Accelerated non-Cartesian MR imaging: From shorter data acquisition to faster image reconstruction

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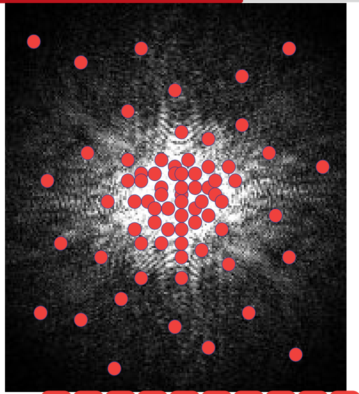
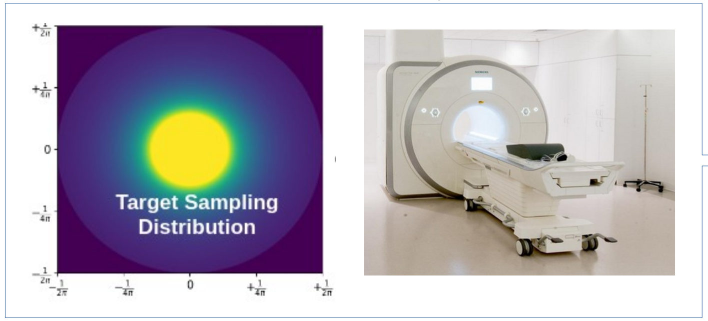
Inria Saclay, Parietal team

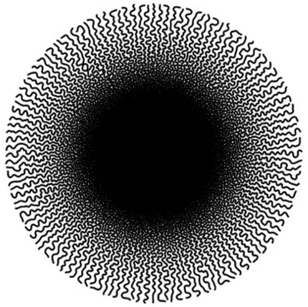
French Ultra-High Field Network (FUN), Oct 21 2021

The Big Picture: Where we are?

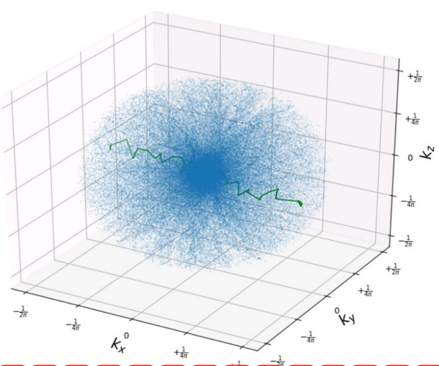


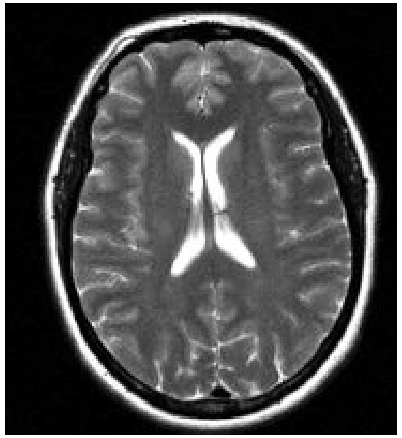
How to efficiently sample under Hardware constraints?





SPARKLING
[Lazarus et al, *MRM* 2019]

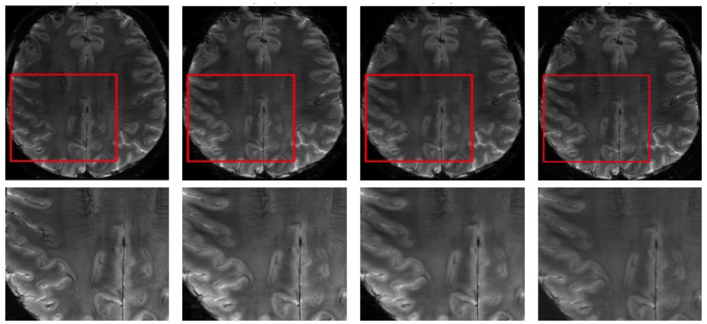




Acquisition Time

Nonlinear Reconstruction

How to efficiently reconstruct from under-sampled data?



Recon Time

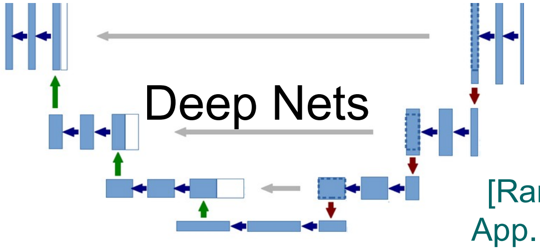
Cartesian Reference | Self Calibrating | L1-ESPIRiT | OSCAR Calibrationless

pysap-mri
[L Gueddari et al, ISMRM WS, 2020]

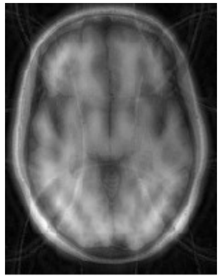
CS Reconstruction

K-Space Data

Recon Time



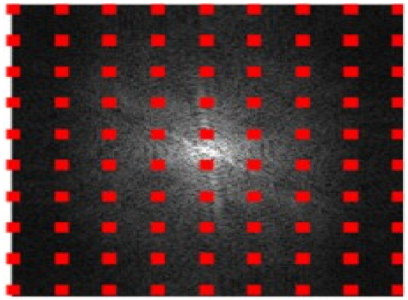
Deep Nets
[Ramzi et al, App. Sci 2020]



Gridded Reconstruction

Accelerating MRI acquisition

k-space

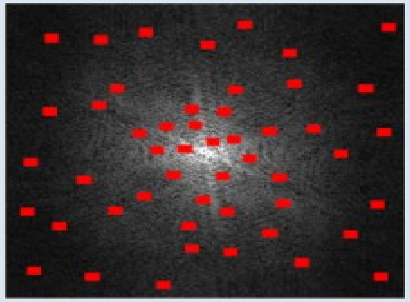


Linear Reconstruction

Image

Compressed Sensing

k-space

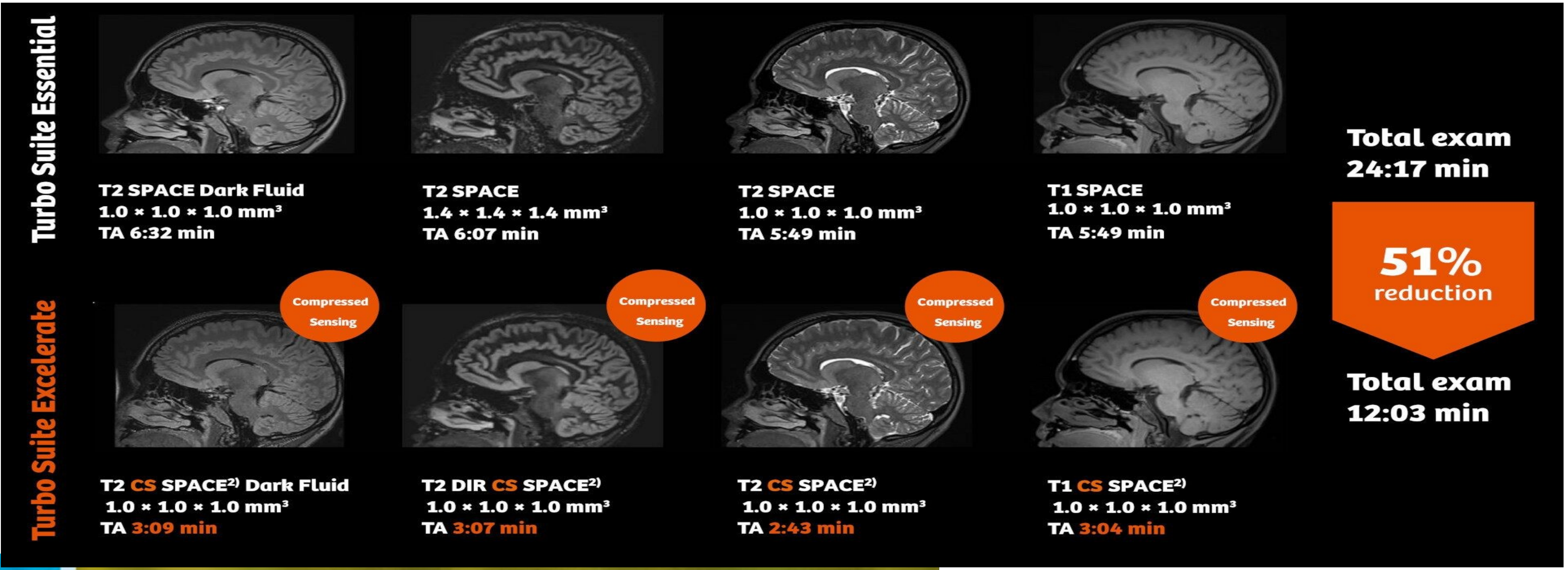


Nonlinear Reconstruction

Image

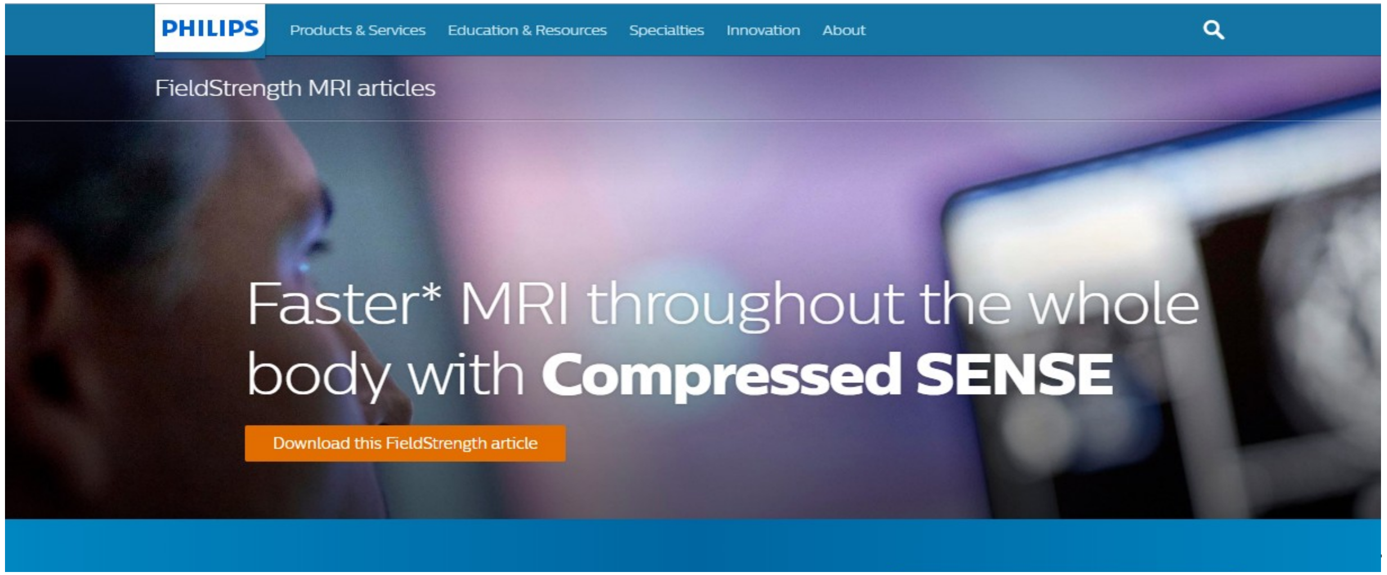
[Lustig et al, *Magn Reson Med*, 2007]

Compressed Sensing in MRI Vendors



SIEMENS Healthineers

FDA approved
& CE marked in 2017



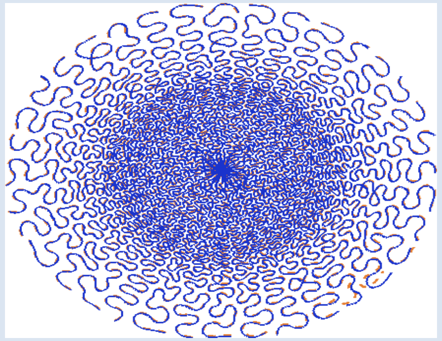
Compressed Sensing for T2*-w Imaging

SPARKLING: Spreading Projection Algorithm for Rapid K-space sampLING

Long Echo Time, long readout

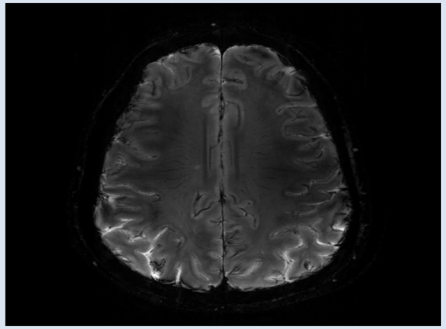
Compressed Sensing

k-space



Nonlinear Reconstruction

Image



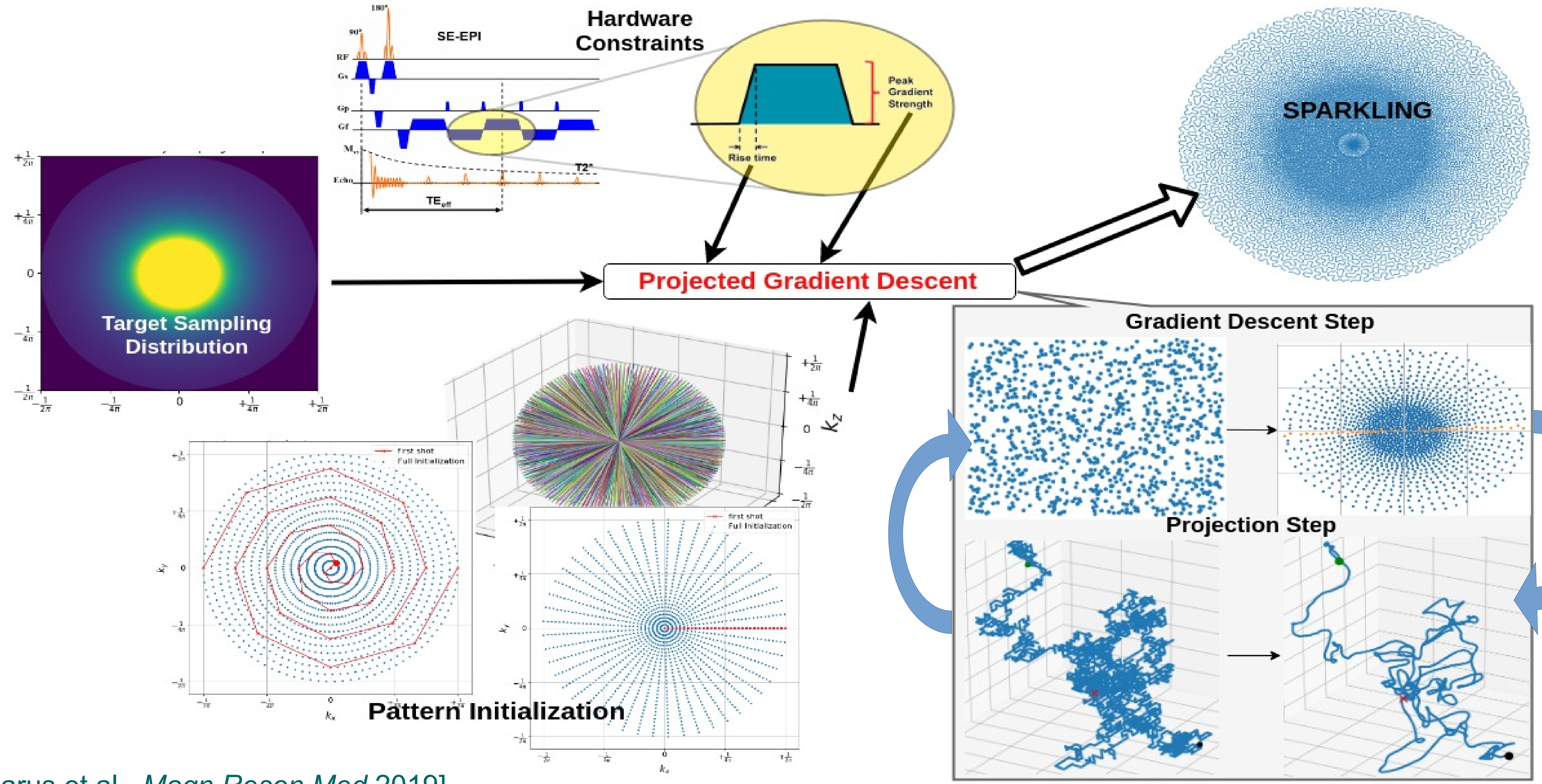
[Lazarus et al, *ISMRM* 2017, *MRM* 2019]

C. Lazarus

2019 I.I.Rabi ISMRM Young Investigator Award Finalist

Best PhD thesis from Chancellery of Paris Universities, 2019, section: Applied Phys Sci

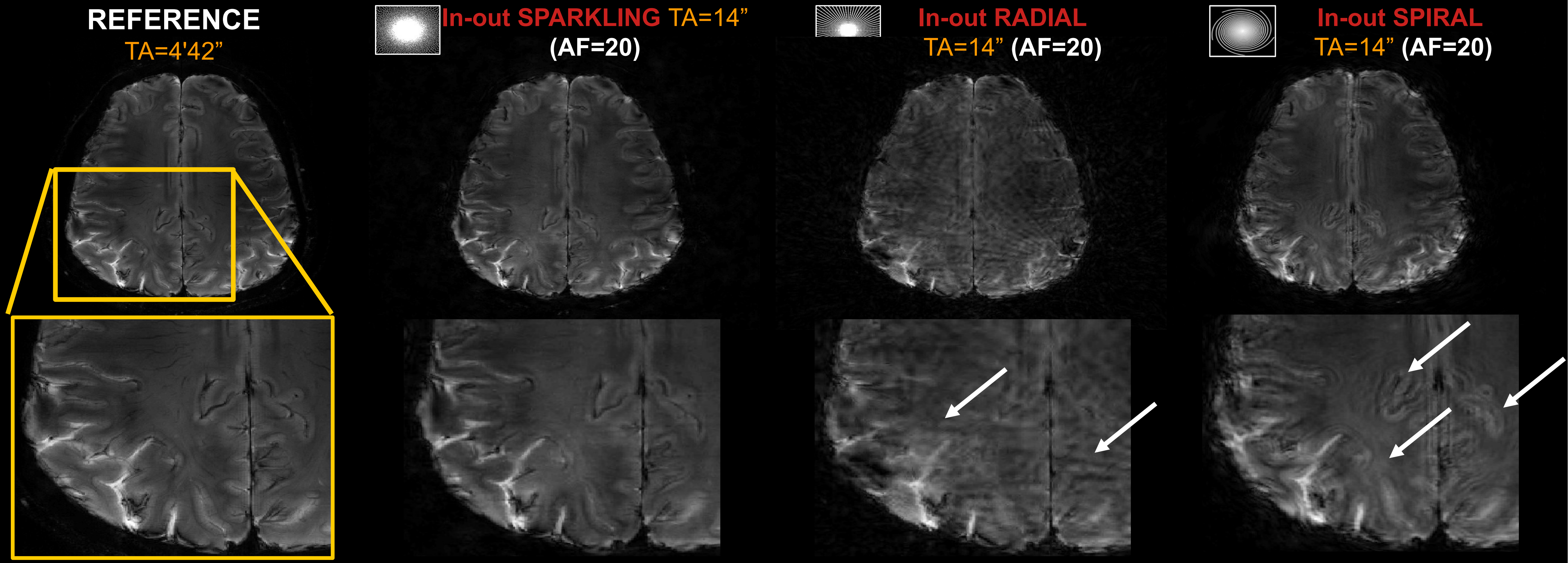
Summary of SPARKLING



[Lazarus et al. *Magn Reson Med* 2019]

2D SPARKLING: Best non-Cartesian imaging

In vivo results at 7 Tesla: 0.39x0.39x3 mm³ (11 slices)



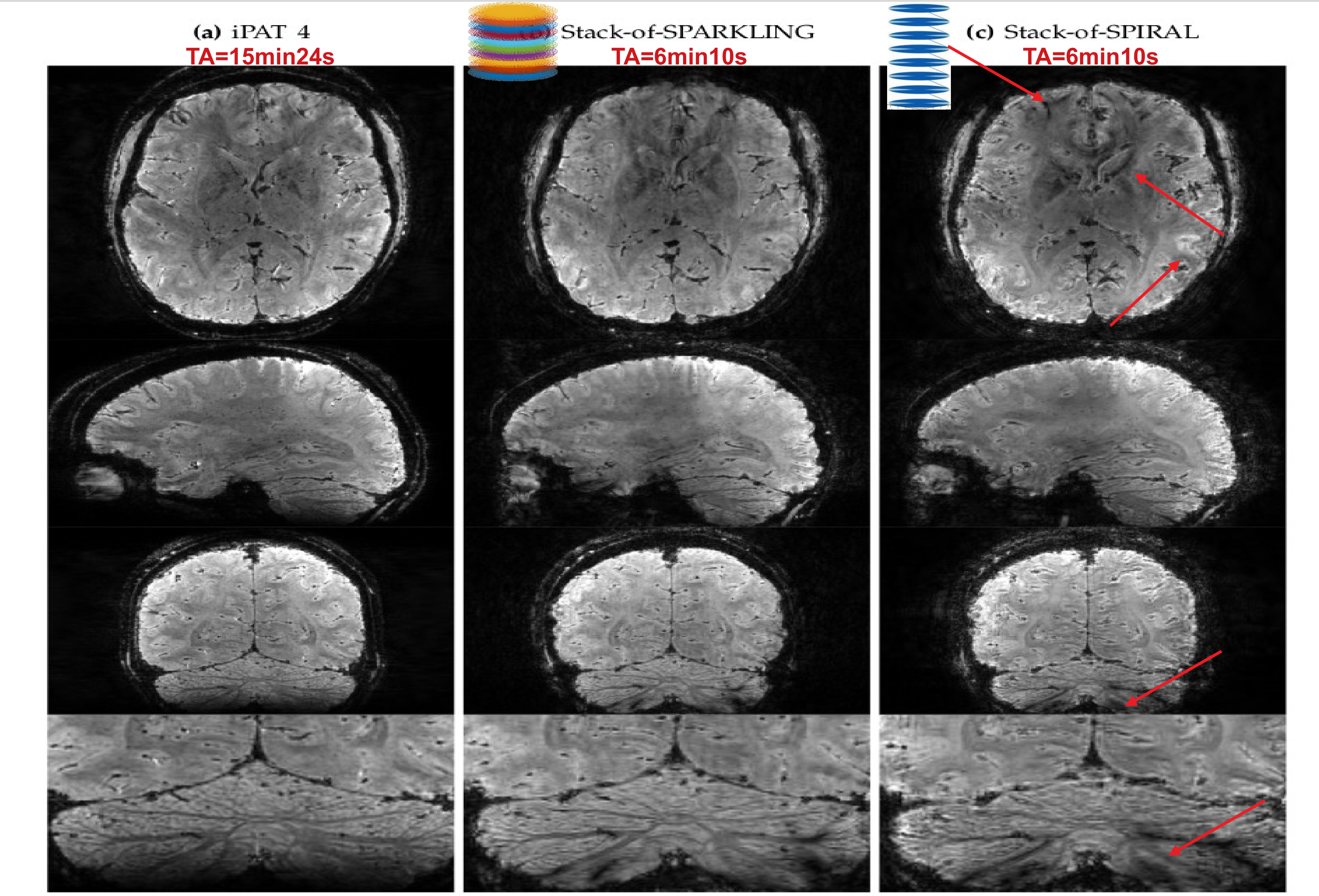
[Lazarus et al, *Magn Reson Med* 2019]

Stack of SPARKLING: in vivo 7T results

T2*-w imaging @600µm isotropic

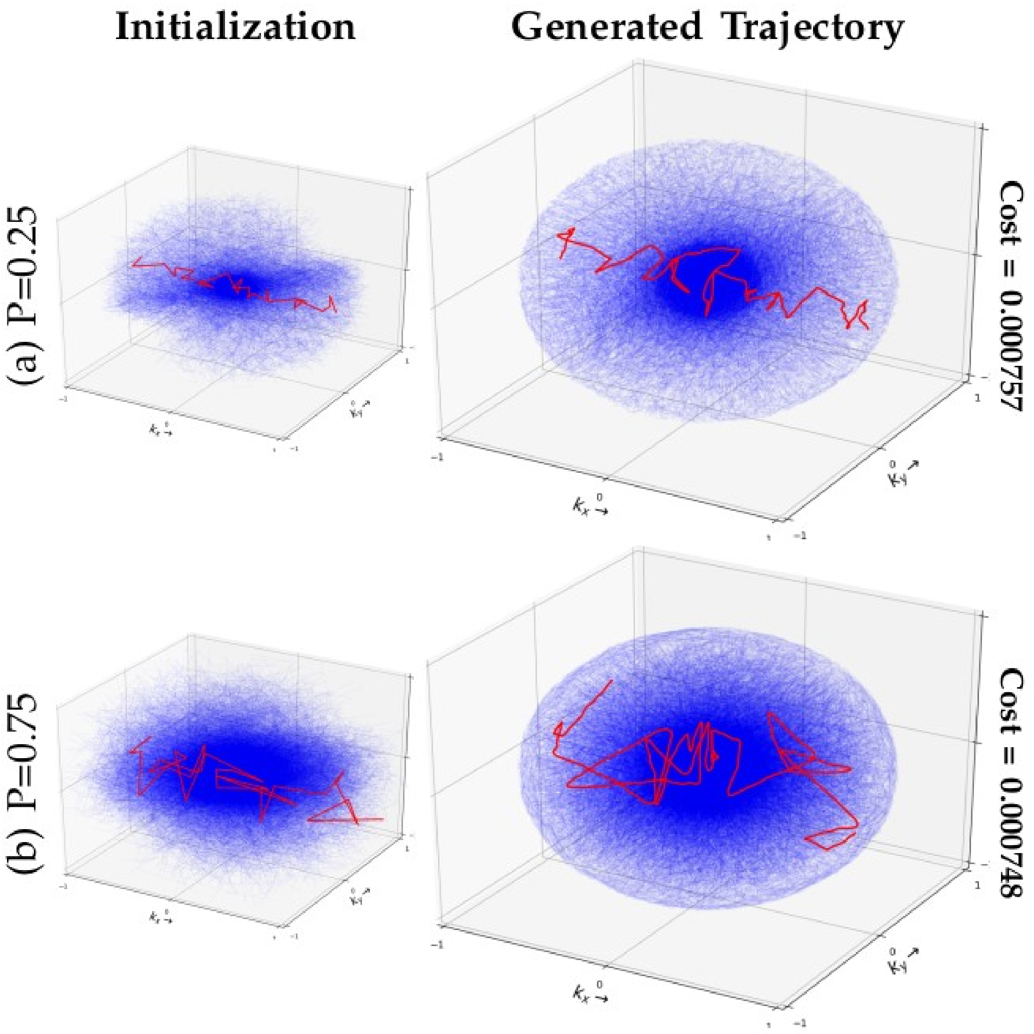
Stack of SPARKLING
AF=10

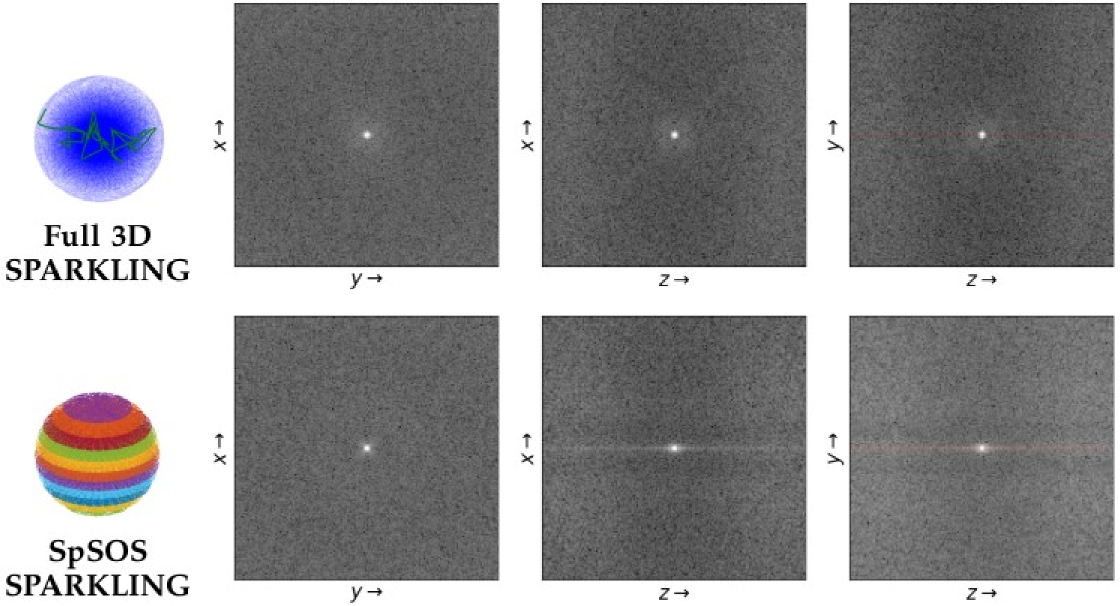
[Lazarus et al, *NMR Biomed* 2020]

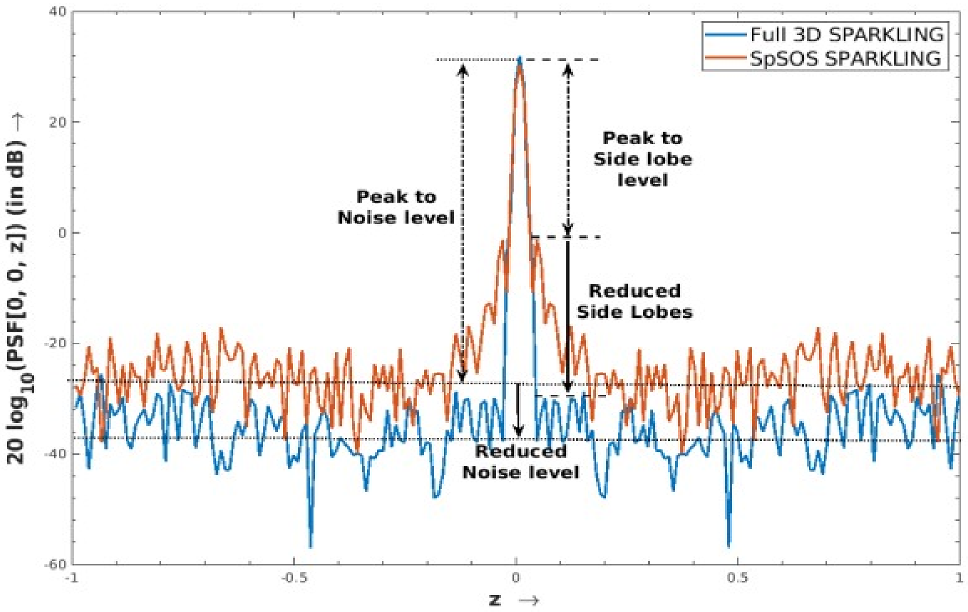


Full 3D SPARKLING: A significant Advancement

Chaithya GR



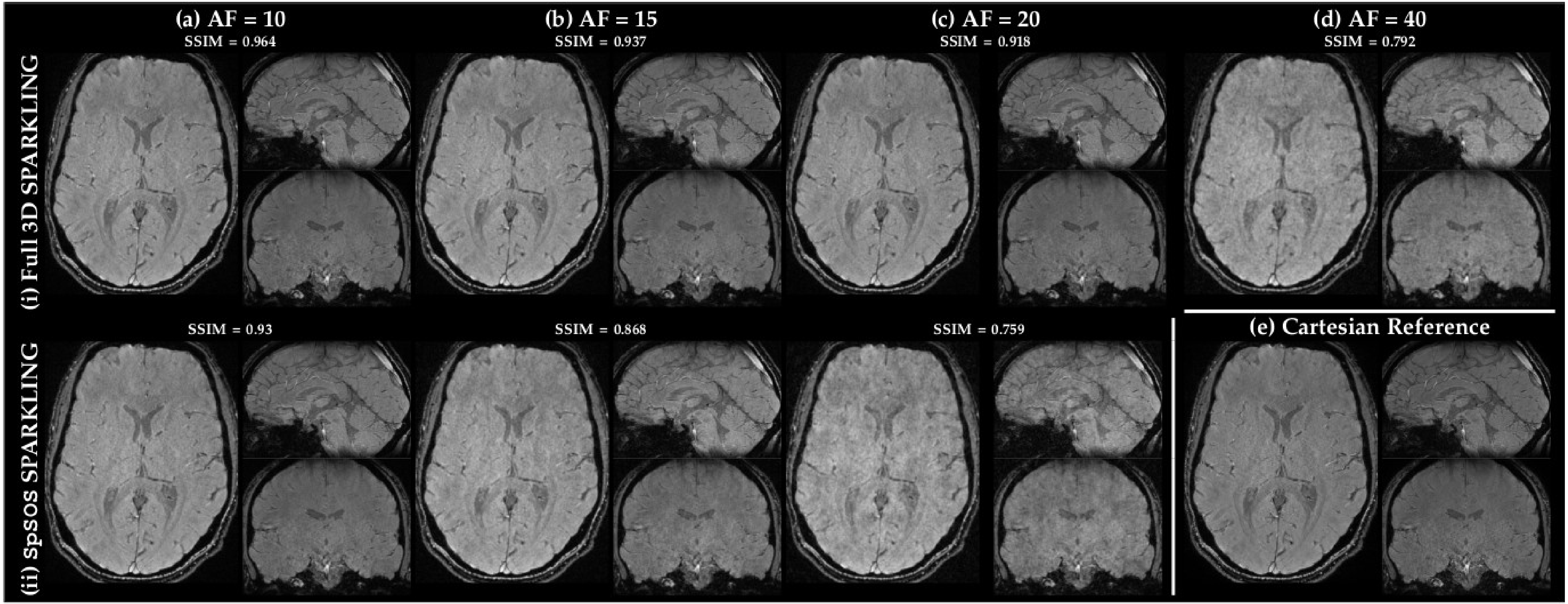




[Chaithya GR et al. under review *IEEE TMI* 2021]

3D SPARKLING: Retrospective Results at 3T

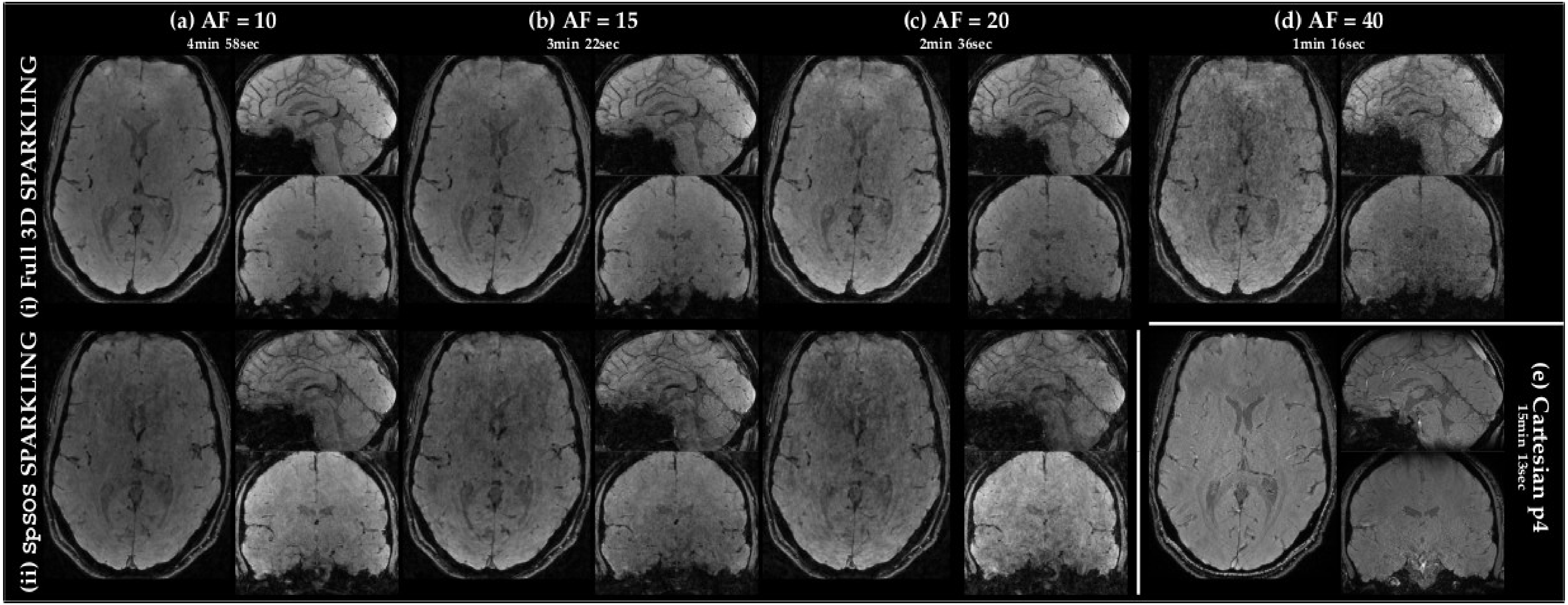
T2*-w imaging @600µm isotropic



[Chaithya GR et al. under review *IEEE TMI* 2021]

3D SPARKLING: Prospective Results at 3T

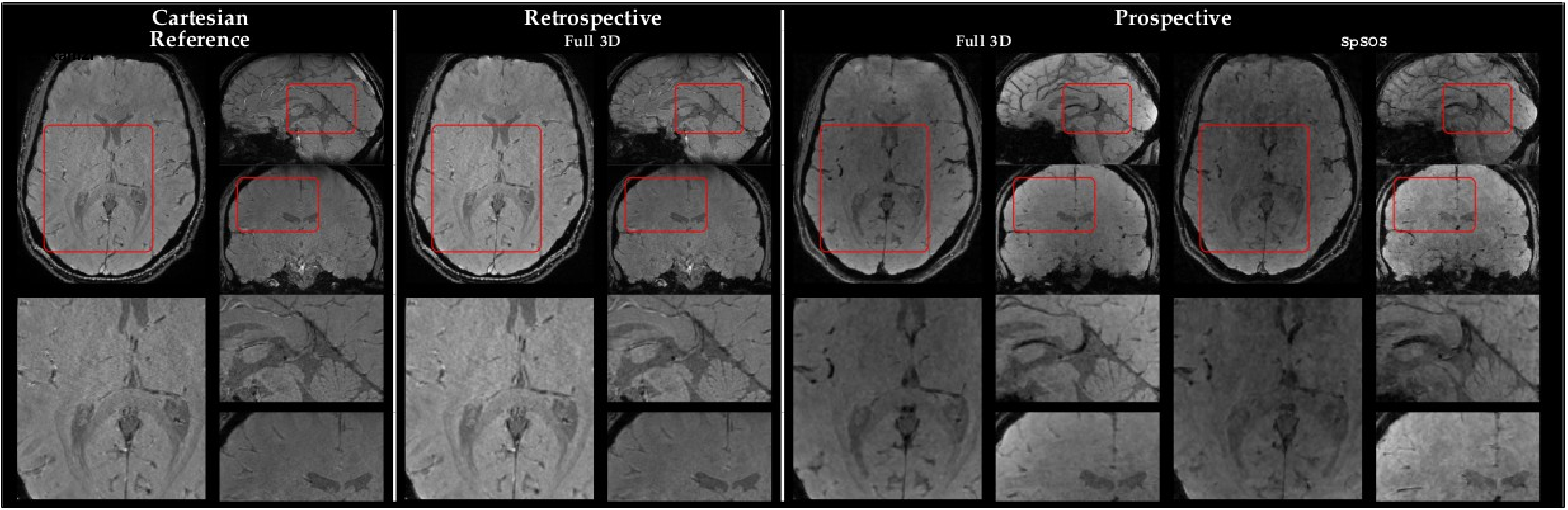
T2*-w imaging @600µm isotropic



[Chaithya GR et al. under review *IEEE TMI* 2021]

3D SPARKLING at 3T: Cartesian vs Retro. vs Prospective

T2*-w imaging @600µm isotropic
AF=10

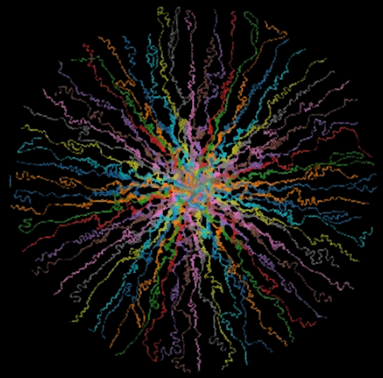


[Chaithya GR et al. under review *IEEE TMI* 2021]

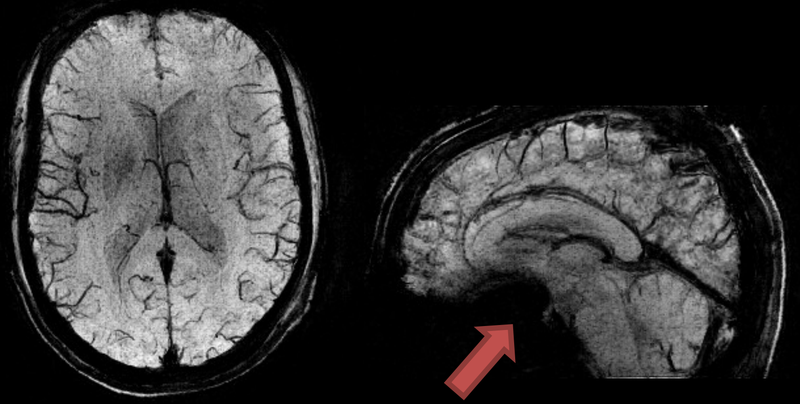
3D SPARKLING for Susceptibility Weighted imaging

Chaithya G R

Acquisition domain
(k-space)



3D SPARKLING
sampling pattern



NeuroSpin 3D SWI SPARKLING acquisition
December 2020

3D SPARKLING Objectives

1. Fast acquisition: 2min30s
2. High resolution: 0.6mm isotropic

Problems

1. Patient-induced inhomogeneities
   - Stronger for non-Cartesian sampling patterns
2. Image quality
   - Isotropic resolution requires more data

Acquisition parameters [1]
- Acquisition time: 2min30s
- Acceleration factor: 20
- Oversampling factor: 5
- Resolution: 0.6x0.6x0.6mm
- FOV: 240x240x124mm
- & : 20ms & 37ms
- 64-channel head/neck coil array
- Sampling: Full 3D SPARKLING (C20D3)

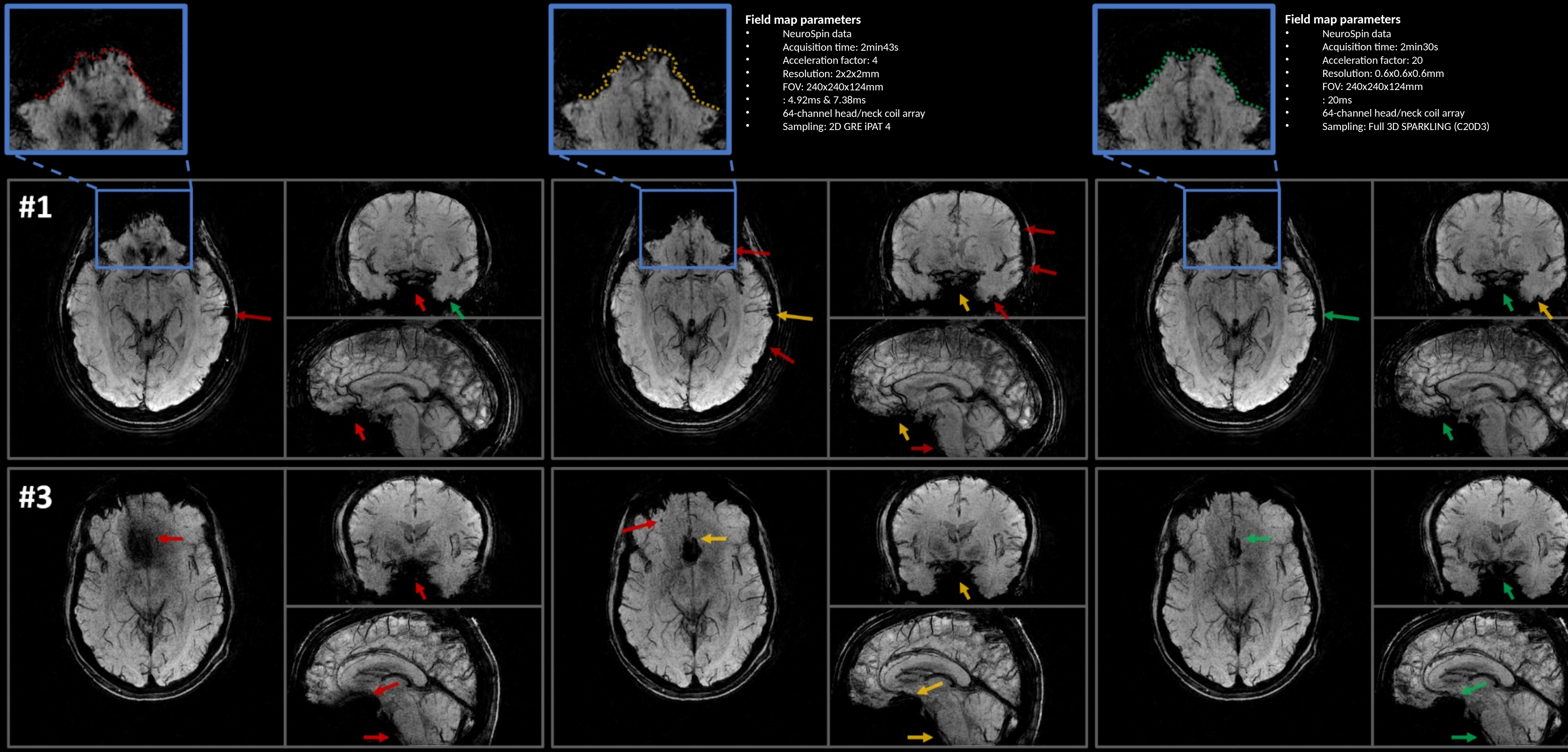
Reconstruction parameters [2]
- Pre-computed density compensation
- PCA-based coil compression (20 channels)
- Iterative self-calibrated reconstruction (20 iterations)
- Soft thresholding regularization (sym8, α=1e-7, 3 scales)

Sources: [1] Lazarus et al. "3D variable-density SPARKLING trajectories for high-resolution T2*-weighted magnetic resonance imaging". In *NMR in Biomedicine 2020*
[2] El Gueddari, Loubna, et al. "Self-calibrating nonlinear reconstruction algorithms for variable density sampling and parallel reception MRI." In *2018 IEEE 10th Sensor Array and Multichannel Signal Processing Workshop (SAM)*. IEEE, 2018.

Internal Estimation of B0 Inhomogeneities Artifacts

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)



AF=10

AF=20

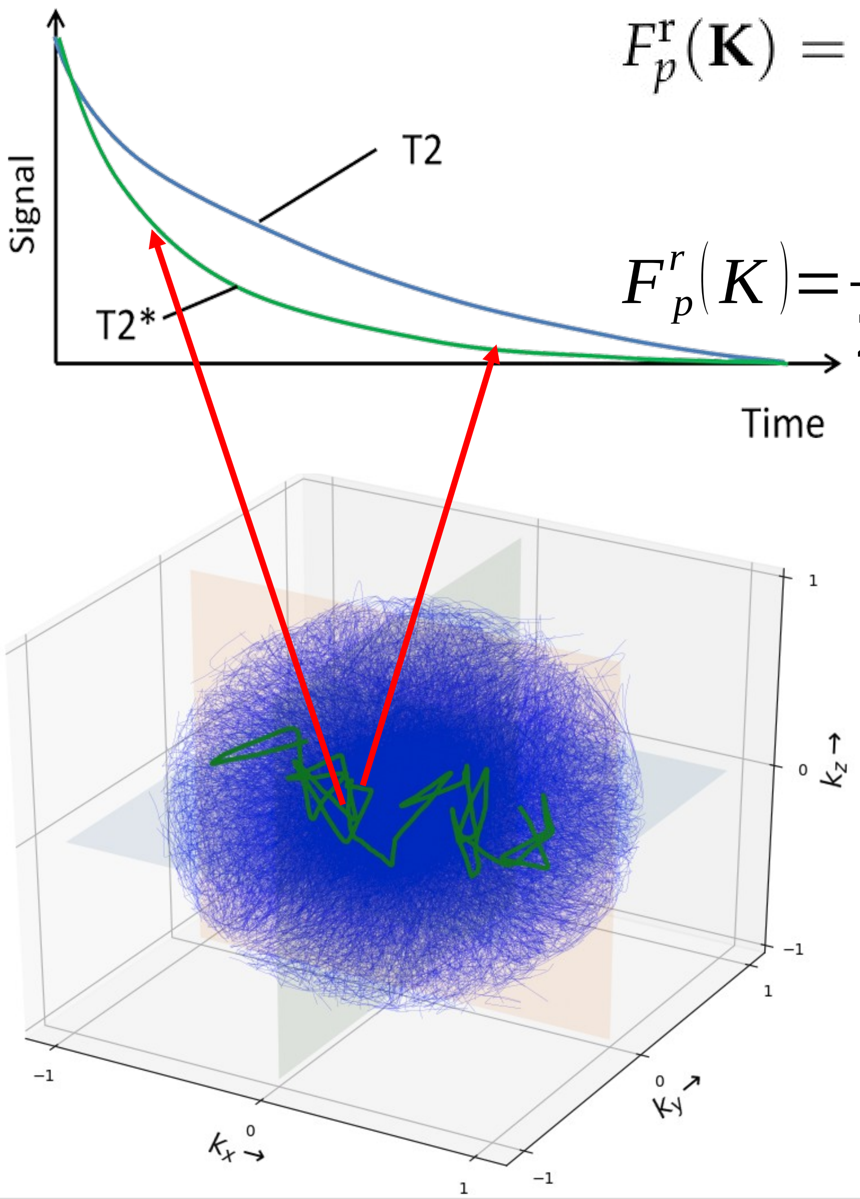
No correction

Corrected
with acquired maps

Corrected
with self-estimated maps

Source: Daval-Frérot et al. "Off-resonance correction with internal field map estimation for susceptibility weighted imaging at 3T". In *Proceedings of the 29th ISMRM 2021* (#3551)

Adding Temporal Weights in the SPARKLING Design



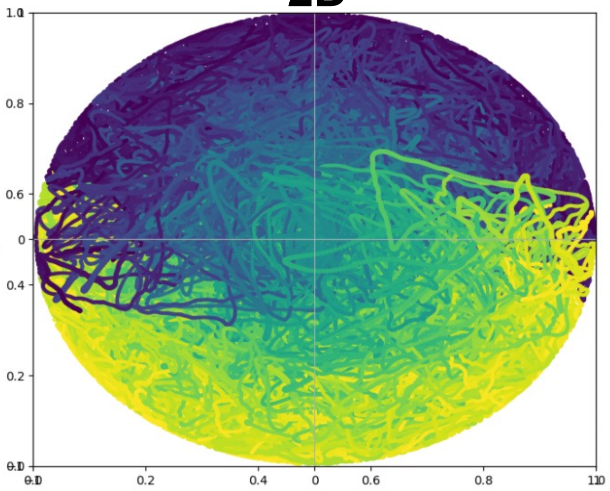
$$F_p^{\mathrm{r}}(\mathbf{K}) = \frac{1}{2p^2} \sum_{1 \le i,j \le p} H(\mathbf{K}[i] - \mathbf{K}[j])$$

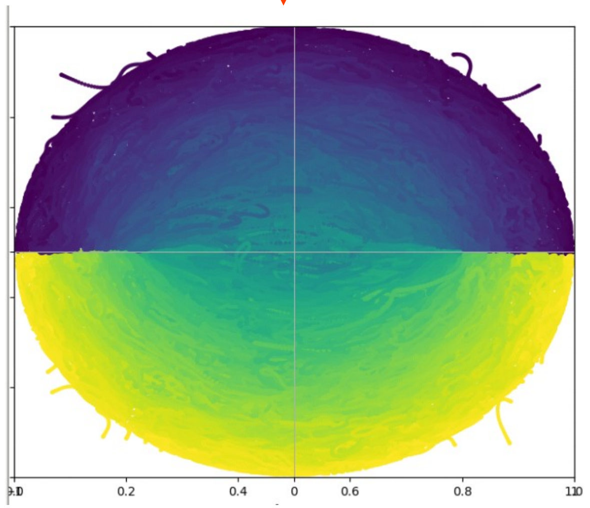
$$F_p^r(K) = \frac{1}{2p^2} \sum_{1 \le i,j \le p} H(K[i] - K[j]) e^{(|t_i - t_j|)}$$

>1 if $t_i \neq t_j$

Increase repulsion in case the shots are far apart temporally

2D



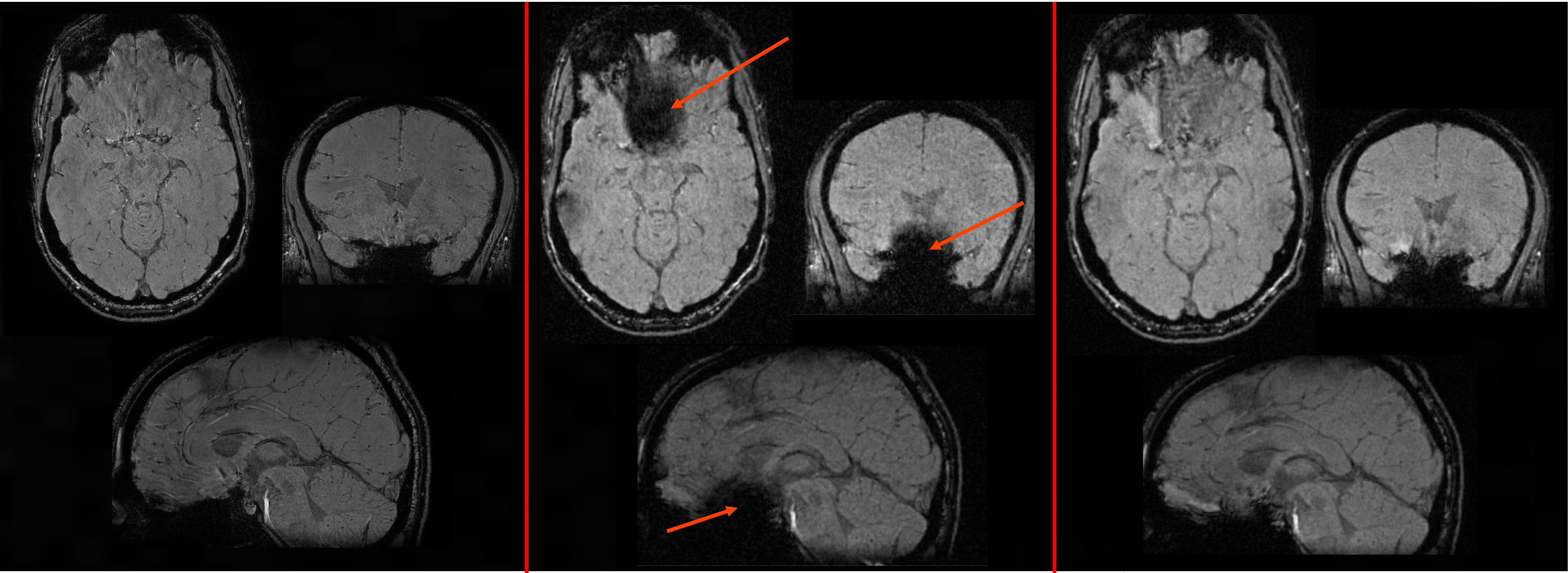


Start of Trajectory

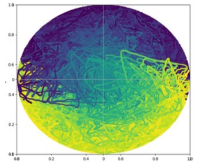
End of Trajectory

Impact of Temporal Weights: Retrospective Study at 3T

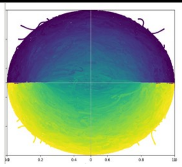
- SPARKLING : C15D3 with and without Temporal weights (TW)



Cartesian Reference

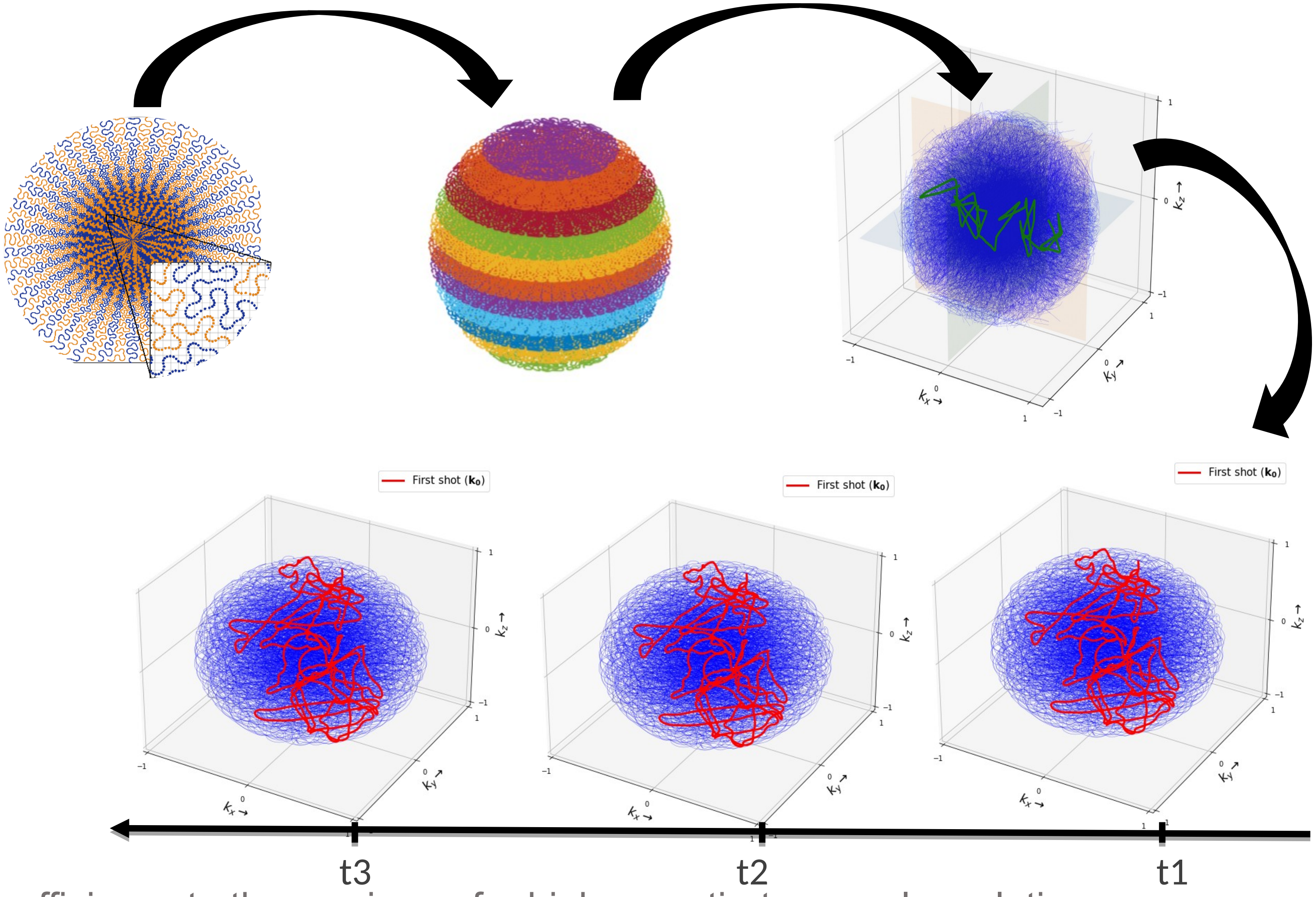


SPARKLING without Temporal Weights



SPARKLING with Temporal Weights

Moving to SPARKLING for functional MRI (fMRI)



- Pushing sampling efficiency to the maximum for higher spatio-temporal resolutions

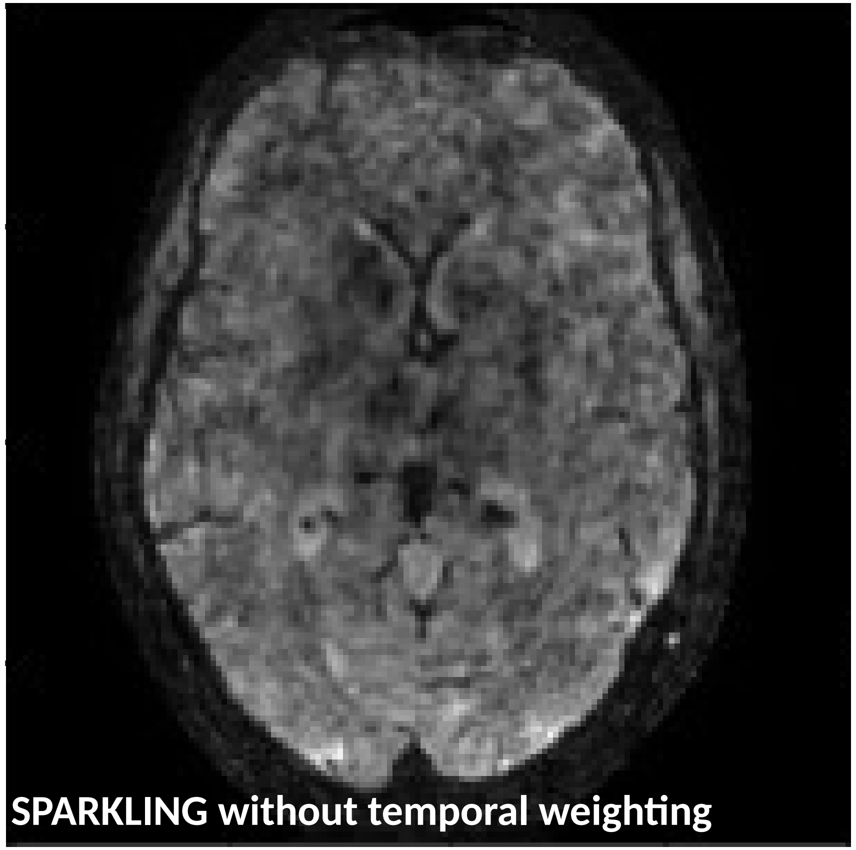
[Amor et al. In prep *ISMRM* 2022]

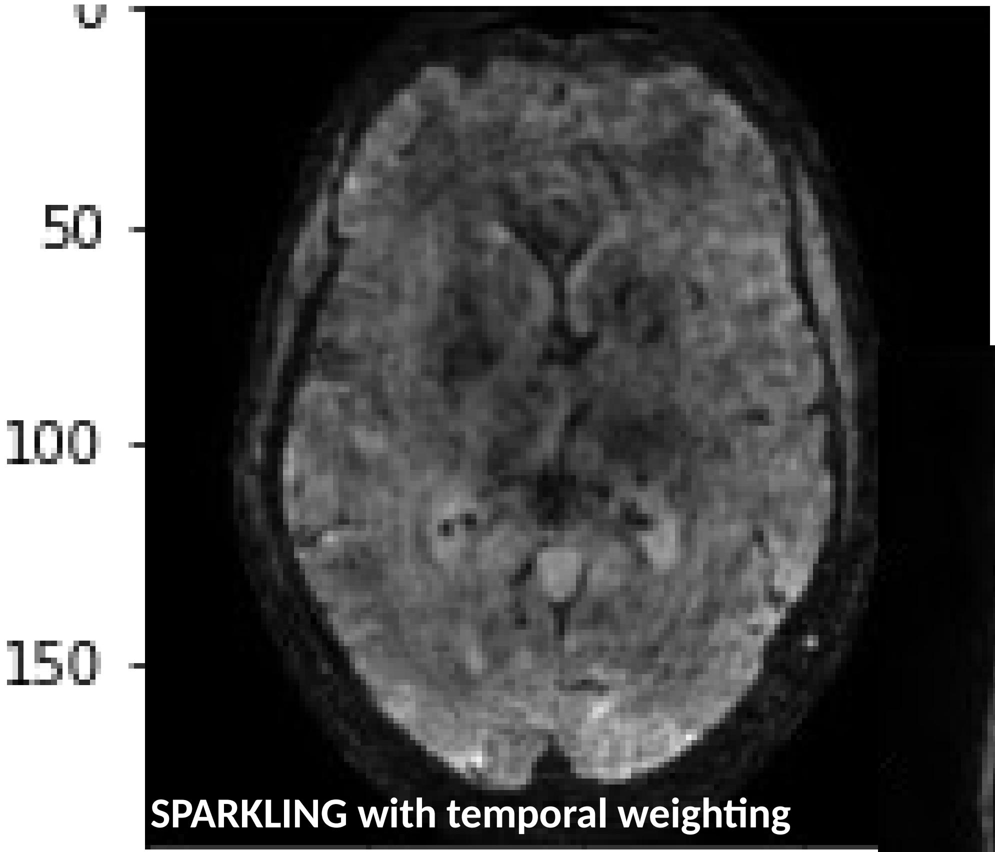
fMRI Experiment at 7Tesla

	3D-SPARKLING		3D-EPI	FLASH	
				B0 map	Sensitivity maps
FOV	(192,192,128)	(192,192,128)	(192,192,128)	(192,192,132)	(192,192,132)
Target Matrix	(192,192,128)	(192,192,128)	(192,192,128)	(64,64,44)	(64,64,44)
Temporal-weighting	None	Up to the 4’th decimation	–	–	–
Resolution	1mm iso	1mm iso	1mm iso	3mm iso	3mm iso
TR (ms)	50	50	50	20	20
TE (ms)	20	20	20	1.80,3.06,5.10	1.80
OS factor	5	5	2	2	2
TA/volume (s)	2.4	2.4	2.4	58	58

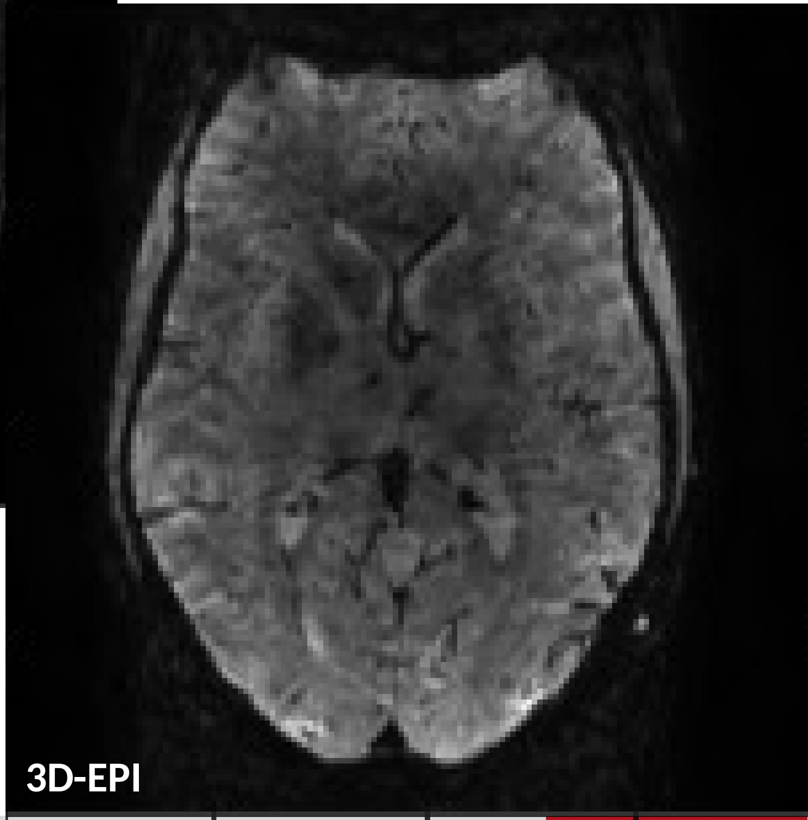
- 7T Siemens Magnetom scanner
- 1Tx-32Rx head Nova coil

Anatomical T2* MR Images from “f-SPARKLING” Pattern


SPARKLING without temporal weighting



SPARKLING with temporal weighting

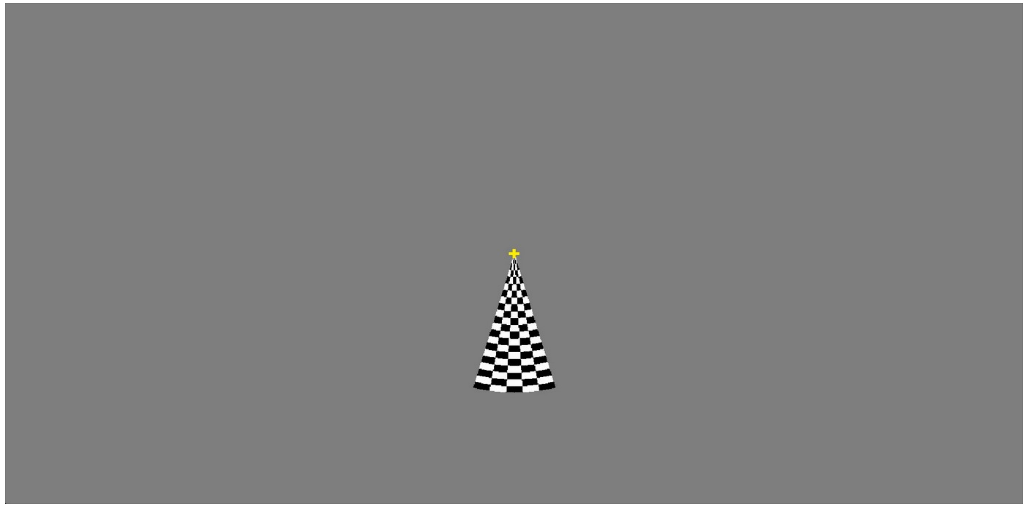

3D-EPI

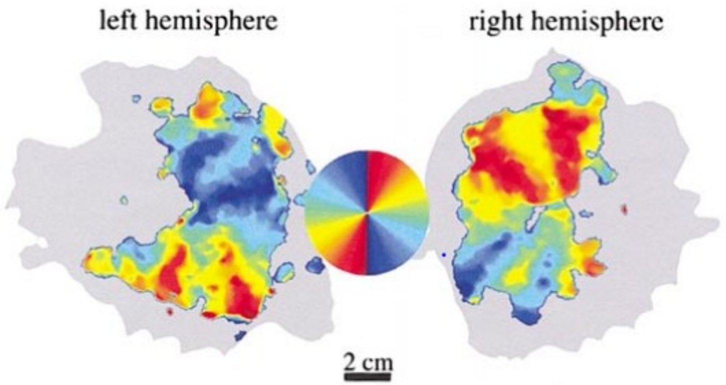
- Overall 3D-EPI image quality is better
- Less B0-induced distorsion on SPARKLING

[Amor et al. In prep *ISMRM* 2022]

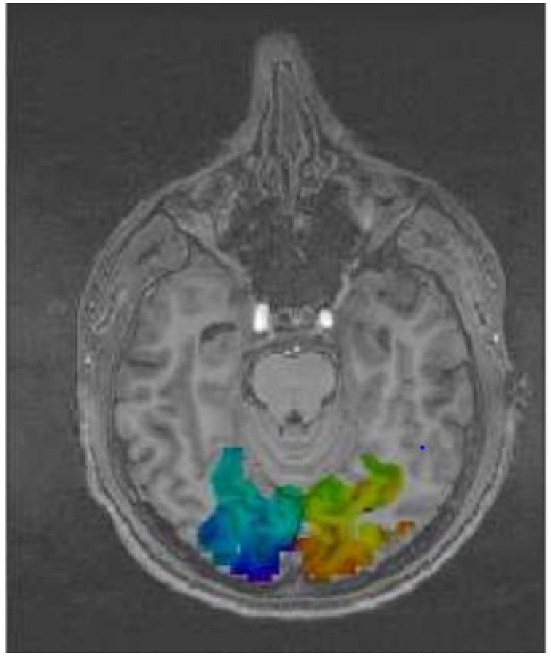
Retinotopic fMRI Experiment

- Retinotpic mapping paradigm

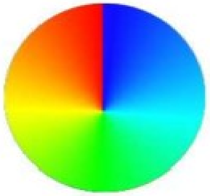




Warnking et al. NeuroImage, (2002)



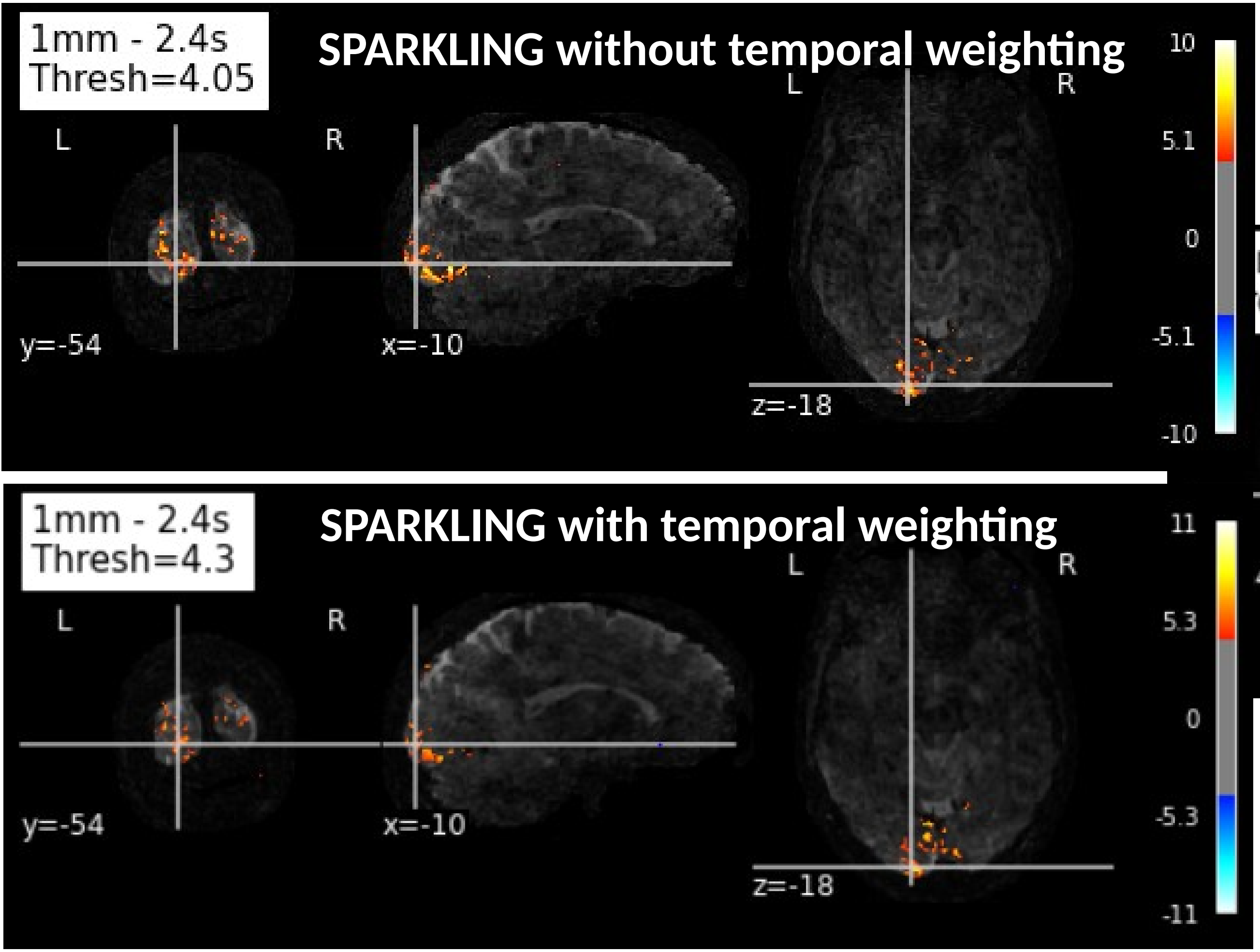
Wotawa et al. RR-5472, INRIA (2006).

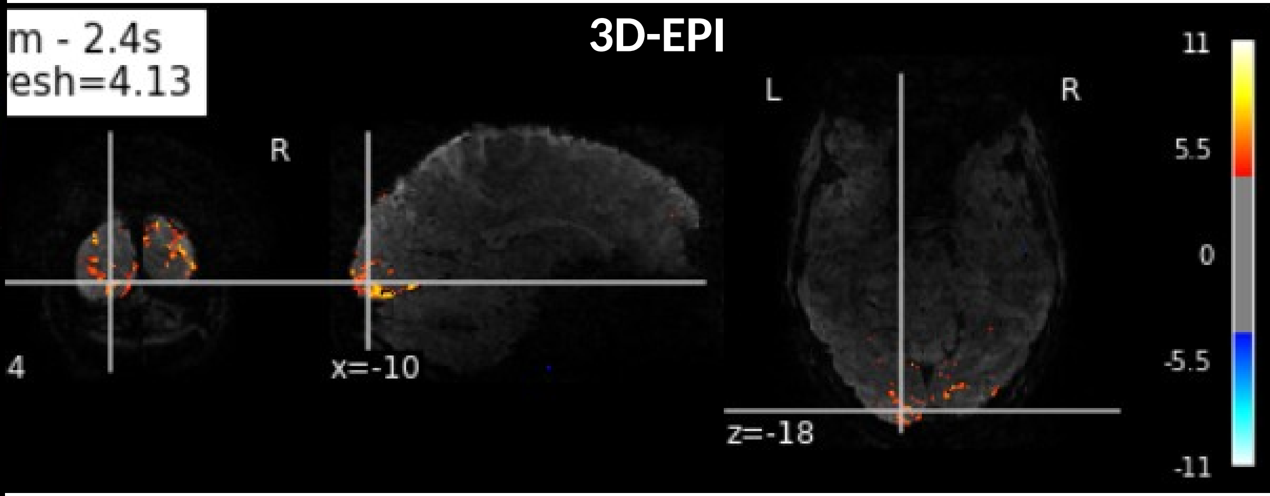


https://github.com/hbp-brain-charting/public_protocols

- Total acquisition time per run: 4’48”
- 9 rotation cycles per run
- One healthy adult subject

“3Df-SPARKLING vs 3D-EPI” Z-score Maps





FDR corrected Z-maps at p=0.05

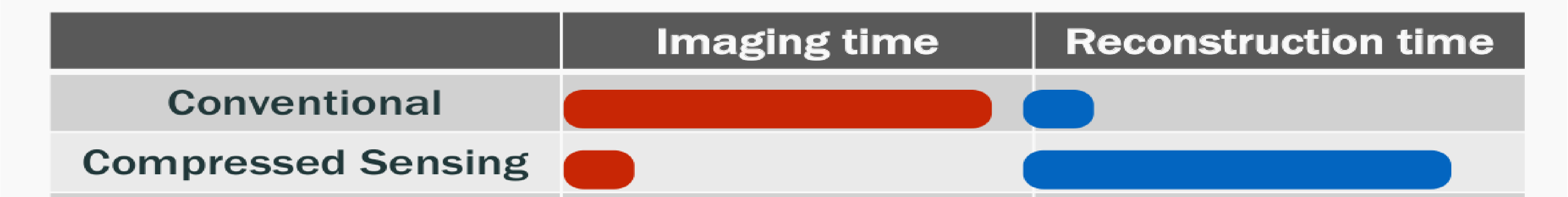
[Amor et al. In prep *ISMRM* 2022]

Interim Summary

- **SPARKLING for morphological imaging**
  - 3D SPARKLING achieves isotropic high resolution in short scan time (2’30”@600µm iso)
  - Full 3D SPARKLING outperforms its SoS competitor (AF=20 is now viable in vivo)
  - High resolution T2*-weighted (and SWI) MR imaging at 7T and 3T
  - Internal estimation of off-resonance effects
  - Recent improvement in regards to off-resonance effects due to the temporal weighting
  - Robustness to system imperfections, T2-decay, eddy currents

- **SPARKLING for fMRI**
  - Massively undersampling 3D sampling pattern
  - Lower image quality as compared to 3D EPI (even after $\Delta B0$ inhomogeneities correction)
  - Similar statistical significance in the detection of evoked activity in task-fMRI

Compressed Sensing Limitations

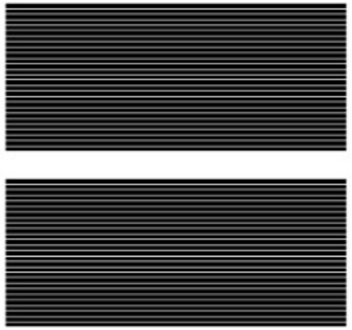


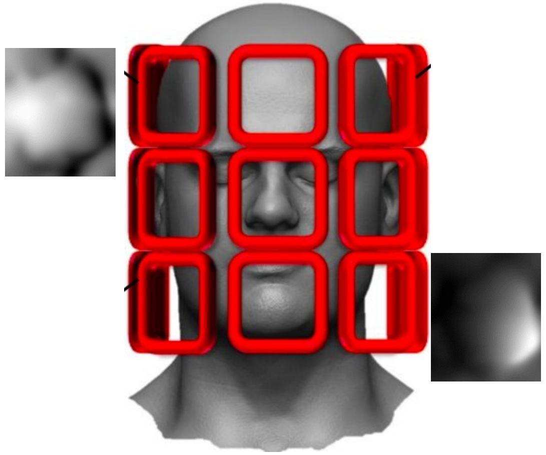
- **Long reconstruction times**
- **Fixed sparsifying transform (e.g., wavelets, Total Variation, etc.)**
- **Require hyperparameter setting**

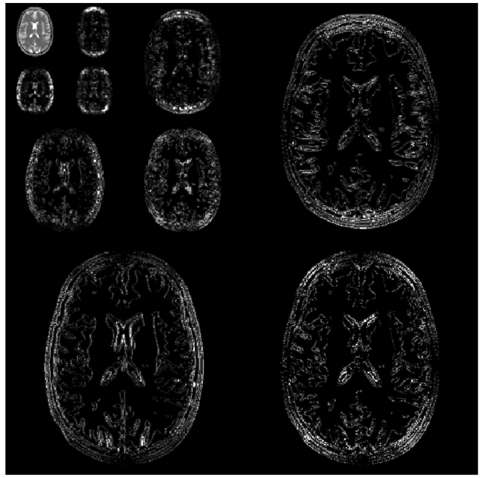
Classical approach for solving MR image reconstruction

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

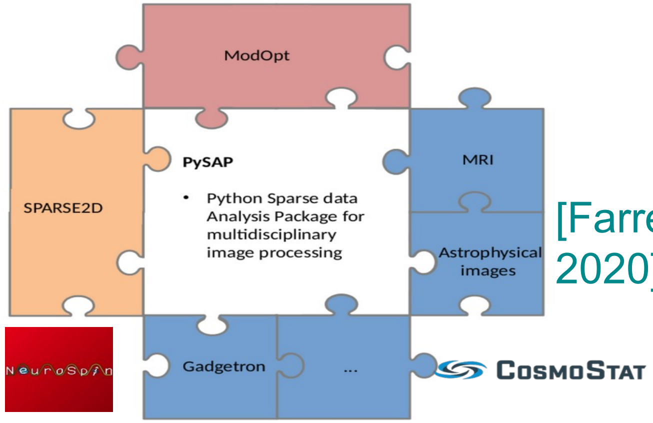
Optimization algorithms
Forward-Backward
FISTA, POGM'
Condat-Vu, PDHG







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



[Farrens et al, As&Comp 2020]

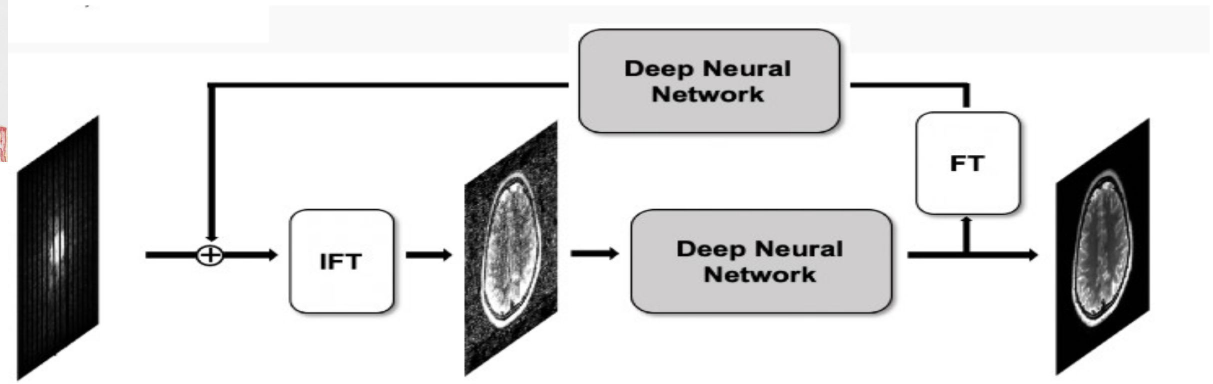
https://github.com/CEA-COSMIC/pysap

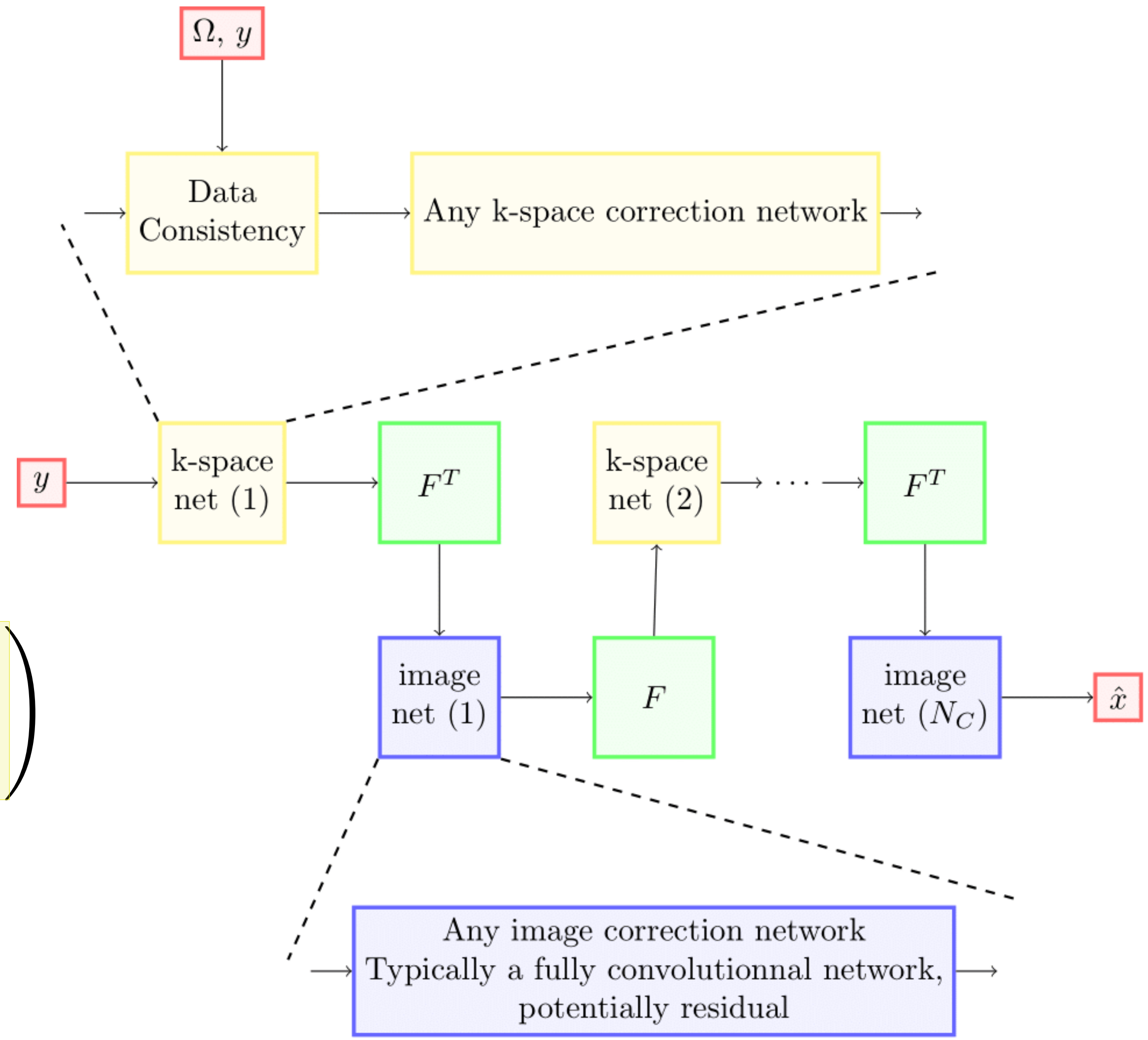
Room for learning:

- Step size of optimization algos, iterates merging
- Sensitivity maps
- Regularization term (weight and its proximity operator)
- Data consistency

Cross-domain Learning in a nutshell

Z. Ramzi





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

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

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

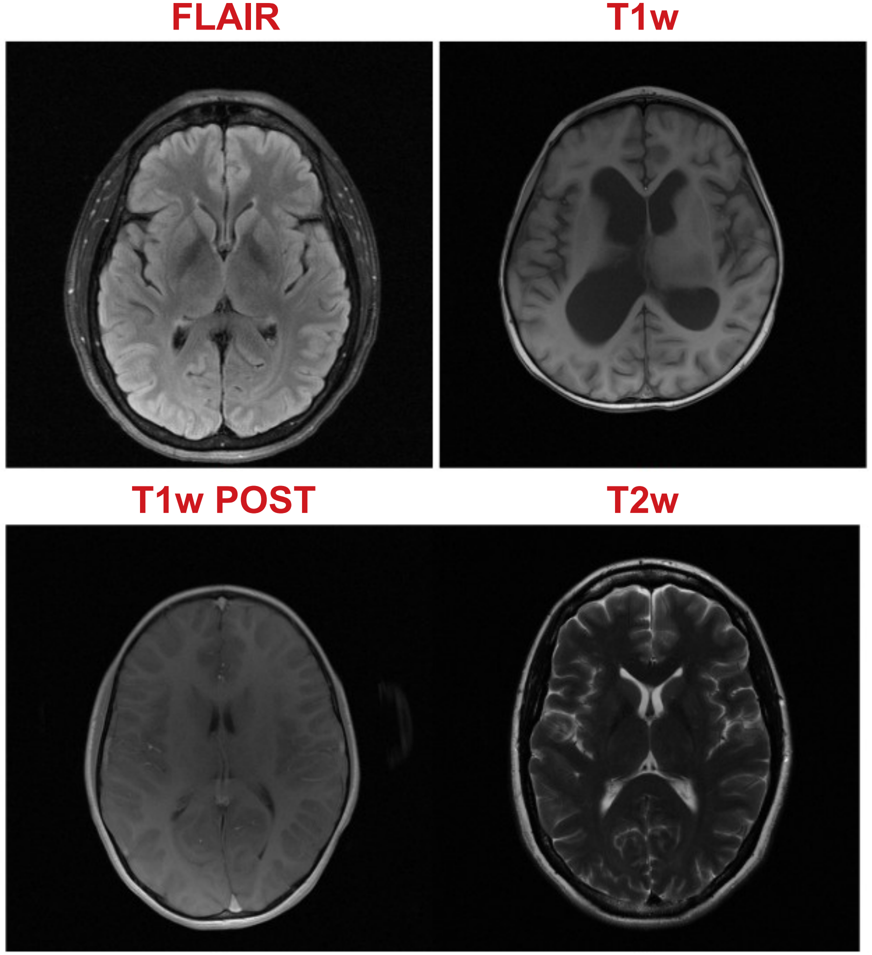
[Adler & Öktem, *IEEE TMI 2018]*
[Ramzi et al, *App. Sci 2020, NeurIPS 2020 WS*]

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



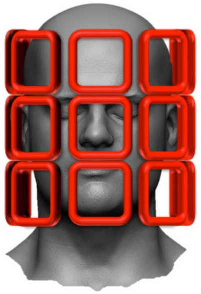


Table 1: Summary of Siemens data for 4X/8X tracks.

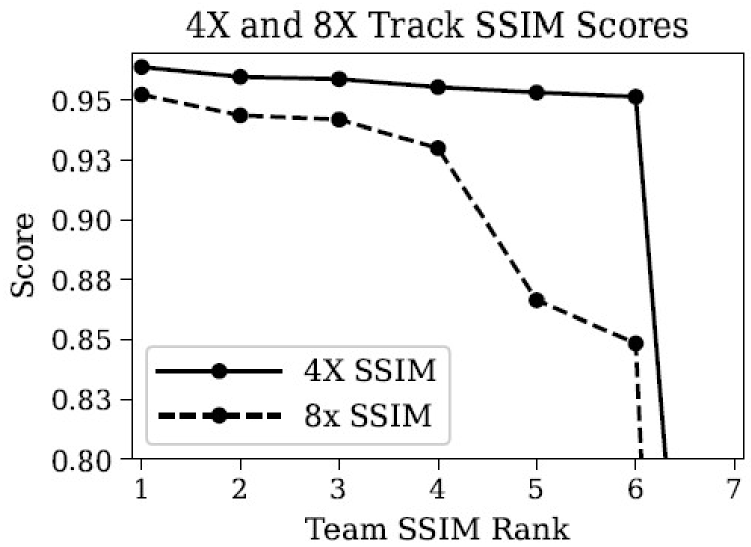
Split	T1	T1POST	T2	FLAIR	Total
Siemens/Main Tracks					
train	498	949	2,678	344	4,469
val	169	287	815	107	1,378
test (4X)	33	54	170	24	281
test (8X)	32	68	152	25	277
challenge (4X)	26	67	192	18	303
challenge (8X)	24	65	159	14	262
Transfer Track (4X, all challenge)					
GE	22	29	83	77	211
Philips	18	0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

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

Quantitative Challenge results

Table 2: Summary of SSIM scores by contrast.

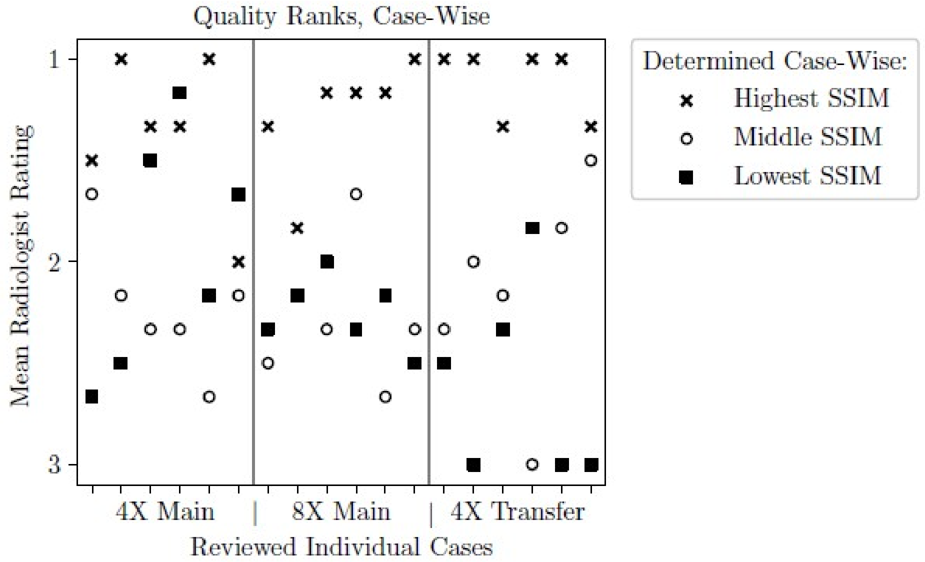
Team	AVG	T1	T1POST	T2	FLAIR
4X Track					
AIRS Medical	**0.964**	**0.967**	**0.969**	**0.965**	**0.930**
ATB	0.960	0.964	0.965	0.961	0.924
Nspin	0.959	0.963	0.965	0.960	0.920
8X Track					
AIRS Medical	**0.952**	**0.953**	**0.969**	**0.951**	**0.918**
ATB	0.944	0.943	0.954	0.943	0.905
Nspin	0.942	0.940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

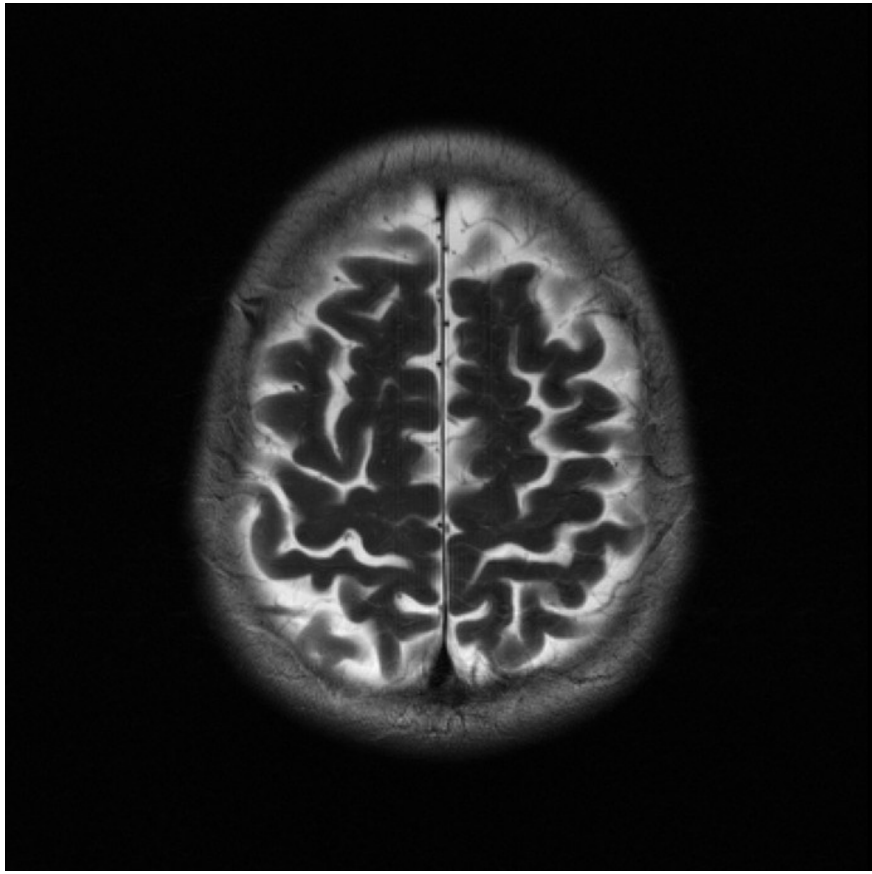


https://nips.cc/Conferences/2020/ScheduleMultitrack?event=16140 (fastMRI keynote)

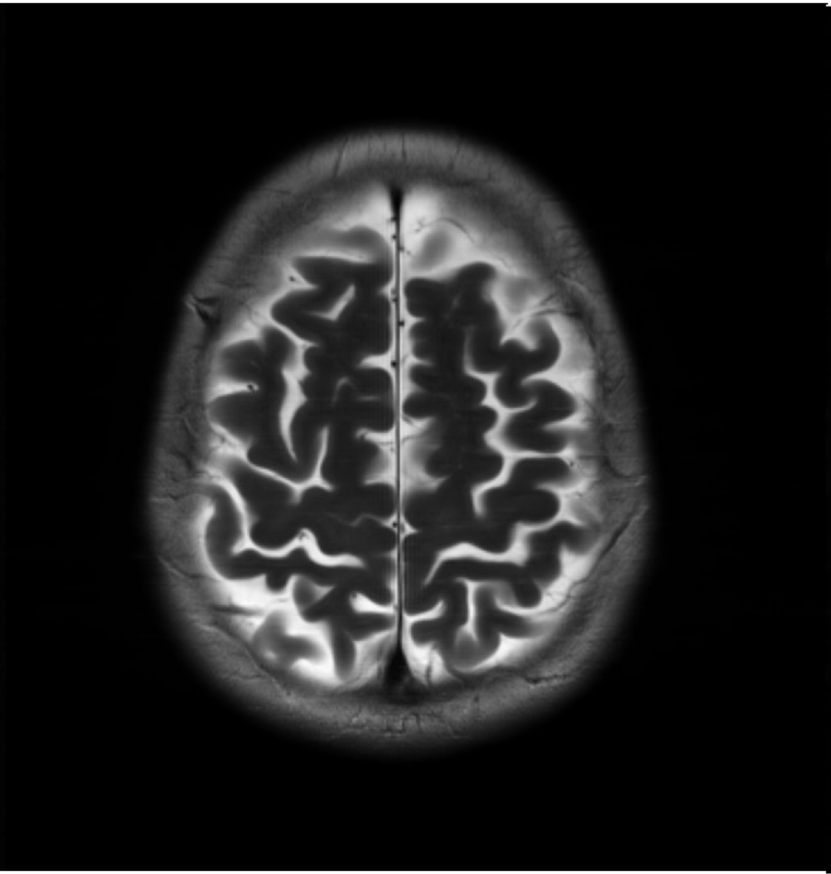
XPDNet-v2 vs GRAPPA recon on validation fastMRI data

T2 contrast – 8X Track

Ground truth

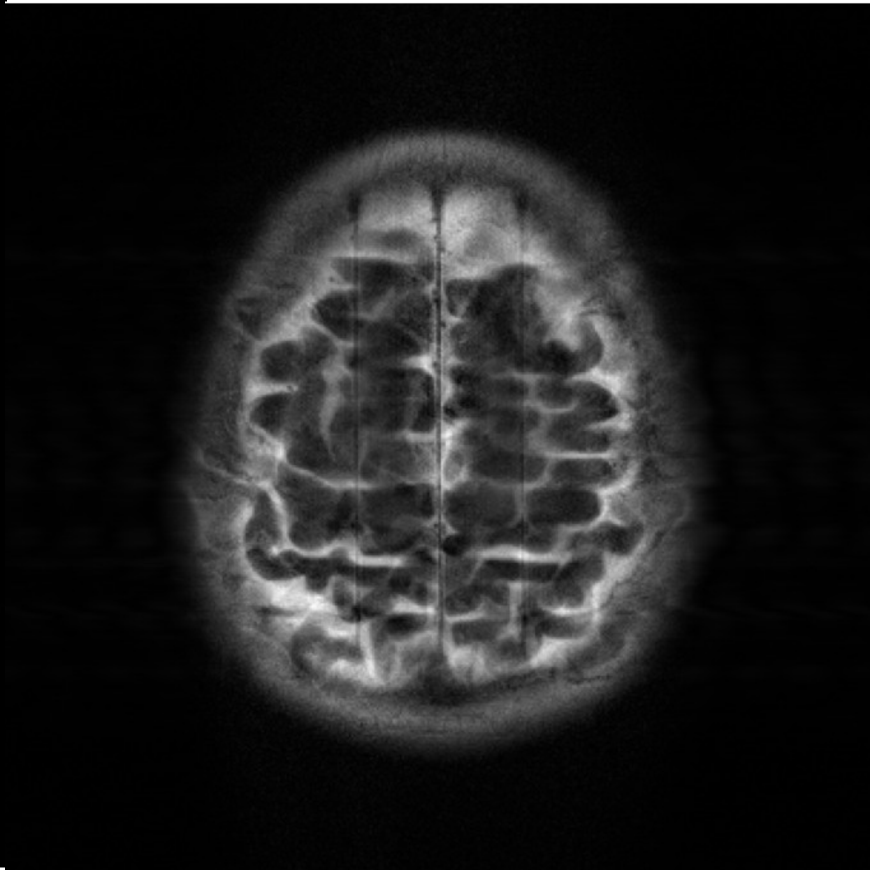


XPDNet recon (PSNR=36.8dB/SSIM=0.96)



Recon time: 0.25 s/slice

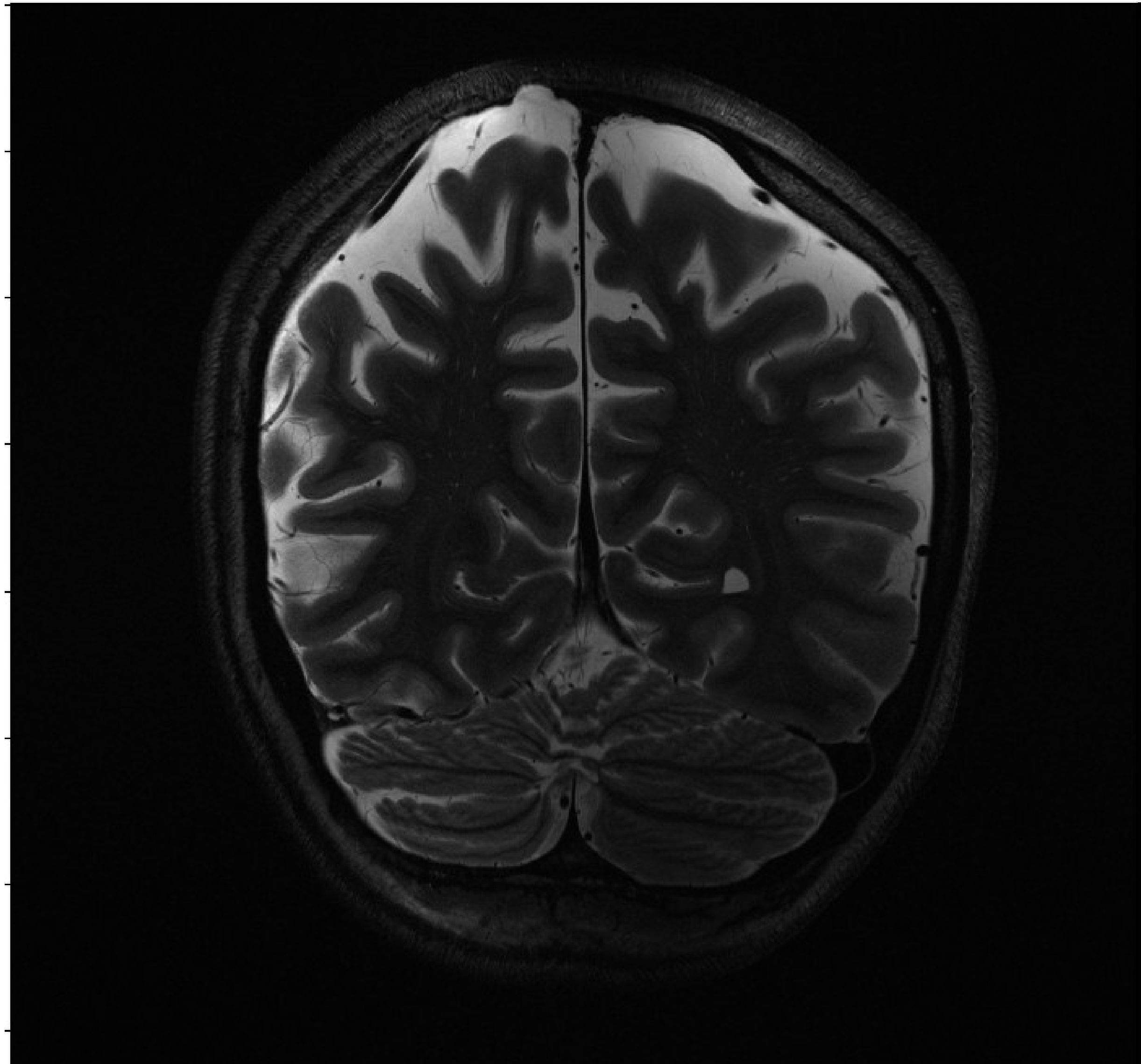
GRAPPA recon
(PSNR=26.1dB/SSIM=0.77)



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

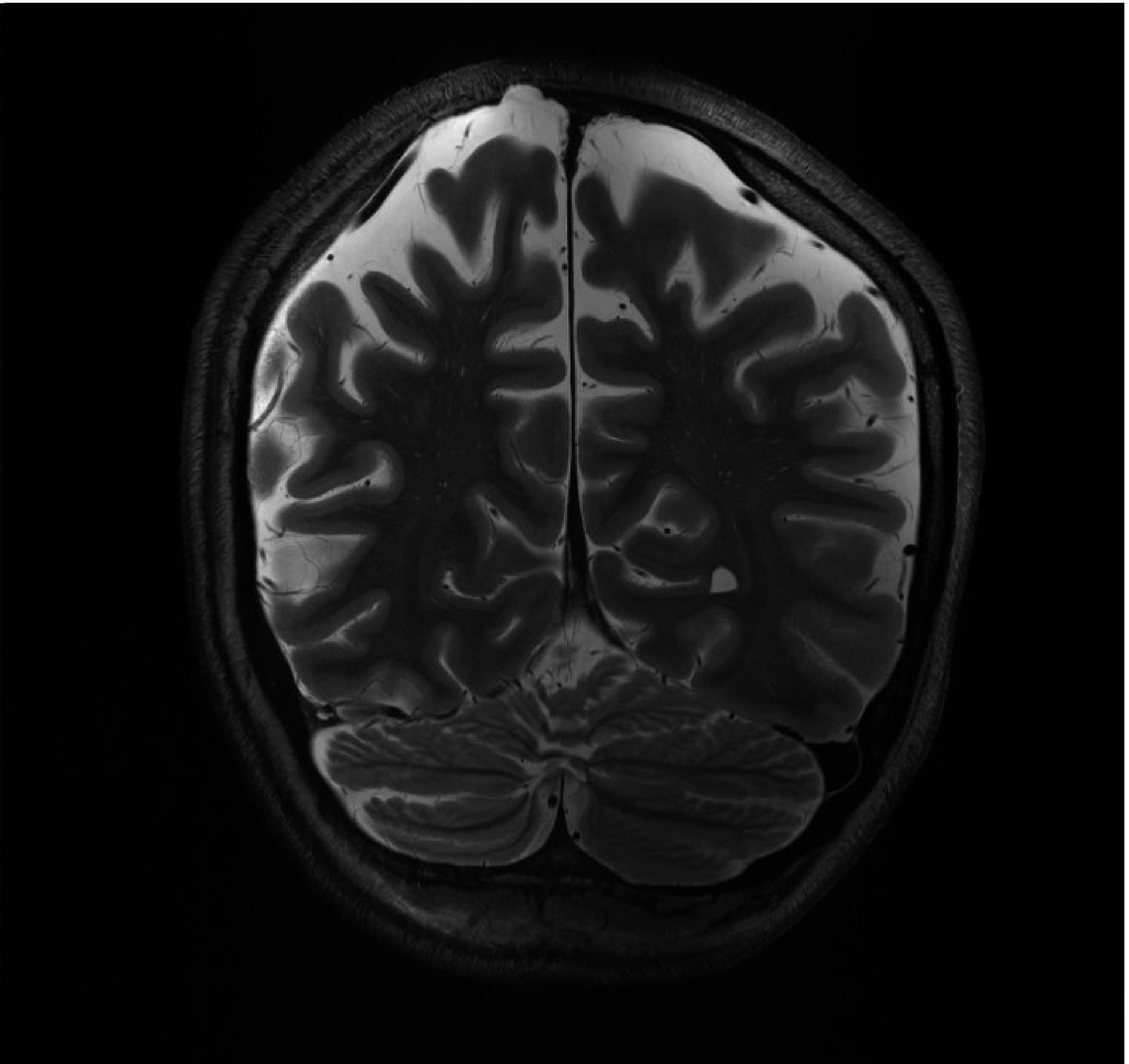
[Ramzi et al, *ISMRM* 2021]

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



Ground truth, T2, GRAPPA, 7T

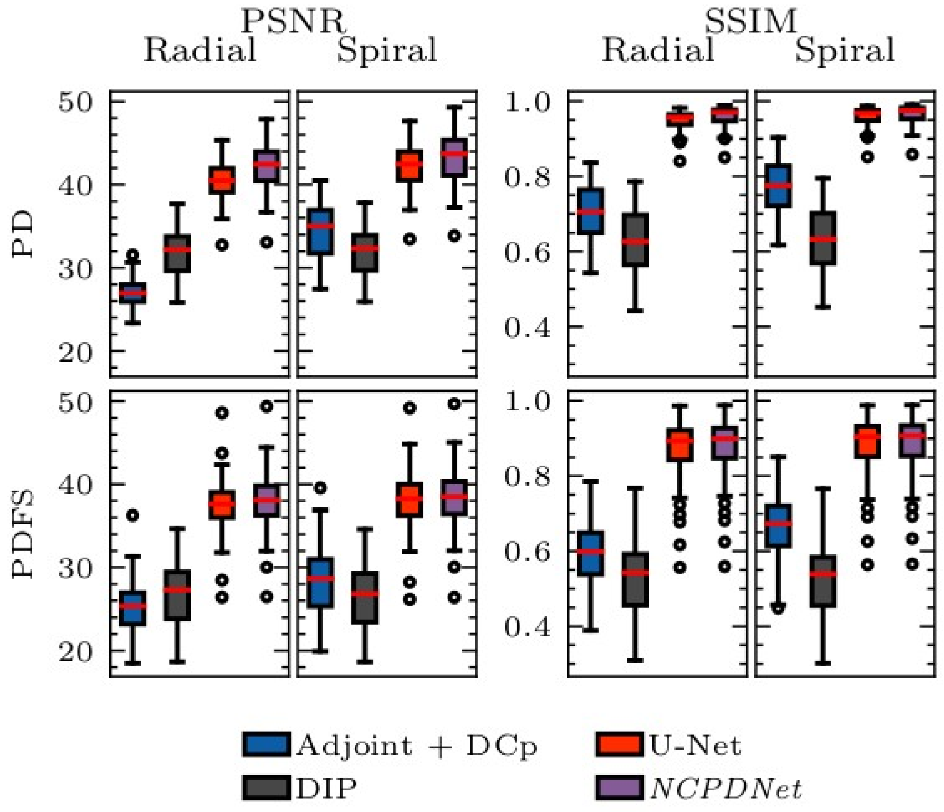
Ramzi et al, ISMRM 2021

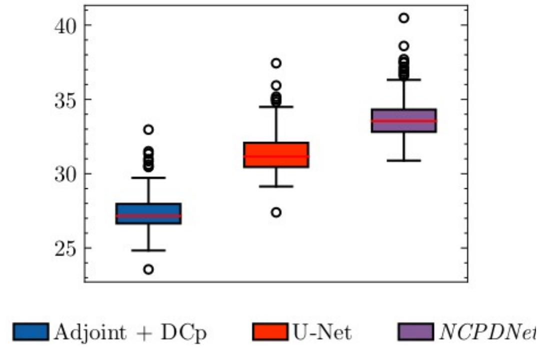


XPDNet recon, trained on R=4, lower res, no cerebellum

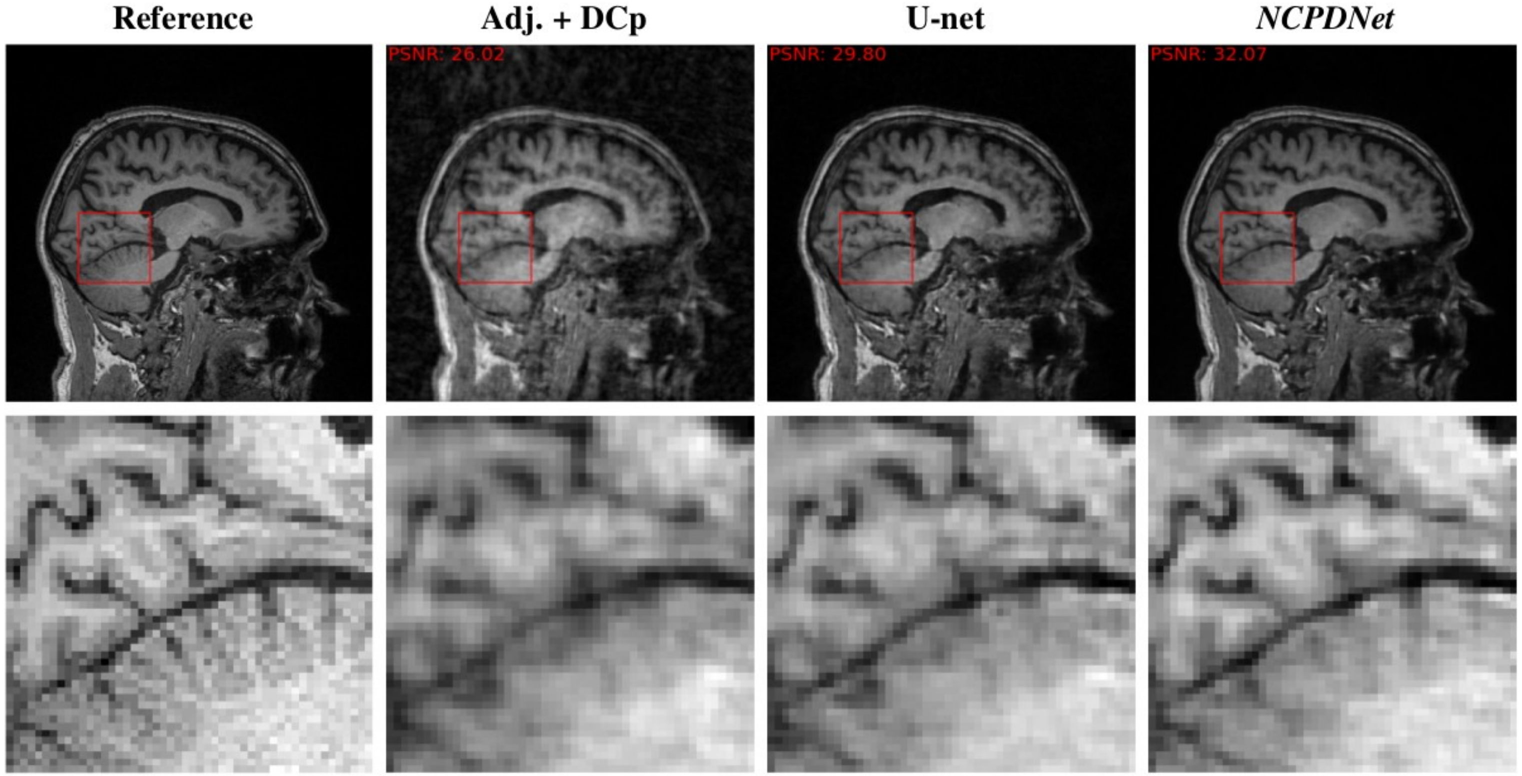
From XPDNet to Non-Cartesian PDNet

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 ISBI 2021, under review IEEE T*

XPDNet 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)
- Outperforms GRAPPA at higher acceleration rates, faster in terms of computation time
- Works for non-Cartesian sampling, in 3D and for multi-contrast reconstruction

Outlook

- Self-supervision for fMRI

Conclusions & Perspectives

- **Shorter acquisition**
  - 3D SPARKLING available for T2* imaging at 3T & 7T scanners
  - SPARKLING for fMRI still under development
  - Next: SPARKLING for T1-w, T2-w and dw-MRI
- **Faster image reconstruction**
  - NC-PDNet for SWI (G. Daval-Frérot): scalability to multi-coil imaging
  - Integrate $\Delta B0$ inhomogeneity correction within the image reconstruction network
- **Perspectives**
  - Hybrid approach for the joint learning of the sampling pattern and image reconstructor
  - SWI/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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- Z. Ramzi

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- M. Ripart (2019-2020)

DRF Impulsion

Cosmic

NUMERICS

2020 call for applications for the CEA PhD NUMERICS programme

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Thank you for your attention!