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Vancouver, Canada

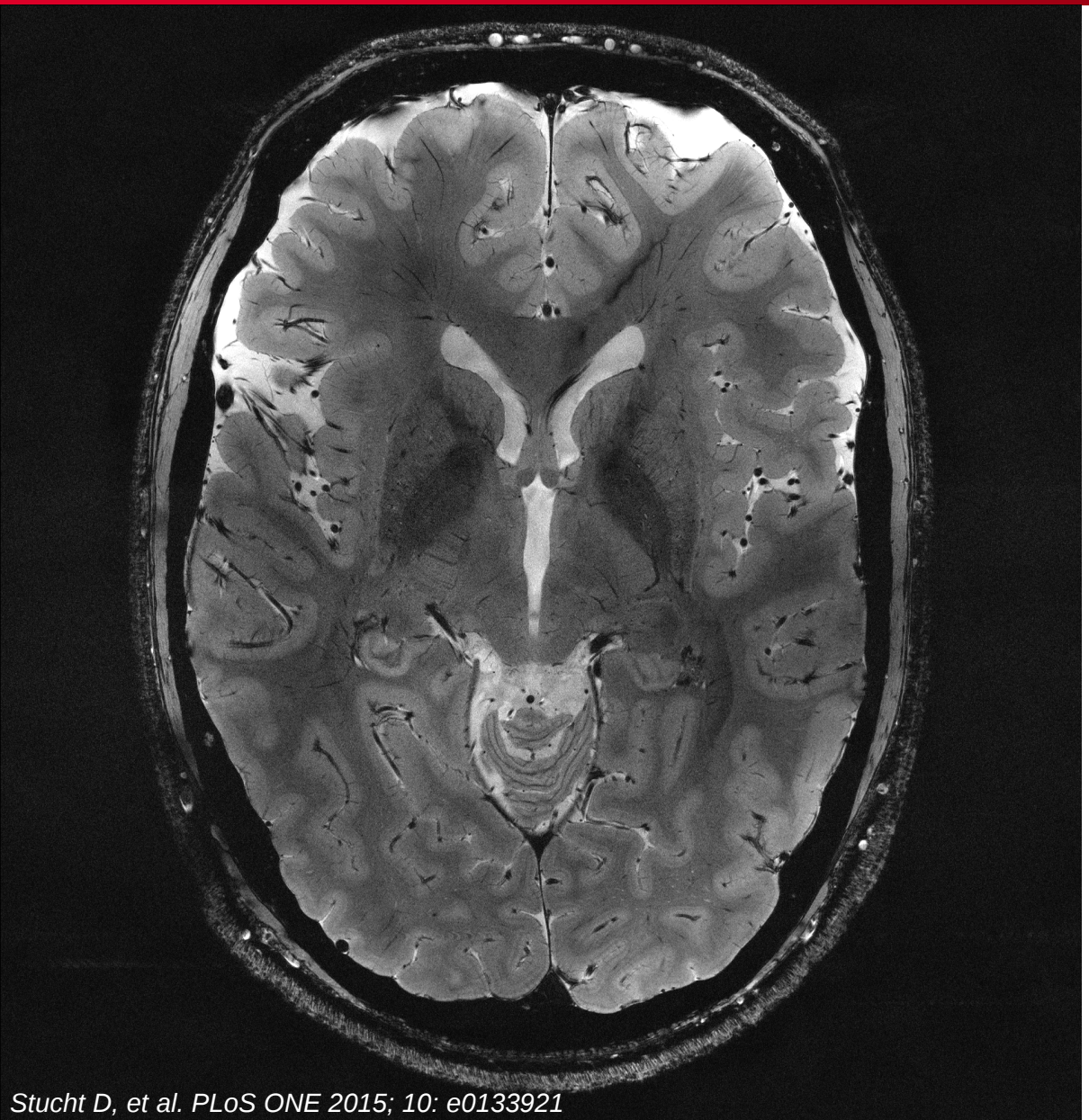
UBC THE UNIVERSITY OF BRITISH COLUMBIA

Retrospective & Prospective SPARKLING Trajectories for Accelerated 2D Anatomical Imaging at 7T Using Compressed Sensing

Philippe Ciuciu
Philippe.ciuciu@cea.fr

IEEE SPS Lecture
Dec, 12 2016

INTRODUCTION: HIGH RESOLUTION IMAGING



Stucht D, et al. PLoS ONE 2015; 10: e0133921

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,

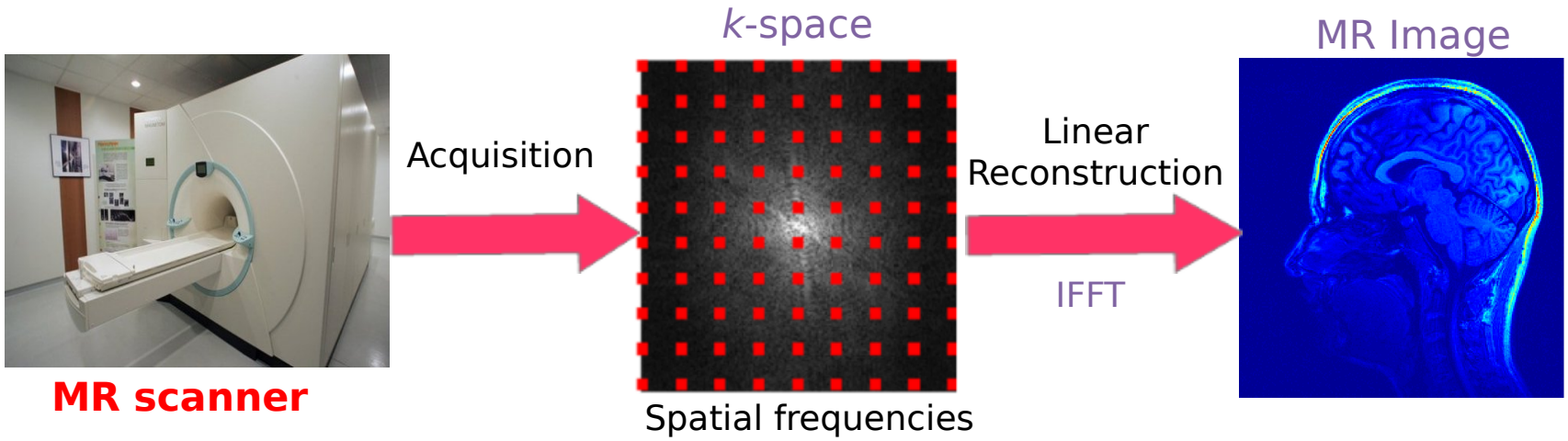
Motion correction, R=1

Acquisition Time of 50 minutes!

How can we accelerate this?

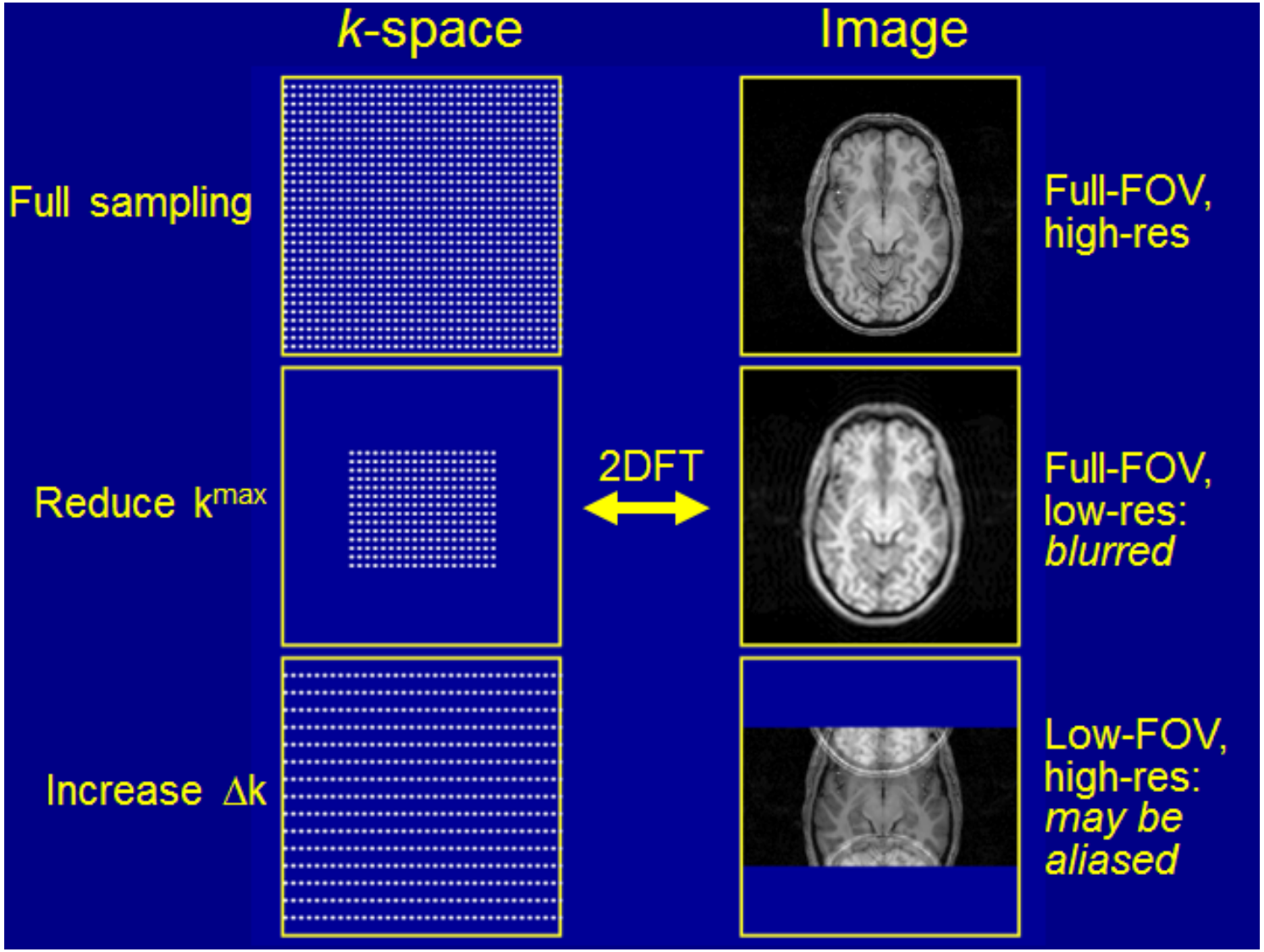
INTRODUCTION: STANDARD MRI ACQUISITION

- Collect Fourier samples over a Cartesian grid

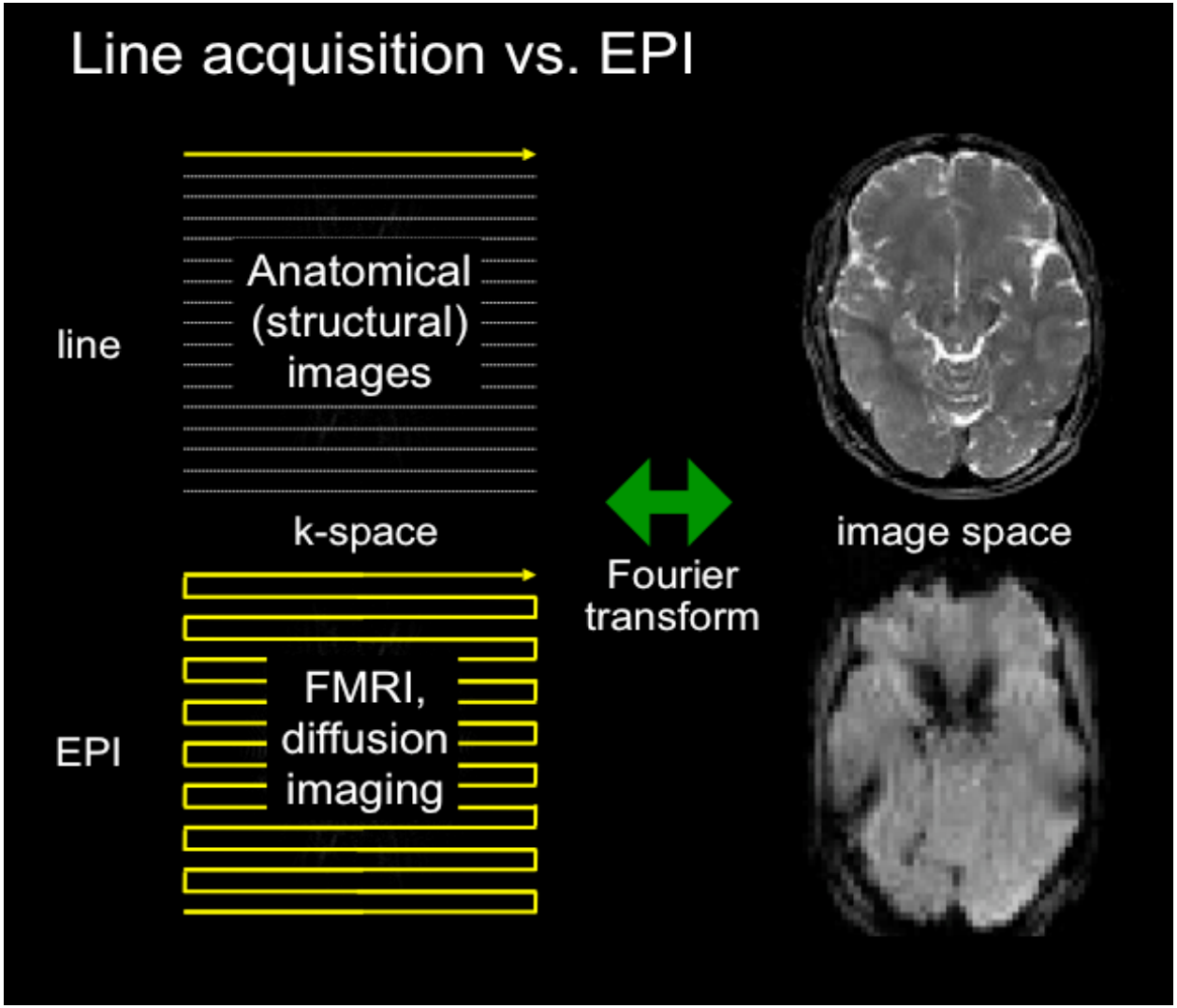


- Idea: collect less Fourier samples to reduce acquisition time

INTRODUCTION: NAIVE PARTIAL FOURIER



MRI ACQUISITION ALONG TRAJECTORIES



K-SPACE TRAJECTORY MODELING

Mathematical modelling:

Let $s : [0, T] \to \mathbb{R}^d$, $(d = 2, 3)$ denote the sampling curve. We have:

$$s(t) = s(0) + \gamma \int_0^t g(\tau) d\tau \text{ avec } g = (g_x, g_y).$$

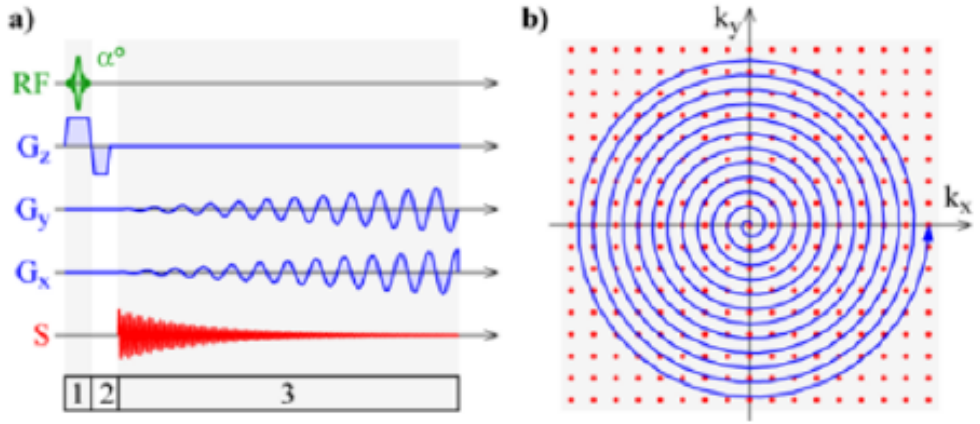


Figure : Spiral imaging: Pulse sequence (Left) and corresponding sampling trajectory (Right).

K-space location is proportional to accumulated area under gradient waveforms

K-SPACE TRAJECTORY CONSTRAINTS

The *gradient encoding* g should satisfy: The g field is called *gradient encoding*, it should satisfy:

- $\|g\|_\infty \leq G_{\max}$: **bounded gradient magnitude**, (eg, 70 $\mathrm{mT.m^{-1}}$).
- $\|\dot{g}\|_\infty \leq S_{\max}$: **bounded slew rate**, (eg, 300 $\mathrm{T.m^{-1}.s^{-1}}$).

Admissible sampling curves

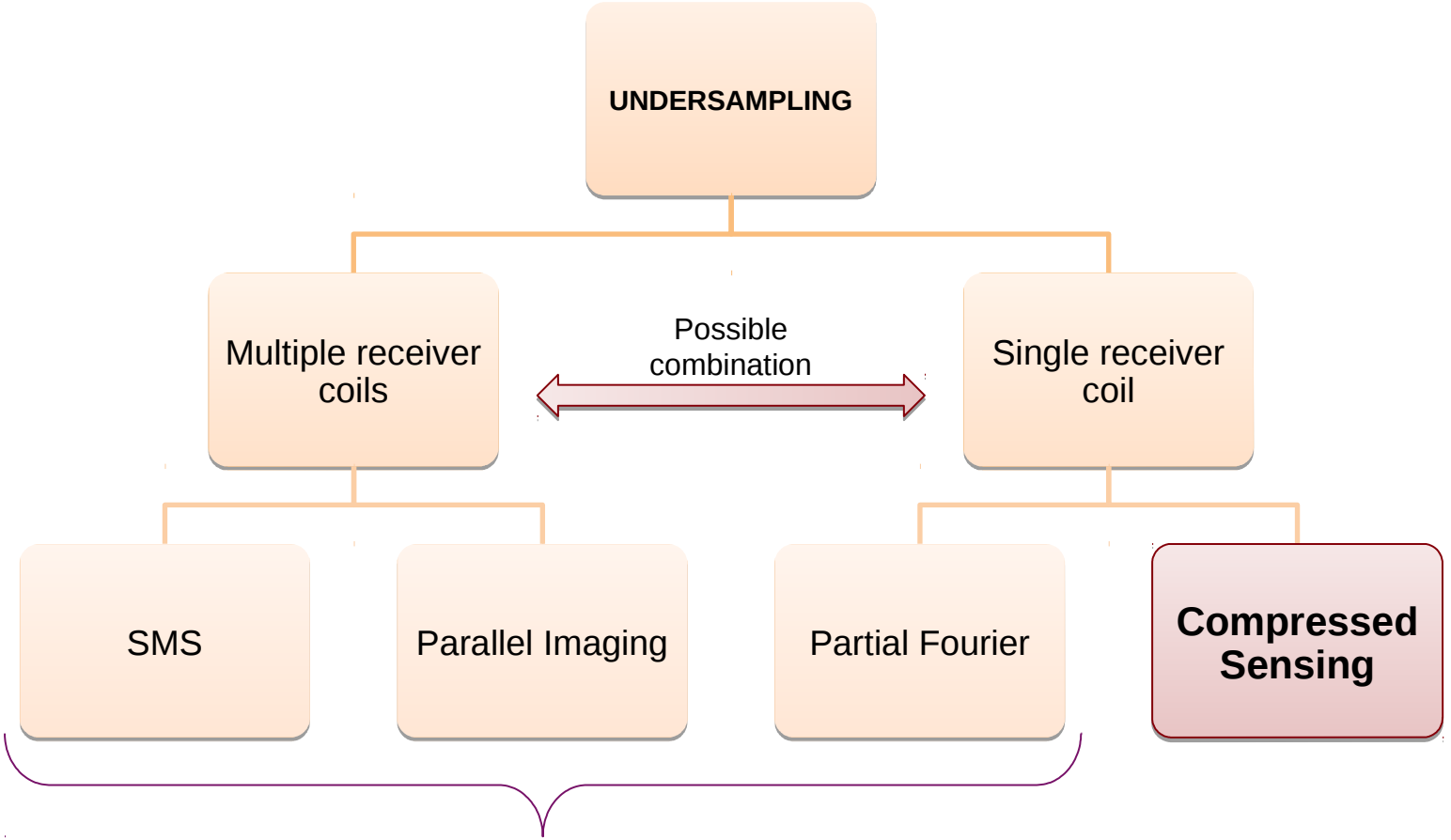
An admissible sampling curve in MRI is a curve belonging to the set:

$$\mathcal{S}_{\mathrm{MRI}} = \left\{ s \in \left(\mathcal{C}^2([0,T])\right)^d, \|\dot{s}\|_\infty \leqslant \alpha = \gamma G_{\max}, \ \|\ddot{s}\|_\infty \leqslant \beta = \gamma S_{\max} \right\}$$

Similar to driving a car on the Fourier plane.

FEASIBLE ACCELERATION SCHEMES

- Can we reduce the acquisition time by measuring fewer samples and still be able to reconstruct nice images?



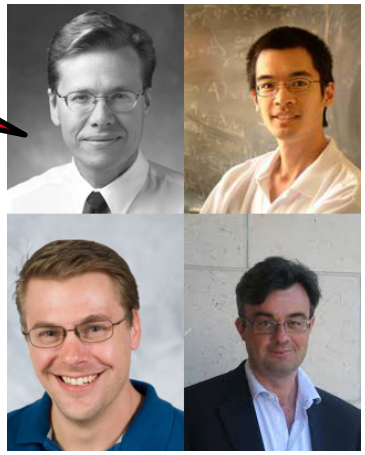
OUTLINE

- Part I: From CS to pointwise Variable Density Sampling
- Part II: Curve-based Variable Density Sampling
- Part III: Projection on measure sets
- Part IV: MRI simulation results
- Part V: Retrospective & Prospective SPARKLING at 7 Tesla

Part I: From Compressed Sensing to pointwise Variable Density Sampling

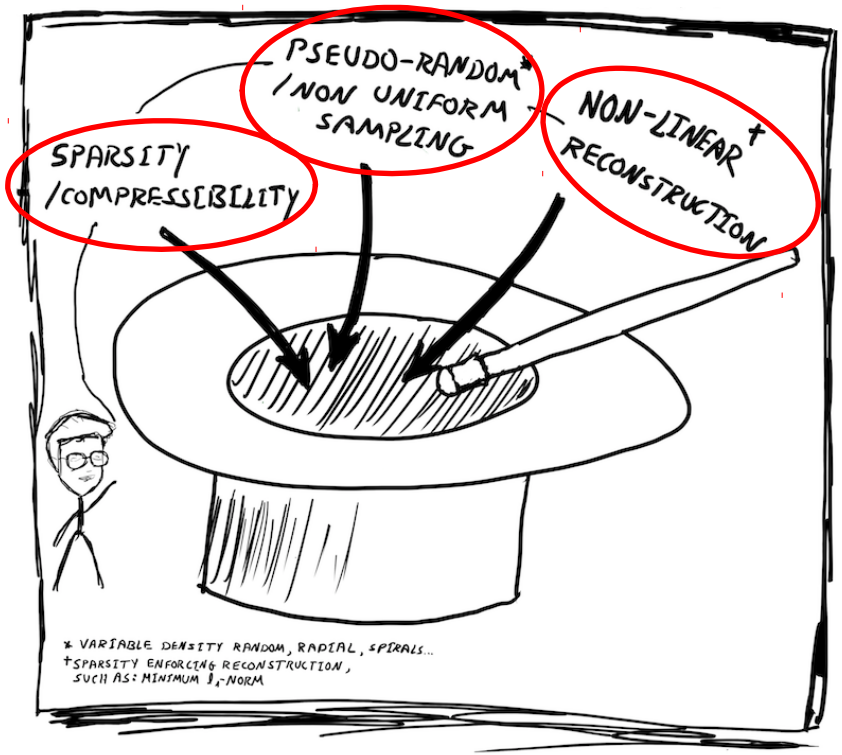
COMPRESSED SENSING RECIPE

Data is sparse, compressible, redundant…
Sense the compressed information directly!



Donoho, Tao, Romberg, Candes

[Candes et al, IEEE IT 2006]
[Donoho, IEEE IT 2006]



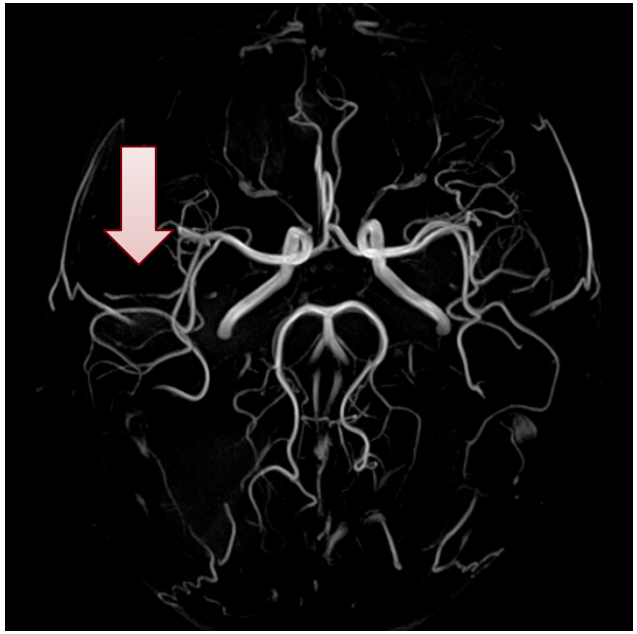
Michael Lustig, http://www.eecs.berkeley.edu/~mlustig/CS.html

WHAT SPARSITY AND COMPRESSIBILITY MEAN?

Sparsity/Compressibility

Sparse
(spärs),
adj. **spars•er, spars•est.**
1. Thinly scattered or distributed; not thic
k or dense.
2. Scanty; meager.
(http://www.thefreedictionary.com/sparse)

Angiography image… is sparse



(www.healthcare.siemens)

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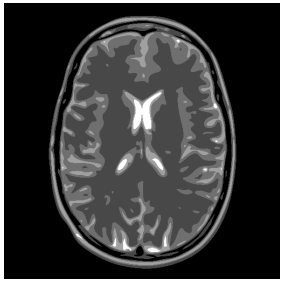
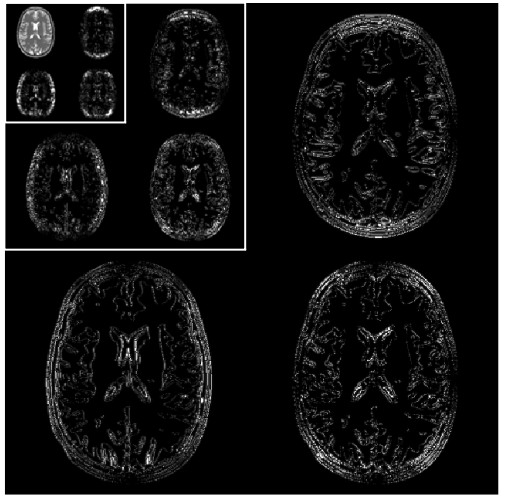
Compressible
1. There exists a basis where the representation has just a few large coefficients and many small coefficients.
2. Compressible signals are well approximated by sparse representations



is not sparse…
… but compressible!

Wavelet Represensation… is sparse!



3 levels of decomposition

COMPRESSED SENSING THEORY (1/4)

Compressed sensing theory:

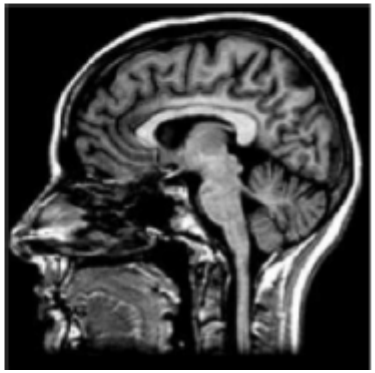
- x is sparse in a given basis (e.g. wavelets): $x = \Psi z$, where $z \in \mathbb{C}^n$ is s-sparse.
- Acquisition matrix: $A = F^* \Psi$.

Let $\Gamma \subseteq \{1, \cdots, n\}$ and $A_\Gamma = (a_i^*)_{i \in \Gamma}$. We acquire a measurement vector:

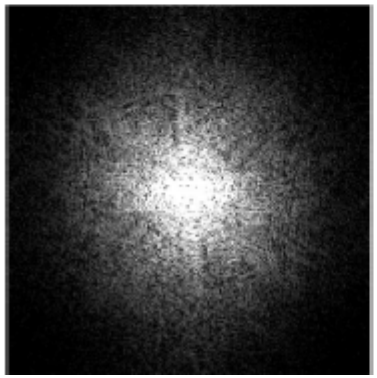
$$y = A_\Gamma z.$$

z

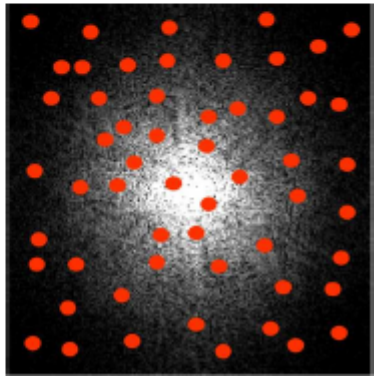
$x = \Psi z$



$F^* \Psi z = Az$



$A_\Gamma z$



COMPRESSED SENSING THEORY (2/4)

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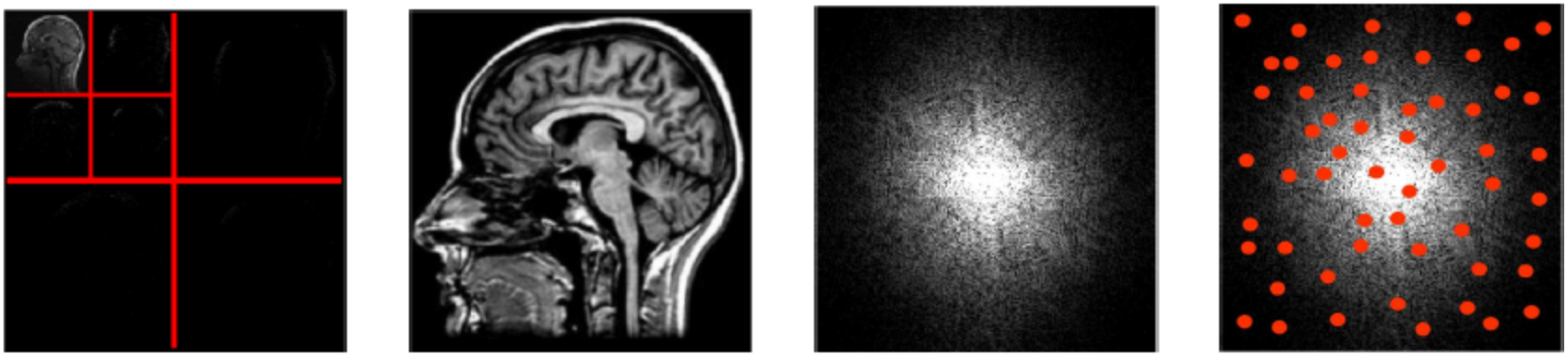
Let $\Gamma \subseteq \{1, \cdots, n\}$ and $A_\Gamma = (a_i^*)_{i \in \Gamma}$. We acquire a measurement vector:

$$y = A_\Gamma z.$$

z | $x = \Psi z$ | $F^* \Psi z = Az$ | $A_\Gamma z$



ℓ_1 reconstruction (promoting sparsity)

$$\min_{z \in \mathbb{C}^n, A_\Gamma z = y} \|z\|_1.$$

COMPRESSED SENSING THEORY (3/4)

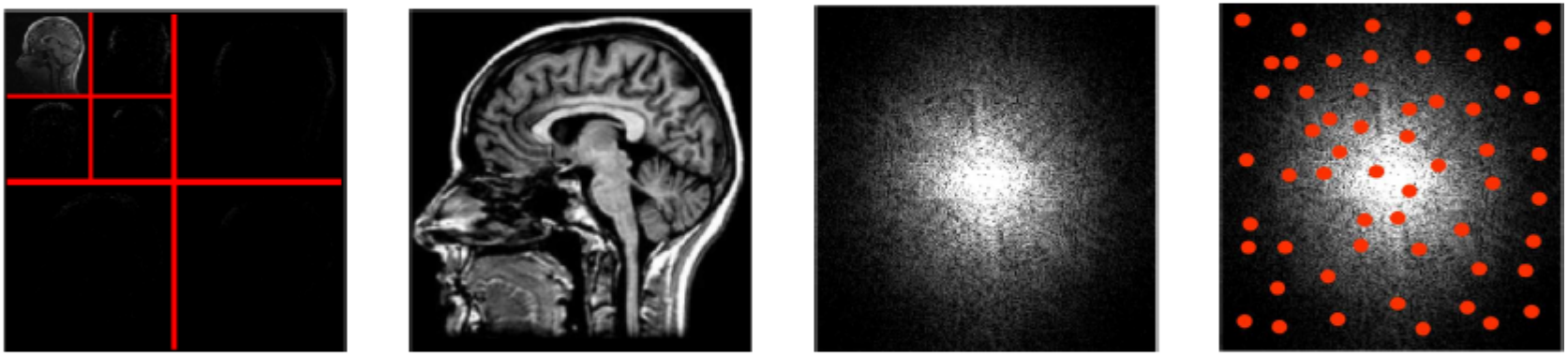
Compressed sensing theory:

- x is sparse in a given basis (e.g. wavelets): $x = \Psi z$, where $z \in \mathbb{C}^n$ is s-sparse.
- Acquisition matrix: $A = F^* \Psi$.

Let $\Gamma \subseteq \{1, \cdots, n\}$ and $A_\Gamma = (a_i^*)_{i \in \Gamma}$. We acquire a measurement vector:

$$y = A_\Gamma z.$$

z | $x = \Psi z$ | $F^* \Psi z = Az$ | $A_\Gamma z$



or in case of noise (synthesis formulation):

$$\widehat{z} = \underset{z \in \mathbb{C}^n}{\operatorname{Arg\,min}} \|y - A_\Gamma z\|_2^2 + \lambda \|z\|_1$$

(FISTA algorithm)

UNIFORM RANDOM UNDERSAMPLING

A first CS theorem [Candès and Plan, 2011]

Theorem

Construct Γ *by* **uniform** *and i.i.d. drawing the lines of* $\boldsymbol{A}$.
Let x *be a sparse vector, containing* s *non-zero entries. Assume that:*

$$m \geqslant C \cdot s \cdot \left(n \cdot \max_{1 \leqslant k \leqslant n} \|a_k\|_\infty^2 \right) \cdot \log\left(\frac{n}{\eta}\right) \tag{1}$$

where C *is a universal constant. Then, with probability* $1-\eta$, x *is the unique solution of:*

$$\min_{z \in \mathbb{C}^n, A_\Gamma z = y} \|z\|_1.$$

In MRI, $\max_{1 \leqslant k \leqslant n} \|a_k\|_\infty^2 = O(1)$, hence $m \gg n$.

This is called the coherence barrier

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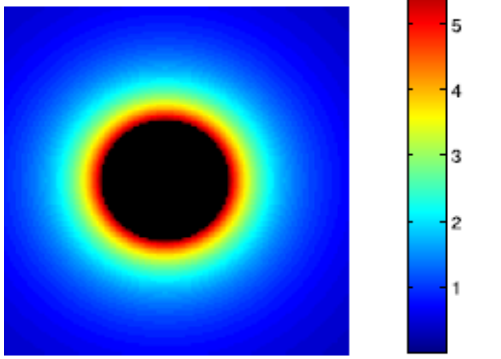
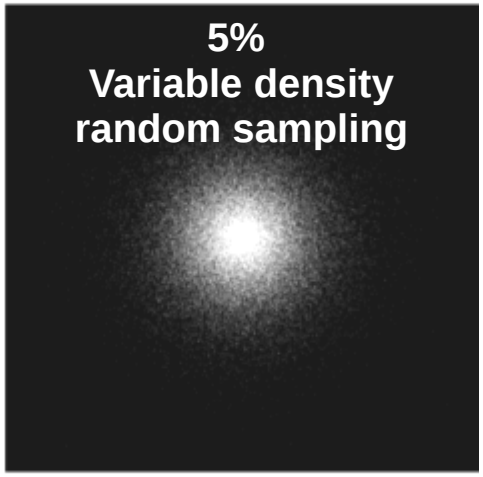
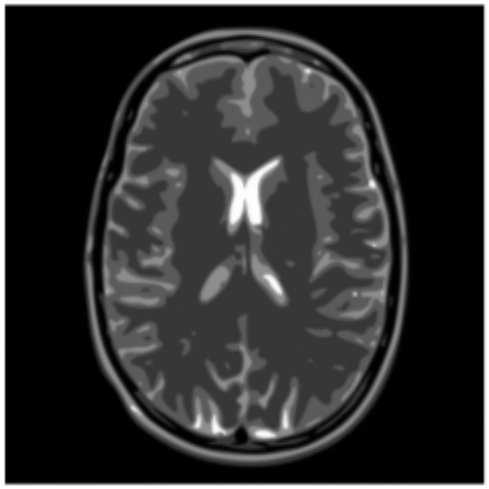
VARIABLE DENSITY UNDERSAMPLING

Sample low frequencies more often





CS reconstruction



(Lustig et al. 2007, Puy et al. 2011, Krahmer & Ward, 2012)

Breaking the coherence barrier: A new theory for Compressed Sensing
Asymptotic incoherence, asymptotic sparsity and multi-level sampling [Adcock et al. 2013; Roman et al, 2014]

THEORETICAL FOUNDATIONS OF VDS

Theorem [Chauffert et al., 2013]

Let x be an arbitrary s-sparse vector. Let $(J_k)_{k\in\{1,\dots,m\}}$ denote a sequence of i.i.d. random variables taking value $i \in \{1,\dots,n\}$ with probability p_i. Generate a random set $\Gamma = \{J_1,\dots,J_m\}$ and measure $y = A_\Gamma x$. Take $\eta \in]0,1[$ and assume that:

$$m \geqslant C \cdot s \cdot \max_{k\in\{1,\dots,n\}} \frac{\|a_k\|_\infty^2}{p_k} \ln\left(\frac{n}{\eta}\right)$$

where C is a universal constant. Then with probability $1-\eta$ vector x is the unique solution of the following problem:

$$\min_{z\in\mathbb{C}^n, A_\Gamma z = y} \|z\|_1.$$

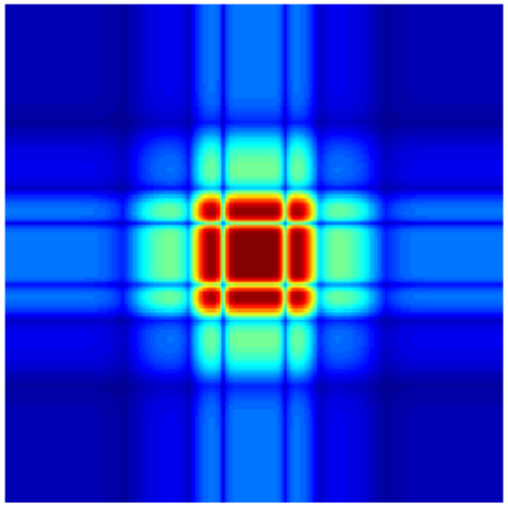
Optimal distribution $\pi_k \propto \|a_k\|_\infty^2$.

Coherence is now $\max_{k\in\{1,\dots,n\}} \frac{\|a_k\|_\infty^2}{p_k} = \sum_k \|a_k\|_\infty^2 = O(\log(n))$ in MRI.

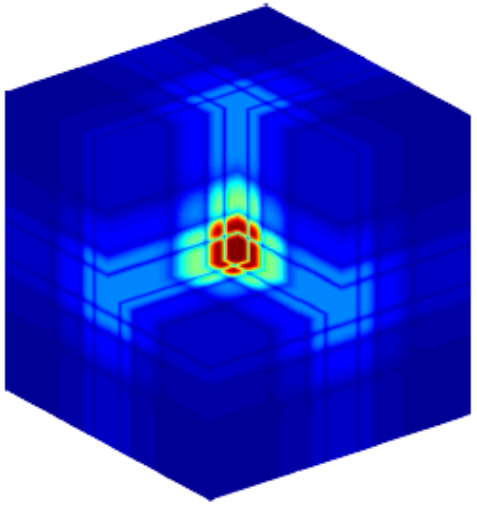
ILLUSTRATION OF VARIABLE DENSITY SAMPLING

Illustration of optimal sampling strategy for $H = F^* \Psi$ (MRI)

Shannon
Wavelets

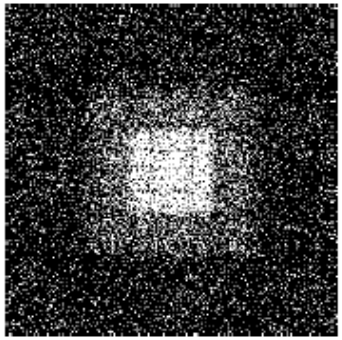


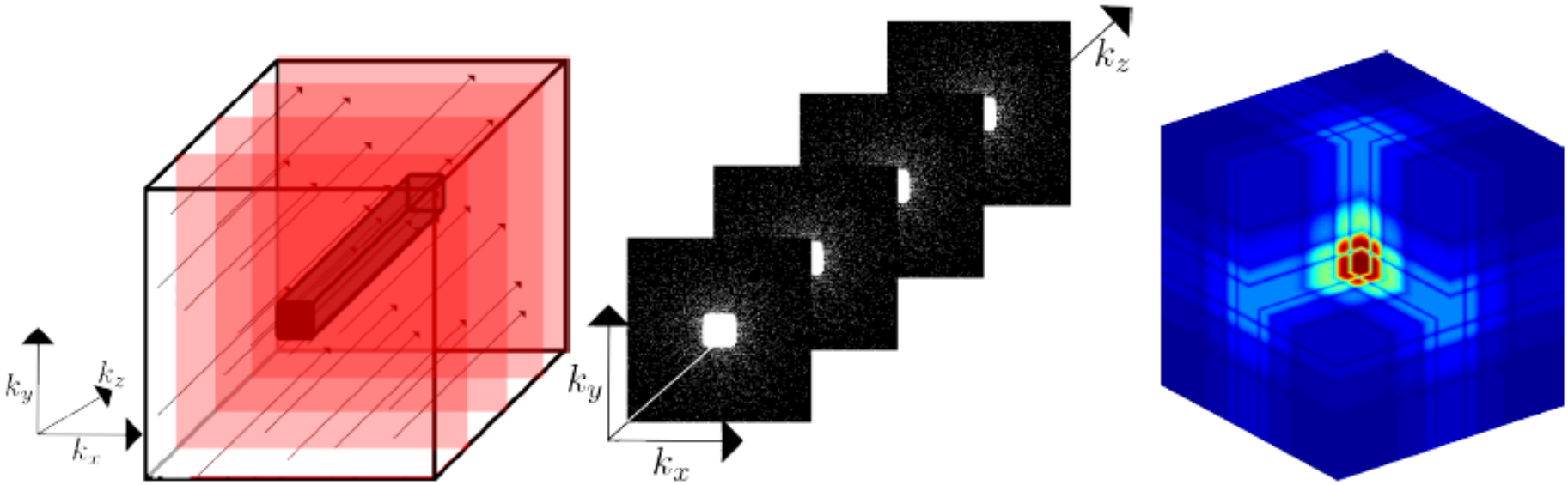
π in 2D



π in 3D

Example of sampling pattern obtained in 2D :





CS-MRI is sub-optimal! [Lustig et al., 2007]

- CS not used to its full potential:
  - Hindered randomness
  - Variable density sampling not fulfilled in 3D
  - K-space oversampled in one direction
  - Undersampling factor generally limited to: $R \leq 10$

Part II: Curve-based Variable Density Sampling

[Chauffert et al, SIAM IS 2014, Chauffert et al, IEEE TMI]

VDS IMPLEMENTATION ON EXISTING TRAJECTORIES

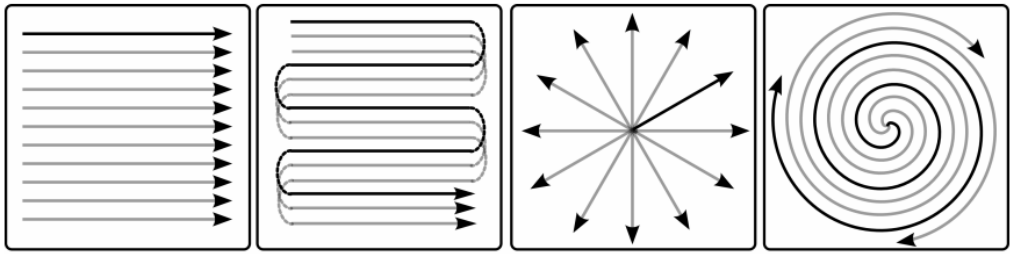
- CS must comply with MR hardware constraints

$$k(t) = k(0) + \gamma \int_0^t G(u)du$$

7T MRI

$$G < G_{max} \approx 50\ mTm^{-1}$$
$$\dot{G} < \dot{G}_{max} \approx 333\ mTm^{-1}s^{-1}$$

➢ Regular trajectories

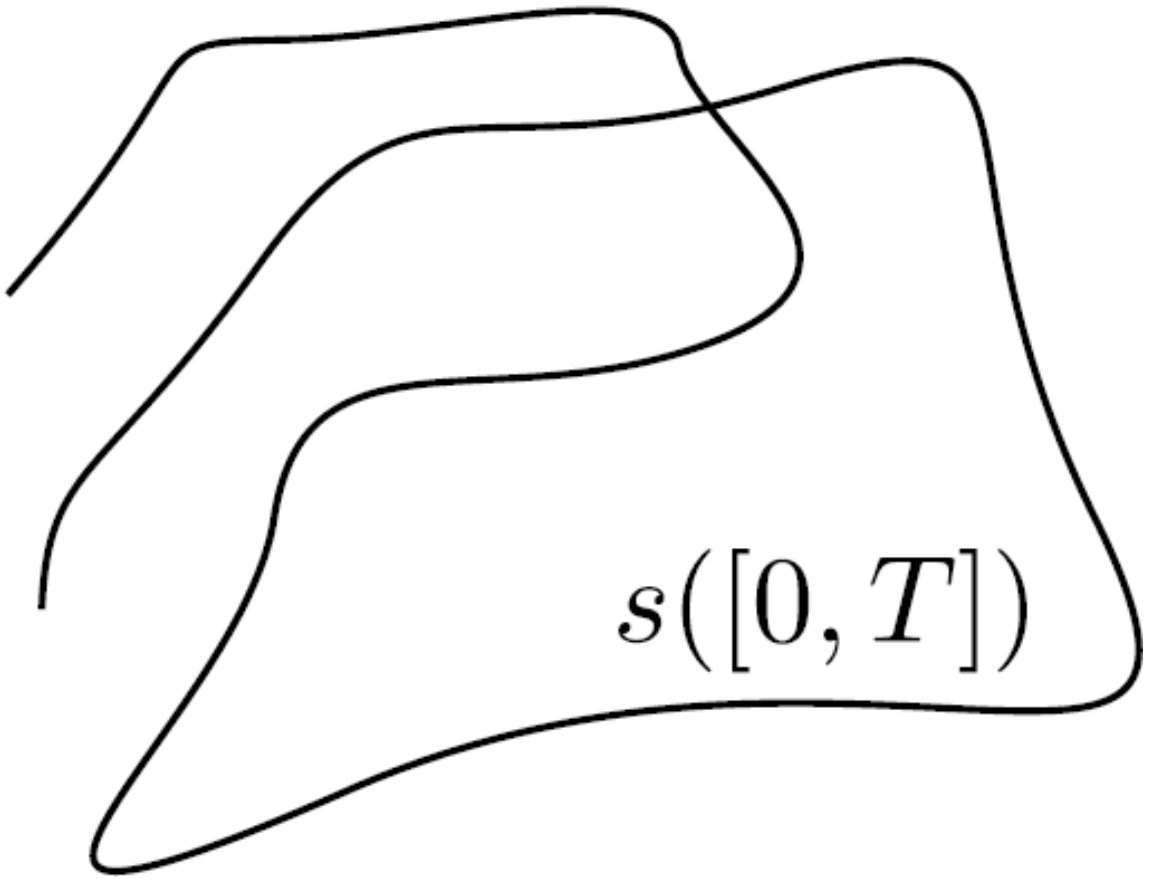


Lustig et al. 2008

- Easy implementation: undersampling standard MR trajectories!
  - Radial for cardiac cine MR imaging (Winkelmann et al. 2007)
  - Spiral or noisy spirals (Lustig et al. 2005)
  - Poisson disk sampling (Vasanawala et al. 2011)

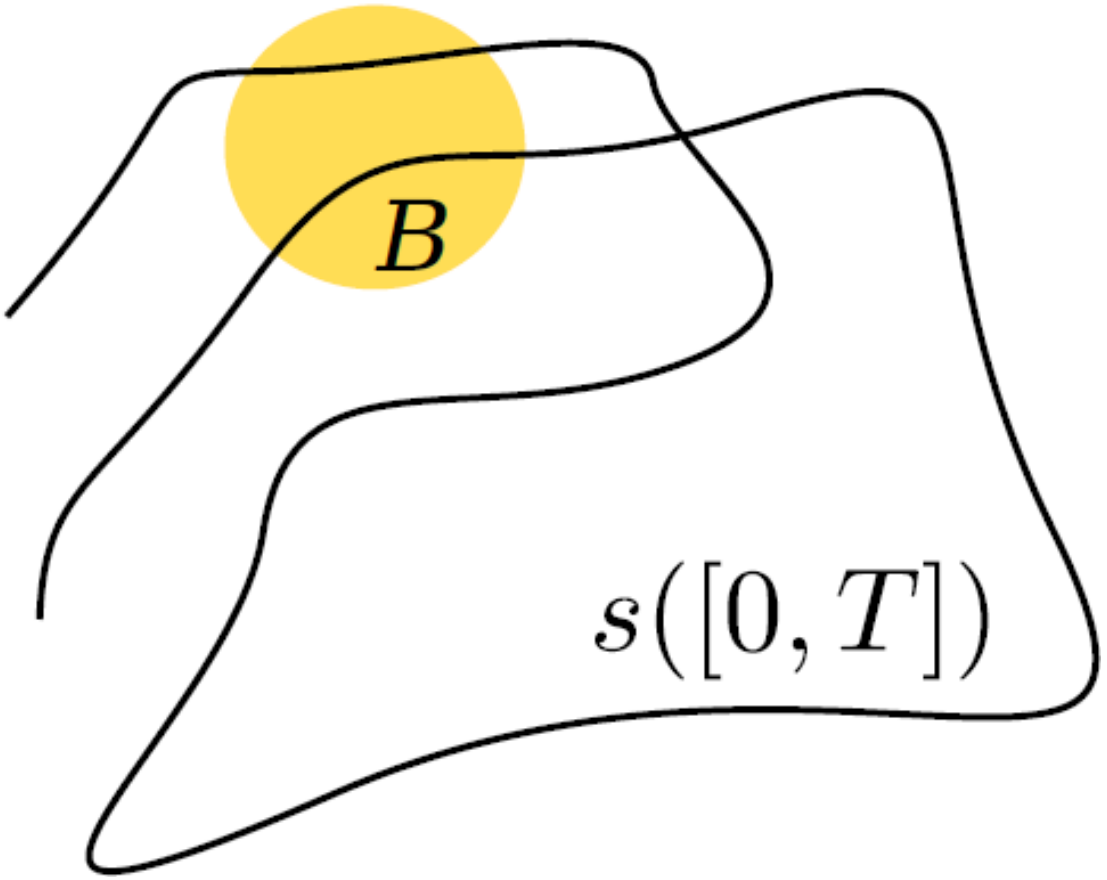
MATHEMATICAL FORMULATION OF VDS

Pushforward measure - illustration



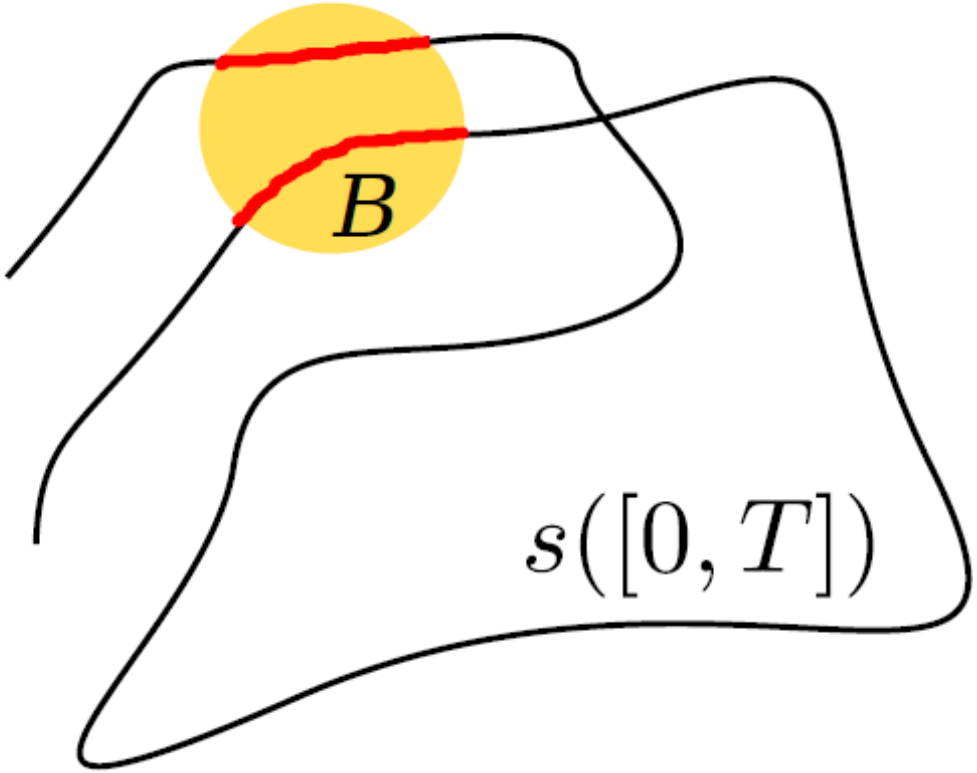
MATHEMATICAL FORMULATION OF VDS

Pushforward measure - illustration



MATHEMATICAL FORMULATION OF VDS

Pushforward measure - illustration



$$\nu(B) = s_* \lambda_T(B) = \lambda_T(s^{-1}(B))$$

λ_T is the (normalized) Lebesgue measure.

VDS - DEFINITIONS

Pushforward measure

Let $\Omega = [0,1]^d$, where $d = 2$ or 3 denote the space dimension. We equip Ω with the Borel algebra $\mathcal{B}$. Let (X, Σ) be a measurable space and $s : X \to \Omega$ be a measurable mapping. $\mu : X \to [0; +\infty[$ denote a measure. The *pushforward measure* ν of μ is defined by:

$$\nu(B) = s_* \mu(B) = \mu(s^{-1}(B)), \quad \forall B \in \mathcal{B}$$

Ex. 1: Measures supported by curves

Ex. 2: Atomic measures

$s : \{1, \ldots, m\} \to \Omega$, where $s(i) = p_i$ denotes the i-th point. Set μ as the *counting measure* defined for any set $I \subseteq \{1, \ldots, m\}$ by $\mu(I) = \frac{|I|}{m}$. Then ν is defined by

$$\nu = \frac{1}{m} \sum_{i=1}^{m} \delta_{p_i}.$$

VDS - DEFINITIONS

Weak convergence [Chauffert et al, SIAM IS 2014]

A sequence of measures (μ_n) is said to weakly converge to μ, if for any bounded continuous function Φ,

$$\int_\Omega \Phi(x)\mathrm{d}\mu_n(x) \to \int_\Omega \Phi(x)\mathrm{d}\mu(x)$$

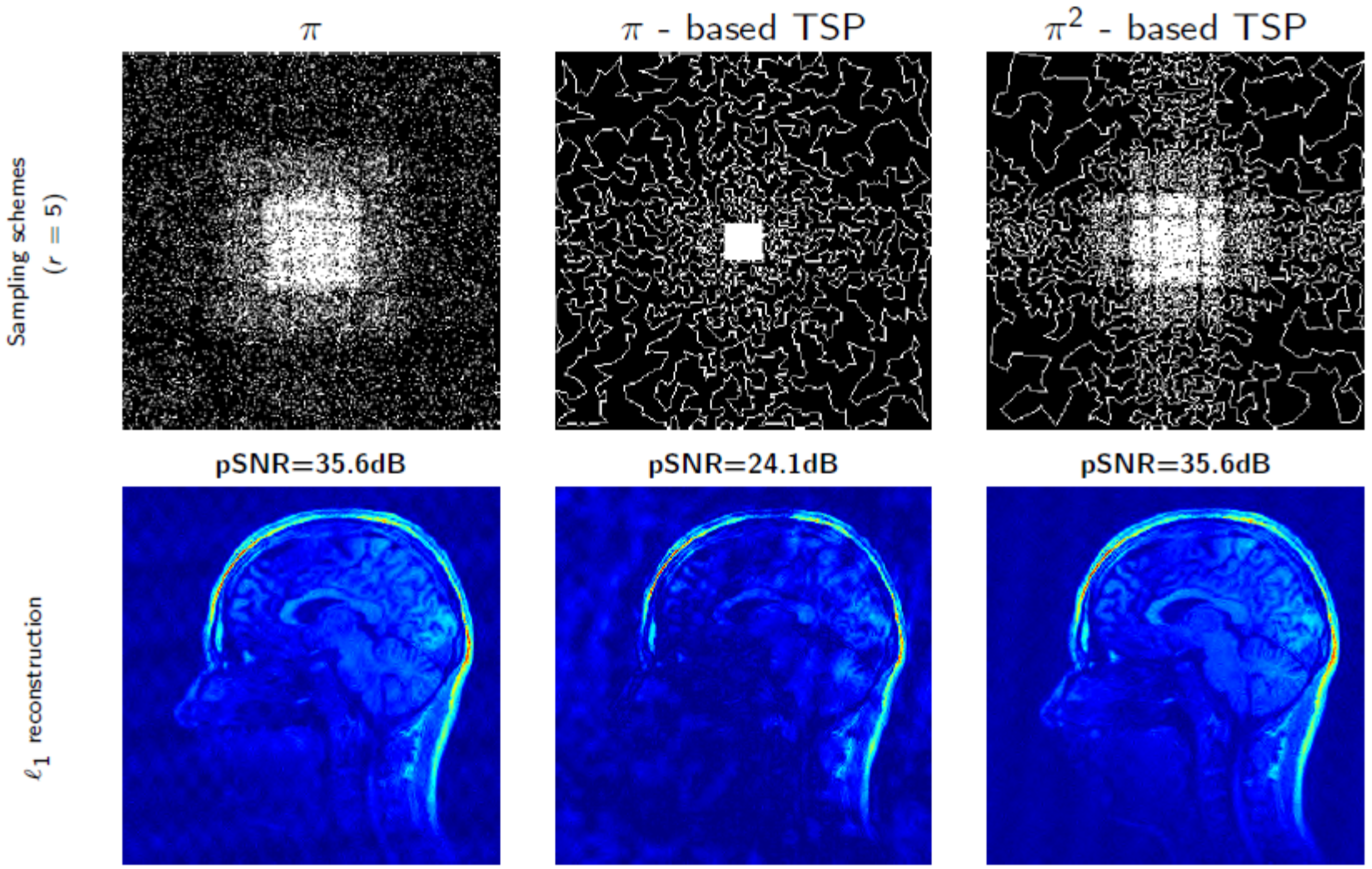
Shorthand notation: $\mu_n \rightharpoonup \mu$.

Variable density sampler

A sequence of (random) trajectories $s_n : X_n \to \Omega$ is said to be a π-Variable Density Sampler if

$$s_{n*}\mu \rightharpoonup \pi \quad \text{almost surely}$$

VDS – EXAMPLE (TSP-BASED)



[Chauffert et al, SIAM IS 2014]

VDS – EXAMPLE (TSP-BASED IN 3D)

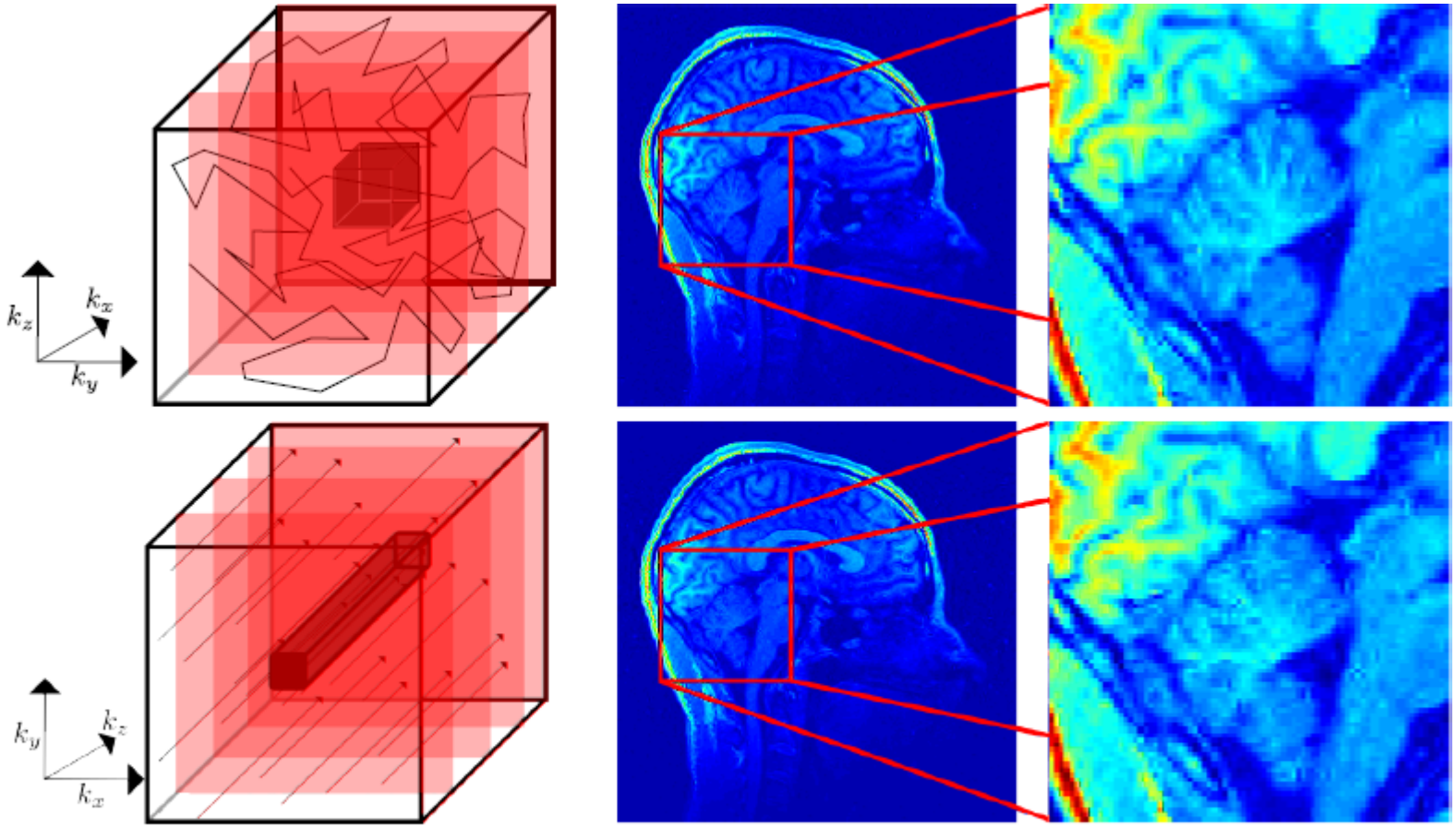


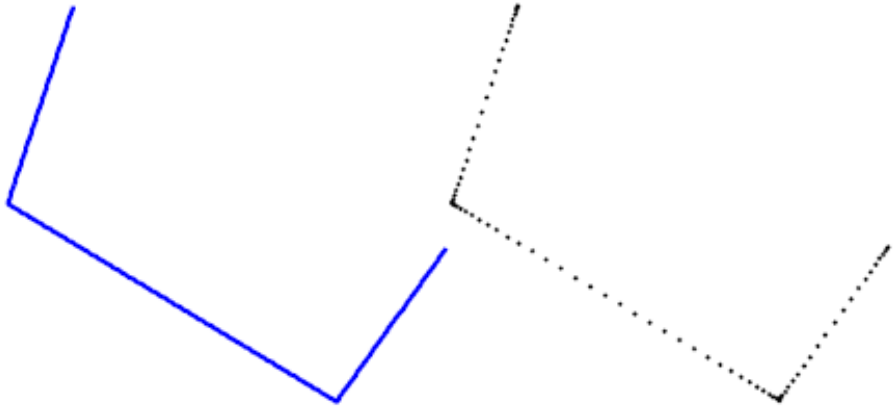
Figure: 3D reconstruction results for $r = 8.8$ for various sampling strategies. **Top row:** TSP-based sampling schemes (PSNR=42.1 dB). **Bottom row:** 2D random drawing and acquisitions along parallel lines [Lustig et al., 2007] (PSNR=40.1 dB).

[Chauffert et al, SIAM IS 2014]

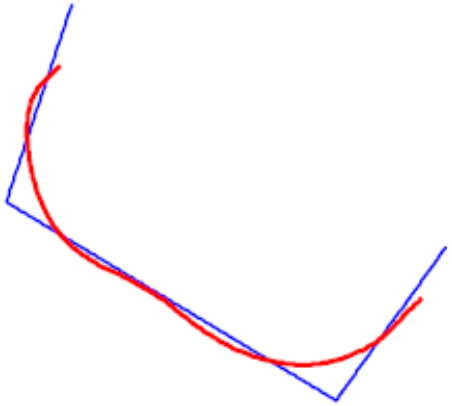
PARAMETERIZATION PROBLEM

Finding a parameterization in $\mathcal{S}_{\text{MRI}}$ corresponding to a curve support is not easy !

- Classical approach, find an admissible parameterization [Hargreaves et al., 2004, Lustig et al., 2008]:



- Projection onto $\mathcal{S}_{\text{MRI}}$ [Chauffert et al, IEEE TMI 2016]



PROJECTION OPERATOR

For an input parameterized curve $c : [0; T] \to \Omega$, define:

$$P_{\mathcal{S}_{\text{MRI}}}(c) = \underset{s \in \mathcal{S}_{\text{MRI}}}{\text{Arg min}} \int_{t \in [0;T]} (s(t) - c(t))^2 \mathrm{d}t$$

Main properties [Chauffert et al, IEEE TMI 2016]

- Fast resolution using accelerated proximal gradient descent on the dual.
- The sampling time is fixed (equal to T).
- The sampling distribution is well preserved (approximation of Wasserstein distance W_2).

$\Rightarrow$ More importantly, $P_{\mathcal{S}_{\text{MRI}}}$ is the cornerstone of a global approach, described in part 3.

INTERIM SUMMARY

Two key properties for a Variable Density Sampler:

- Sampling distribution
- Fast k-space coverage

Suboptimal two-step approaches:

- Eg, “Travelling Salesman Problem” sampler

Part III: Projection on measure sets

[Chauffert et al, Const Approx 2016; Boyer et al, SIAM IS 2016]

INTRODUCTION OF A NEW METRIC

Useful to compare parameterizations and (probability) distributions.
Here : $s : \{1, \ldots, m\} \to \Omega$ and $\pi : \Omega \to \mathbb{R}$ a distribution.

"s" π

Related to dithering problem [Teuber et al., 2011].

INTRODUCTION OF A NEW METRIC

Useful to compare parameterizations and (probability) distributions.
Here : $s : \{1, \ldots, m\} \to \Omega$ and $\pi : \Omega \to \mathbb{R}$ a distribution.

"s"

$h \star s$

π

$h \star \pi$

h: a Gaussian kernel.

A PROJECTION PROBLEM

Working with measures

Let $\mathcal{P}$ denote a set of admissible parameterizations and $\mathcal{M}(\mathcal{P})$ the set of pushforward measures associated with elements of $\mathcal{P}$: Sampling trajectories $s \in \mathcal{P} \to \Omega$ are seen through $s_* \mu \in \mathcal{M}(\mathcal{P})$.

$$\mathcal{M}(\mathcal{P}) = \{\nu = s_* \mu, \ s \in \mathcal{P}\}.$$

m-point measures:

Set of sums of m Dirac delta functions: $\mathcal{M}(\Omega^m) = \left\{\nu = \frac{1}{m} \sum_{i=1}^{m} \delta_{p_i}, \ p_i \in \Omega\right\}$.

Admissible curves for MRI:

$$\mathcal{M}(\mathcal{S}_{\text{MRI}}) = \{\nu = s_* \mu, s \in \mathcal{S}_{\text{MRI}}\}.$$

We want $\nu \in \mathcal{M}(\mathcal{P})$ to be "as close as possible to" π, the target distribution.

MEASURING DISTANCE BETWEEN MEASURES

Constructing a metric

Let π denote the *target density*.
Let ν denote the *pushforward measure*.

Let $h : \Omega \to \mathbb{R}$ denote a continuous function with a Fourier series that does not vanish. The following mapping:

$$dist(\pi, \nu) = \|h \star (\pi - \nu)\|_2^2$$

defines a distance (or metric) on $\mathcal{M}_\Delta$, the space of probability measures on Ω.

PROPERTIES OF THE PROJECTION PROBLEM

Goal: solve numerically, for arbitrary $\mathcal{M}(\mathcal{P})$:

$$\inf_{\nu \in \mathcal{M}(\mathcal{P})} dist(\pi, \nu)$$

Theorem [Chauffert et al, Const Approx 2016]

- If $\mathcal{P} = \Omega^m$, the sequence of solutions $\nu_m \rightharpoonup \pi$.
- If $\mathcal{P} = \mathcal{S}_{\text{MRI}}$, the sequence of solutions $\nu_T \rightharpoonup \pi$.

NUMERICAL IMPLEMENTATION

The general construction (similar to finite elements)

- Approximate $\mathcal{M}(\mathcal{P})$ by a subset $\mathcal{N}_p \subset \Omega^p$ of p-point measures:

$$\mathcal{N}_p = \mathcal{M}(\mathcal{Q}_p) = \left\{ \nu = \frac{1}{p} \sum_{i=1}^{p} \delta_{q_i}, \quad \text{for } q = (q_i)_{1 \leq i \leq p} \in \mathcal{Q}_p \right\},$$

  where $\mathcal{Q}_p$ is the discretized version of $\mathcal{P}$.

- Use a projected gradient descent to obtain an approximate projection ν_p^* on $\mathcal{N}_p$:

$$\nu_p^* \in \operatorname*{Arg\,min}_{\nu \in \mathcal{N}_p} \frac{1}{2} \| h \star (\nu - \pi) \|_2^2 ,$$

- Reconstruct an approximation $\nu \in \mathcal{M}(\mathcal{P})$ from ν_p^*.

NUMERICAL RESOLUTION

Variational formulation:

$$\min_{\nu \in \mathcal{N}_p} \frac{1}{2} \|h \star (\nu - \pi)\|_2^2 =$$

$$\min_{q \in \mathcal{Q}_p} J(q) = \underbrace{\frac{1}{2} \sum_{i=1}^{p} \sum_{j=1}^{p} H(q_i - q_j)}_{\textit{Repulsion potential}} - \underbrace{\sum_{i=1}^{p} \int_{\Omega} H(x - q_i) d\pi(x)}_{\textit{Attraction potential}},$$

where H is defined by $\hat{H}(\xi) = |\hat{h}|^2(\xi)$.

- Repulsion potential: fast k-space coverage
- Attraction potential: right target density π
- Generalization of Poisson disk sampling strategy [Bridson, 2007, Vasanawala et al., 2011]

NUMERICAL RESOLUTION (CONT'D)

Projected gradient descents in the non-convex case

Assume that H is differentiable with L-Lipschitz continuous gradient. Consider the following algorithm:

$$q^{(k+1)} \in P_{\mathcal{Q}_p}\left(q^{(k)} - \tau \nabla J(q^{(k)})\right).$$

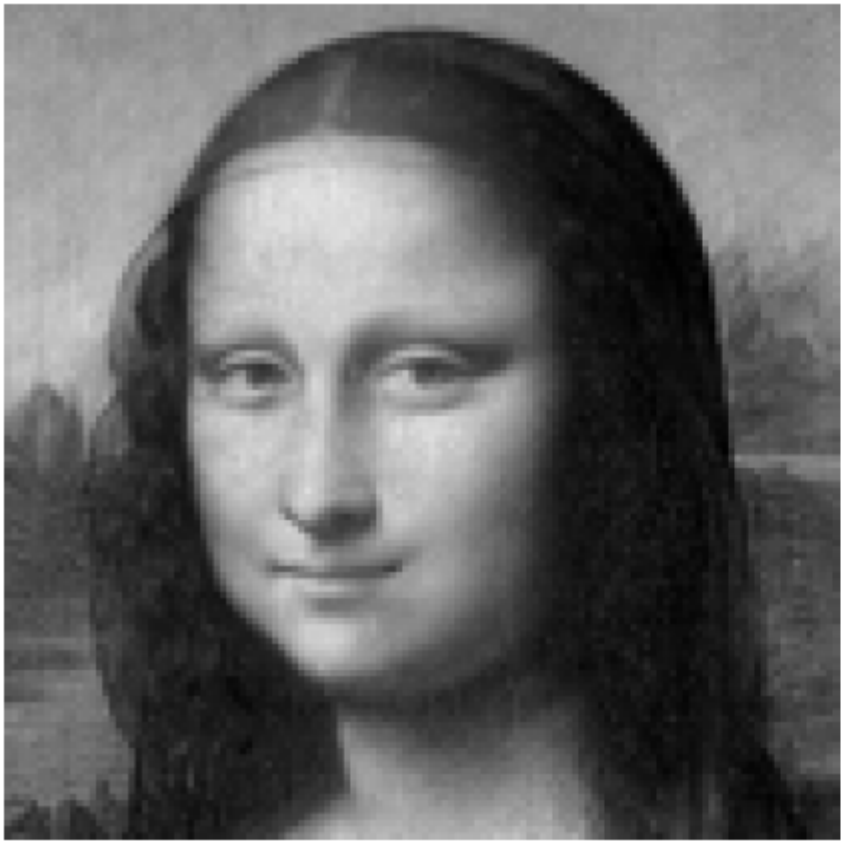
The sequence $(q^{(k)})_k$ converges to a critical point of the functional J.[Attouch et al., 2013].

Remark

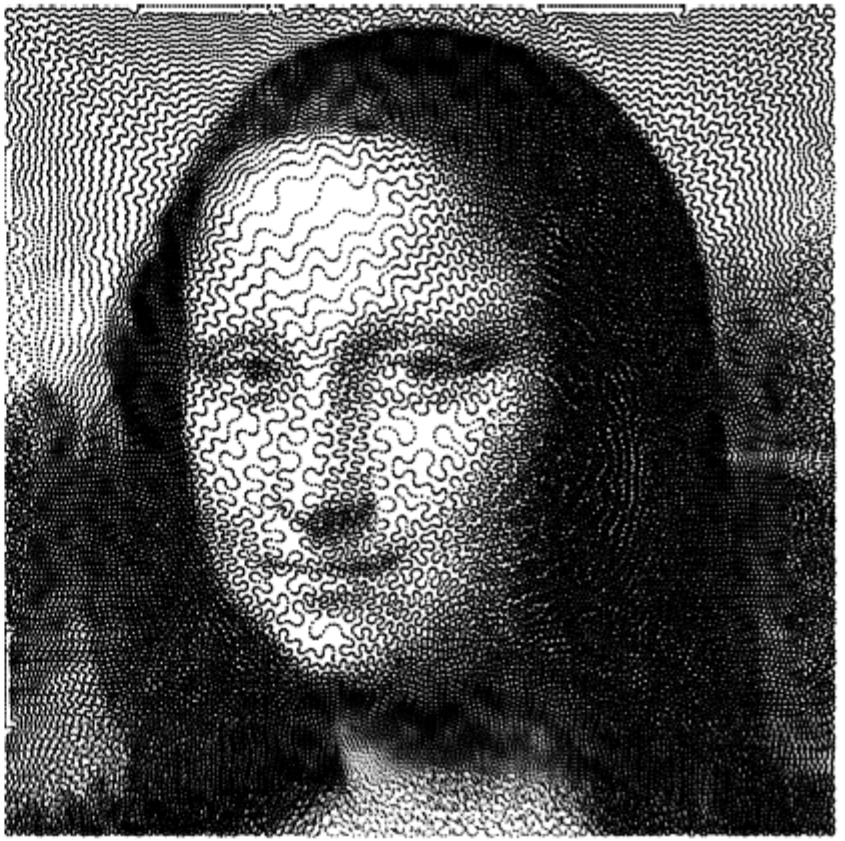
In MRI, $P_{\mathcal{Q}_p} = P_{\mathcal{S}_{MRI}}$!

EXAMPLE : CONTINUOUS LINE DRAWING

π = Mona Lisa



Representation of Mona Lisa by $s \in \mathcal{S}_{\text{MRI}}$

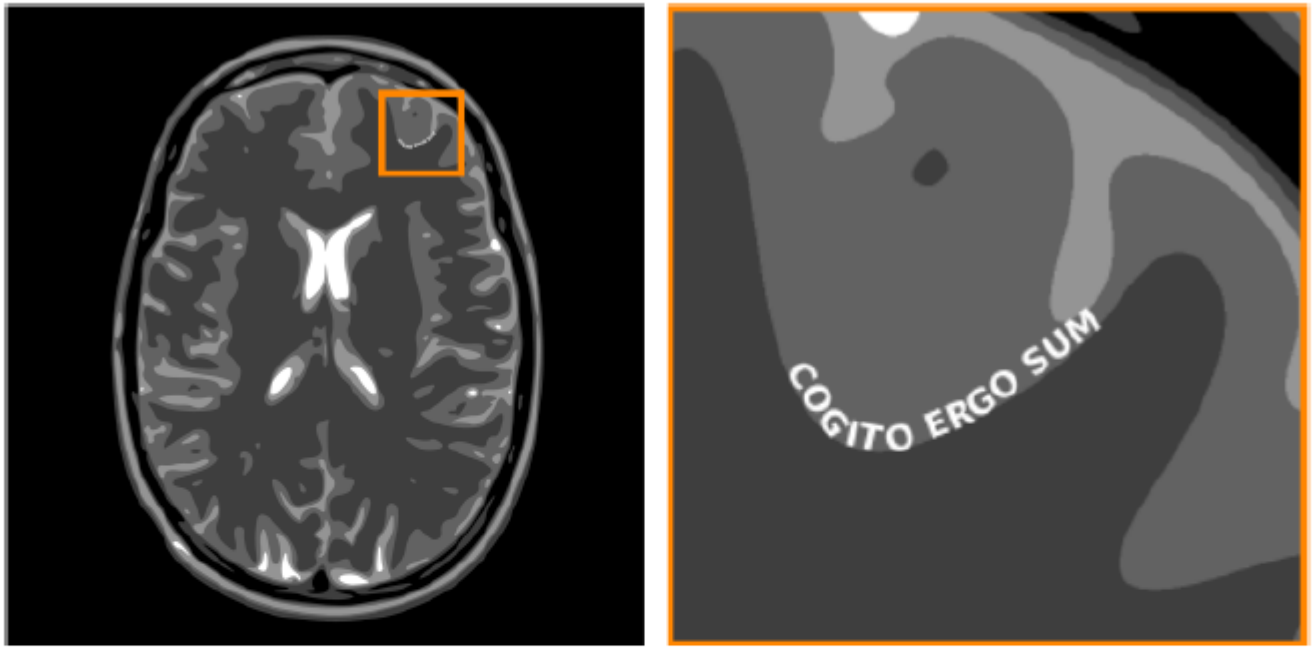


[Chauffert et al, Const Approx 2016]

Part IV: MRI Simulations Results

[Boyer et al, SIAM IS 2016]

VERY HIGH RESOLUTION IMAGING: SIMULATION SETUP

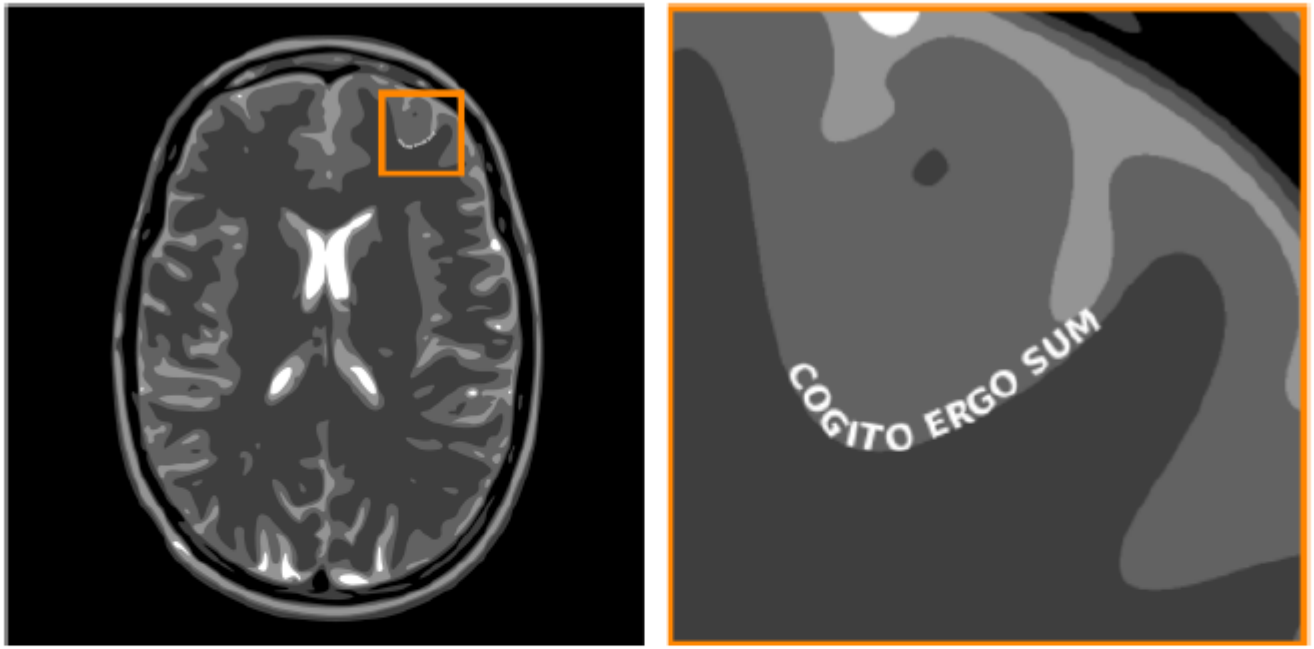


Parameters:

Image size: $n = 2048 \times 2048$ (100 μm isotropic). $m = 0.048n$ decomposed in:

- 196 radial lines of 1, 024 equispaced samples
- 8 rotated versions of the same spiral made up by 25,000 samples
- 8 curves of 25,000 samples each

VERY HIGH RESOLUTION IMAGING: SIMULATION SETUP



MRI hardware constraints:

- $G_{max} = 40\,\mathrm{mT.m^{-1}}$ and $S_{max} = 150\,\mathrm{mT.m^{-1}.ms^{-1}}$.
- For proton imaging, $\gamma = 42.57\,\mathrm{MHz.T^{-1}} \quad \Longrightarrow \quad \alpha = 1,703\,\mathrm{m^{-1}.ms^{-1}}$ and $\beta = 6,386\,\mathrm{m^{-1}.ms^{-2}}$.

VERY HIGH RESOLUTION IMAGING: COMPETING TRAJECTORIES (1/2)

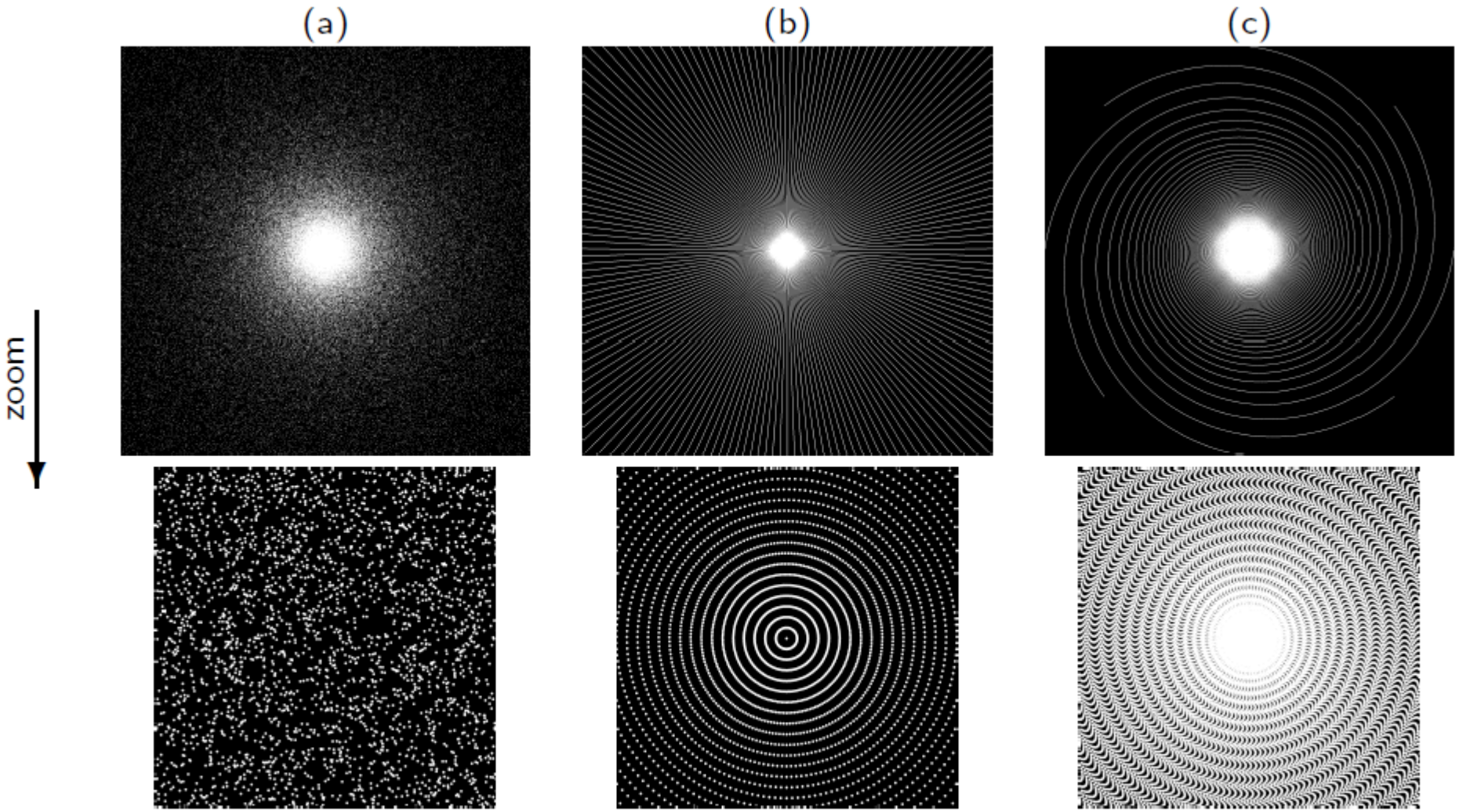


Figure : Standard sampling schemes composed of 200,000 samples. (a): i.i.d. drawings. (b): Radial lines; (c): 8 interleaved spirals.

VERY HIGH RESOLUTION IMAGING: COMPETING TRAJECTORIES (2/2)

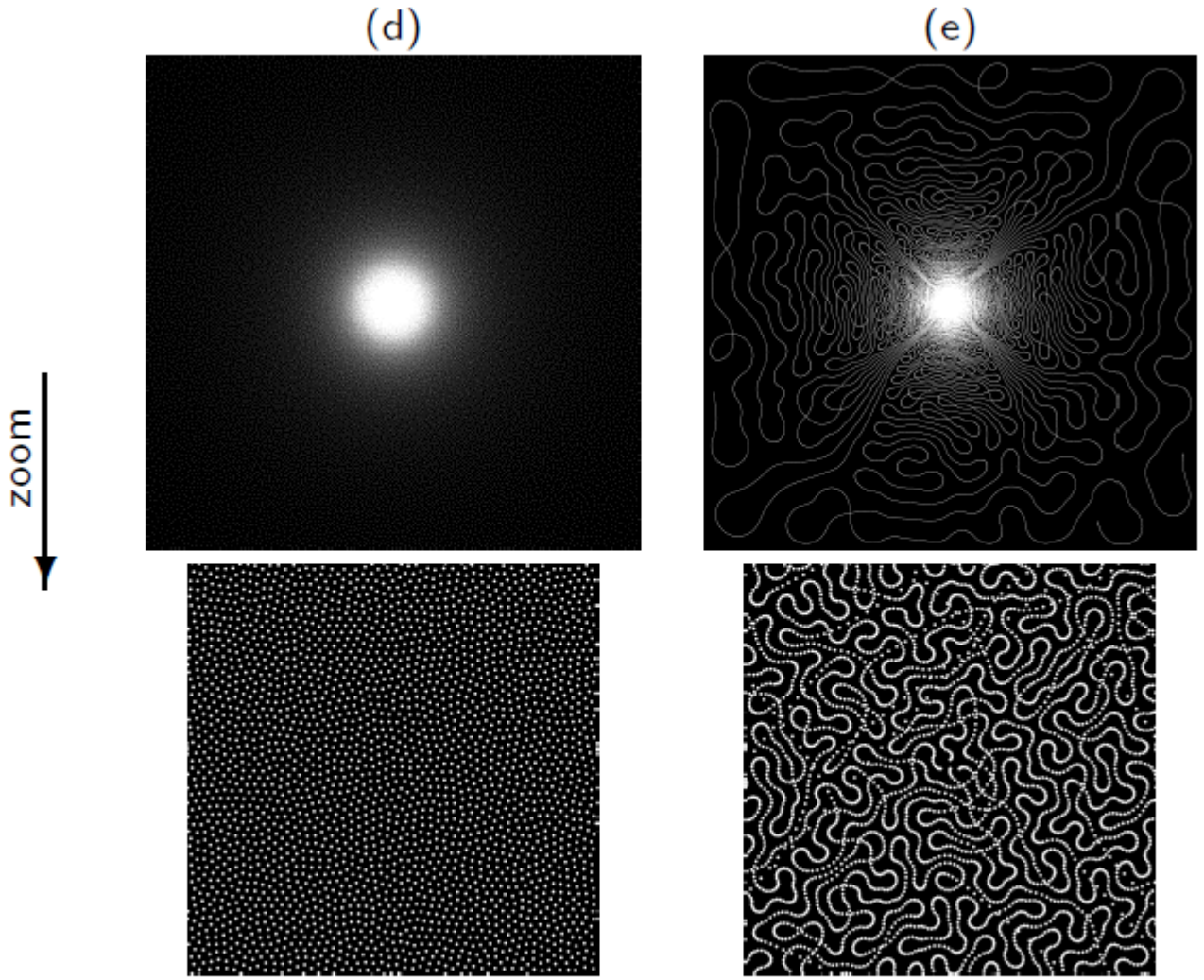
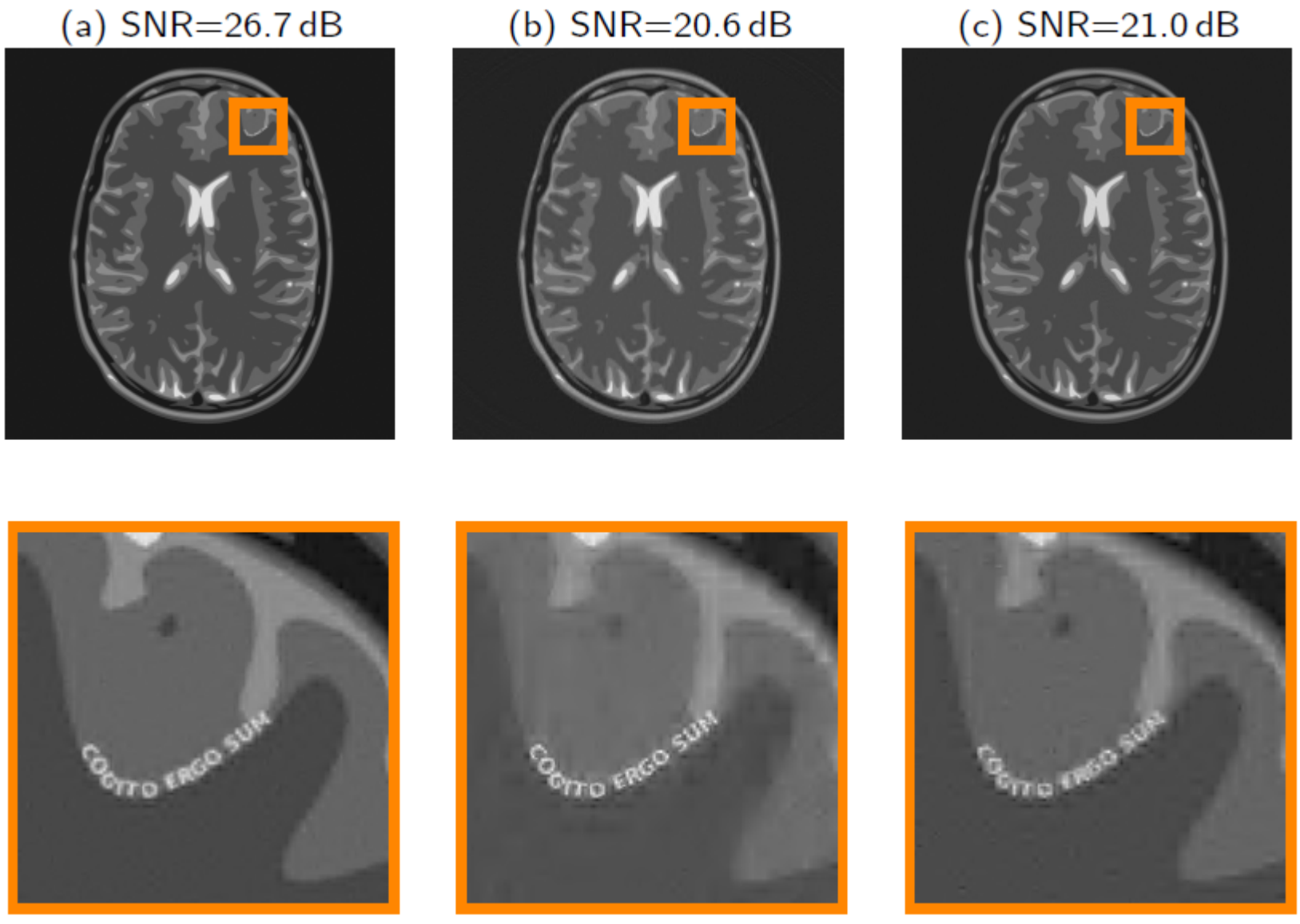


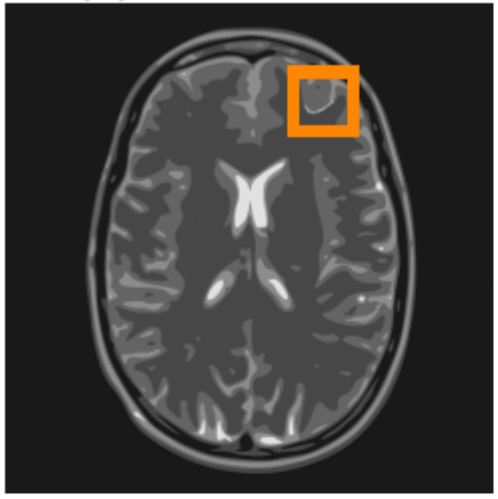
Figure : Sampling schemes yielded by our algorithm and composed of 200,000 samples. (d): isolated points with repulsion; (e): 8 feasible curves in MRI.

VERY HIGH RESOLUTION IMAGING CS RESULTS (1/2)

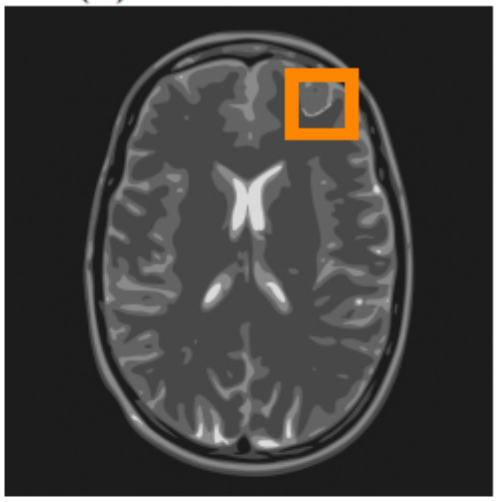


VERY HIGH RESOLUTION IMAGING CS RESULTS (2/2)

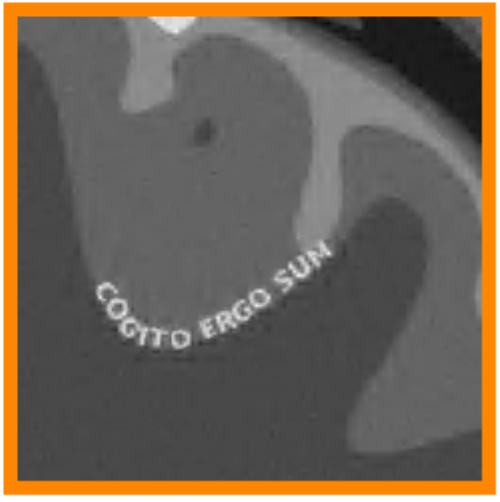
(d) SNR=27.0 dB



(e) SNR=23.5 dB



(*m*-points measure)



(admissible curve for MRI)

INTERIM SUMMARY

Higher undersampling factors achieved at higher resolution

- Up to 20-fold acceleration at 100 µm in-plane

Better image quality achieved using projection on measure sets

- Best results given by the projection on *m*-points measures
- Projection on admissible curves for MRI outperforms radial and spiral sampling schemes by 2-3 dB

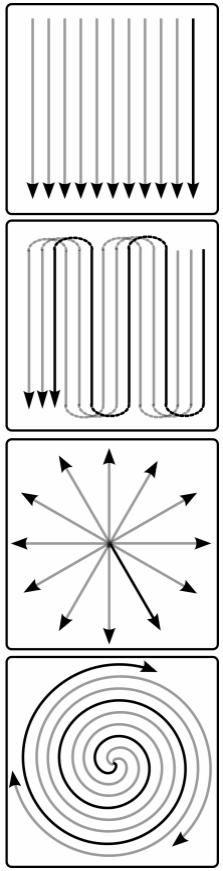
Part V: Retrospective & Prospective SPARKLING at 7T

SPARKLING: Segmented Projection Algorithm for Random K-space sampLING

[Lazarus et al, submitted to ISMRM'17 & to IEEE TMI]
[Lazarus et al, in prep. to MRM]

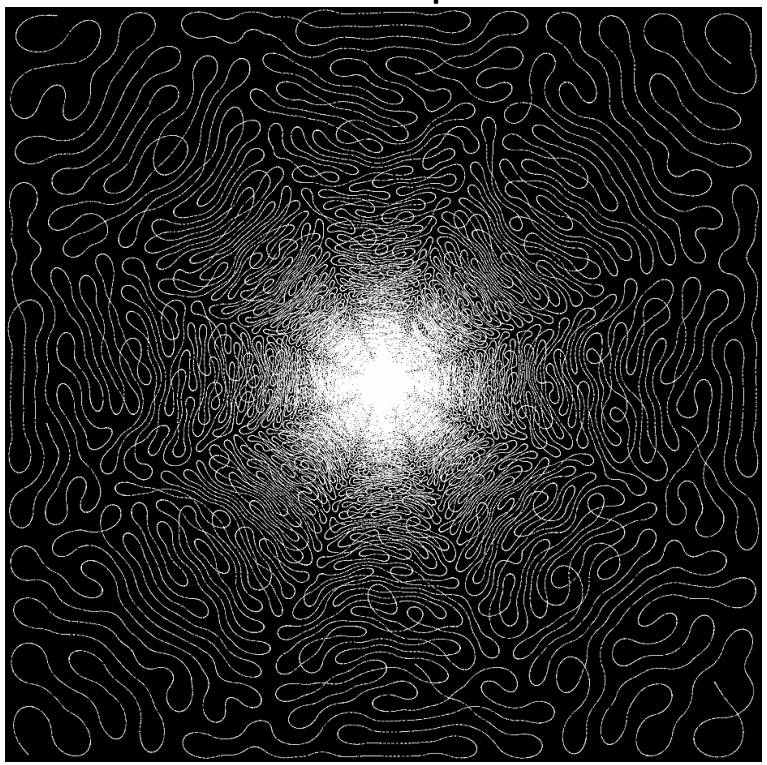
FROM MATHS TO MR PHYSICS

- **SPARKLING** outperforms classical sampling schemes (eg, radial, spiral) in simulations but in the real life?



VS.

Fourier space



+2-3 dB in SNR of reconstructed images!

Segment duration=200 ms
N = 2048
R = 20
8 segments

- Collect enough samples in one shot

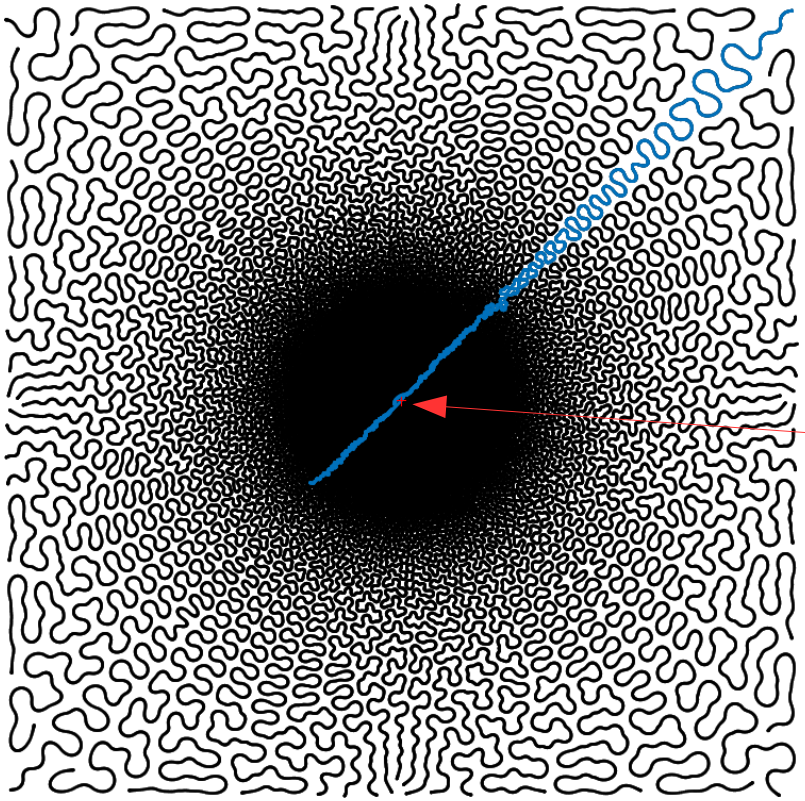
➔ **Too Long time of observation**

ADAPT TRAJECTORIES TO MR PHYSICS

1) Shorter observation time & optimized T2* contrast

- Shorter T_{obs} ≈ 35 ms
- Echo time adapted to contrast: TE ≈ 30 ms (directed trajectories)

K-space



N = 1024
R = 16

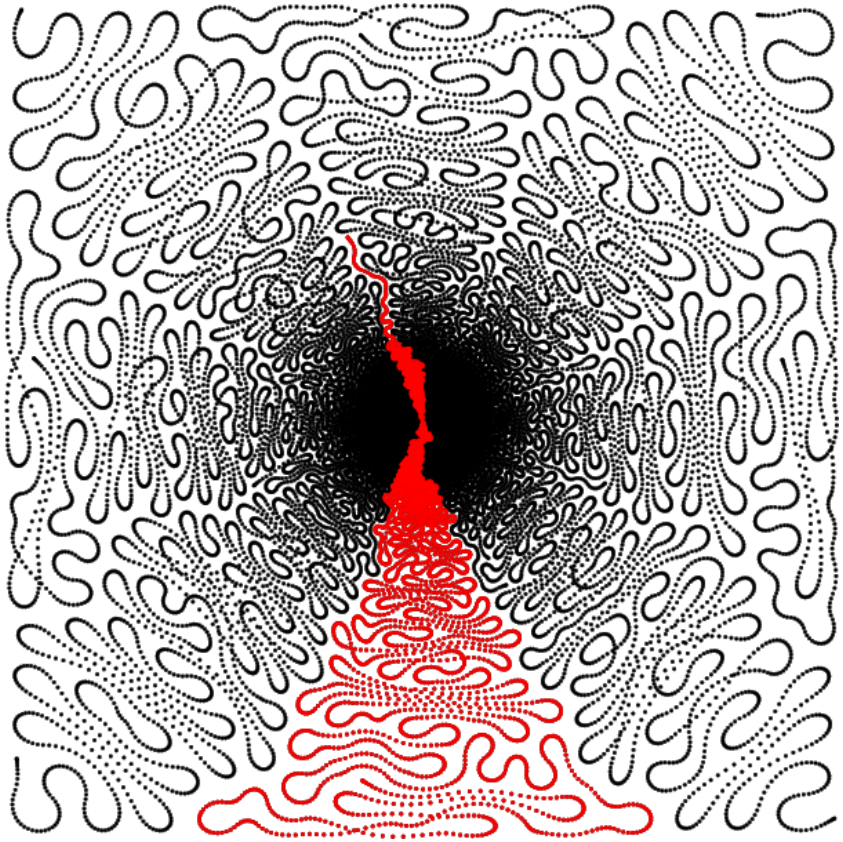
- 64 segments lasting 33.3 ms and collecting 1024 ADC samples each.
- Each segment (one is in blue) passes trough the k-space center at echo time TE=30 ms.
- Gmax = 40 mT/m
- Smax = 200 T/m/s

CHECK FOR CONSISTENCY OF TRAJECTORIES

2) Check for gradient errors

Goal: Estimate gradient errors on novel trajectories.

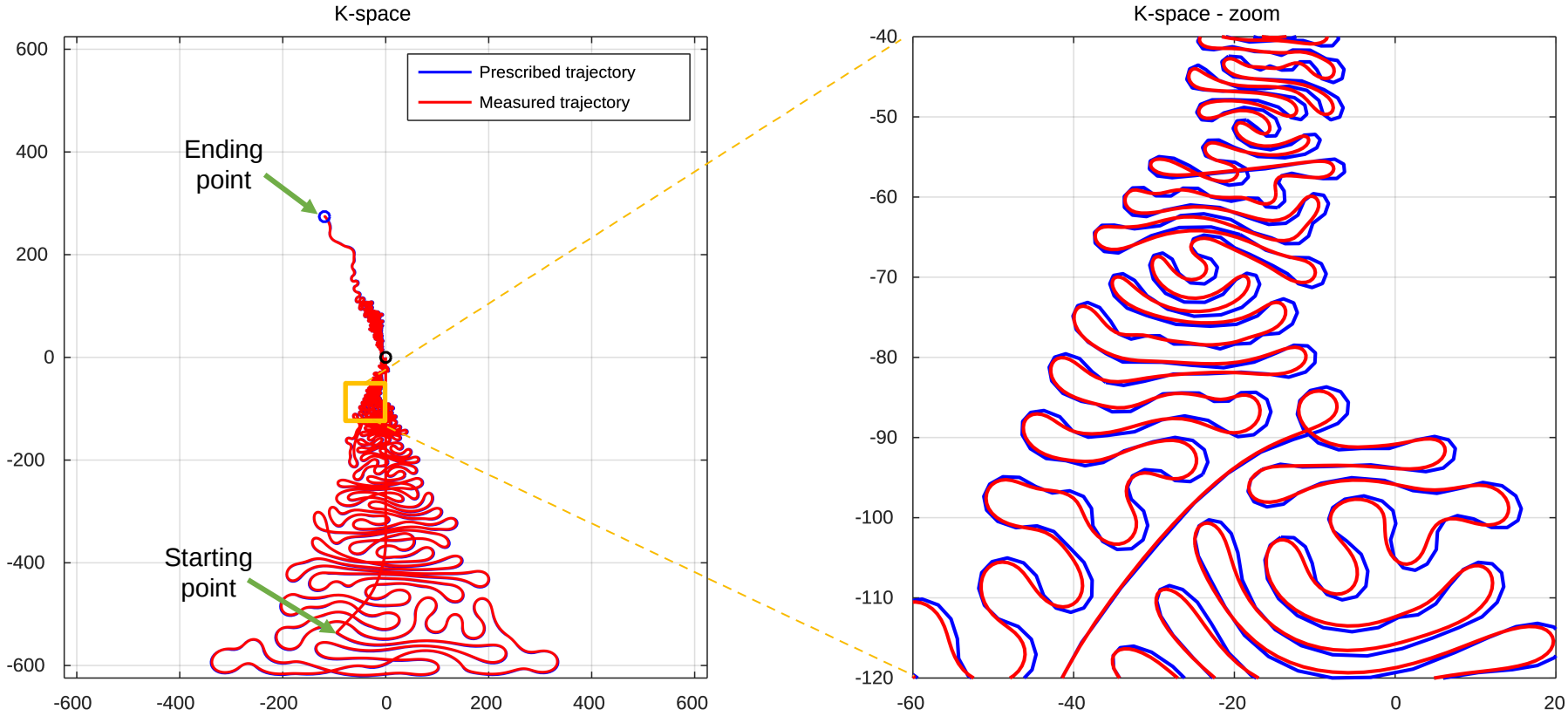
Methods: LPM (Local Phase Measurement) to measure actual gradients values



N = 256
R = 4

2) Check for gradient errors

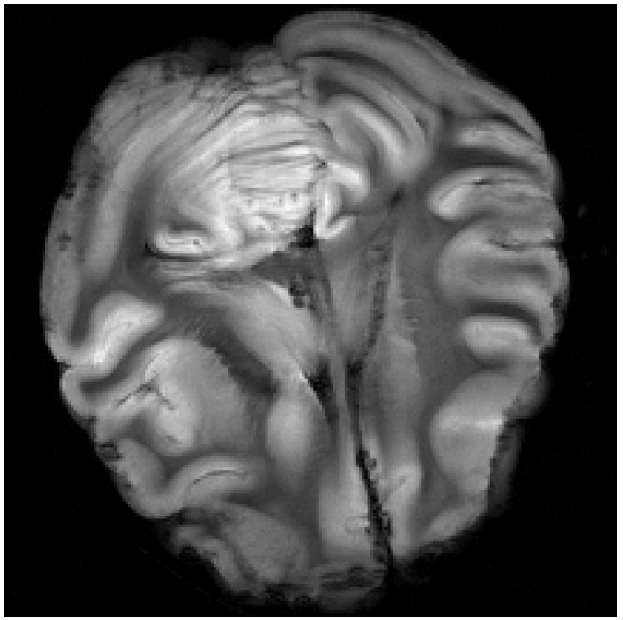
Results: The measured k-space locations are **very close** to the prescribed sampling scheme. Largest errors are observed in regions of high curvatures.



EXPERIMENTS

- *Ex-vivo* brain baboon in fluorinert solution

- **Sequence parameters**
  - 7T Siemens healthineers scanner
  - In vivo Corp Birdcage 1Tx/1Rx coil
  - T2* weigthing
  - Slice thickness: 3 mm
  - TR = 60 ms
  - TE = 30 ms
  - α = 25°
  - Axial slice

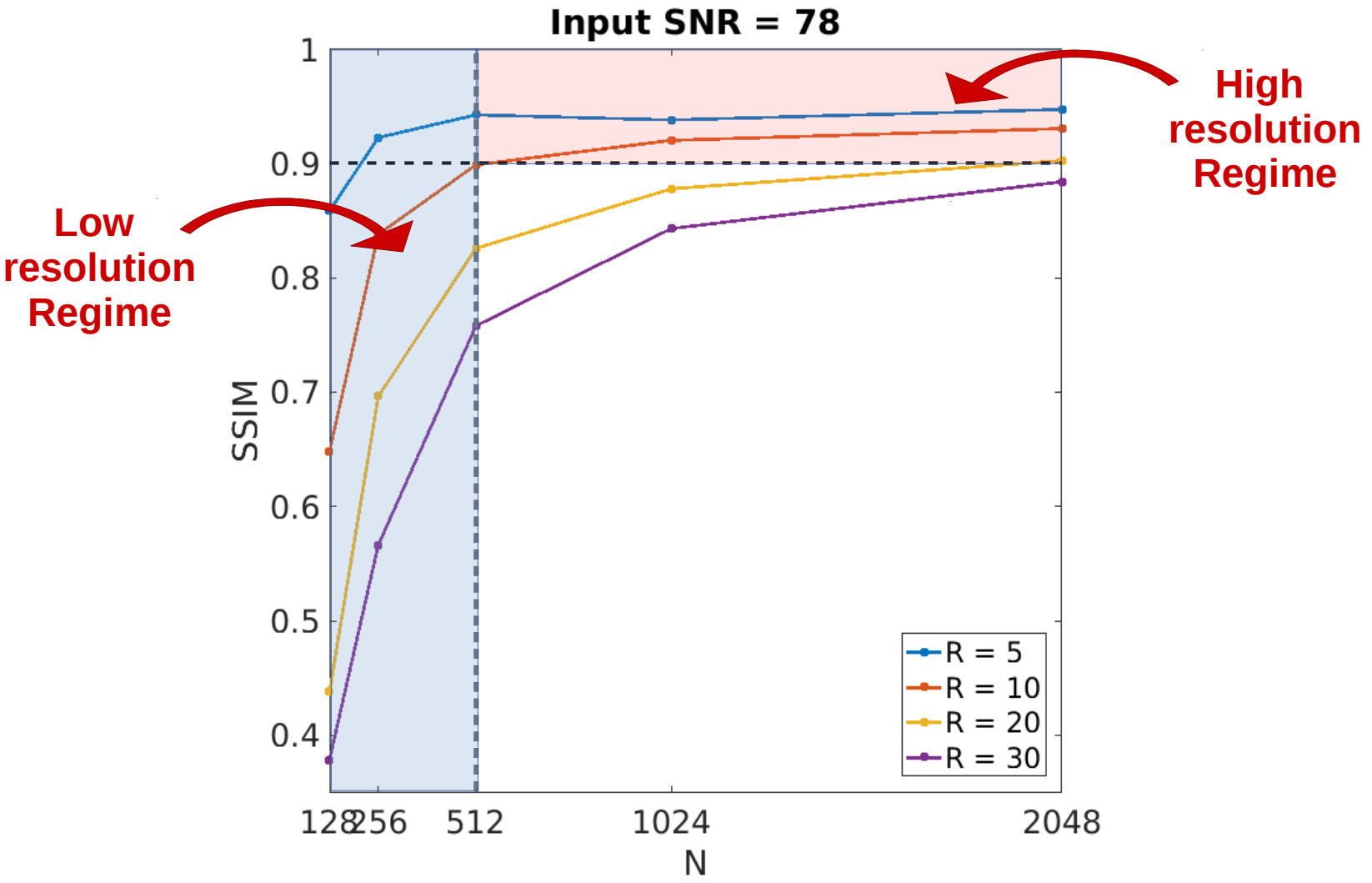


Full Cartesian acquisition at N=512 and N=1024

- Signal averaging to increase *input SNR*

- Retrospective undersampling with the same samples as for simulated images

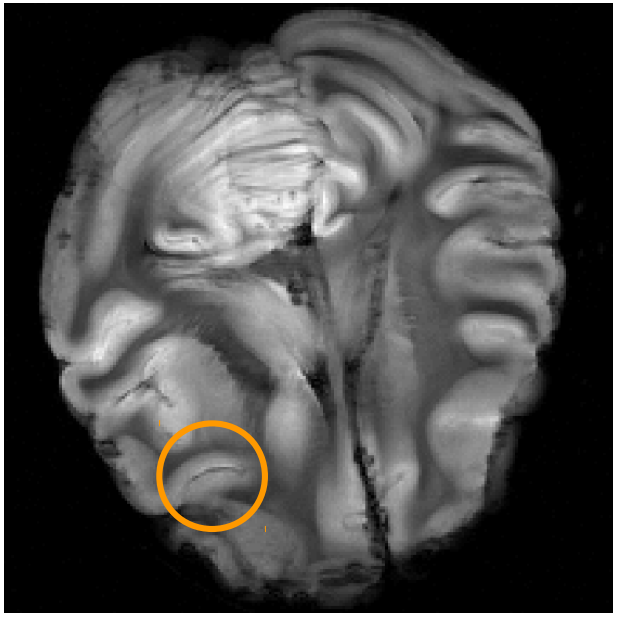
RESOLUTION DEPENDENCE



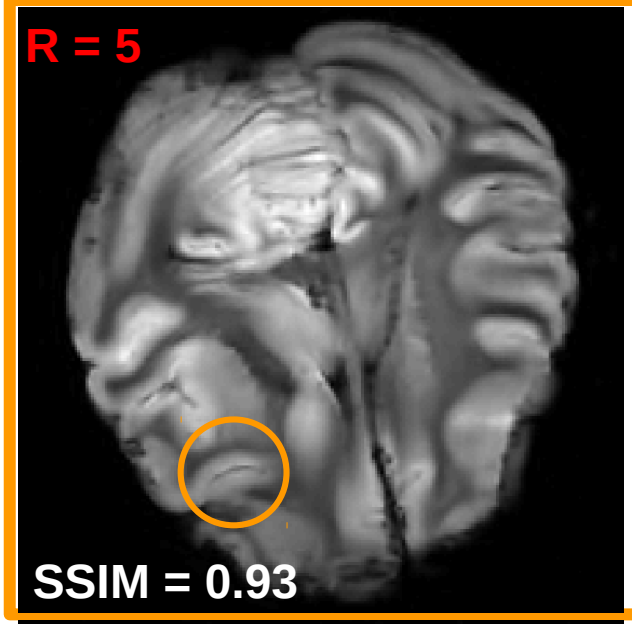
RESOLUTION DEPENDENCE: RETROSPECTIVE EXPERIMENTS

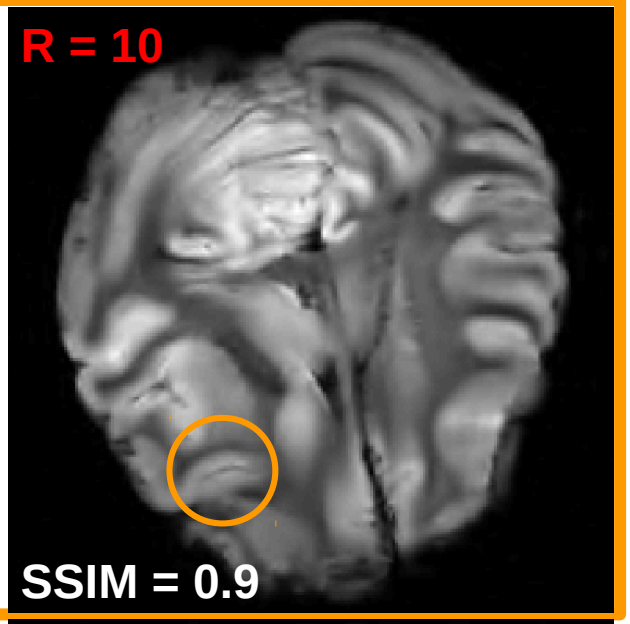
N = 512

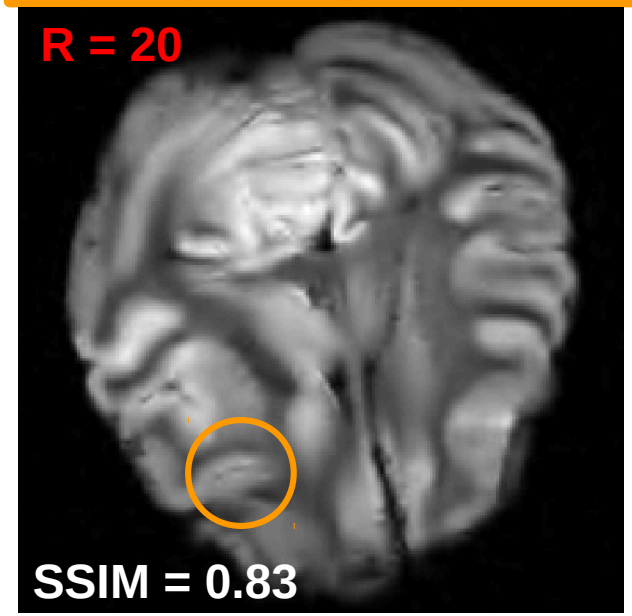
Input SNR = 78

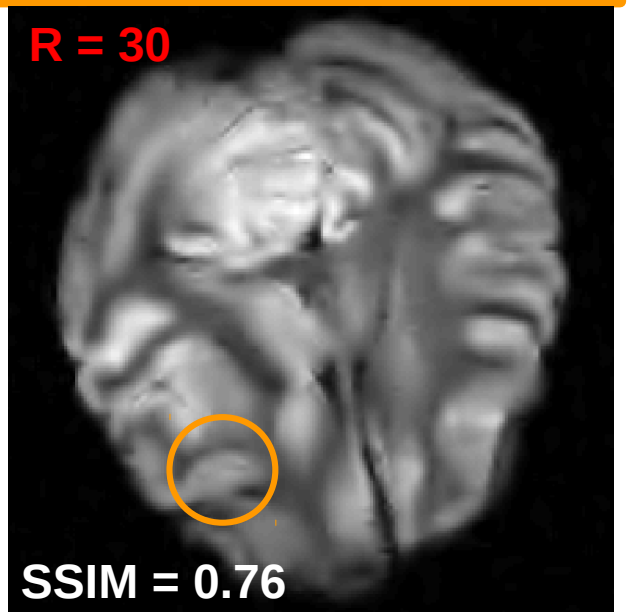


Reference





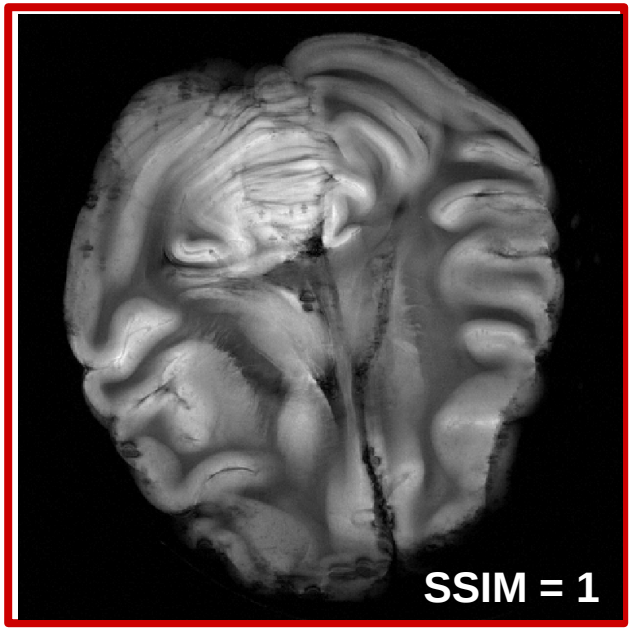




RETROSPECTIVE CS RESULTS – N = 1024

Full Cartesian sampling
TA = 1 min 04s/NEX

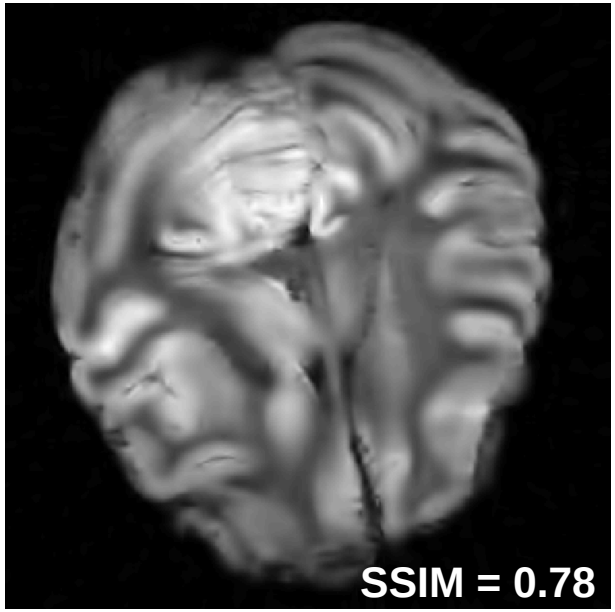
Reference (NEX=10)



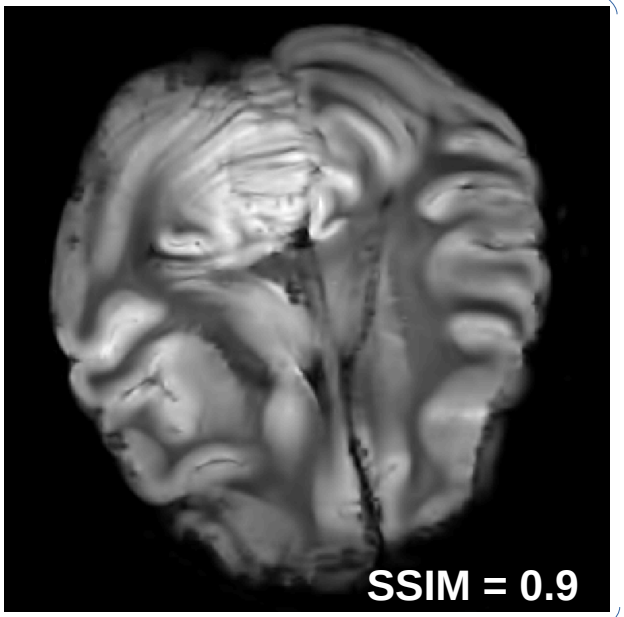
FFT

16-fold acceleration
Virtual TA = 3.8s/NEX

Radial GA



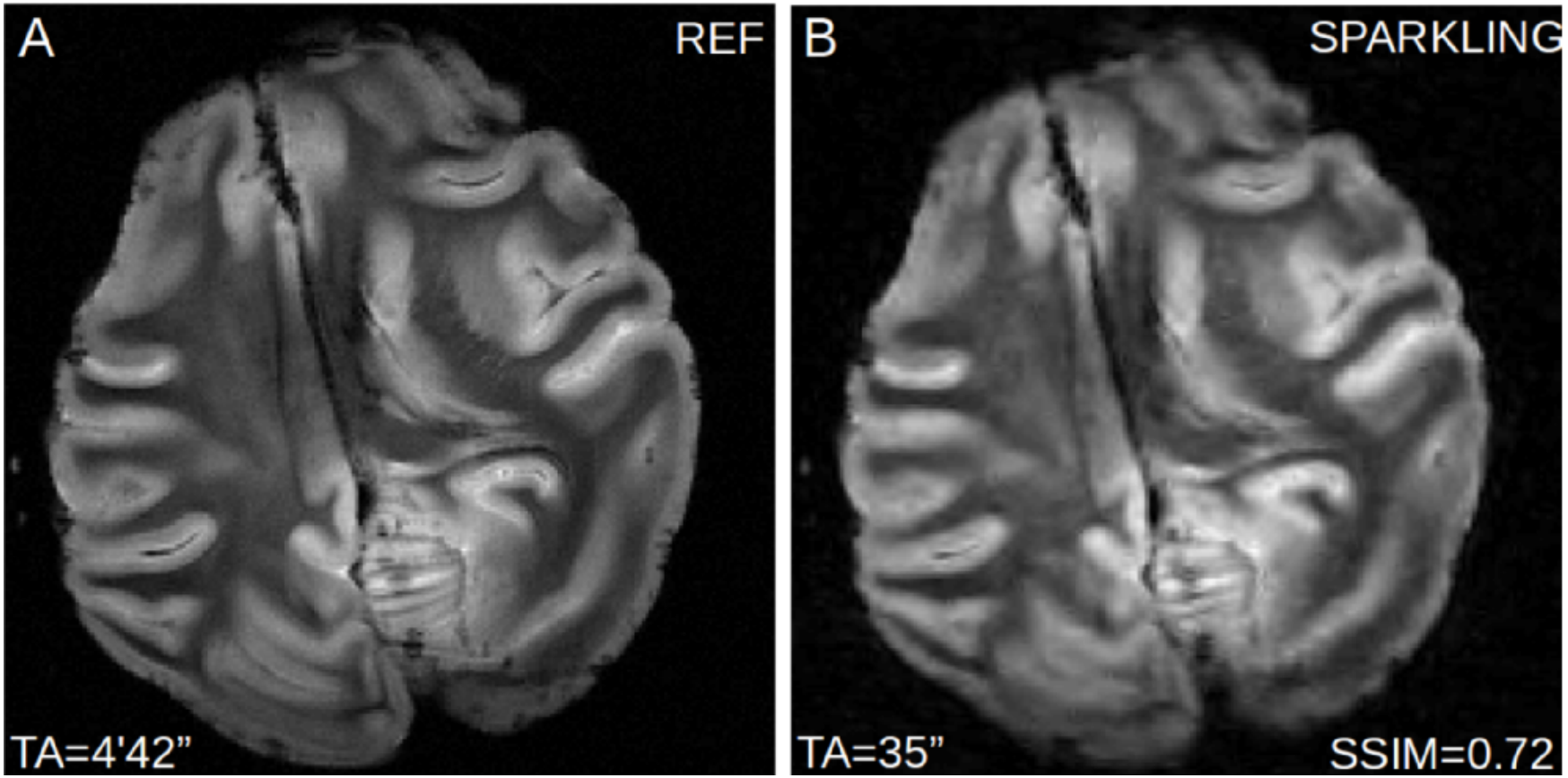
SPARKLING



FISTA reconstructions (Rice wavelets)
$\lambda = 10^{-4}$

PROSPECTIVE CS RESULTS – N = 512

Full Cartesian sampling | **8-fold acceleration**



CONCLUSIONS

- **Retrospective CS results:**
  - SPARKLING trajectories outperform Golden Angle radial ones on real data at 7 Tesla
  - Are consistent with synthetic simulations: **16-fold** acceleration
  - Confirm the dependence of the acceleration factor on the pixel size (or image resolution defined by k_{max})

- **Prospective CS results**
  - Our CS-GRE T2*-weighted sequence works!
  - Lower acceleration achieved so far (8-fold) as compared to retrospective CS
  - Gradient imperfections and B_0 inhomogeneities must be accounted for.

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IMT, U. Toulouse

Jonas Kahn
CNRS/IMT

DE LA RECHERCHE À L'INDUSTRIE

cea

Thanks for your attention!

Any questions?