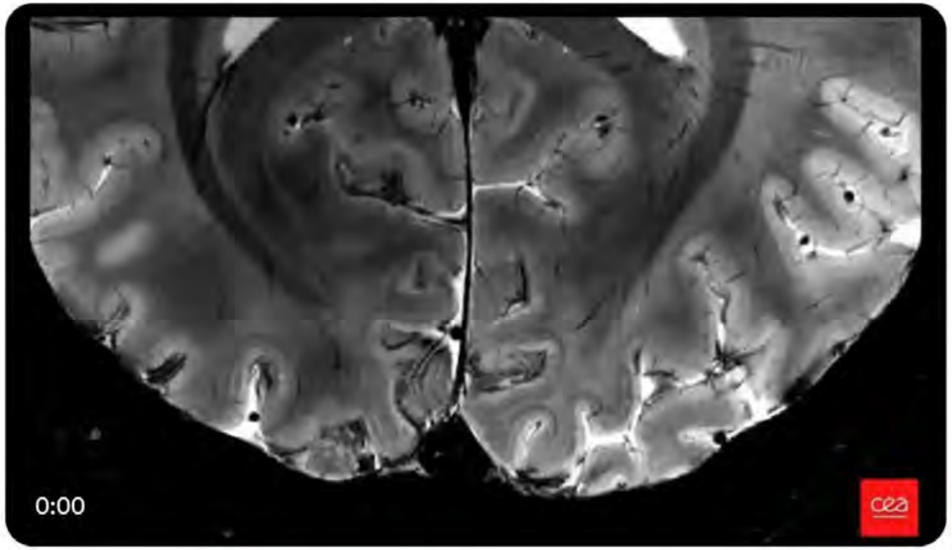
Impact?

Emmanuel Macron @EmmanuelMacron · 2 avr.

Voici l'image du cerveau la plus précise de l'Histoire, obtenue grâce au **scanner** IRM du CEA, le plus puissant au monde.

C'est une avancée majeure et un espoir immense pour l'étude de notre santé. Félicitations à l'équipe du projet **Iseult**.

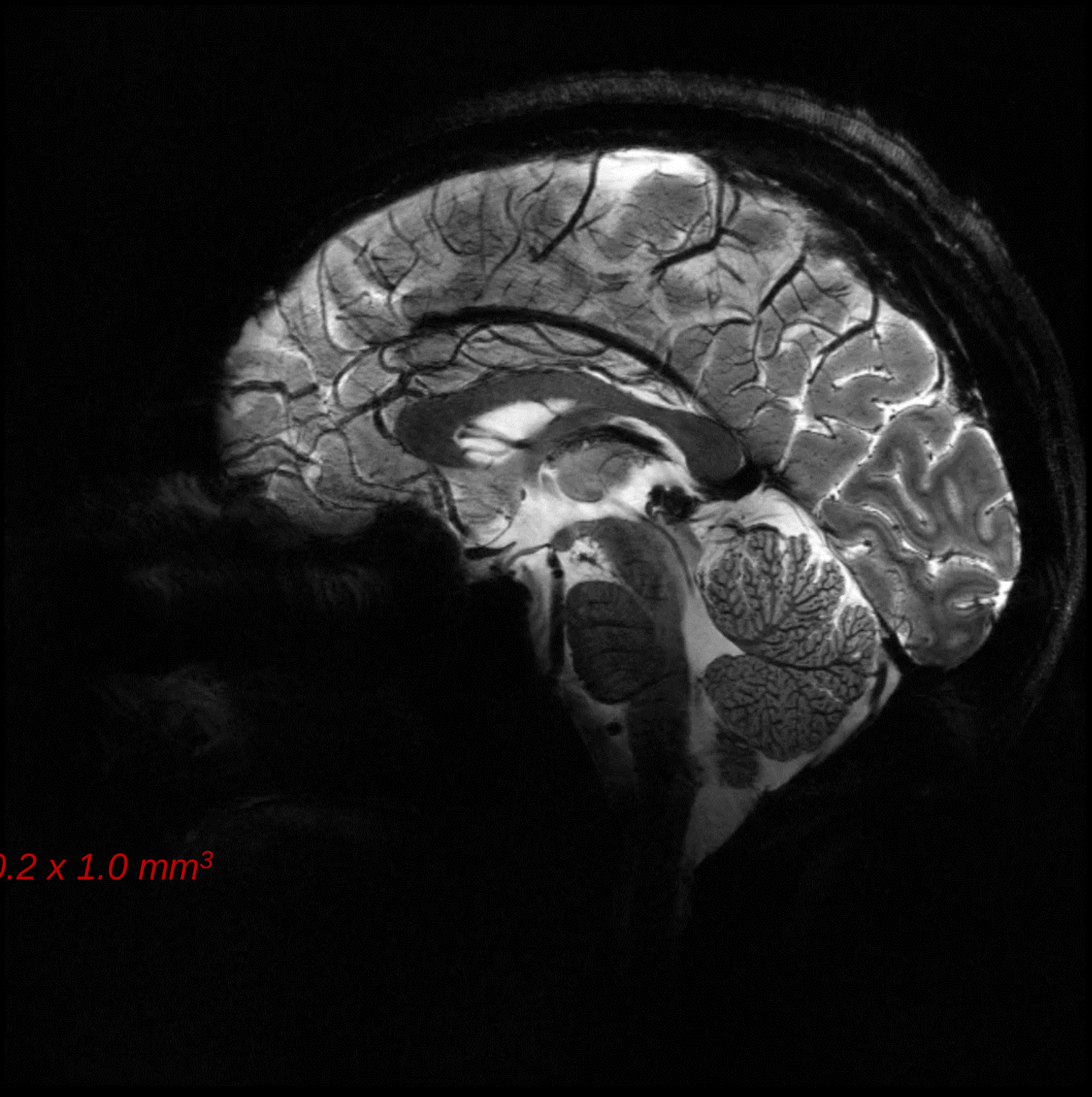
Fierté française !



1 k · 1 k · 11 k · 1 M

Huge impact!


BFM TV 06.12 DIRECT
ALERTE INFO • Crues : la vigilance rouge est maintenue pour le département de l'Yonne (Météo-France)
CE MATIN 08.30 INVITÉ LOUIS ALIOT VICE-PRÉSIDENT DU RN, MAIRE DE PERPIGNAN
Le cerveau comme vous ne l'avez jamais vu: l'IRM la plus puissante au monde a été dévoilée
Le 03/04/2024 à 6:40 | Durée : 2:00
TF1 INFO
SCIENCES · CERVEAU
Le cerveau
puissante du
Après plus de vingt années
premières images de cerveau
Par Hervé Morin
images de cerveau
IRM la plus puissante du
Recherche
Se connecter
Votre avis
Podcasts
Catégories
inter
Radios
Abonnez-vous
LIRE PLUS TARD
PARTAGER
Newsletter Médecine et Santé
Chaque mercredi, une sélection de contenus pour mieux comprendre l'actualité de la santé
3T
S'abonner
cerveau dévoilée



Spatial resolution: 0.2 x 0.2 x 1.0 mm^3
TA 8 min 30s

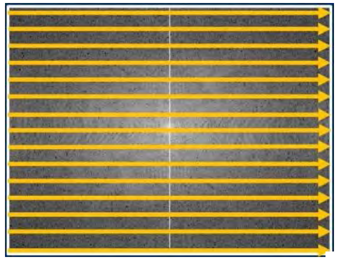
Sampling & Under-sampling in MRI

K-space

Image

k_y

$\boldsymbol{y} \in \mathbb{C}^N$



k_x

IFFT

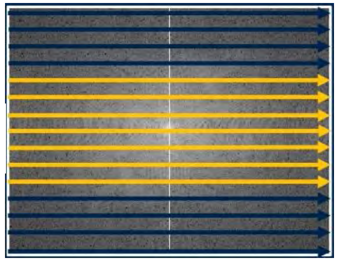
$\boldsymbol{x} \in \mathbb{C}^N$

$$\boxed{\boldsymbol{y} = \mathcal{F}_\Omega \boldsymbol{x} + \boldsymbol{n}}$$

Reduce scan time by a factor of R=2

k_y

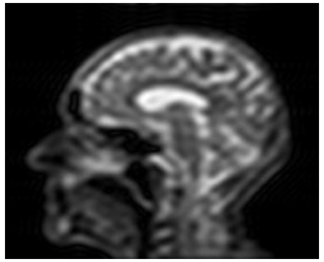
$\boldsymbol{y} \in \mathbb{C}^{N/2}$



k_x

IFFT

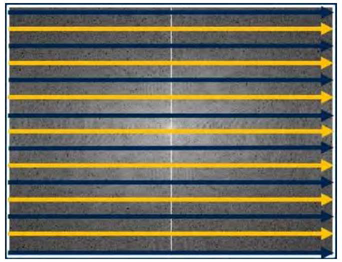
Resolution loss



R=2

k_y

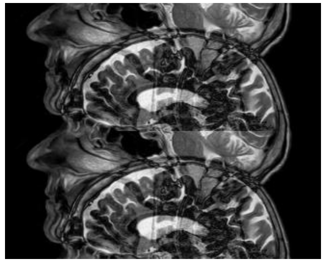
$\boldsymbol{y} \in \mathbb{C}^{N/2}$



k_x

IFFT

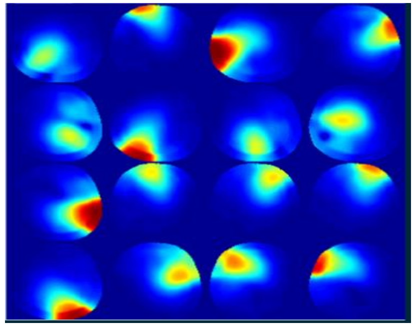
Folding along PE direction



Parallel Imaging vs Compressed Sensing framework

Cartesian under-sampled data

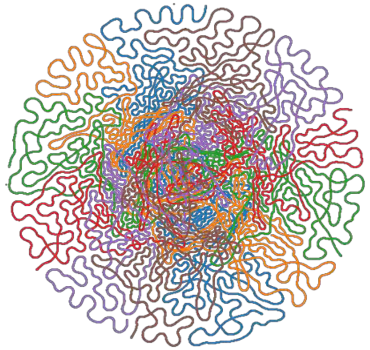
Multiple Receiver Coils



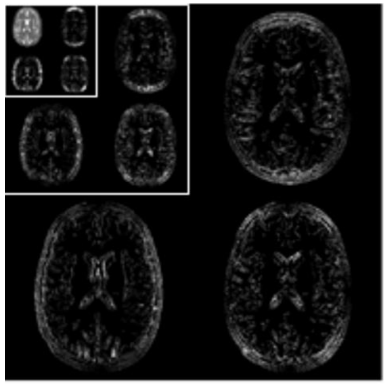
Linear Recon Algorithm

Accelerated PI Acquisition

non-Cartesian under-sampled VDS data (e.g. SPARKLING)

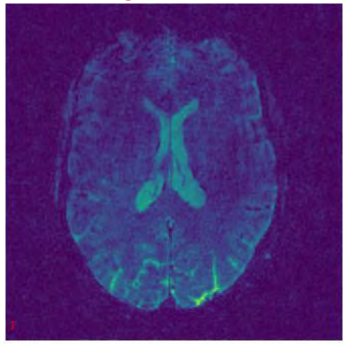


Sparsity in a dictionary



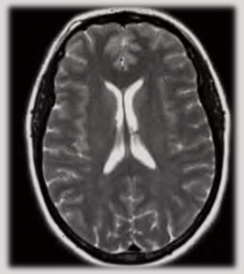
***Nonlinear* Recon Algorithm**

Accelerated CS Acquisition



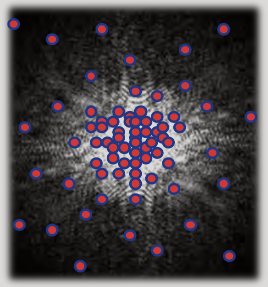
Summarizing accelerated MRI: The big picture

MRI Image



Fourier Transform

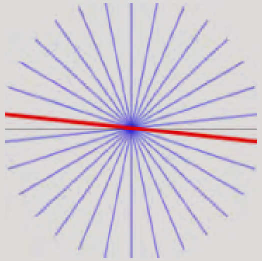
K-Space



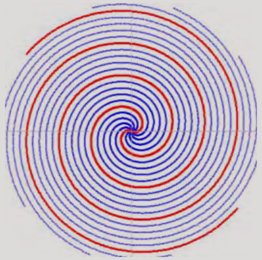
Variable density density

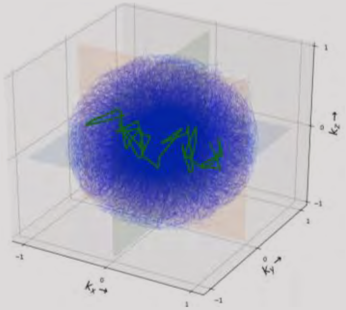
Non-Cartesian sampling

Radial



Spiral

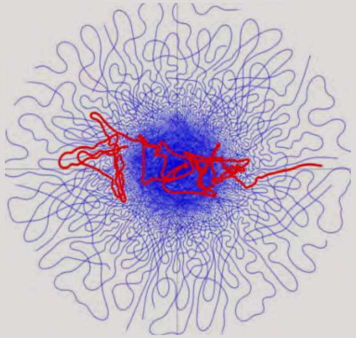




6-10H

Chaithya et al, Full 3D *SPARKLING*, IEEE TMI 2022

SPARKLING Trajectories



10-15min

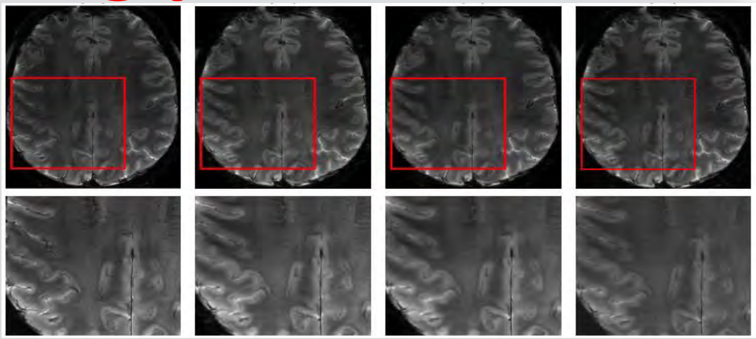
Lazarus et al, *SPARKLING*, MRM 2019

Acquisition

K-space Data

CS Reconstruction

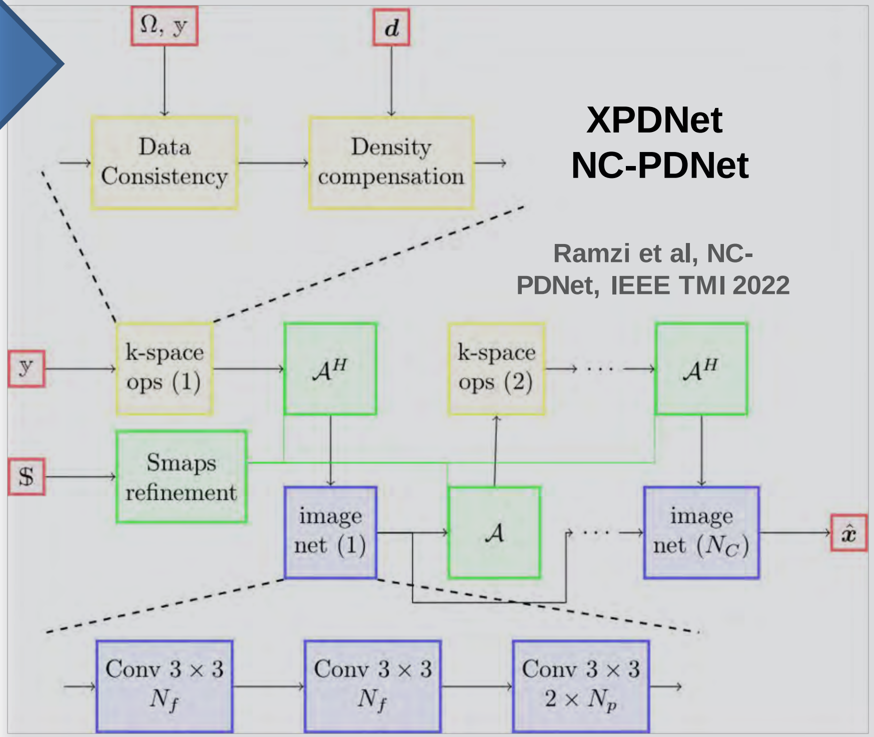
PySAP-MRI



Cartesian Reference	Self Calibrating	L1-ESPIRiT	OSCAR Calibrationless

L Gueddari et al, ISMRM WS, Jan 2020

L Gueddari et al, Journal of Imaging, 2021

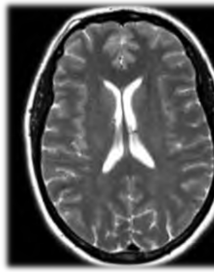


XPDNet

NC-PDNet

Ramzi et al, NC-PDNet, IEEE TMI 2022

Recon Time

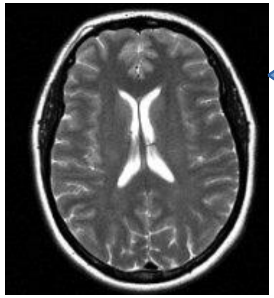


Recon Time

Reconstruction

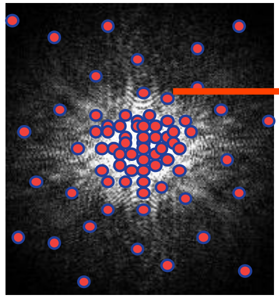
Accelerated acquisition using SPARKLING

MRI Image



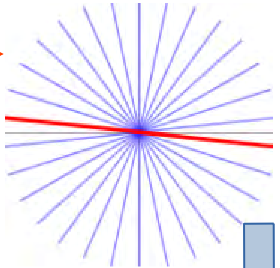
Fourier Transform

K-Space

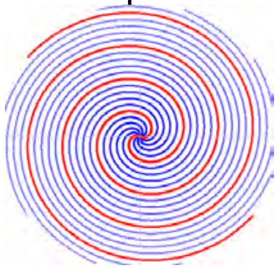


Non-Cartesian sampling

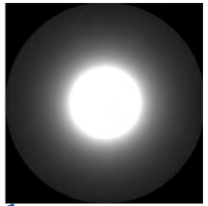
Radial



Spiral



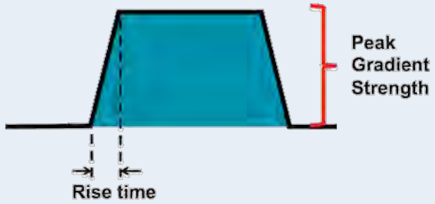
Target sampling Density



π

Target Sampling Density

Scanner Can Sample only on Curves



Hardware Constraints

Trajectory speed and acceleration constraints

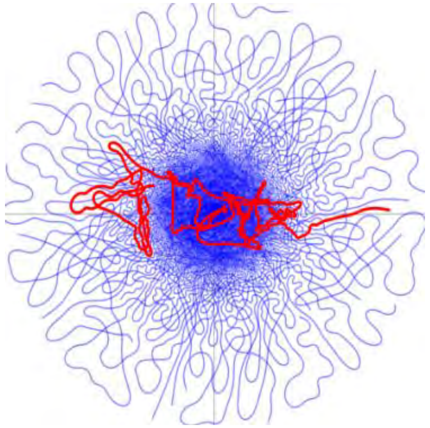
Trajectory Initialization

SPARKLING

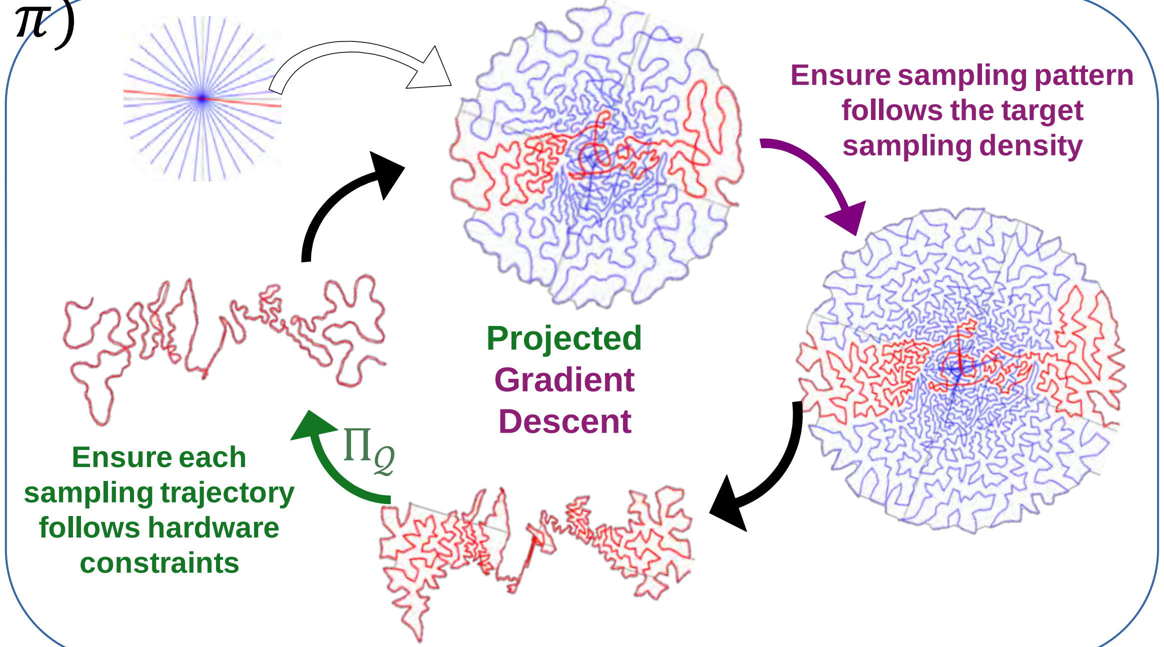
$$\widehat{\boldsymbol{K}} = \arg\min_{\boldsymbol{K}\in Q} F_N\ (\boldsymbol{K}, \pi)$$

$$\boldsymbol{K} = [\boldsymbol{k_i}]_{i=1}^{N_c}$$

N_c= Number of Curves



$$\boldsymbol{K}^{t+1} = \Pi_Q\left(\boldsymbol{K}^t - \eta^t \nabla F_N(\boldsymbol{K}^t, \pi)\right)$$



$$Q = \left\{ \begin{array}{c} \forall i \in \{1, 2, \ldots N_c\} \\ \left|\left| \dot{\boldsymbol{k}}_i \right|\right|_{2,\infty} \leq \alpha \\ \left|\left| \ddot{\boldsymbol{k}}_i \right|\right|_{2,\infty} \leq \beta \\ \boldsymbol{k_i}[TE] = [0,0,0]^T \end{array} \right\}$$

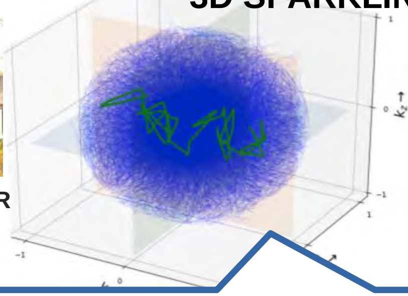
TE = Echo time

Lazarus et al, *SPARKLING: variable-density k-space filling curves for accelerated T_2 *-weighted MRI*, MRM 2019

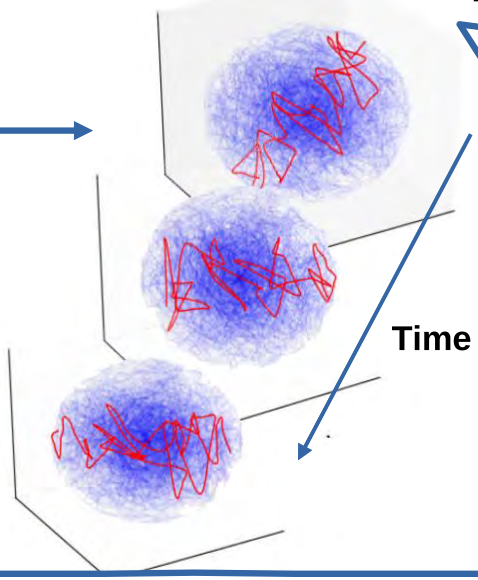
Impact of SPARKLING

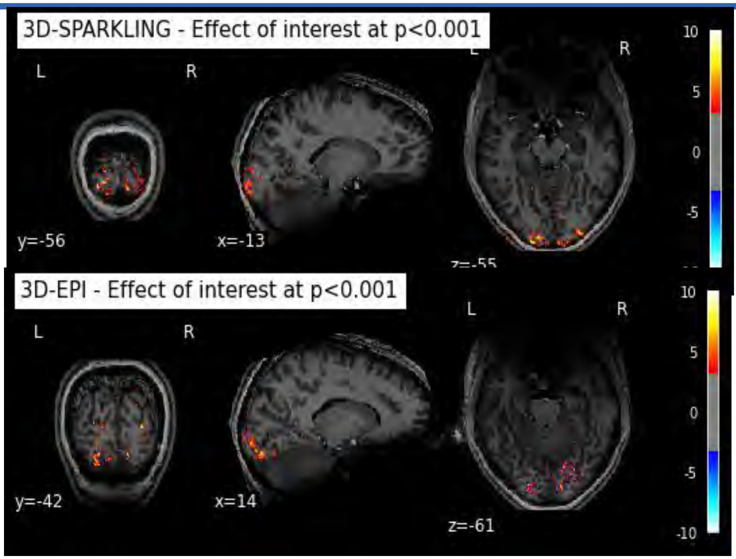

Chaithya G R

3D SPARKLING



Scan & Repeat





fMRI

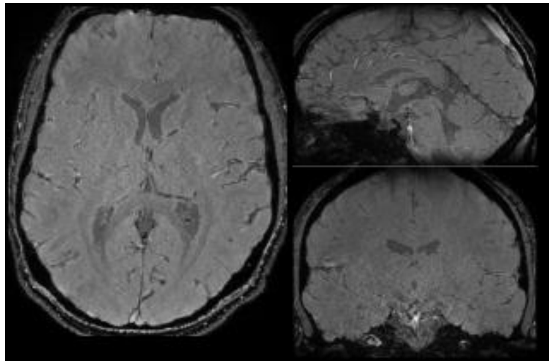
Z. Amor

Amor, et al, *Impact of field imperfections correction on BOLD sensitivity in 3D-SPARKLING fMRI*, **MRM 2023**

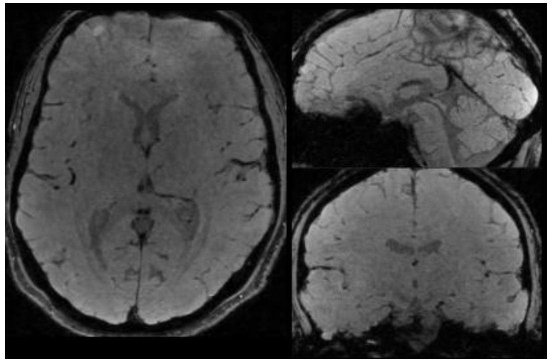
Coming soon to Anatomical imaging with MP2RAGE

T2* GRE: SWI

Cartesian p4
Scan Time: 15min 13s



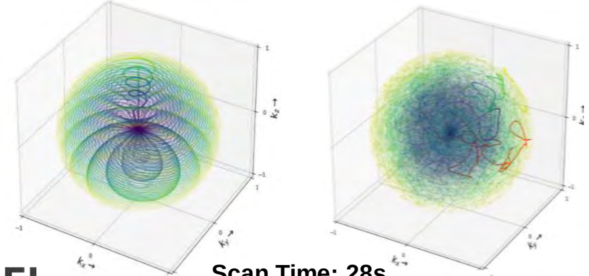
SPARKLING
Scan Time: 4min 58s



Chaithya et al, *Optimizing full 3D SPARKLING trajectories for high-resolution Magnetic Resonance Imaging*, **IEEE TMI 2022**

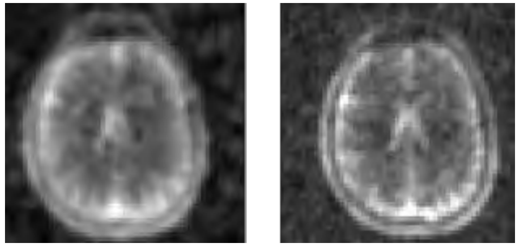
Sodium Imaging

TPI | SPARKLING



Scan Time: 28s

R. Baptista



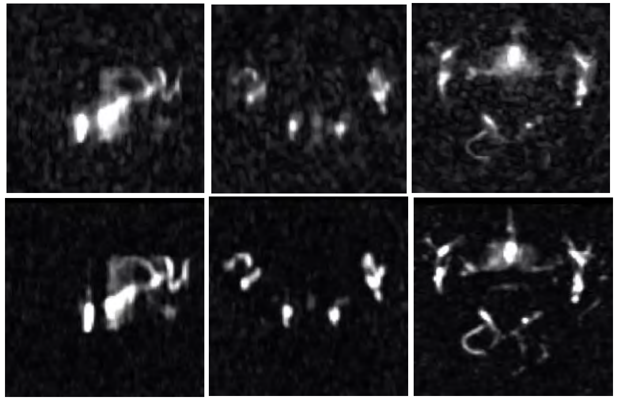
R Baptista et al, *IRM cerebrale du sodium rapide avec SPARKLING 3D sous-echantillonnee a 7*, **Journal of Neuroradiology 2023**

Angiography and Perfusion imaging

Q. Shen
T. Okell

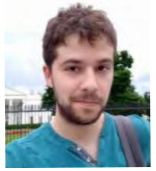
SOTA

SPARKLING



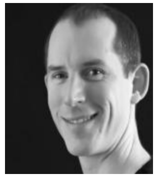
A. Vignaud

G. Daval-Frérot

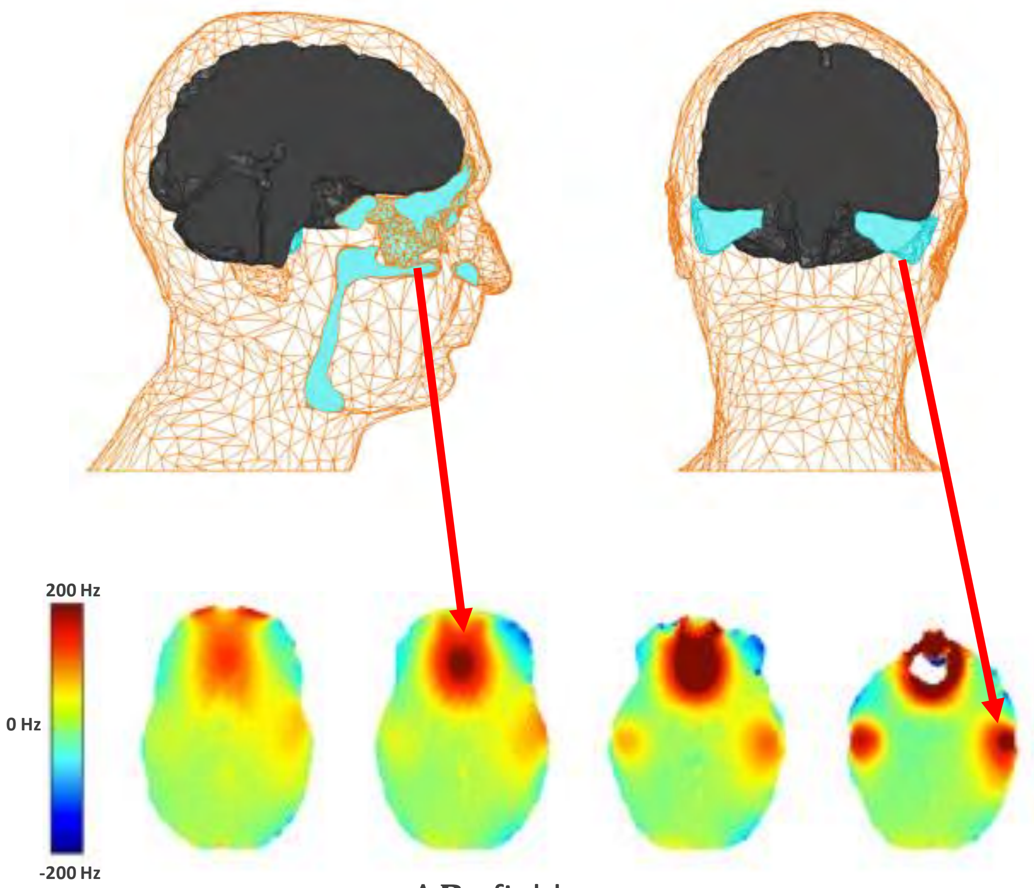


A. Massire

F. Mauconduit

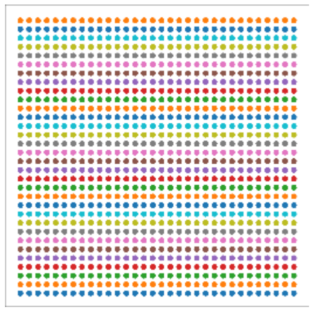


Spatial B_0 inhomogeneities & off-resonance effects



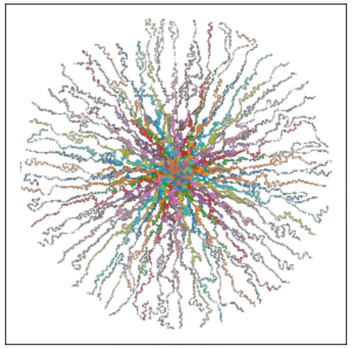
$\Delta \boldsymbol{B_0}$ field maps

Cartesian example

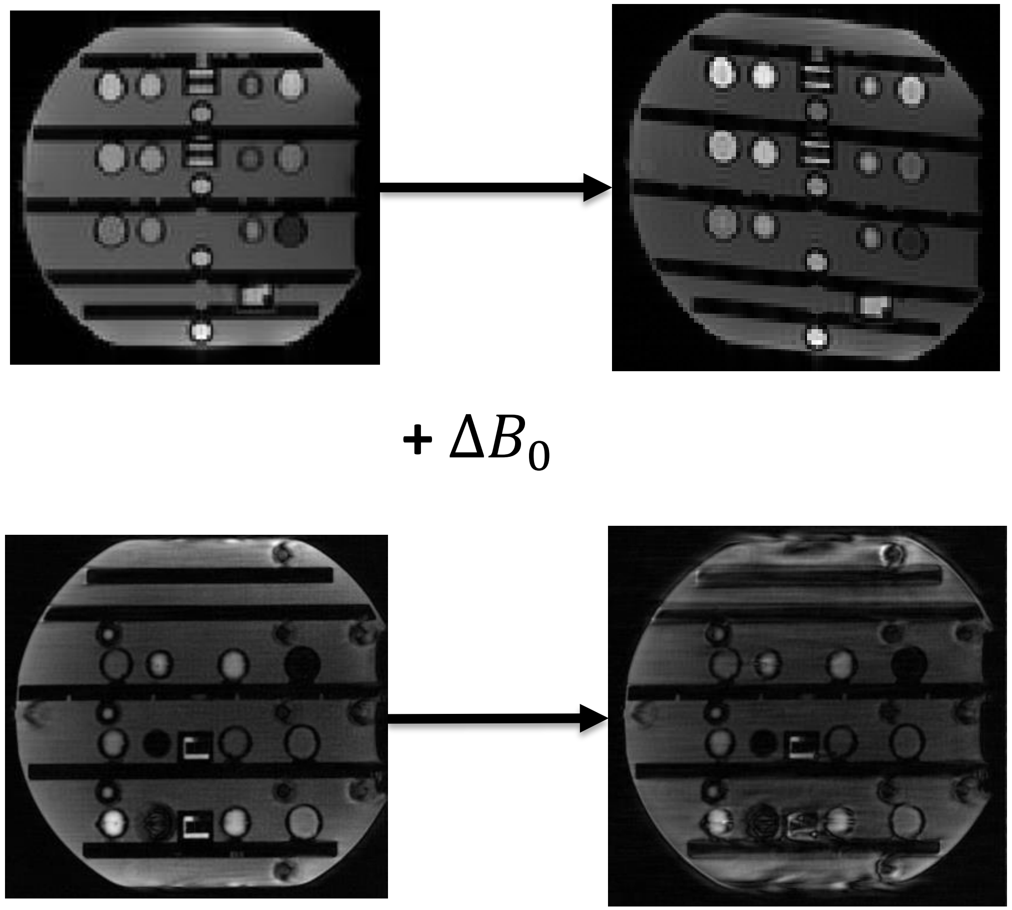


Line by line Cartesian trajectory

Non-Cartesian example



SPARKLING trajectory



$$\boldsymbol{\omega(r) = \gamma \Delta B_0}$$

$$s(t) = \int_{FOV} \rho(r,t)\, \boldsymbol{e^{j\omega(r)t}} e^{j\gamma(k(t).r)} \longrightarrow s(t_m) = \sum_{n=1}^{N} \rho(r_n, t_m)\, \boldsymbol{e^{j\omega(r_n)t_m}} e^{j\gamma(k(t_m).r_n)}$$

Need for field map acquisitions

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

Off-resonance correction: Beyond the Fourier model

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

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

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

[Sutton et al. *IEEE TMI 2003*]

$$(\widehat{\mathbf{B}}, \widehat{\mathbf{C}}) = \arg \min_{\mathbf{B}\in\mathbb{C}^{M\times L}, \mathbf{C}\in\mathbb{C}^{L\times N}} \| \mathbf{E} - \mathbf{B}\mathbf{C}\|_{Fro}^2$$

$$\text{with} \quad \mathbf{E} = (E_{mn}),\ E_{mn} = e^{-2\imath\pi\Delta B_0(r_n)t_m}$$

[Fessler et al. *IEEE TSP 2005*]

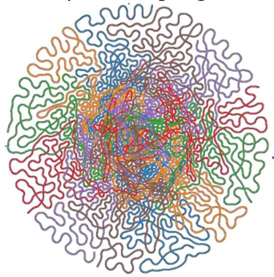
Sutton et al, *Fast, iterative image reconstruction for MRI in the presence of field inhomogeneities*, TMI 2003

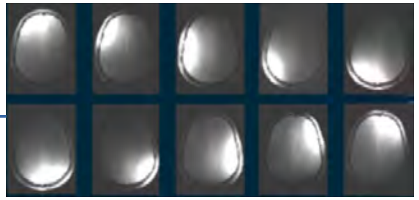
Multicoil CS MR image reconstruction

Take the acceleration factor into account
- Parallel Imaging
- k-Space subsampling

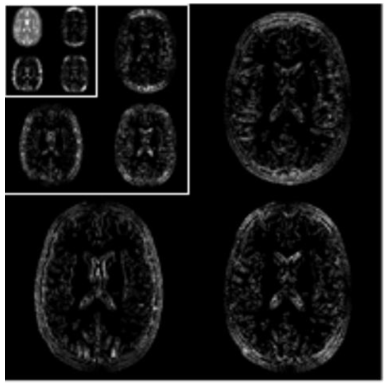
MRI-nufft

Non Uniform Sampling



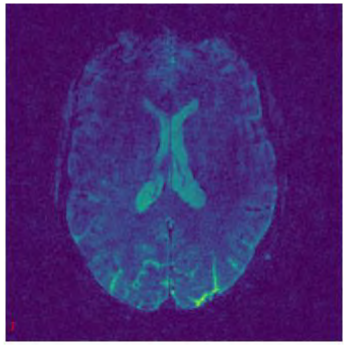


Sensitivity Maps



Wavelet Decomposition

PySAP
Python Sparse data Analysis Package



Anatomical Volume

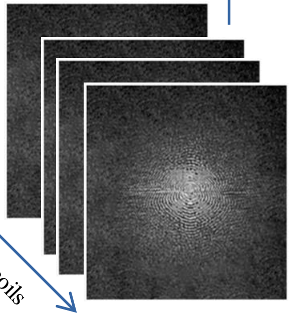
$$\hat{\boldsymbol{x}} = \underset{\boldsymbol{x}\in\mathbb{C}^N}{\arg\min}\ \frac{1}{2}\sum_{\ell=1}^{L} \|\boldsymbol{\mathcal{F}}_\Omega \boldsymbol{\mathcal{S}}_\ell \boldsymbol{x} - \boldsymbol{y}_\ell\|_2^2 + f(\boldsymbol{\Psi}\boldsymbol{x})$$

Non Linear iterative solver
FISTA, POGM, ...

Sparsity Promotion
L1, Group LASSO, ...

Pierre-Antoine Comby, MSc

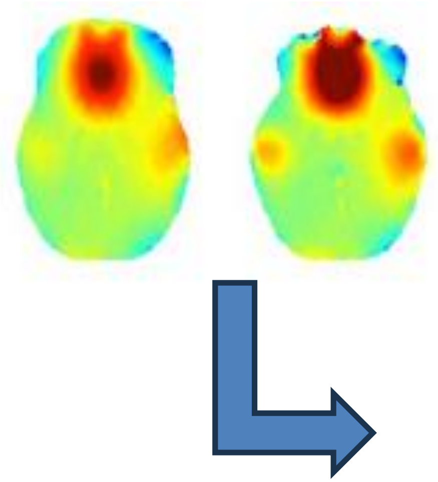
MOD|OPT



L coils

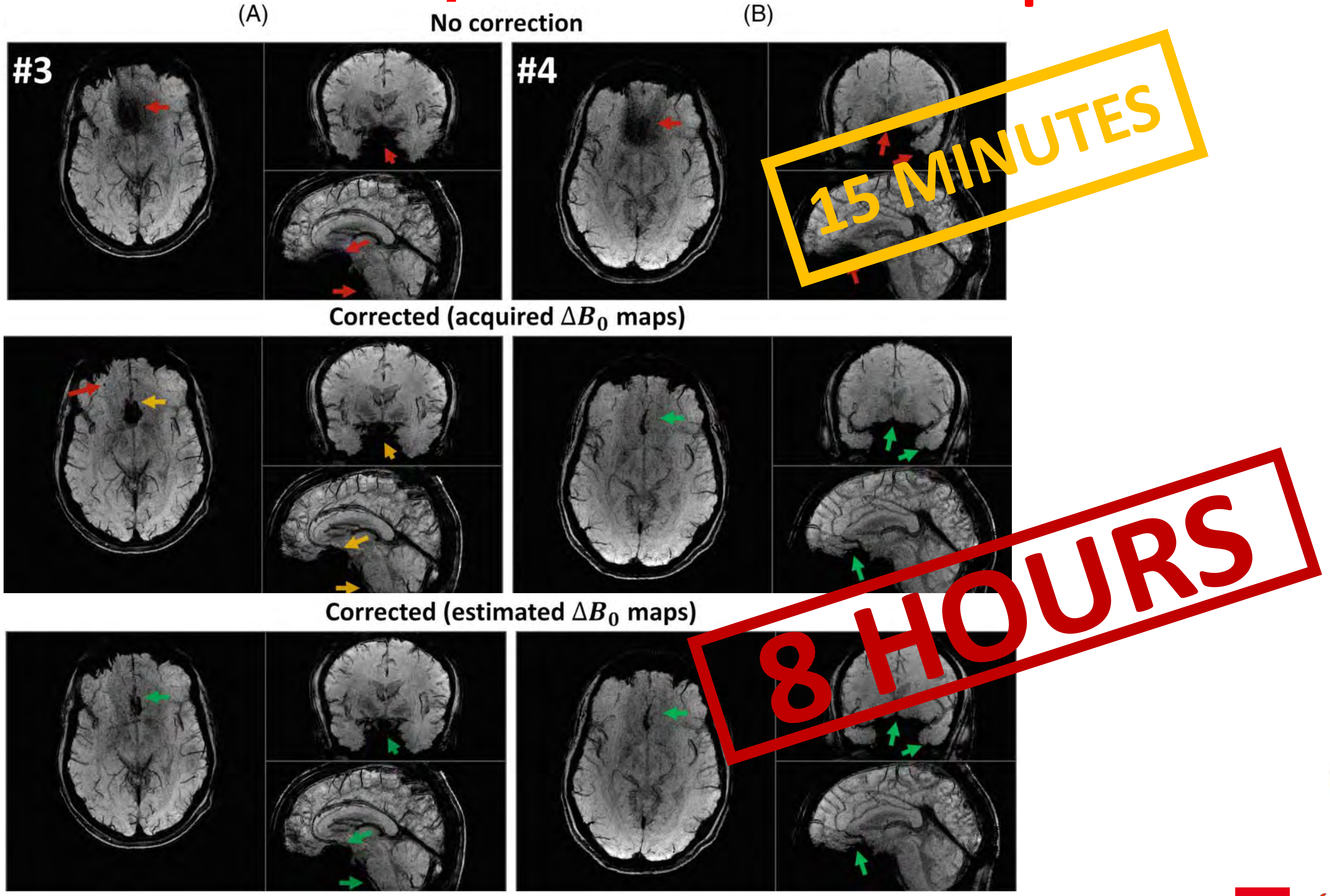
Kspace Data

Correction in SWI: Internally estimated field maps



With additional field map scan

No additional field map scan



G. Daval-Frérot

SIEMENS Healthineers

Sutton et al, *Fast, iterative image reconstruction for MRI in the presence of field inhomogeneities*, **TMI 2003**
Daval-Frérot et al, *Iterative static field map estimation for off-resonance correction in SWI*, **MRM 2022**

Unrolling MR image reconstruction algorithms

Traditional MR Scans	Accelerated acquisitions	Deep Neural network for reconstruction
Acq Time	Acq Time	Acq Time
Recon Time	Recon Time	Recon Time

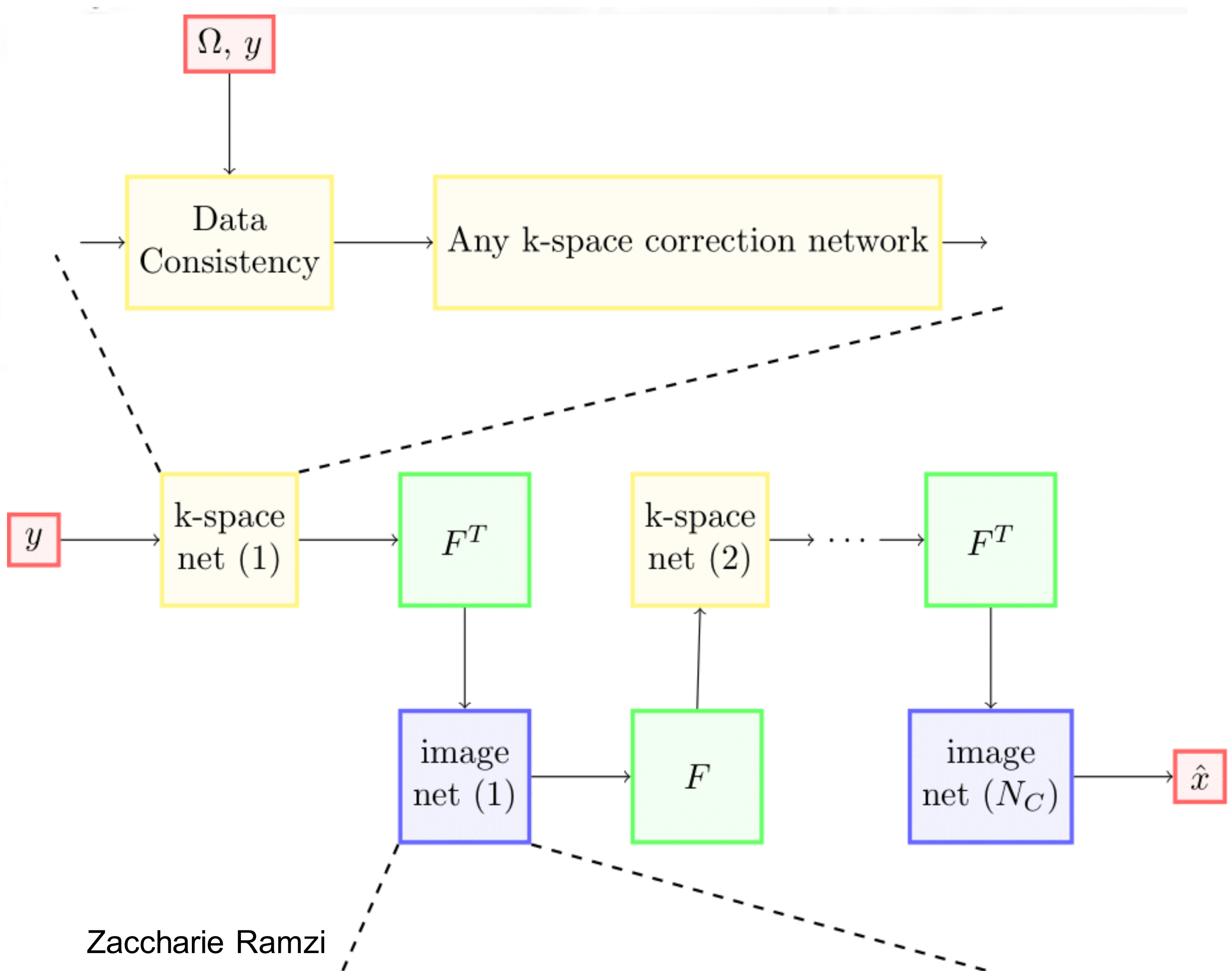
Compressed sensing, Non-Cartesian imaging, SPARKLING

$$\underset{\boldsymbol{x}\in\mathbb{C}^n}{\arg\min} \sum_{\ell=1}^{L} \frac{1}{2}\|\boldsymbol{y}_\ell - \mathcal{F}_\Omega \boldsymbol{S}_\ell \boldsymbol{x}\|_2^2 + \mathcal{R}(\boldsymbol{x})$$

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

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

$$\boldsymbol{x}_0 \rightarrow \underbrace{\mathrm{DC} \rightarrow \mathrm{Prx}}_{\times N} \rightarrow \cdots \rightarrow \mathrm{DC} \rightarrow \mathrm{Prx} \rightarrow \boldsymbol{x}_N$$



Zaccharie Ramzi

Ramzi et al. *XPDNet,* App. Sci. 2020 Adler and Ötkem, IEEE TMI 2018

The 2020 fastMRI Challenge

FACEBOOK AI · NYU Langone Health

Objectives:

- Run an international challenge to benchmark the DL solutions for MR brain image recon
- Acquisition setup that fits the clinical realm (multi-coil acquisition, multiple 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)

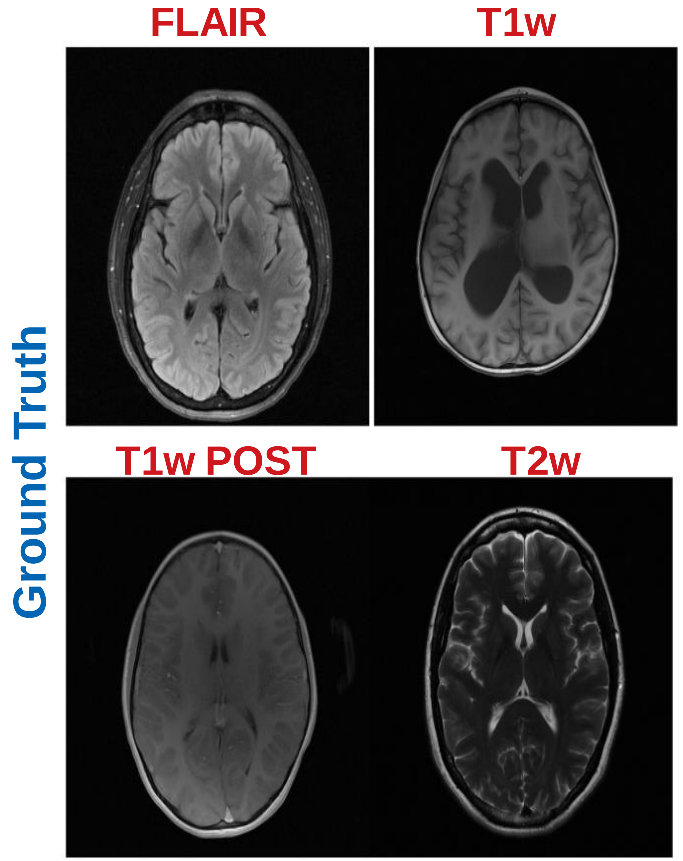


Table 1: Summary of Siemens data for 4X/8X tracks.

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

$$\forall \ell = 1, \ldots, L, \quad \widehat{\mathbf{x}}_\ell = \mathcal{F}^{-1}(\mathbf{y}_\ell) \qquad \mathbf{x}^{\mathrm{rss}} = \left(\sum_{\ell=1}^{L} \left| \widehat{\mathbf{x}}_\ell \right|^2 \right)^{1/2}$$

2020 fastMRI Challenge: Quantitative results

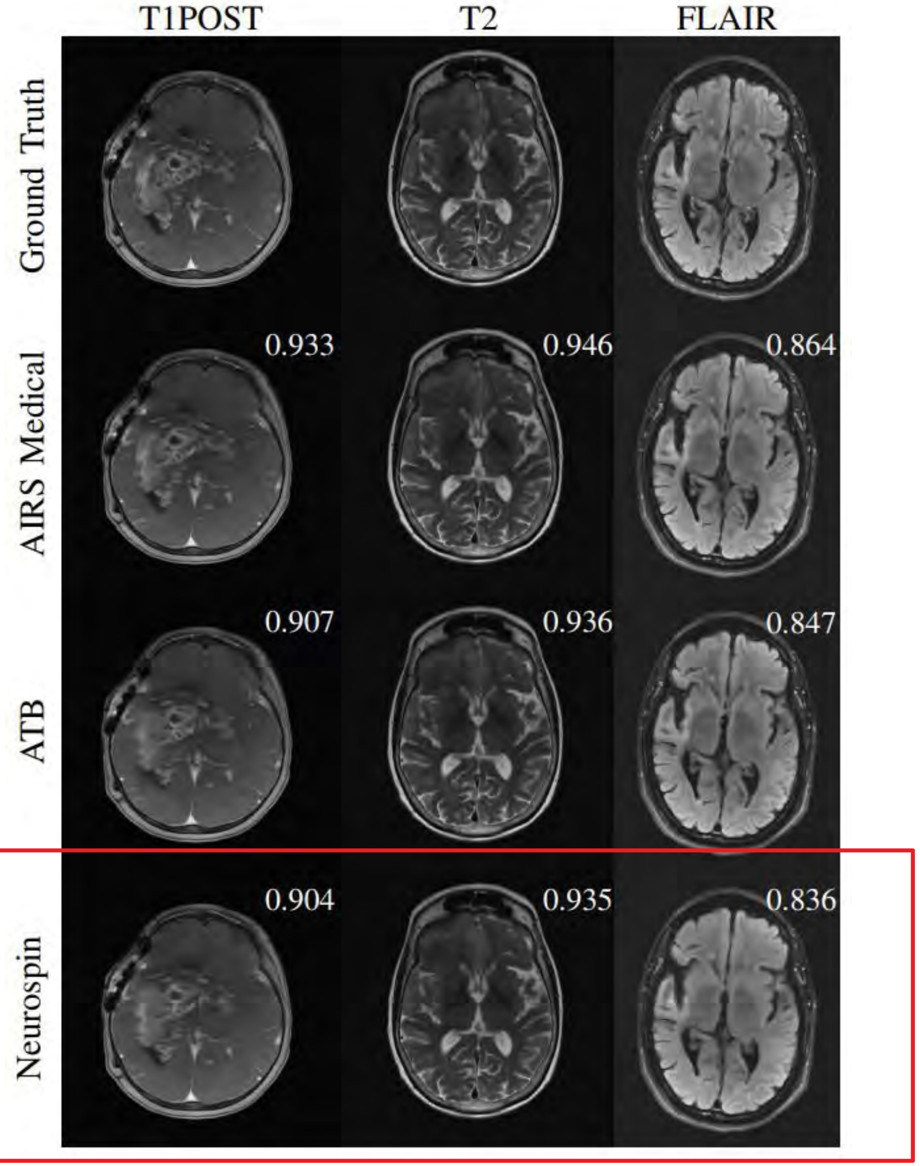


Table 3: Summary of quality ranks and Likert scores (lower is better).

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

Our submissions was ranked 2nd in the fastMRI challenge based on radiologists evaluations (1st in the academic research)

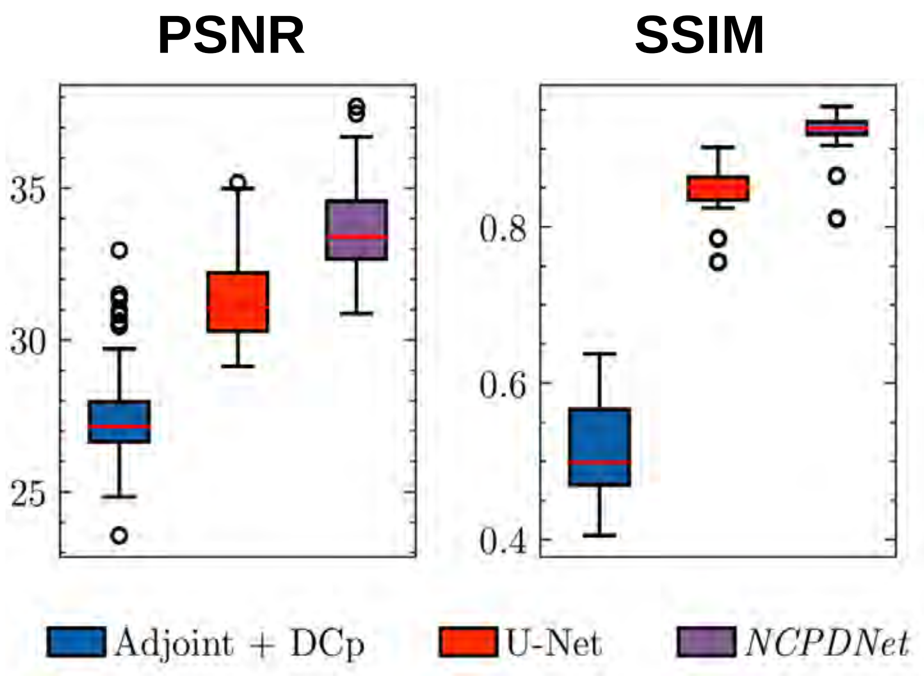
Ramzi et al. *XPDNet*, App. Sci. 2020
Muckley, et al, *Results of the 2020 fastMRI Challenge*, IEEE TMI 2021
https://nips.cc/Conferences/2020/ScheduleMultitrack?event=16140 (fastMRI keynote)

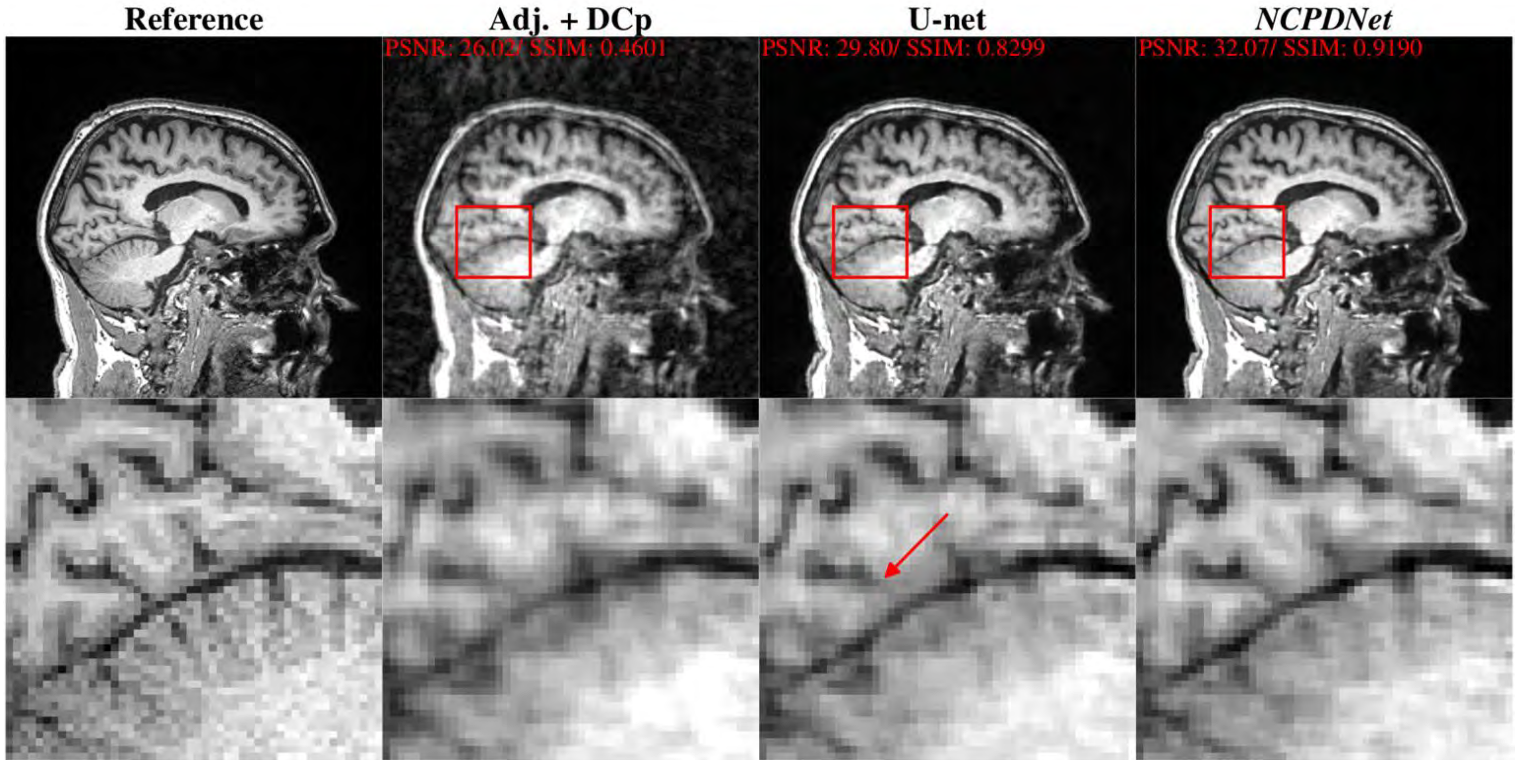
Robustness test on 7T out-of-distribution data

[12] L. Marrakchi-Kacem et al. (2016). "Robust imaging of hippocampal inner structure at 7T: in vivo acquisition protocol and methodological choices". In: *Magnetic Resonance Materials in Physics, Biology and Medicine* 29.3, pp. 475–489.

NC-PDNet : Evaluation on 3D single-coil dataset

3D radial acquisition (OASIS dataset, T1 contrast) with AF = 4





OASIS data is magnitude-only images

Shimron E, Tamir JI, Wang K, Lustig M. Implicit data crimes: Machine learning bias arising from misuse of public data. *Proc Natl Acad Sci U S A*. 2022;119(13):e2117203119. doi:10.1073/pnas.2117203119

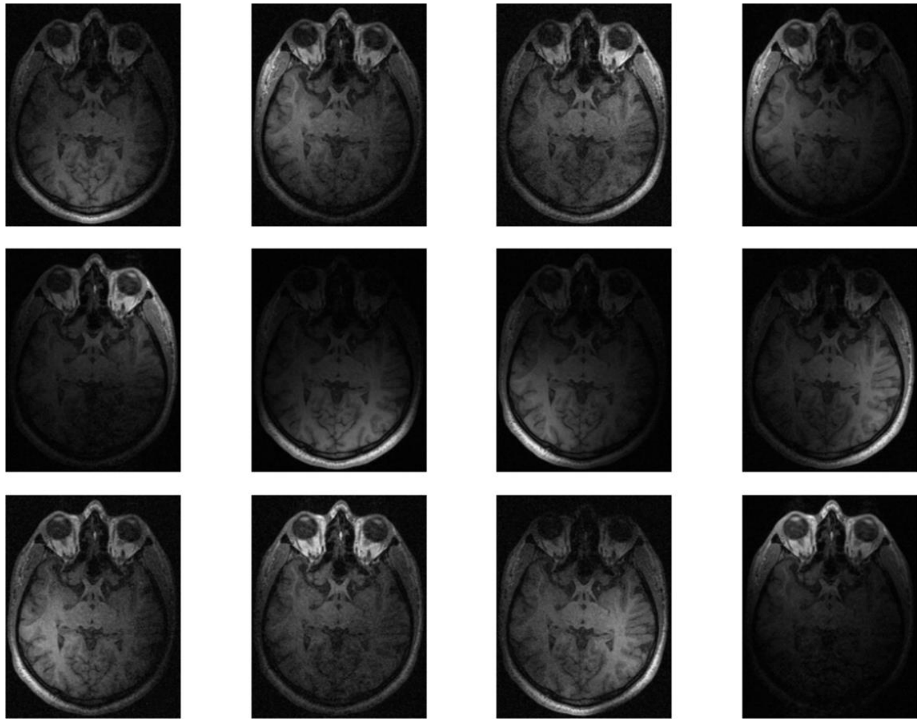
NC-PDNet Training on Multi-coil Dataset

CALGARY-CAMPINAS PUBLIC BRAIN MR DATASET : **12-Channel** Coil Data:

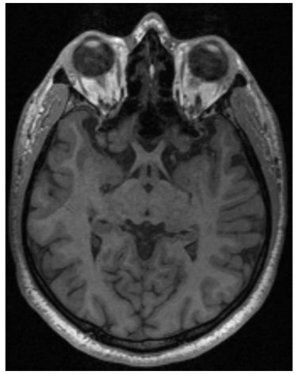
- Raw **fully-sampled**, **complex-valued** k-space data
- T1-weighted, MPRAGE acquisition
- 1 mm isotropic acquisitions
- Acquisition matrix size for each channel:
  Nx x Ny x Nz = 256 x 218 x [170,180].

	Split	#Multi-coil 3D volumes
12-channel dataset	Train	47
	Val	20
	Test	50

Multi-channel images



Root Sum Of Squares



Experiments with Calgary Dataset

Preprocessing:

- Use Golf-Sparkling (AF = 6.7) as a non-Cartesian sampling trajectory: **Radial -> Golf-Sparkling**
- Due to memory constraints, we perform SVD compression on coil dimension (select the first 5 orthonormal compressed coils): **Single-Coil -> Multi-Coil extension**
- Ground truth image is RSS (Root Sum of Squares) of the 5 compressed coils

Evaluation metrics: PSNR and SSIM are the quantitative metrics + visual quality of recon results

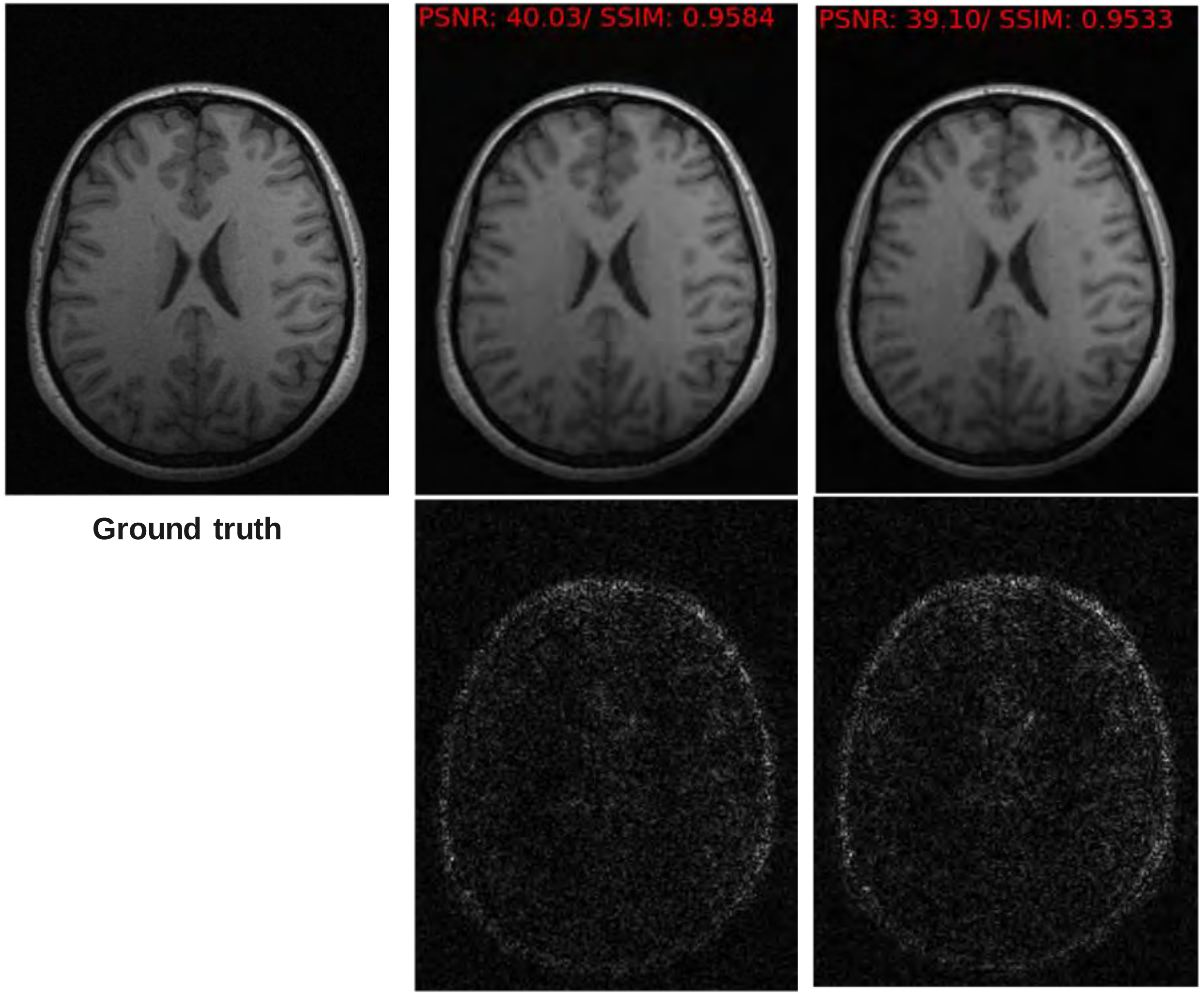
Deep Learning network hyper-parameters:

- 6 iterations, buffer-size of 2, and filter size 16
- Running experiments with MAE loss and Compound Loss (0.5 MAE + 0.5 MSSIM)
- Both presented models were trained for 50 epochs.

Epoch = A single pass through the entire training dataset

Evaluation Results : MAE Loss V.S. Compound Loss

- NC-PDNet trained on 47 (3D 5-compressed coils) volumes
- Evaluation is performed on 20 volumes of validation calgary dataset split



Ground truth

Compound Loss

MAE Loss

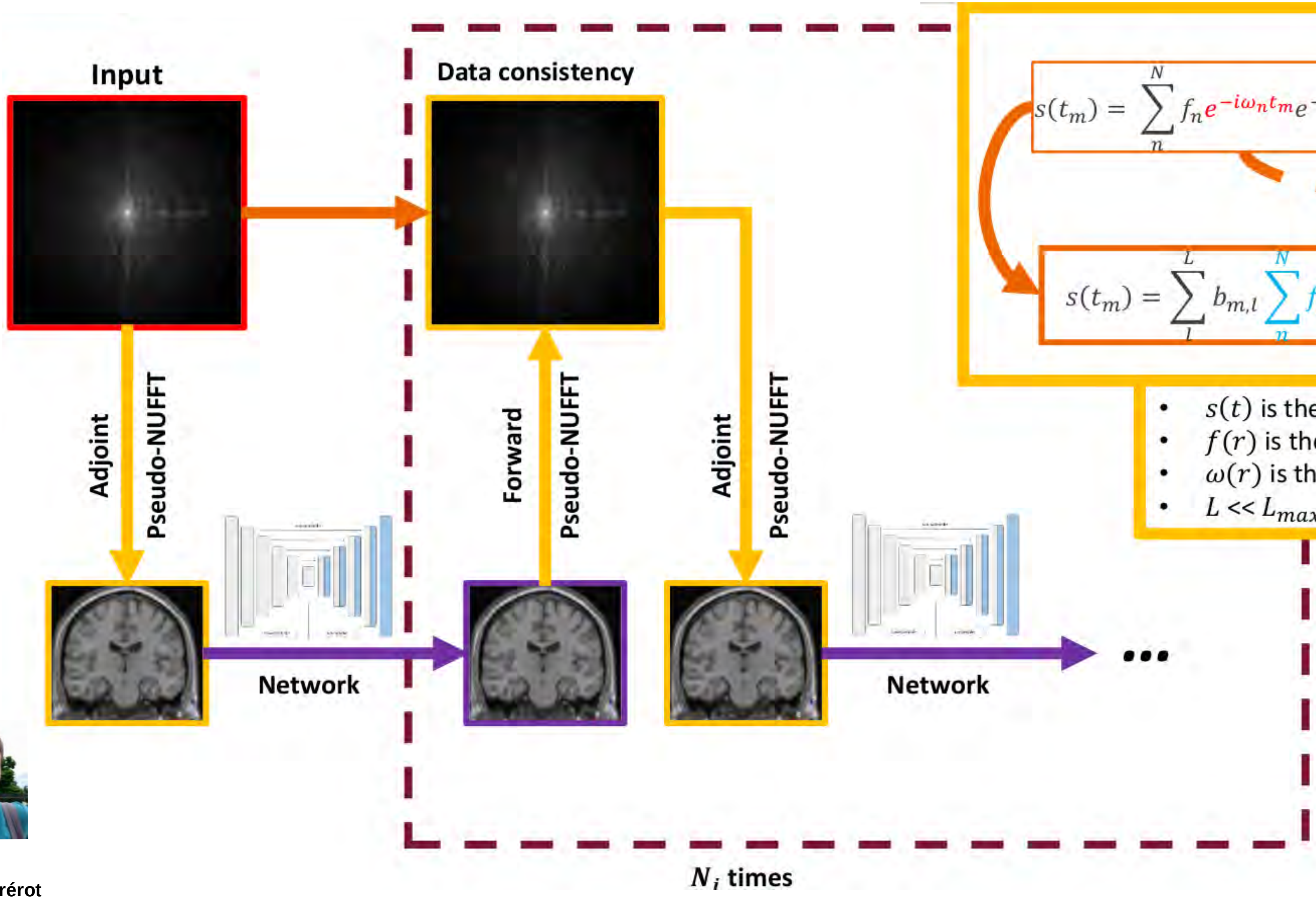
Loss	Mean± Sd PSNR	Mean± Sd SSIM
MAE Loss	36.76 ± 1.30	0.93 ± 0.013
Compound Loss	**37.87 ± 1.24**	**0.94 ± 0.011**

Table 7 : 3D NC-PDnet quantitative comparison w.r.t loss function on 20 5-channel compressed validation volumes

Asma Tanabene

SIEMENS Healthineers

Deep Learning Stacked ΔB_0-PDNet architecture



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

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

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

- $s(t)$ 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

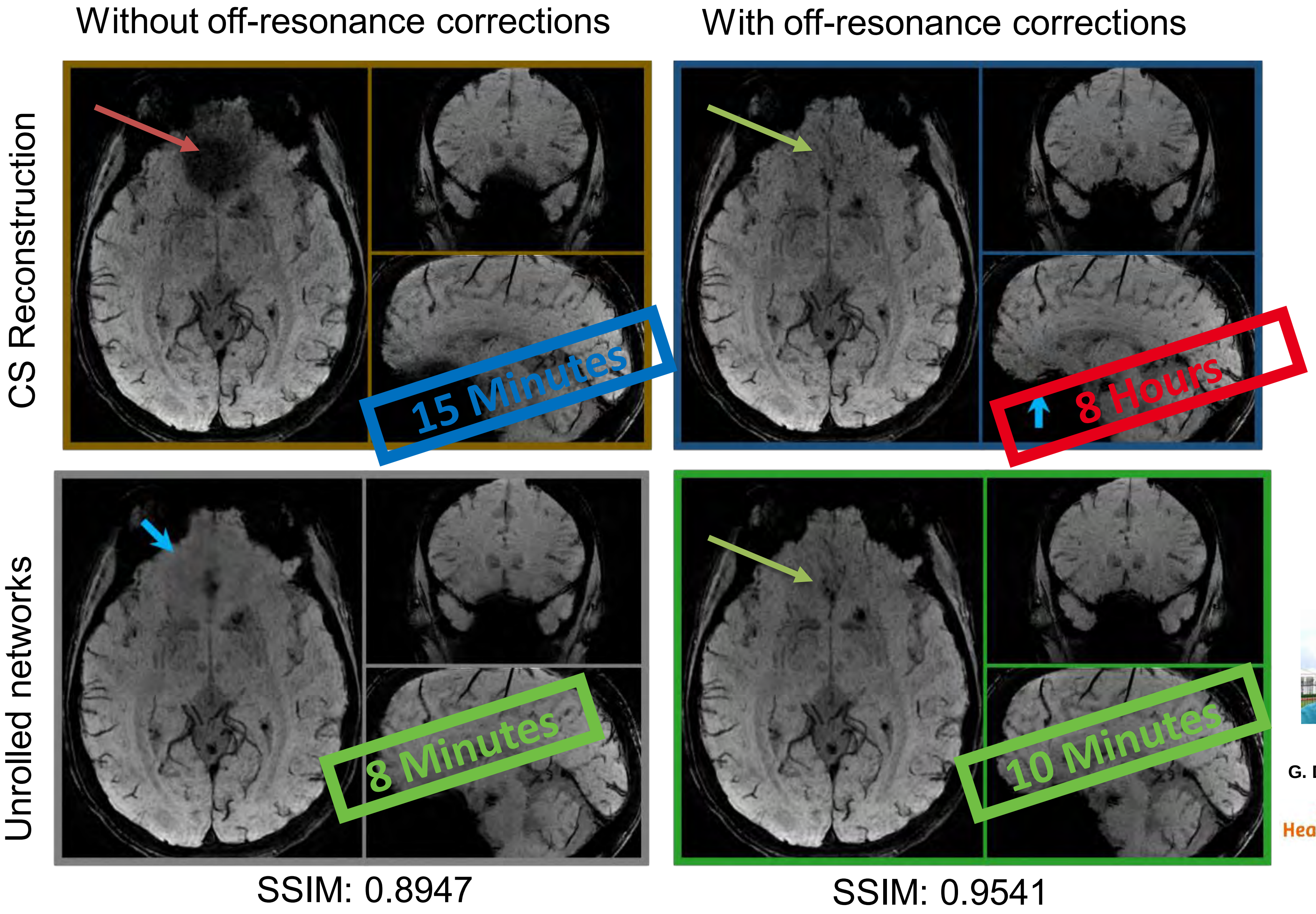
G. Daval-Frérot

SIEMENS Healthineers

Incorporating ΔB_0 correction into neural network

For realistic reconstructions on actual scanner data

0.6mm isotropic SPARKLING,
Scan time = 3 min
AF=15



G. Daval-Frérot

SIEMENS Healthineers

Daval-Frérot et al, *Deep learning assisted off-resonance correction for SWI*, MRM 2023

Back-propagation on the network parameters

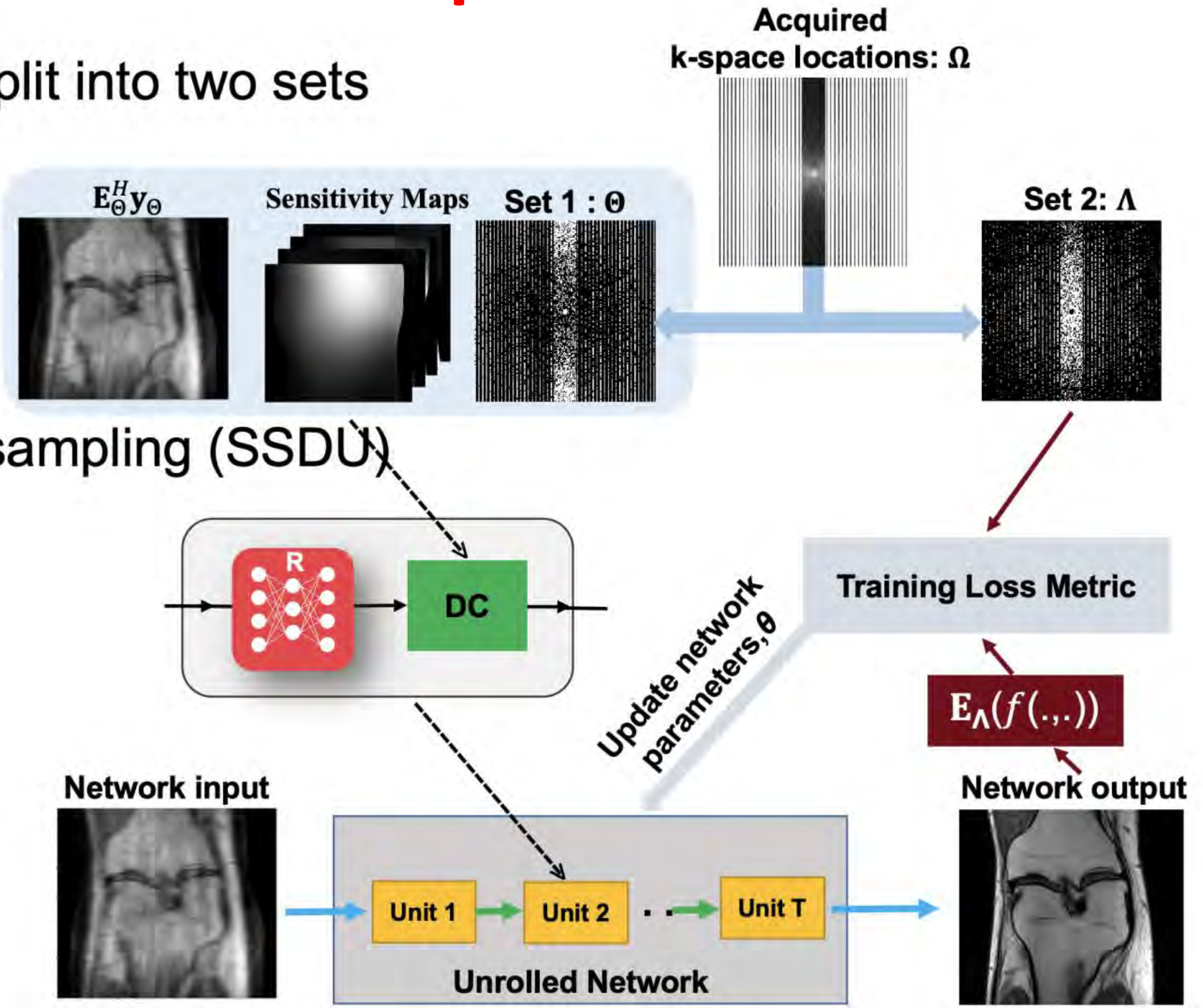
- Acquired k-space locations Ω, split into two sets

$$\Omega = \Theta \cup \Lambda$$
$$\Theta = \Omega \backslash \Lambda$$

- Self-supervision via data undersampling (SSDU)

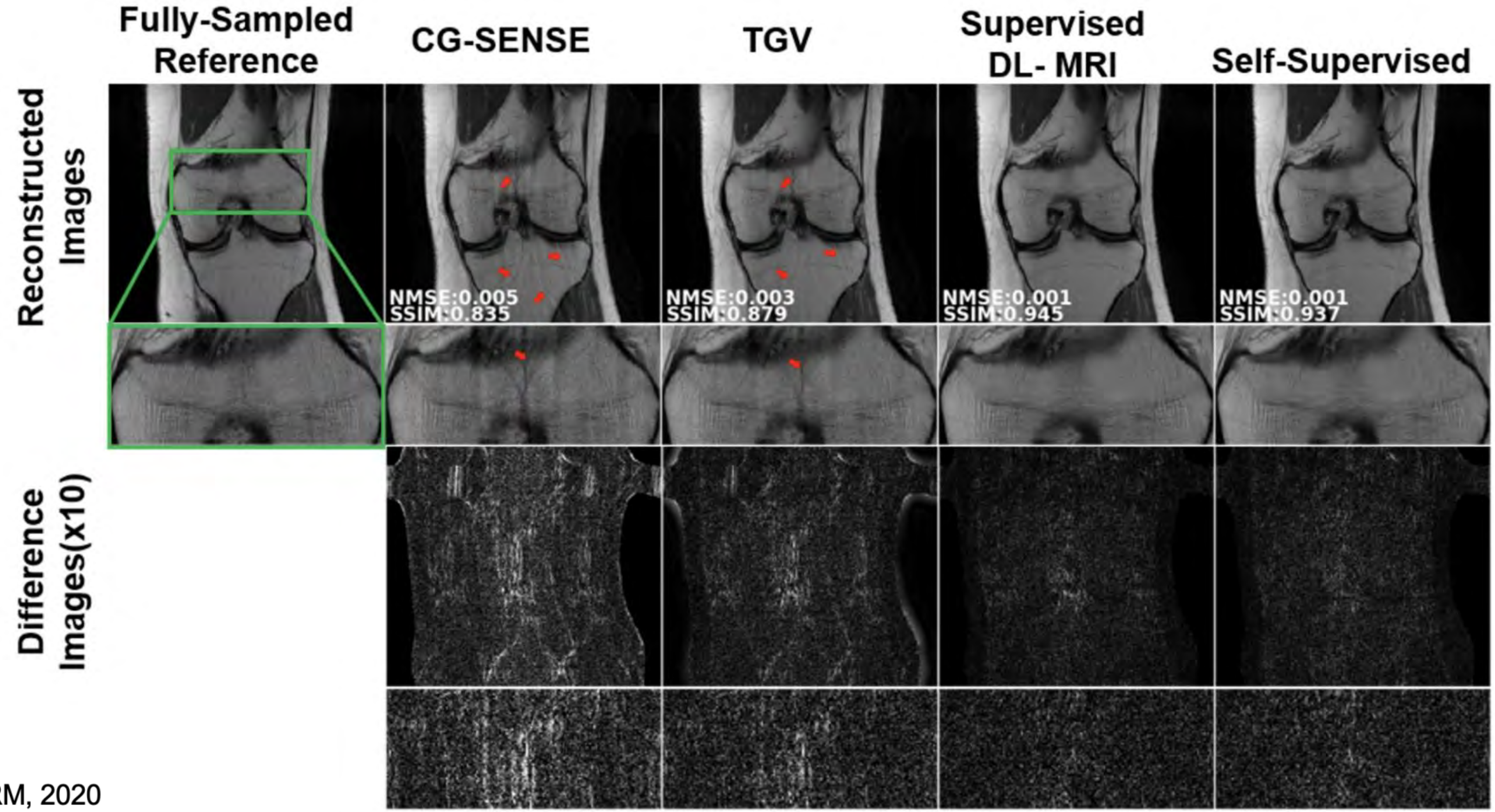
- End-to-end minimization

$$\min_{\theta} \frac{1}{N} \sum_{i=1}^{N} \mathcal{L}\left(\mathbf{y}_{\Lambda}^{i}, \mathbf{E}_{\Lambda}^{i}\left(f\left(\mathbf{y}_{\Theta}^{i}, \mathbf{E}_{\Theta}^{i}; \boldsymbol{\theta}\right)\right)\right)$$



Yaman et al, MRM, 2020

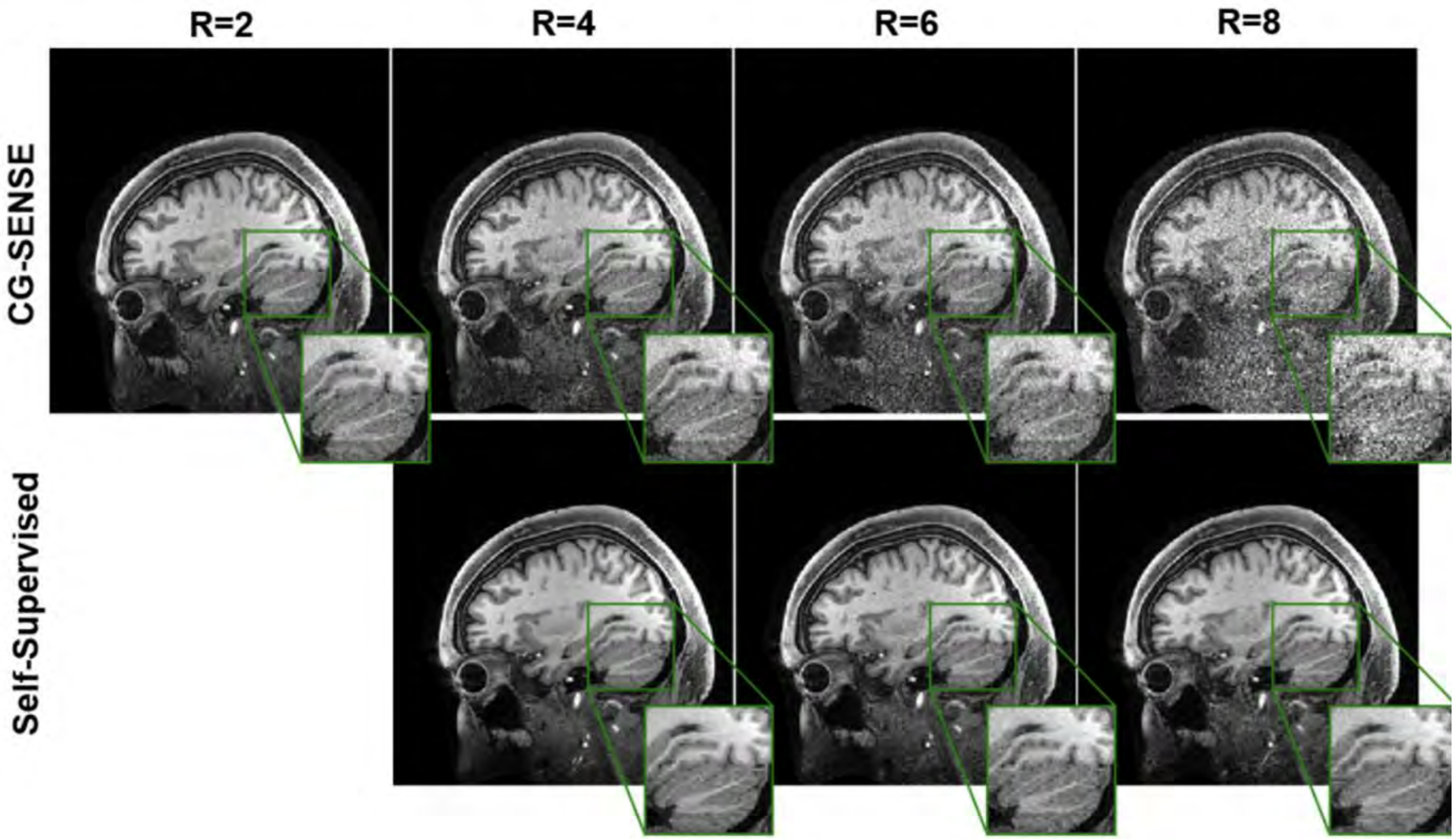
Supervised vs Self-Supervised DL reconstruction



Yaman et al, MRM, 2020

Supervised vs Self-Supervised DL reconstruction

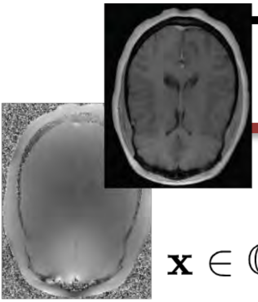
- Prospectively subsampled (R = 2)
- Supervised DL MRI not available (no ref data)
- Self-supervised successful reconstruction at high rates



PROJeCTOR: Blending Acquisition & Reconstruction Worlds

PROjection for Jointly lEarning non-Cartesian Trajectories while Optimizing Reconstructor

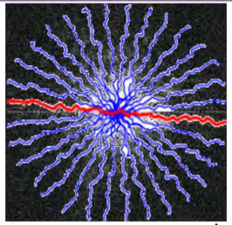

Chaithya G R



$\mathbf{x} \in \mathbb{C}^{N \times N}$

Acquisition Model $\mathbf{F}_{\mathbf{K}_{t+1}}$

Simulated k-space data



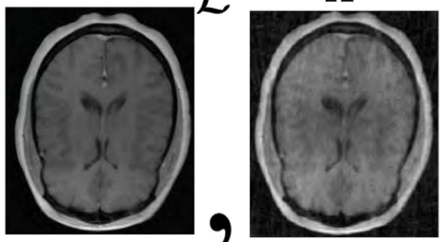
$\mathbf{y} \in \mathbb{C}^{N_c \times N_s \times \frac{\Delta t}{\delta t}}$

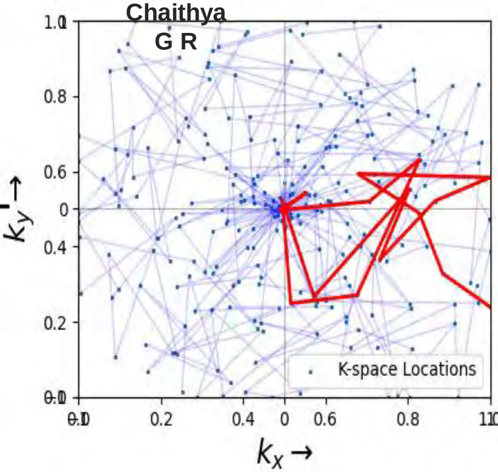
Reconstruction Model $\mathcal{R}_{\boldsymbol{\theta}}^{\mathbf{K}_{t+1}}$

Ramzi et al, *NCPDNet*, TMI 2022

Loss

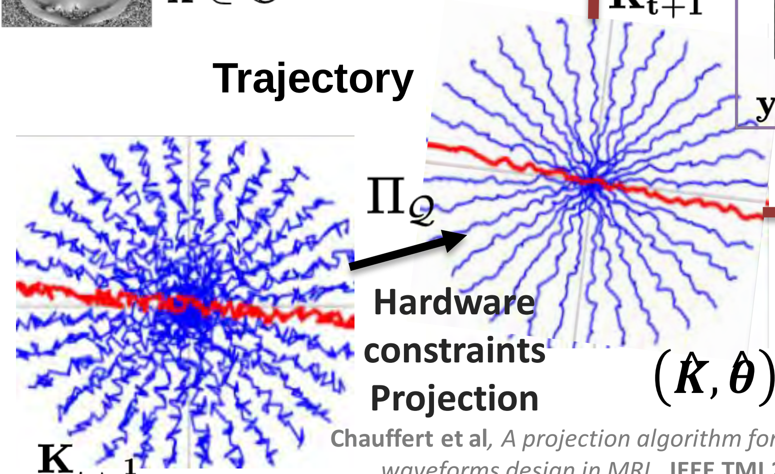
$\left\{ \mathbf{x} \;\mathcal{L}\; , \; \hat{\mathbf{x}} \right\}$





$\mathbf{K}_{t+1}$

Trajectory



$\Pi_{\mathcal{Q}}$

Hardware constraints Projection

$\mathbf{K}_{t+\frac{1}{2}}$

Density Compensators $\mathbf{D}_{\mathbf{K}_{t+1}}$

$$(\hat{K}, \hat{\theta}) = \underset{K \in \mathcal{Q}, \theta}{arg\,min}\, \mathcal{L}_r\left(x, \mathcal{R}_K^{\theta}\left(F_{\mathcal{S}(K)}x\right)\right)$$

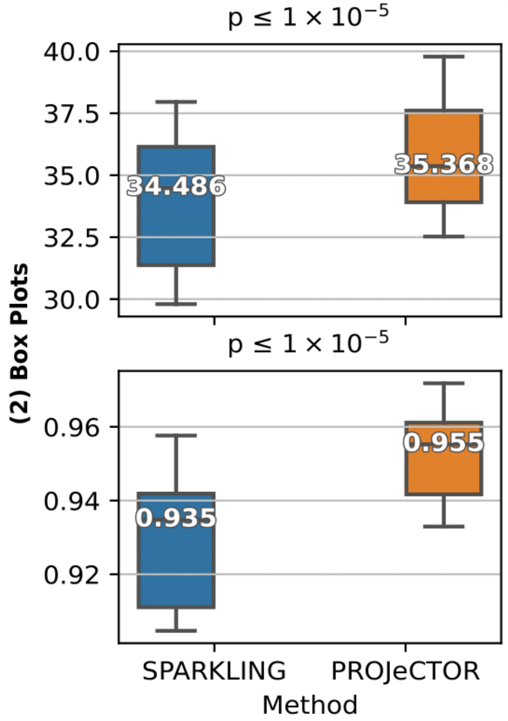
Chauffert et al, *A projection algorithm for gradient waveforms design in MRI*, IEEE TMI 2016

Backpropagation: Trajectory and reconstructor parameters update

Reconstruction time ≈1min

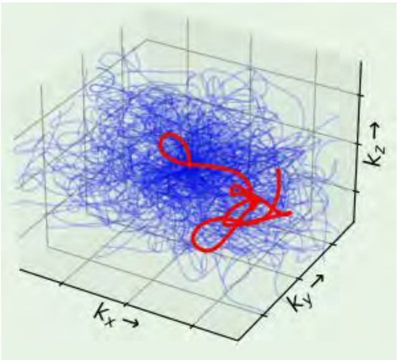
SSIM=0.95

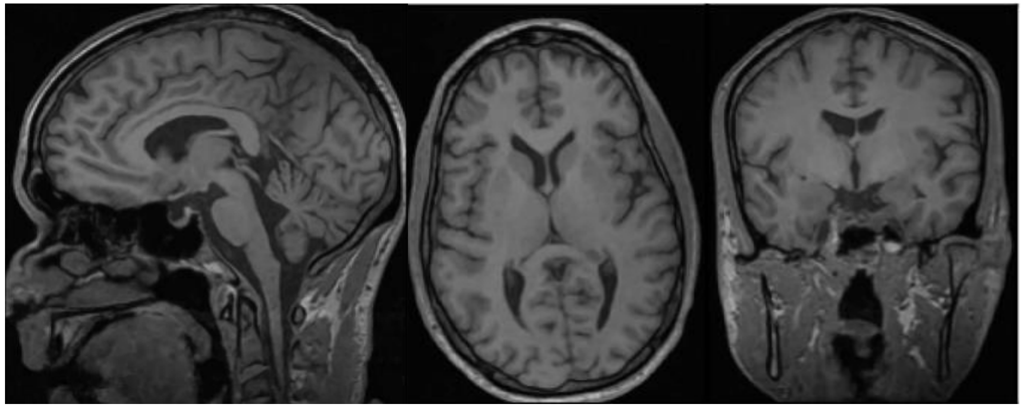
PSNR=35.14



PROJeCTOR 3D

3D Calgary Dataset
167 Raw k-space data





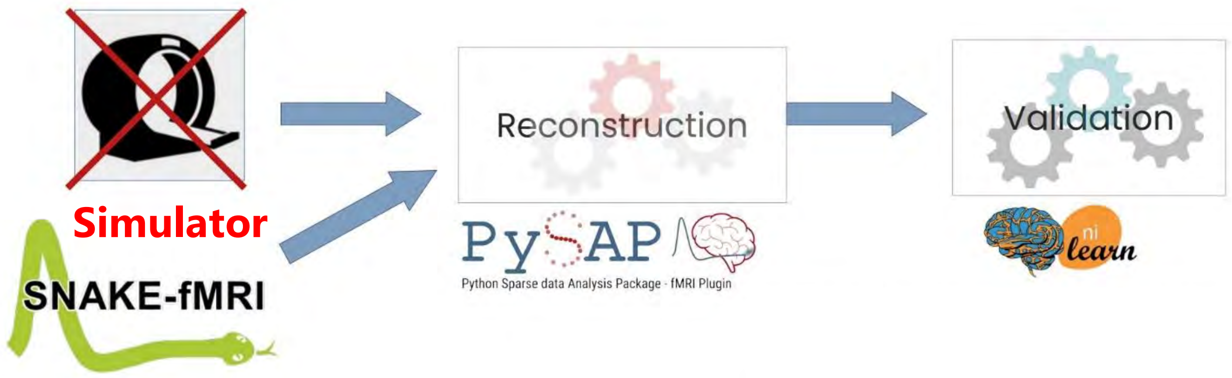
Acceleration Factor=20

Weiss et al, MELBA 2021; Wang et al IEEE TMI 2022
Chaithya GR et al, BioEng 2023

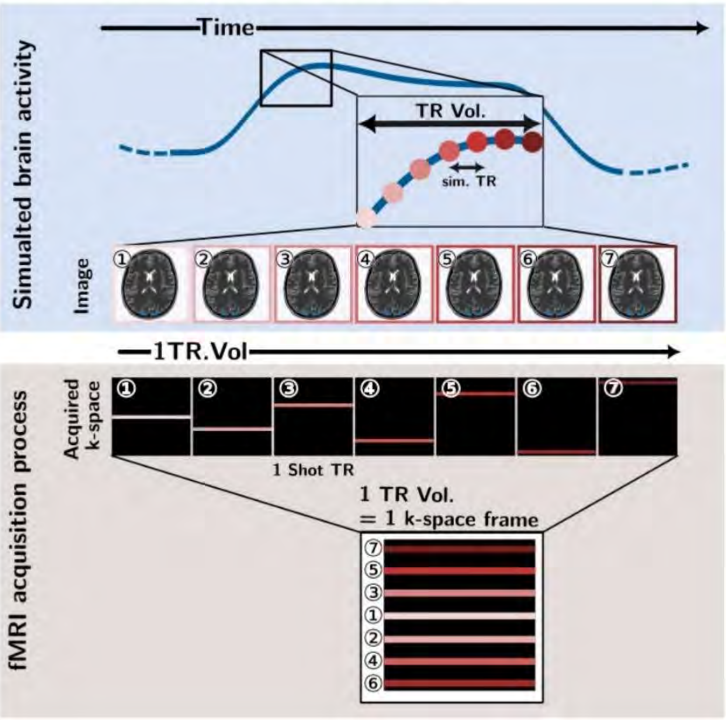
Conclusion and Perspectives

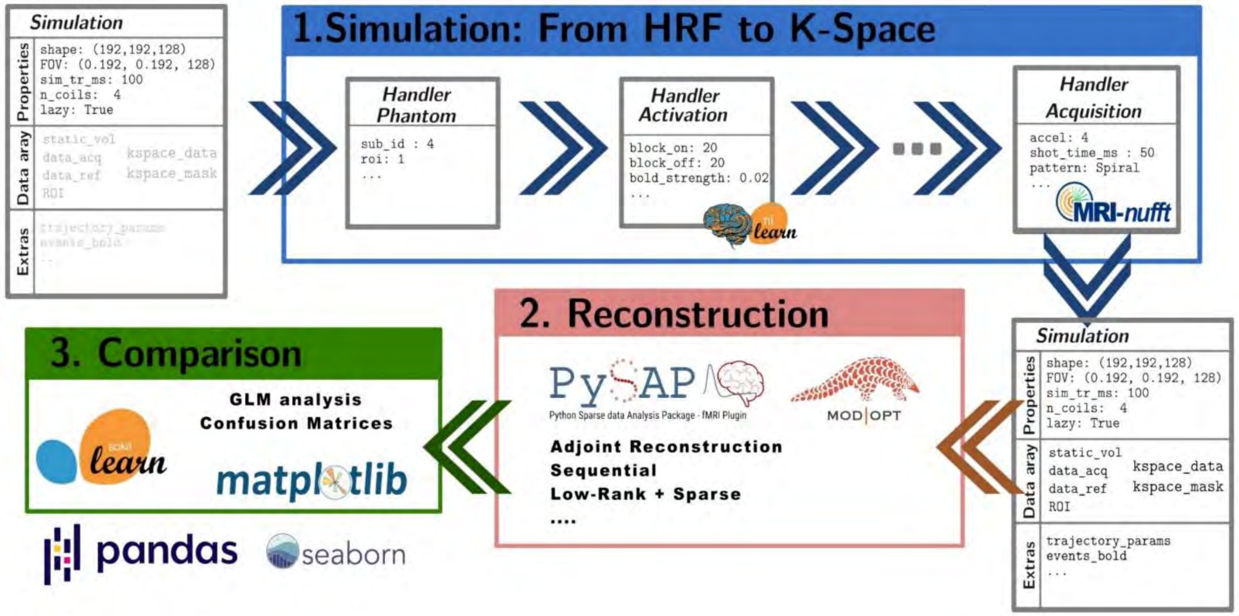
- Ultra-high field imaging allows neuroscientists to probe the human brain in vivo at unprecedented spatial resolution (200µm isotropic) thanks to high SNR
- However, to meet clinical examination constraints, scan time must be short without impeding image quality
- SPARKLING: a news CS-driven accelerated MR data acquisition technique
- Complexity of imaging was transferred to image reconstruction
  - Fortunately, deep learning went to the rescue to provide fast and ultra-clear image quality
  - NC-PDNet scales to 3D non-Cartesian imaging and off-resonance correction
  - Scalable to multi-coil imaging thanks to a new era of GPU boards (A100 and currently H100)0
  - Unsupervised learning either using SSDU or PnP approaches
- Ongoing work: extension to fMRI with SNAKE-fMRI

Q2.3 - Supervision with realistic synthetic fMRI data



Principle of high temporal resolution for shot-wise acquisition





- Functional API for prototyping

```python
from snkf.simulation import SimData
from my_local_package import ScannerDriftHandler
from snkf.handlers import H

sim = SimData(shape=(64,64), fov=(.192, .192), sim_time=300, sim_tr= 0.1, )
simulator = H["phantom-big"] >> H["activation-block"] >> H["scanner-poly-drift"]
sim = simulator(sim)  # update the simulation by running it through the handlers.
```

https://github.com/paquiteau/snake-fmri

- Configuration file and CLI

https://hal.science/hal-04533862v1/document

```
$ pip install snake-fmri
$ snkf-main --config-name="scenario1"
# Using Hydra, parameters can be modified and run over a grid of parameter.
$ snkf-main --config-name="scenario2" -m ++reconstructors.sequential.restart_strategy=cold,warm,refine
```

To reproduce data of the previous slide

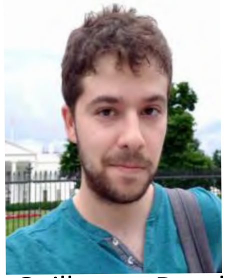
Acknowledgements

MIND NeuroSpin

Chaithya GR, PhD

Asma Tanabene, MSc

Pierre-Antoine Comby, MSc



Guillaume Daval-Frérot, PhD

Zaccharie Ramzi, PhD

Carole Lazarus, PhD

Loubna El Gueddari PhD

METRIC NeuroSpin

Alexandre Vignaud, PhD

Nicolas Boulant, PhD

Franck Mauconduit, PhD

Caroline Le Ster, PhD

Alexis Amadon, PhD

Zaineb Amor, PhD

Aurelien Massire, PhD

SIEMENS Healthineers

Vincent Gras, PhD

cea irfu

Head of the Superconducting Magnet Lab

Lionel Quettier, PhD

Q. Guihard
G. Dilasser
F-P. Juster
J. Belorgey
O. Dubois
F. Molinié
H. Lannou
R. Touzery
A. Sinanna
M. Luong
G. Aubert

CosmoStat

Samuel Farrens, PhD

Jean-Luc Starck, PhD

Thanks for your attention

Questions?

Philippe CIUCIU
CEA SACLAY
91191 Gif-sur-Yvette Cedex
France
Philippe.ciuciu@cea.fr

2-year postdoc fellow position at NeuroSpin (France), immediately available

TOPIC: High resolution SPARKLING fMRI imaging on humans at 11.7T

Towards 3D SPARKLING

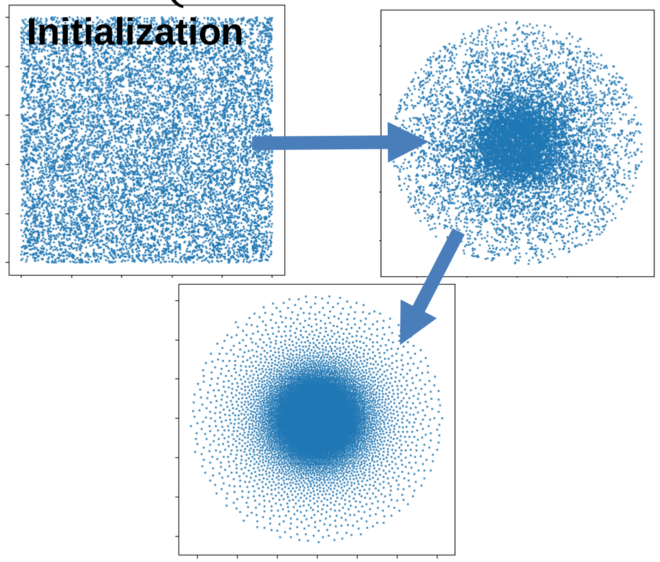
$$\widehat{\boldsymbol{K}} = \arg\min_{\boldsymbol{K}\in Q} F_N(\boldsymbol{K},\pi) = F_N^a(\boldsymbol{K},\pi) - F_N^r(\boldsymbol{K})$$

$$Q = \left\{ \begin{array}{c} \forall i \in \{1,\ldots N_c\},\ \boldsymbol{k_i}[TE] = [0,0,0]^T \\ \left\|\dot{\boldsymbol{k}}_{\boldsymbol{i}}\right\|_{2,\infty} \leq \alpha, \left\|\ddot{\boldsymbol{k}}_{\boldsymbol{i}}\right\|_{2,\infty} \leq \beta \end{array} \right\}$$

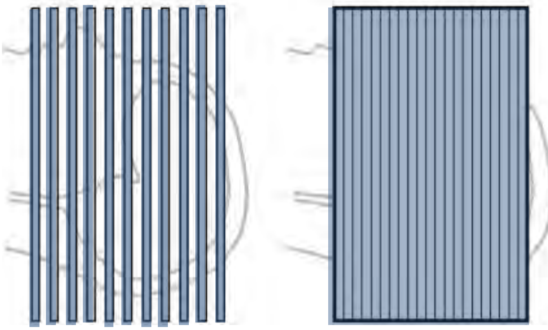
$$F_N^a(\mathbf{K},\pi) = \frac{1}{N}\sum_{i=1}^{N}\int_{\omega} ||x - \boldsymbol{K}[i]||_2 \pi(x)dx$$

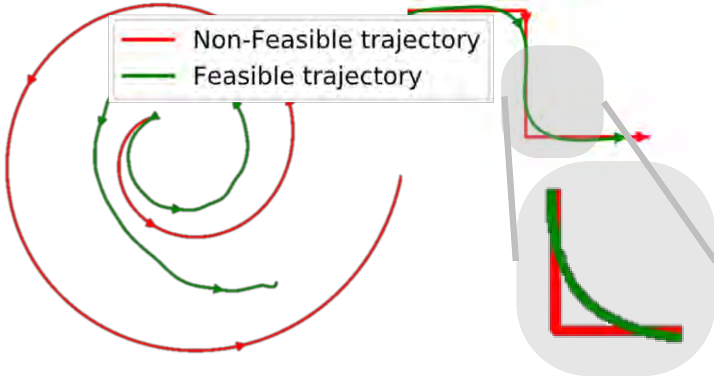
$$F_N^r(\mathbf{K}) = \frac{1}{2N^2}\boxed{\sum_{1\leqslant i,j\leqslant N}} ||\mathbf{K}[i] - \mathbf{K}[j]||_2 \rightarrow \boldsymbol{O(N^2)}$$

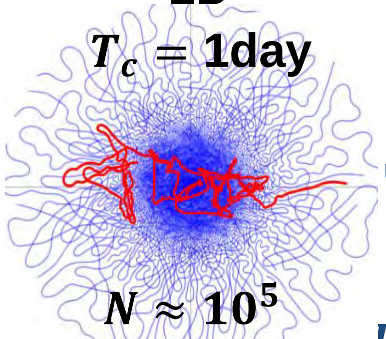
$$\boldsymbol{K^{t+1}} = \boxed{\Pi_Q}\left(\boldsymbol{K^t} - \eta^t \nabla F_N(\boldsymbol{K^t},\pi)\right) \rightarrow \boldsymbol{O(N_c)}$$



$SNR \propto$ Excited Volume







$16 \leq N_c \leq 64$

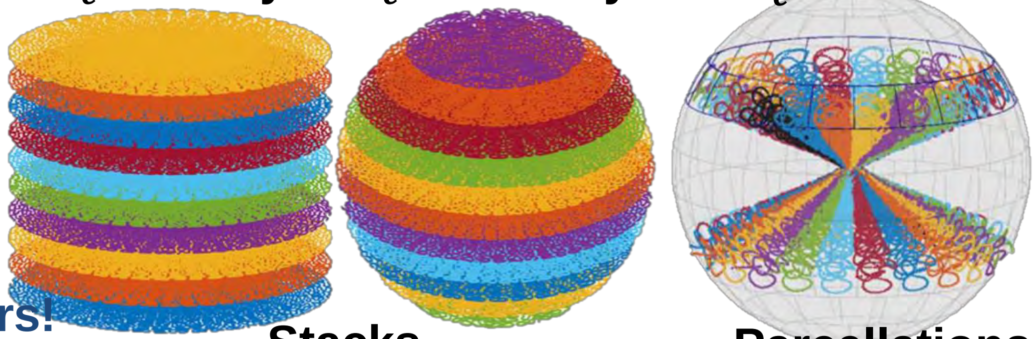
3D

$$\boldsymbol{N \approx 10^7}$$

$$4000 \leq N_c \leq 8000$$

$\boldsymbol{T_c}$ **= Months to Years!**

$\boldsymbol{T_c}$ **= 1 day** $\boldsymbol{T_c}$ **= 3-4 days** $\boldsymbol{T_c = 4\ Hrs}$



Stacks **Parcellations**

Lazarus et al, *SPARKLING: variable-density k-space filling curves for accelerated T_2*-weighted MRI*, MRM 2019

Lazarus et al, 3D *SPARKLING for high resolution T_2*-weighted MRI*, NMR Biomed 2020

Accelerating for Fully 3D SPARKLING

GPU

$$F_N^r(\mathbf{K}) = \frac{1}{2N^2} \sum_{1 \leqslant i,j \leqslant N}^{N} ||\mathbf{K}[i] - \mathbf{K}[j]||_2$$

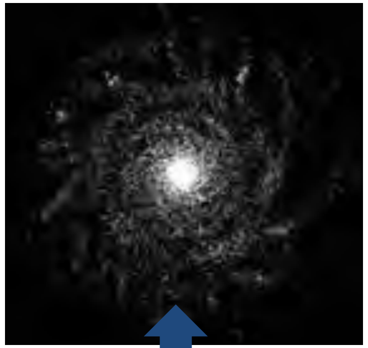
N-Body problem

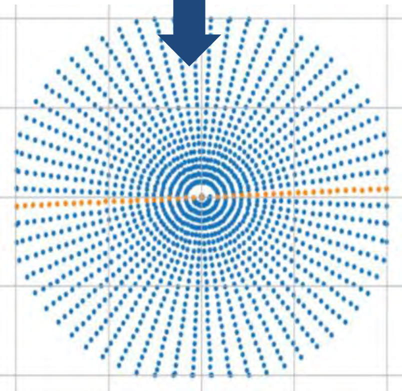
$$\Pi_Q(\boldsymbol{K}) = [\Pi_Q(\boldsymbol{k_i})]_{i=1}^{N_c}$$

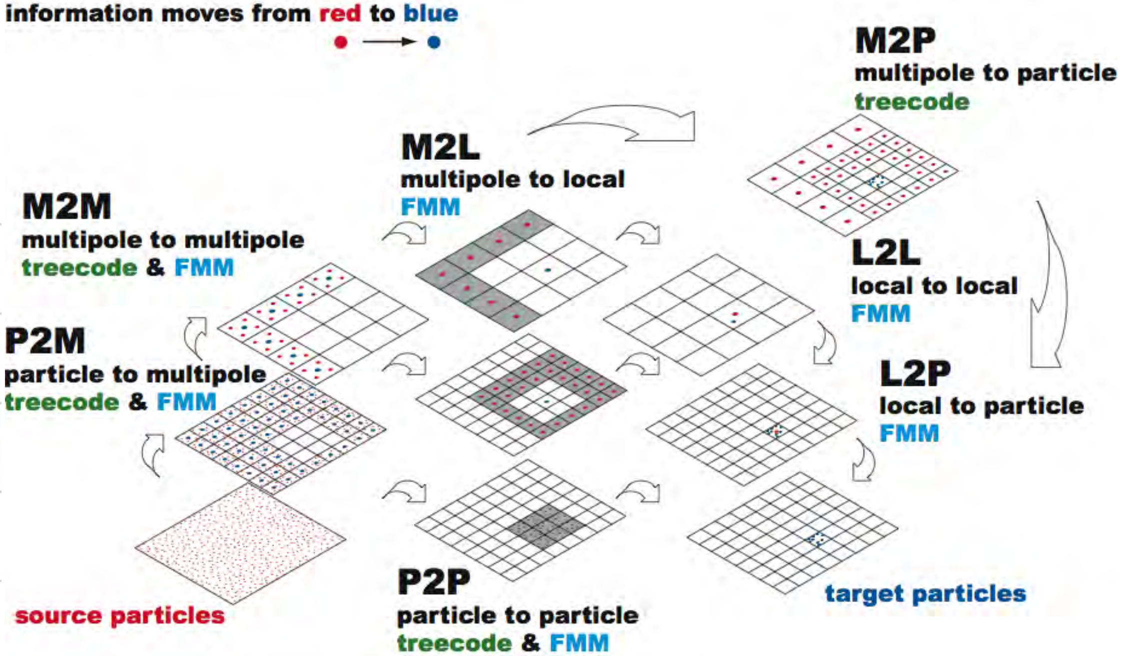
$\boldsymbol{O}(\boldsymbol{N_c})$

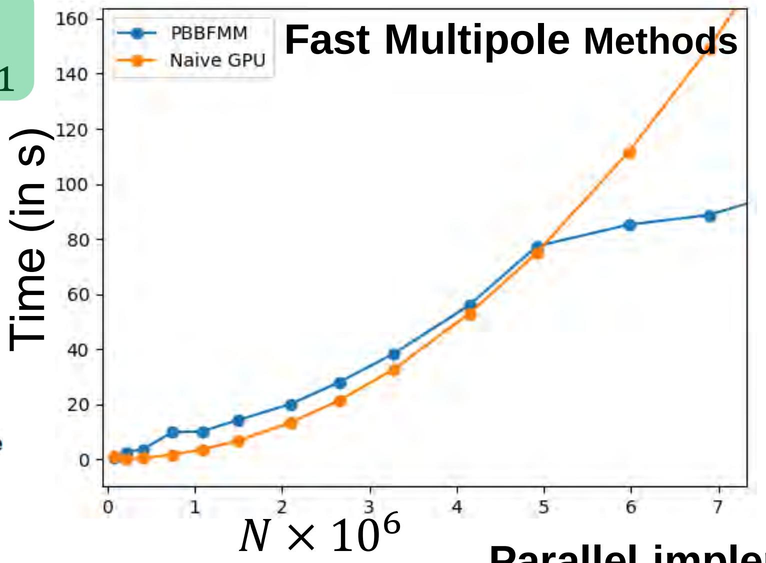
Highly parallel

$\boldsymbol{O}(\boldsymbol{N}^2) \rightarrow \boldsymbol{O}(\boldsymbol{N} \log \boldsymbol{N})$

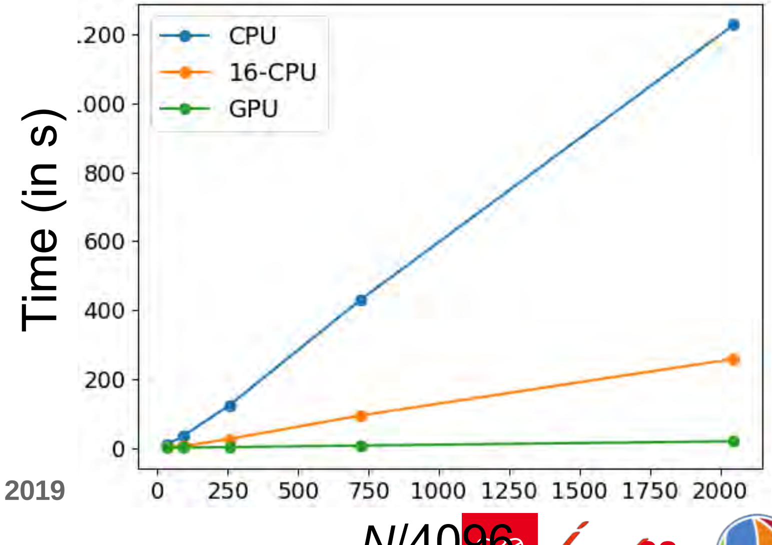








Parallel implementations

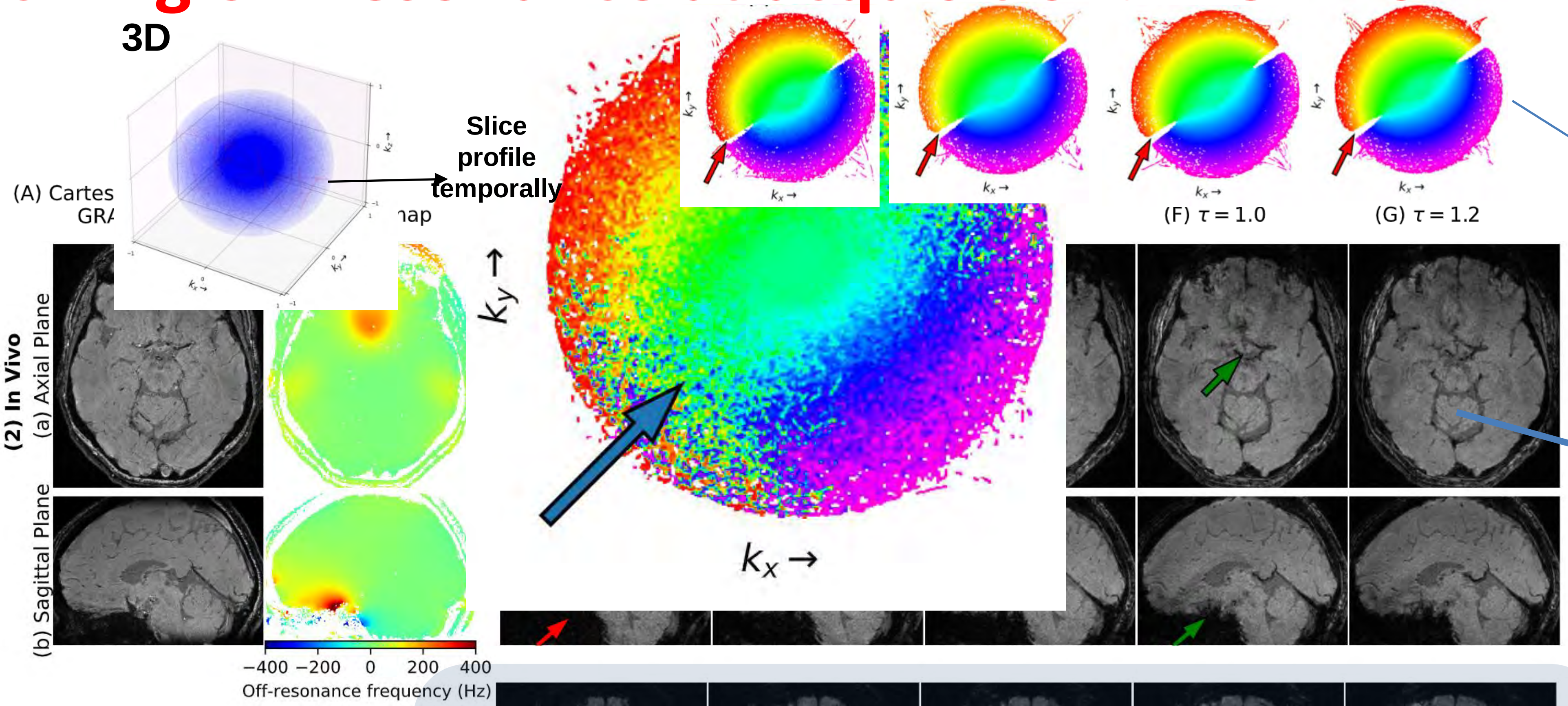


Wang et. al. PBBFMM3D: a Parallel Black-Box Fast Multipole Method for Non-oscillatory Kernels, arxiv 2019

https://www.bu.edu/pasi/courses/12-steps-to-having-a-fast-multipole-method-on-gpus/

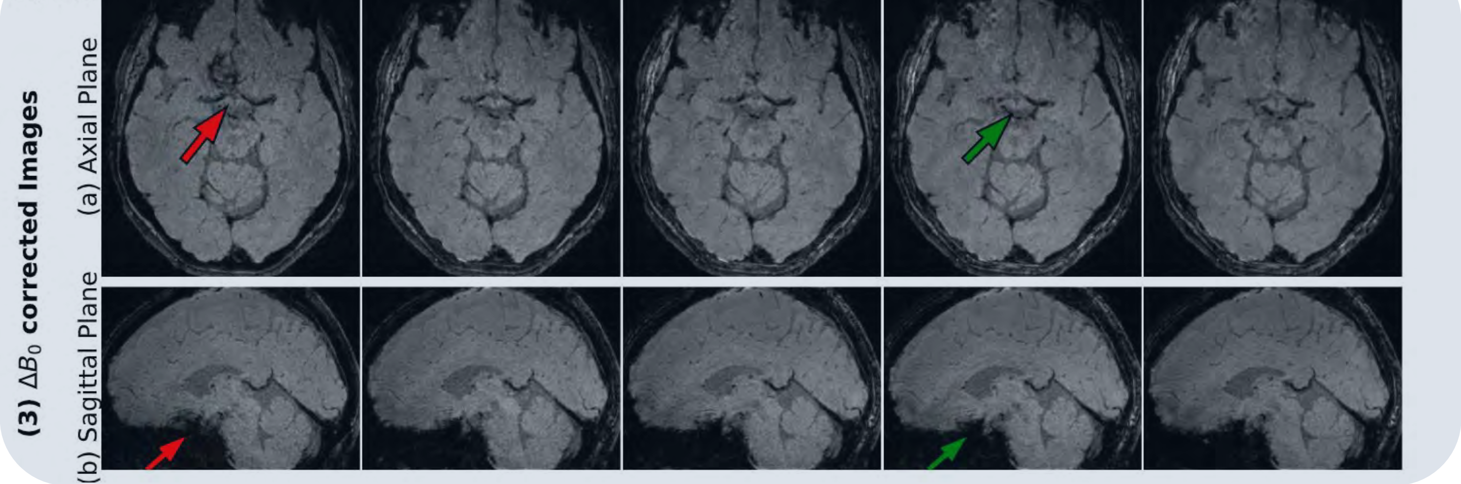
Chaithya et al, IEEE TMI 2022

Tackling off-resonance at acquisition: MORE-SPARKLING



- No need for internal field map estimation
- 15 min reconstruction time

Chaithya GR et al. *MORE-SPARKLING*, ***MRM 2023***



- Additional internal field map estimation
- 8 hours reconstruction time

Daval-Frérot et al, *Iterative static field map estimation for off-resonance correction in SWI*, **MRM 2022**