New Physically Plausible Compressive Sampling Schemes for high resolution MRI

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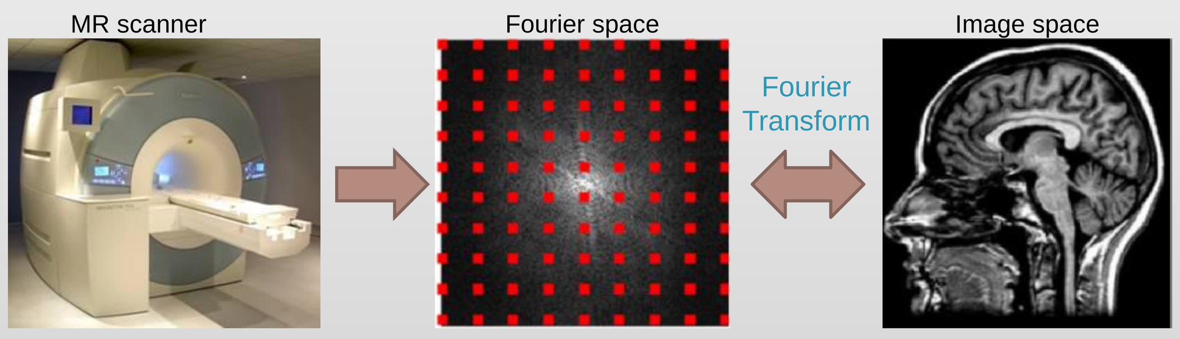
ABSTRACT

Magnetic resonance imaging (MRI) is a medical imaging technique used in radiology to image the anatomy and function of the body in both health and disease. MR image resolution improvement in a standard scanning time (e.g., 200µm isotropic in 15 min) would allow neuroscientists and doctors to push the limits of their current knowledge and to significantly improve both their diagnosis and patients' follow-up. This could be achieved thanks to the recent Compressed Sensing (CS) theory, which has revolutionized the way of acquiring data by overcoming the Shannon-Nyquist criterion. This breakthrough has been achieved by combining three key ingredients: (i) *variable density sampling*, (ii) image representation using sparse decompositions (e.g., wavelets) and (iii) nonlinear image reconstruction. Using CS, data can be massively under-sampled by a given acceleration factor "*R*" while ensuring conditions for optimal image recovery. In this work, we use an in-house algorithm [Boyer et al, 2016, Chauffert et al, 2016,17] to design novel physically plausible sampling schemes adapted to CS-MRI in order to fasten MR acquisitions. The MR images reconstructed from data (i.e. Fourier samples) collected over the proposed *k*-space trajectories have a significantly higher SNR (2-3 dB) than those reconstructed from data collected over more standard sampling patterns (e.g. radial, spiral) for a given reconstruction. Likewise, on real data collected on a 7T SIEMENS Magnetom scanner at NeuroSpin, recent reconstructions from highly undersampled data that was acquired with an adapted GRE T2* weighted sequence showed promising results on ex-vivo brain baboon. These results proved that our methods are practically feasible for very high resolution MRI with unprecedented acceleration factors.

MATERIALS AND METHODS

Sampling in MRI



In MRI, data is collected in the *Fourier space*, i.e. the 2D Fourier transform of the image. Usually, data points (represented by the red points) are located on a Cartesian grid of a chosen size .

Displacement in the Fourier space is performed via magnetic field gradients. At time t, the k-space position $s(t)$ and gradient waveform $G(t)$ are related (γ is the gyromagnetic ratio):

$$s(t) = s(0) + \int_0^t G(\tau)d\tau$$

Hardware constraints in MRI

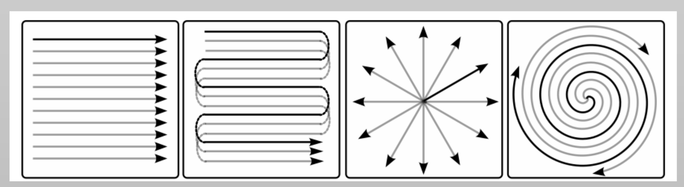
The constraints on G read:

$\|G(t)\| \leq G_{max}$, $\|\dot{G}(t)\| \leq S_{max}$

On NeuroSpin 7T MR scanner:

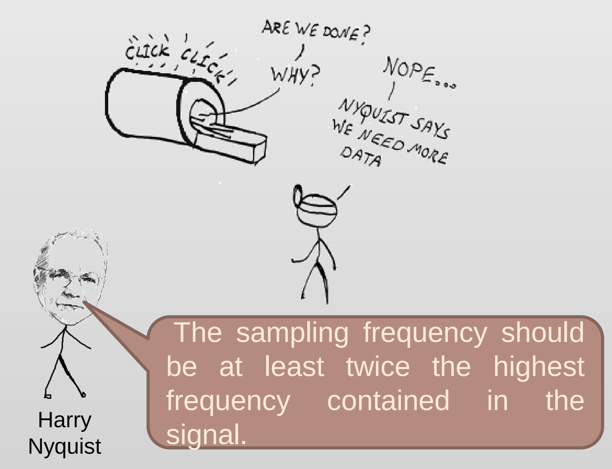
- $G < G_{max} \approx 50\, mT.m^{-1}$
- $\dot{G} < S_{max} \approx 333\, T.m^{-1}.s^{-1}$

> *How to design an optimal and feasible sampling scheme?*



Examples of classical MR sampling schemes [Lustig et al, 2008]

MRI is slow…



How can MRI exams be fastened?

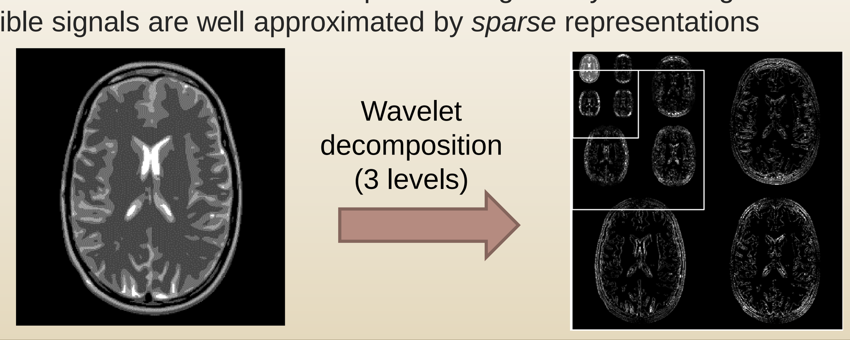
A solution is to reduce the acquisition time by collecting less data than prescribed by the Nyquist criterion. This is called « undersampling ». Compressed Sensing theory allows to do this.

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

Compressed Sensing in MRI: a 3-ingredient recipe

1. MR images are compressible:

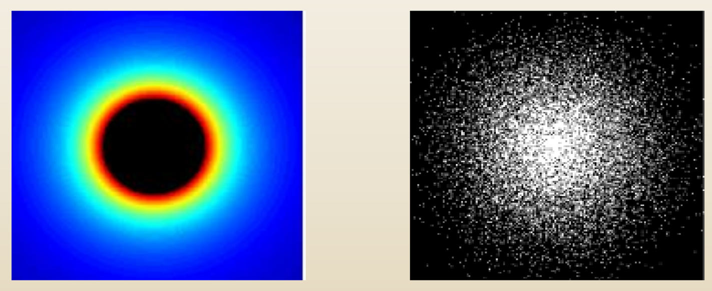
- There exists a basis where their decomposition is given by a few large coefficients
- Compressible signals are well approximated by *sparse* representations



✓ Wavelet Represensation of MR brain image is sparse!

2. Random Variable Density Sampling (VDS)

- Sample more frequently the low frequencies (center of Fourier space)



3. Non-linear reconstruction

$$\underset{z}{minimize}\ \underbrace{\|Az - y\|_2^2}_{\text{Data consistency}} + \overbrace{\lambda\|z\|_1}^{\text{Enforces sparsity}}$$

- Iterative algorithms (e.g. FISTA)

F : NFFT
ψ : sparsifying transform
$A = F\psi^{-1}$
y : acquired data
x : image
$z = \psi x$: sparse representation of x
λ : regularization parameter

The general construction (discretized version)

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

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

υ : searched admissible measure
π : target measure
h : kernel
P : set of admissible parametrizations
N_p : set of measure points
Q_p : parametrization set

- Specific projection algorithm: $P_{\mathcal{Q}_p}$ [Chauffert et al, 2016]
- Gradient computation by fast summation using the NFFT library [Potts and Steidl, 2003]

Design of feasible gradient waveforms

Projection on a target density on a measures set of admissible curves for MRI

✓ Target probability density
✓ Gradient constraints
✓ Coverage speed

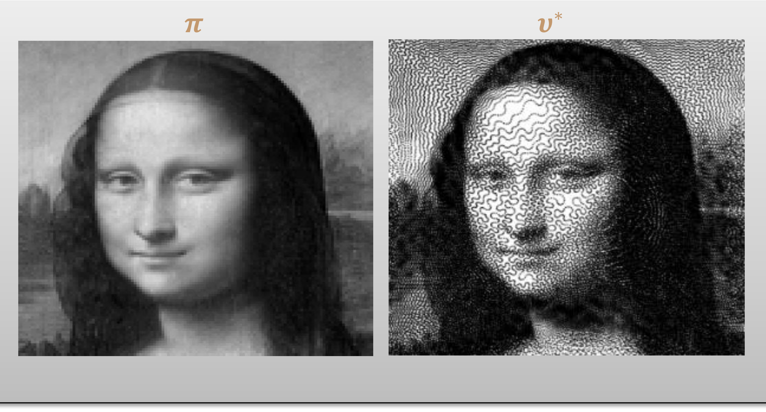


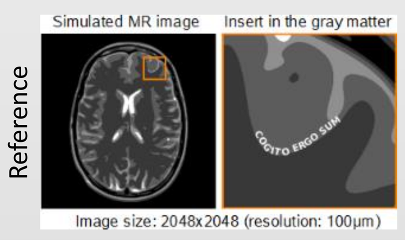
Illustration: Approximating Mona Lisa by a spaghetti i.e. by projecting onto the set $\mathcal{S}_{MRI}$ ($p = 100{,}000$) after 10,000 iterations

[Chauffert et al, 2017]

RESULTS

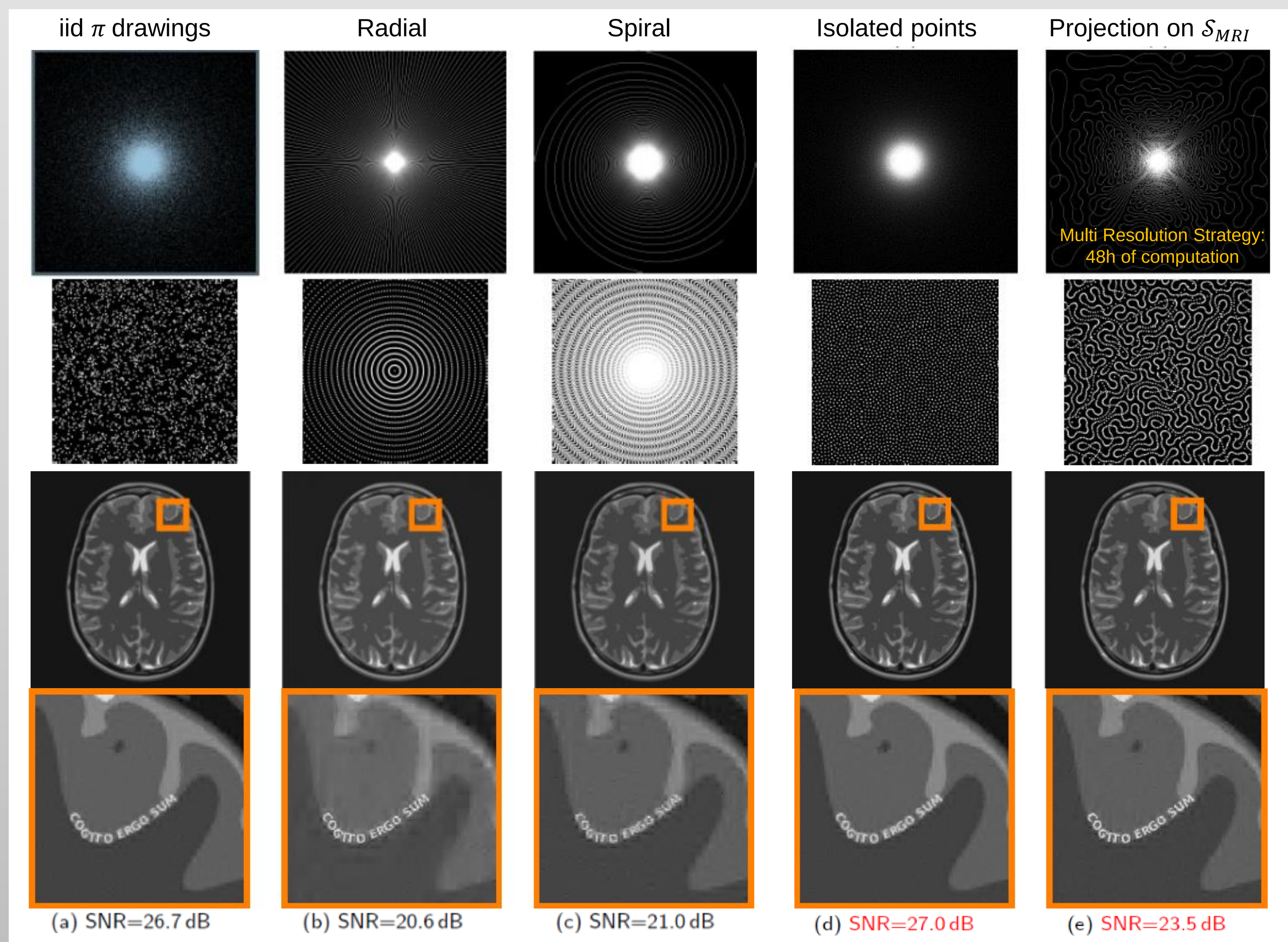
From simulations… Application to Design of *k*-space Trajectory

[Boyer et al, 2016]



$n = 2048 \times 2048$, G_{max}=40 mT.m⁻¹, S_{max} = 150 T.m⁻¹.s⁻¹
Only **4.8% of full k-space** data were sampled ($m = 200{,}000$).
For projection, we used $p = 25{,}000$ points/curve ($T = 200$ms) and 8 segments.

- 20-fold acceleration compared to whole Fourier space acquisition

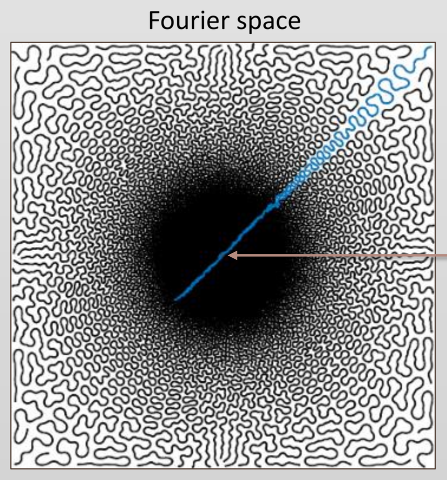


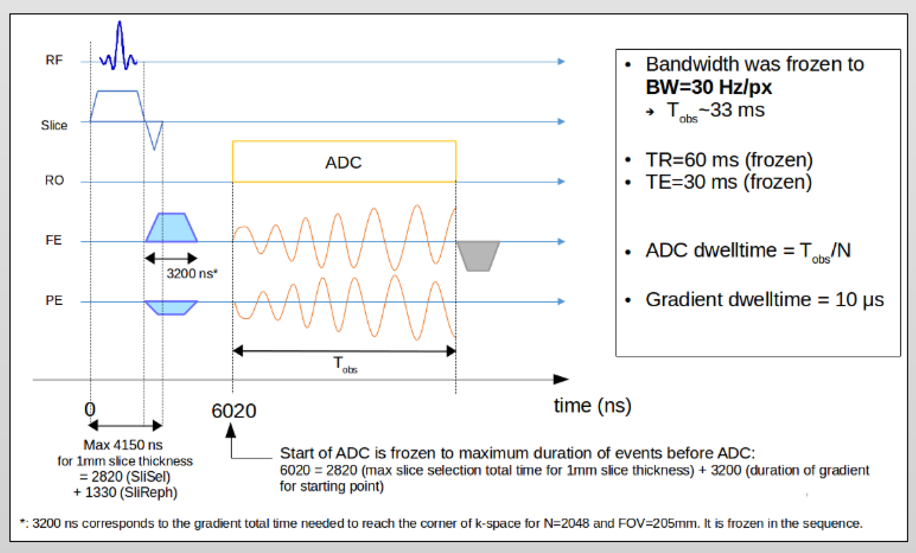
- Projection on measures brought by curves in $\mathcal{S}_{MRI}$ outperforms radial and spiral imaging by 2 to 3 dB

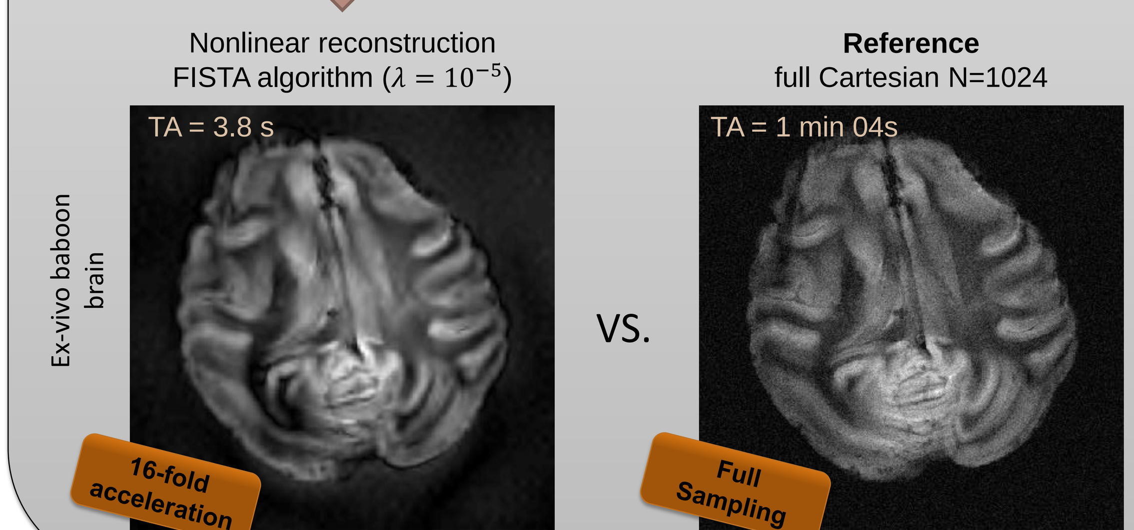
… To MRI acquisitions *CSGRE*: an accelerated sequence for T2* weigthed imaging

- 2D-acquisitions performed on 7T SIEMENS MAGNETOM MR scanner with an adapted T2* weighted sequence « **CSGRE** » - for Compressed Sensing with Gradient Recalled Echo (GRE) - with a single-channel receiver coil (InVivo corps).
- Very high in plane resolution : 0.2 x 0.2 x 3 mm^3 – Matrix size: 1024x1024 – FOV = 205 mm²
- 16-fold accelerated trajectory composed of 64 segments of 1024 ADC samples each.

[Lazarus et al, 2017]







Future work

- Use a multi-channel receiver coil to increase the SNR
- Improve reconstruction (penaltiy terms, curvelets, primal-dual or MM optimization algorithm)
- Account for gradient errors in reconstructions by characterizing the gradient system (GIRFs, LPM,…)
- 3D imaging & fMRI

CONCLUSION

In this work, we have proposed an original approach to design efficient *k*-space sampling trajectories complying with the hardware constraints of MRI gradient systems. On the reconstructed images we have shown significant improvements in terms of image quality (pSNR) in very high resolution anatomical imaging, which is relevant for in-vivo exams at ultra-high magnetic field (≥ 7 Tesla). MR acquisitions performed on 7T MR scanner showed that our sequence ***CSGRE*** allows to traverse new complex undersampled sampling schemes whose data can then be used to reconstruct high resolution T2* weighted images. Acquisitions for a very high target in-plane resolution of 0.2 mm showed that very large acceleration factors (up to 16-fold) are practically achievable using our method.

REFERENCES

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