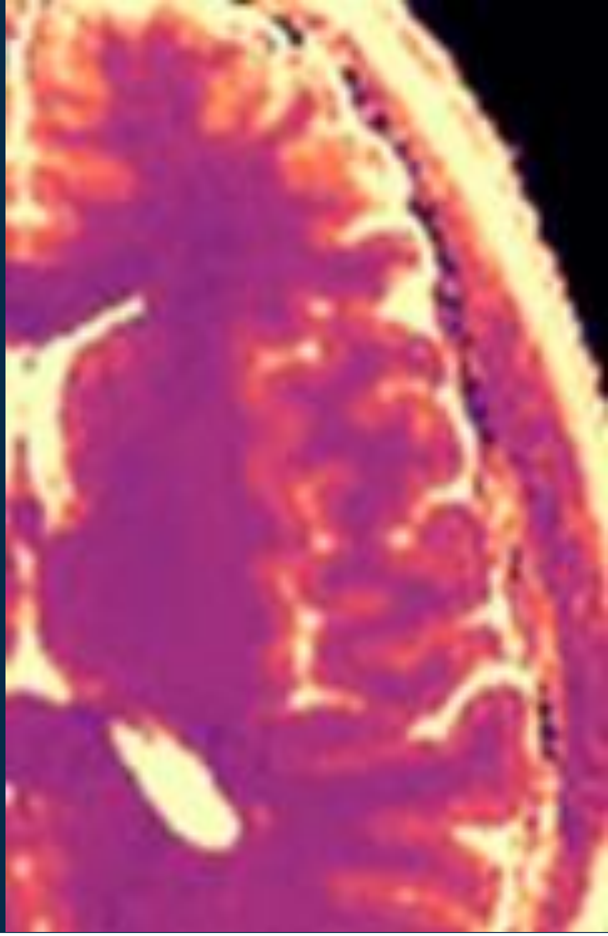
Deep inverse problems – a novel approach to MRI image reconstruction



Matteo Cencini – INFN

Overview

1. Background: a short introduction on MRI
2. AI-based MR image reconstruction
3. DeepMR framework

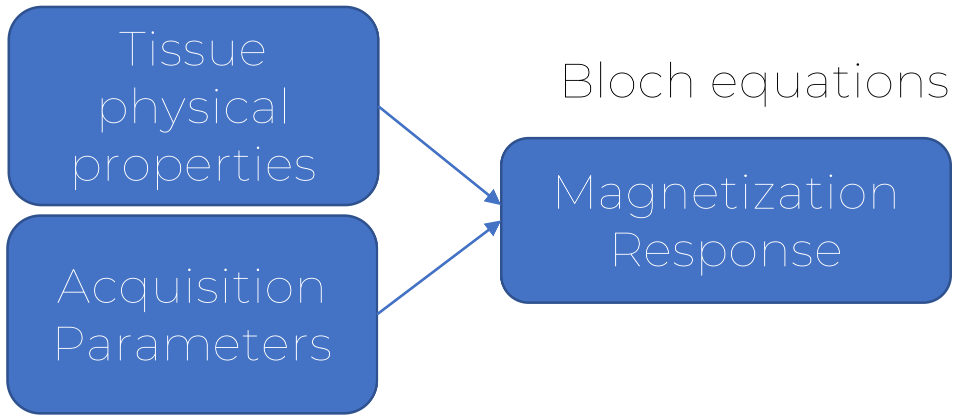
Magnetic Resonance Imaging

Magnetic Resonance Imaging

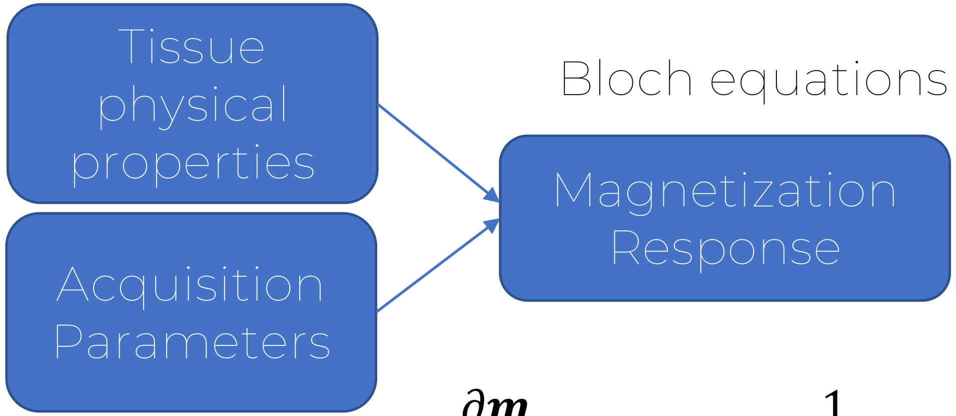
Versatile imaging technique based on the interaction of nuclear spins within the human body with magnetic fields

- ✓ Excellent soft tissue contrast
- ✓ It is non invasive! (non-ionizing radiation)
- – Relatively slow due to the characteristics of MR signal encoding

Magnetic Resonance Imaging



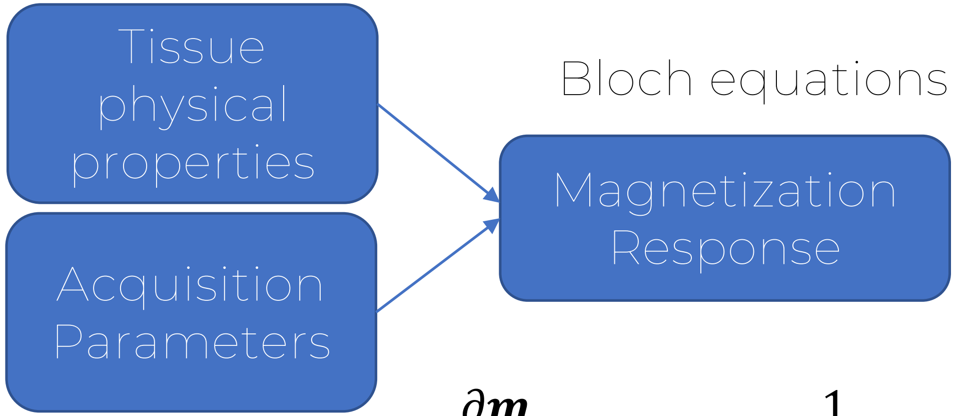
Magnetic Resonance Imaging



$$\frac{\partial \boldsymbol{m}}{\partial t} = \gamma \boldsymbol{m} \times \boldsymbol{B} + \frac{1}{T_1}(m_0 - m_z)\hat{z} + \frac{1}{T_2}\boldsymbol{m}_\perp$$

Contrast encoding

Magnetic Resonance Imaging



$$\frac{\partial \boldsymbol{m}}{\partial t} = \gamma \boldsymbol{m} \times \boldsymbol{B} + \frac{1}{T_1}(m_0 - m_z)\hat{z} + \frac{1}{T_2}\boldsymbol{m}_{\perp}$$ Contrast encoding

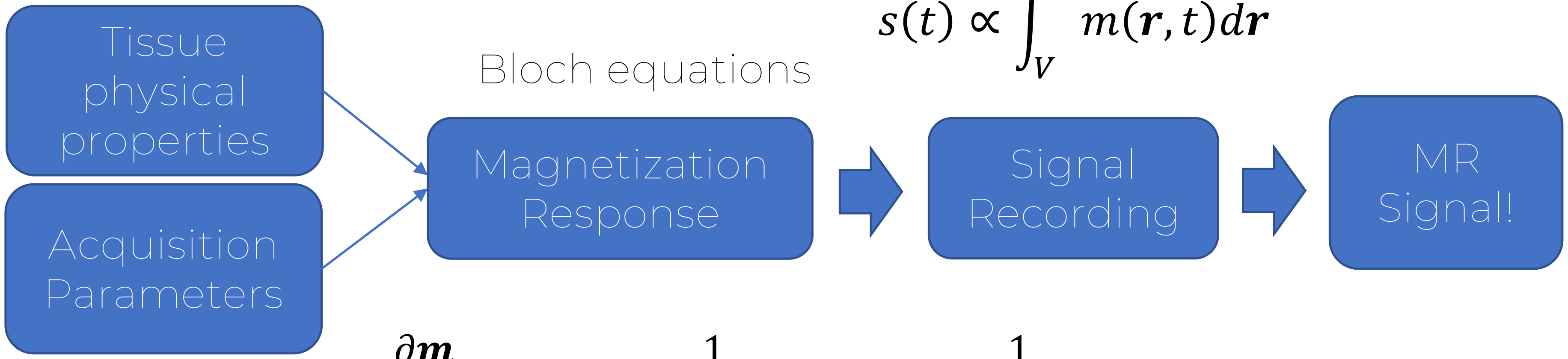
$$\boldsymbol{B}(r) = B_0\, \hat{z} + \boldsymbol{G}(t) \cdot \boldsymbol{r}$$ Spatial encoding

Magnetic Resonance Imaging

Faraday's law

$$s(t) \propto \int_V m(\boldsymbol{r}, t) d\boldsymbol{r}$$

Bloch equations



$$\frac{\partial \boldsymbol{m}}{\partial t} = \gamma \boldsymbol{m} \times \boldsymbol{B} + \frac{1}{T_1}(m_0 - m_z)\hat{z} + \frac{1}{T_2}\boldsymbol{m}_\perp$$ Contrast encoding

$$\boldsymbol{B}(r) = B_0\, \hat{z} + \boldsymbol{G}(t) \cdot \boldsymbol{r}$$ Spatial encoding

Magnetic Resonance Imaging

Faraday's law

$$s(t) \propto \int_V m(\boldsymbol{r}, t) d\boldsymbol{r}$$

Bloch equations

Tissue physical properties

Acquisition Parameters

Magnetization Response

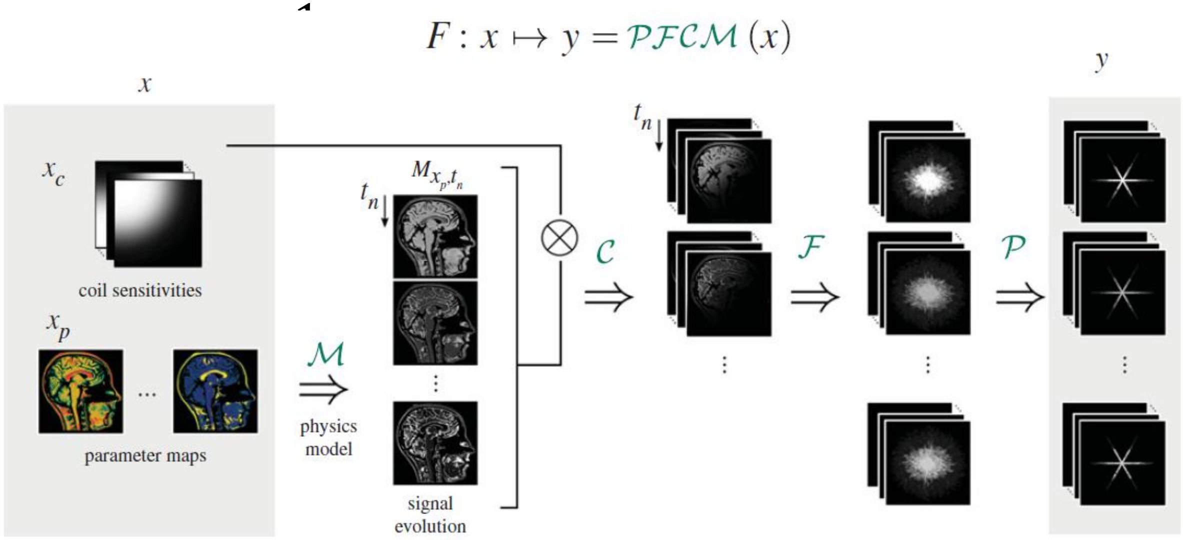
Signal Recording

MR Signal!

$$\frac{\partial \boldsymbol{m}}{\partial t} = \gamma \boldsymbol{m} \times \boldsymbol{B} + \frac{1}{T_1}($$

$$\boldsymbol{B}(r) = B_0\, \hat{z} + \boldsymbol{G}(t) \cdot$$

Signal Encoding $y = PFCM(x) + n$



n = noise

Wang, X., Tan, Z., Scholand, N., Roeloffs, V., & Uecker, M. (2021). Physics-based reconstruction methods for magnetic resonance imaging. Philosophical Transactions of the Royal Society A, 379(2200), 20200196.

Magnetic Resonance Imaging

Faraday's law

$$s(t) \propto \int_V m(\boldsymbol{r}, t) d\boldsymbol{r}$$

Bloch equations

Tissue physical properties → Magnetization Response

Acquisition Parameters → Magnetization Response

Magnetization Response → Signal Recording → MR Signal!

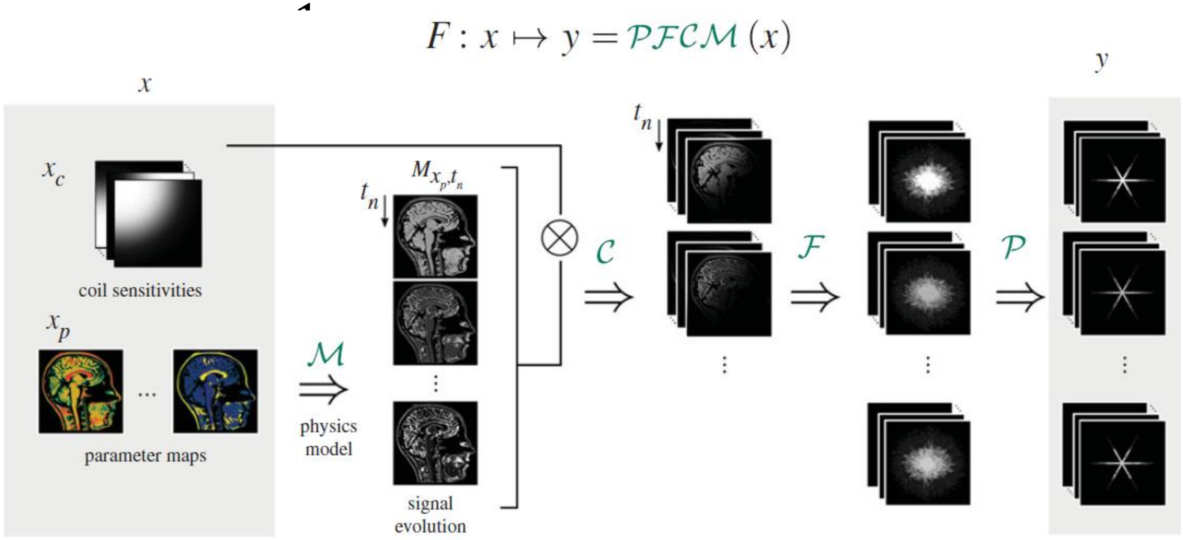
$$\frac{\partial \boldsymbol{m}}{\partial t} = \gamma \boldsymbol{m} \times \boldsymbol{B} + \frac{1}{T_1}($$

$$\boldsymbol{B}(r) = B_0\, \hat{z} + \boldsymbol{G}(t) \cdot$$

Signal Encoding

$$y = PFCM(x) + n$$

$$y = PFCx' + n$$



n = noise

Problem formulation

Direct inversion

Encoding operator

$$\hat{x} = F^H(y)$$

Reconstructed image

Acquired data

Problem formulation

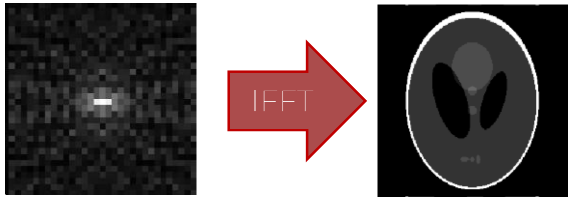
Direct inversion

Encoding operator

$$\hat{x} = F^H(y)$$

Reconstructed image

Acquired data



Problem formulation

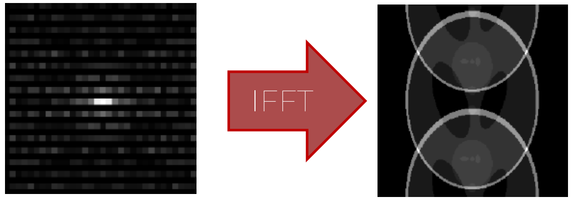
Direct inversion

Encoding operator

$$\hat{x} = F^{H}(y)$$

Reconstructed image

Acquired data



Wang, X., Tan, Z., Scholand, N., Roeloffs, V., & Uecker, M. (2021). Physics-based reconstruction methods for magnetic resonance imaging. Philosophical Transactions of the Royal Society A, 379(2200), 20200196.

Problem formulation

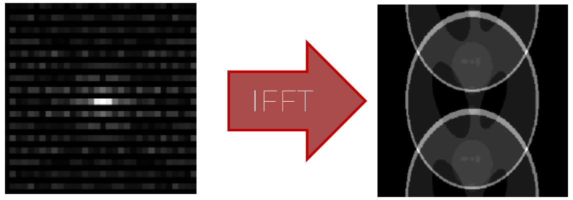
Direct inversion

Encoding operator

$$\hat{x} = F^H(y)$$

Reconstructed image

Acquired data



Imaging Equation

$$\hat{x} = \overbrace{\operatorname{argmin}_x \|F(x) - y\|_2^2}^{\text{Data consistency term}} + \underbrace{\sum_i \lambda_i R_i(x)}_{\text{Regularization term}}$$

Problem formulation

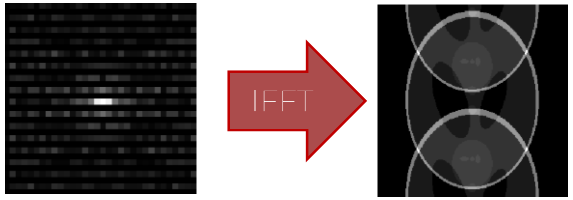
Direct inversion

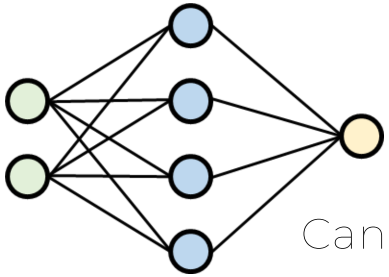
Encoding operator

$$\hat{x} = F^H(y)$$

Reconstructed image

Acquired data





Can AI help here?

Imaging Equation

$$\hat{x} = \overbrace{\operatorname{argmin}_x \|F(x) - y\|_2^2}^{\text{Data consistency term}} + \underbrace{\sum_i \lambda_i R_i(x)}_{\text{Regularization term}}$$

Wang, X., Tan, Z., Scholand, N., Roeloffs, V., & Uecker, M. (2021). Physics-based reconstruction methods for magnetic resonance imaging. Philosophical Transactions of the Royal Society A, 379(2200), 20200196.

AI-based MR reconstruction

AI-recon classification

Supervised

Both ground-truth and undersampled data are available

AI-recon classification

Supervised

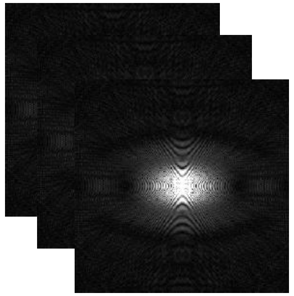
Both ground-truth and undersampled data are available

Self-Supervised

Undersampled data only are available

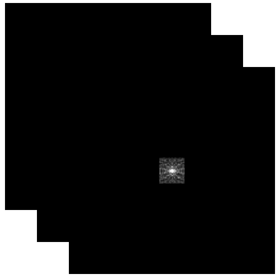
AI-recon classification

Supervised



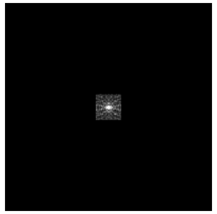
Both ground-truth and undersampled data are available

Self-Supervised



Undersampled data only are available

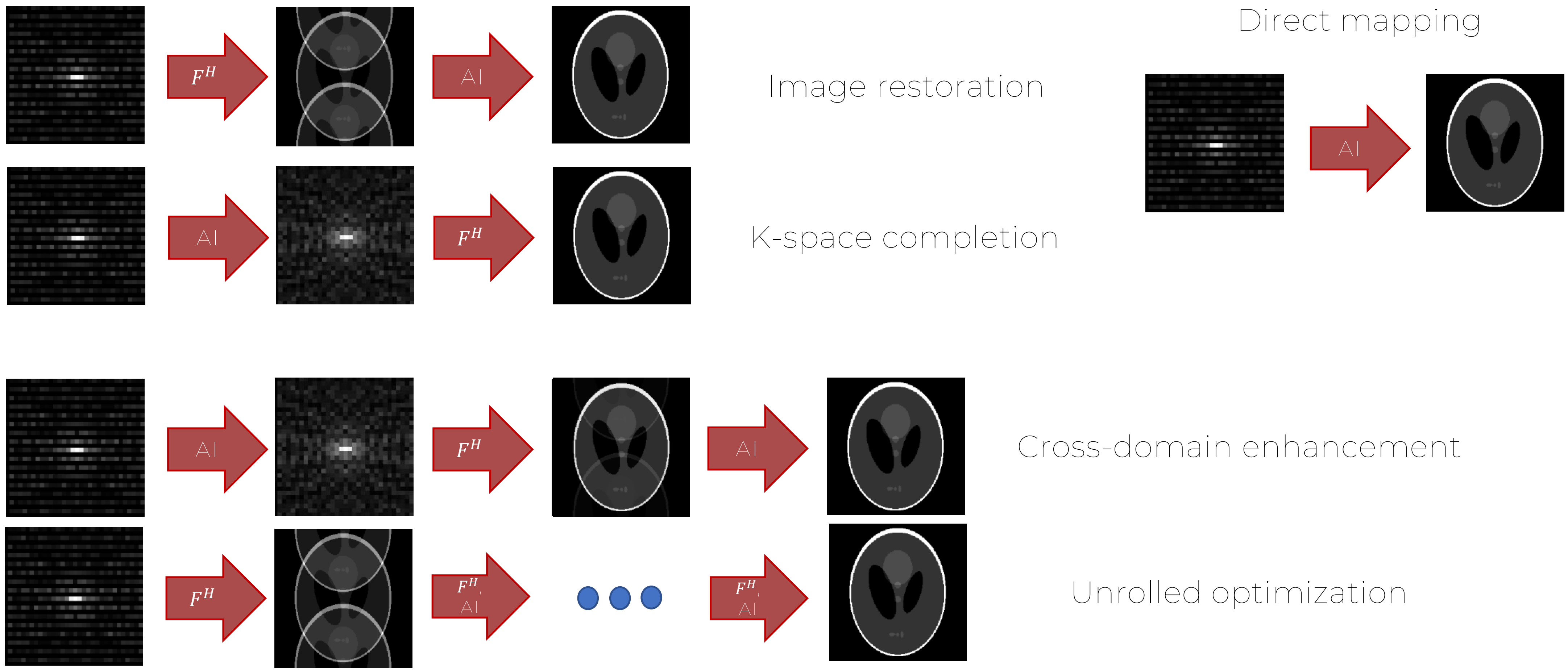
Unsupervised



Neither are available (single subject)

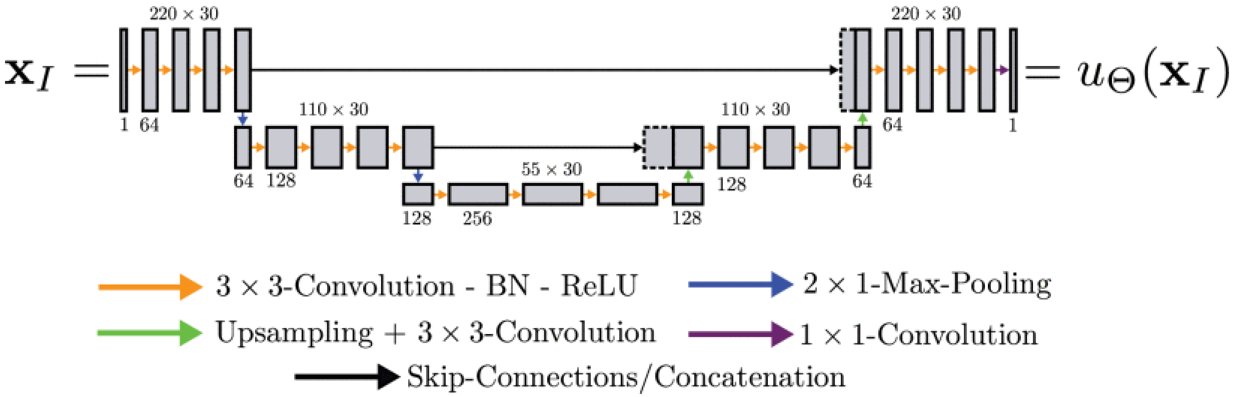
Supervised DL models

Ground truth image is available → can compute loss both in measurement and image space



Javier Montalt-Tordera, Vivek Muthurangu, Andreas Hauptmann, Jennifer Anne Steeden, Machine learning in Magnetic Resonance Imaging: Image reconstruction, Physica Medica, Volume 83, 2021, Pages 79-87, https://doi.org/10.1016/j.ejmp.2021.02.020.

Image restoration

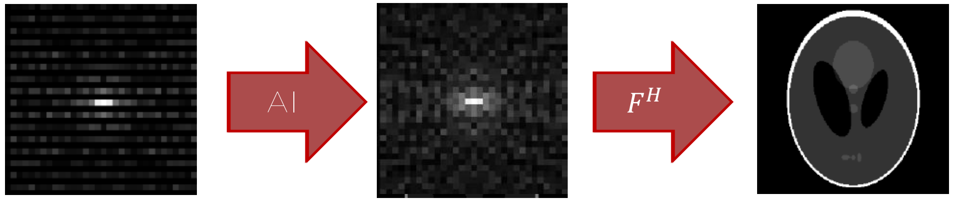


Can rely on rich body of literature on CNN-based denoising (also from non-medical context) – e.g., U-Net

Aliasing should have noise-like pattern → does not apply well to common undersampling artifact

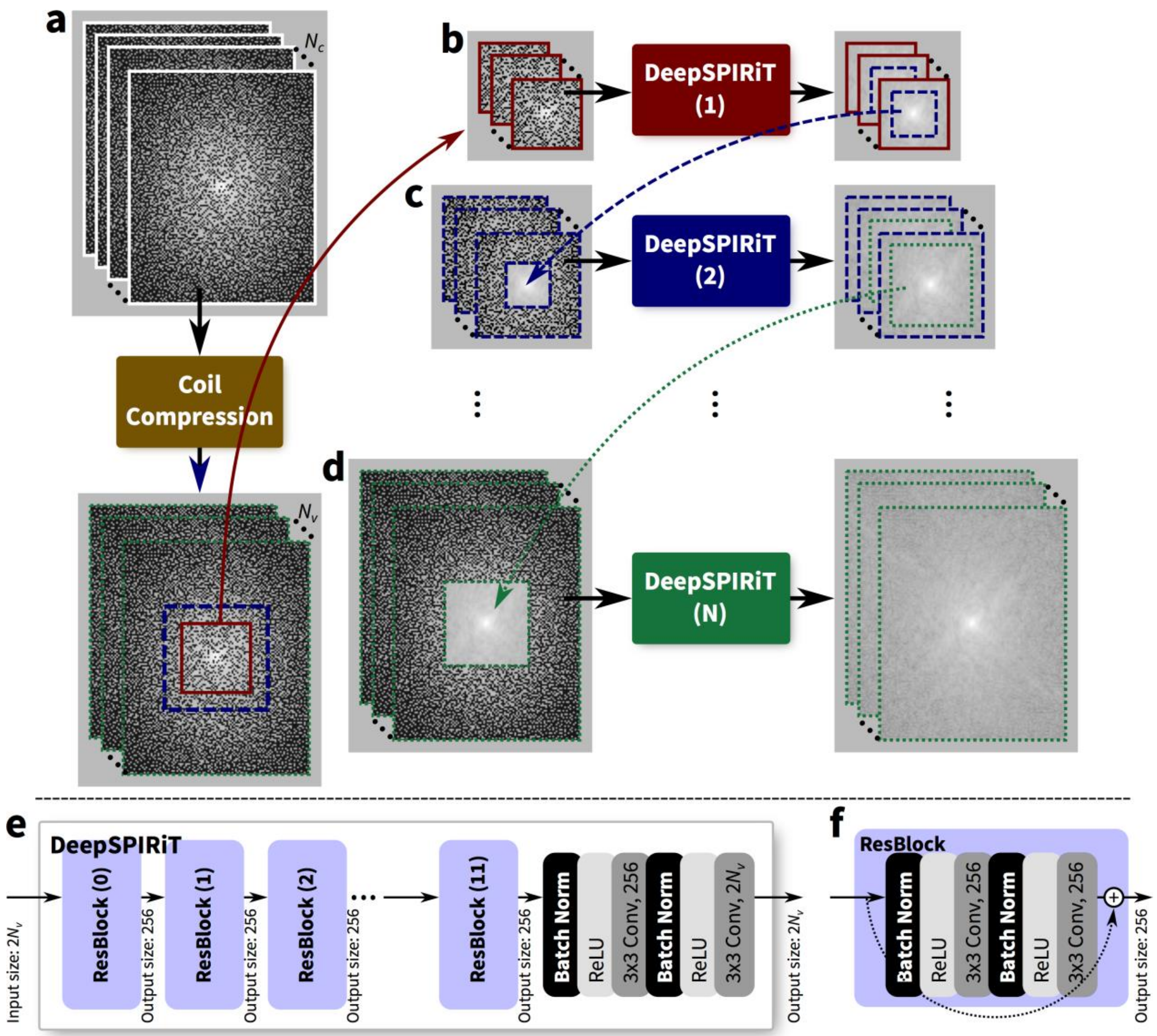
Kofler et al., (2020)

K-space completion



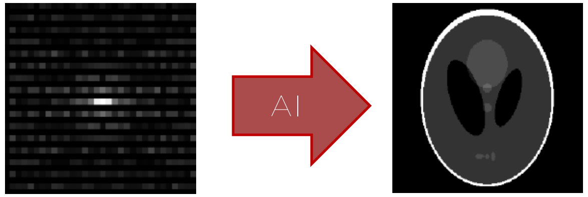
More closely related to the natural representation of MR data (k-space)

More complicated data pre-processing and overall architecture



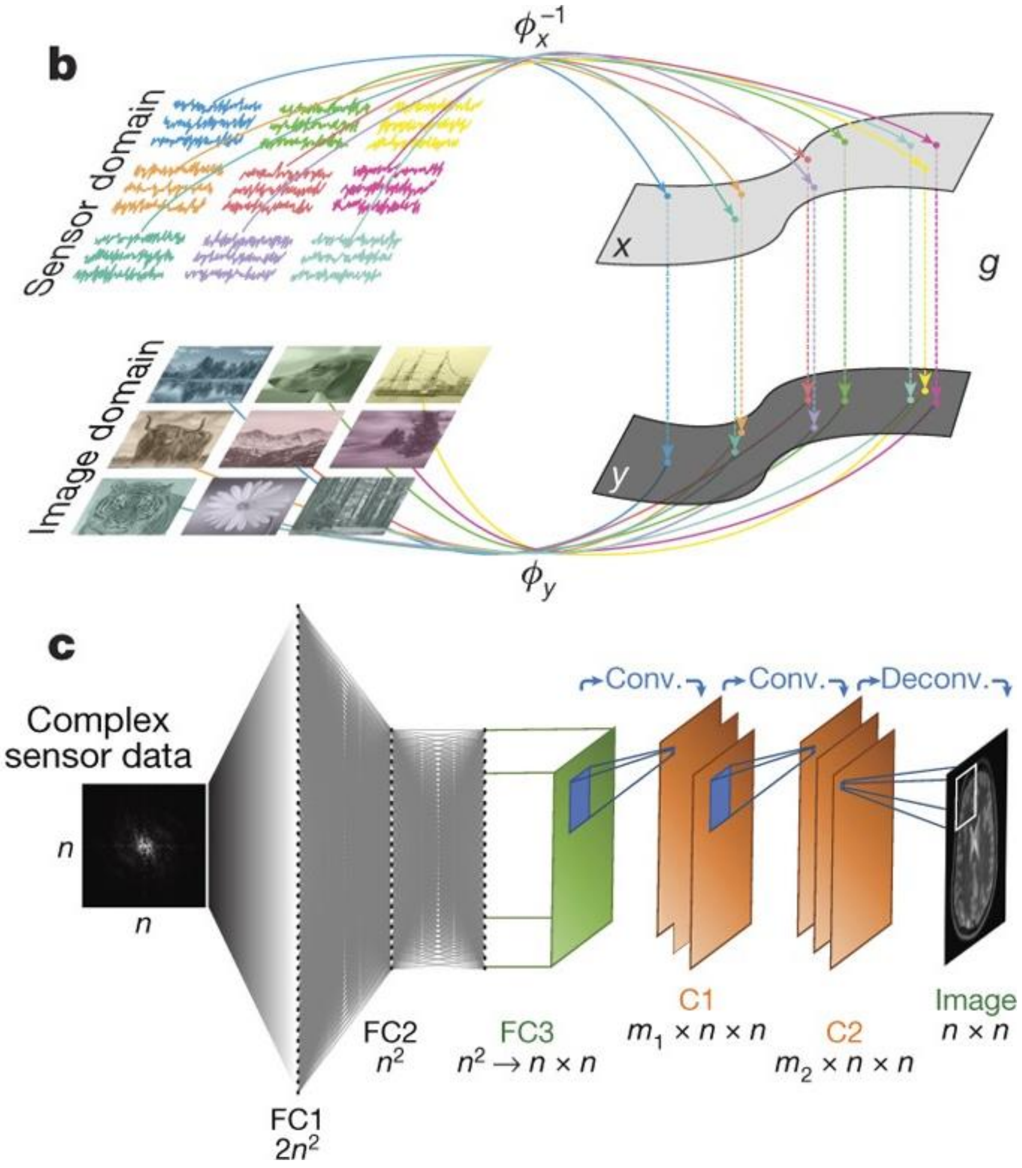
Cheng et al., (2018)

Direct mapping



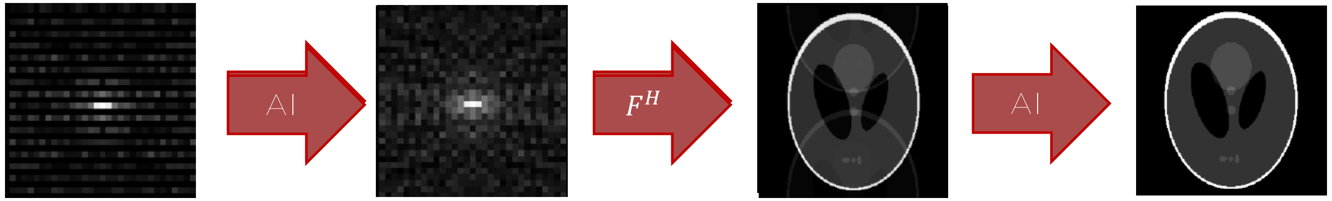
Can capture (and correct) artifacts related to system imperfections

High memory footprint – limited to low dimensional data



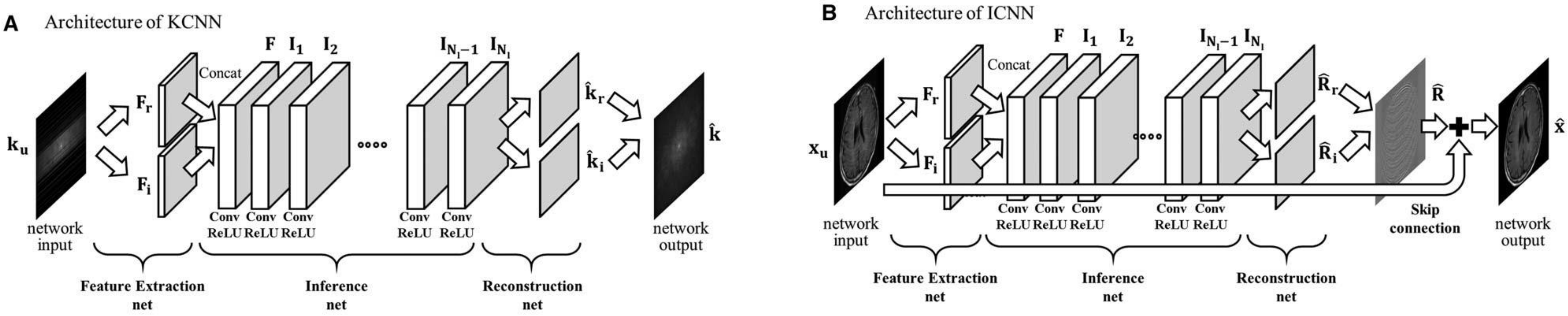
Zhu et al., (2018)

Cross-domain enhancement



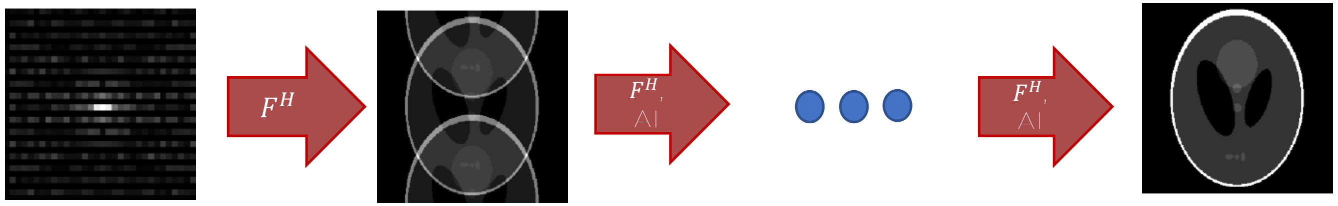
Improved performances by exploiting highly coupled information between the image and k-space domains

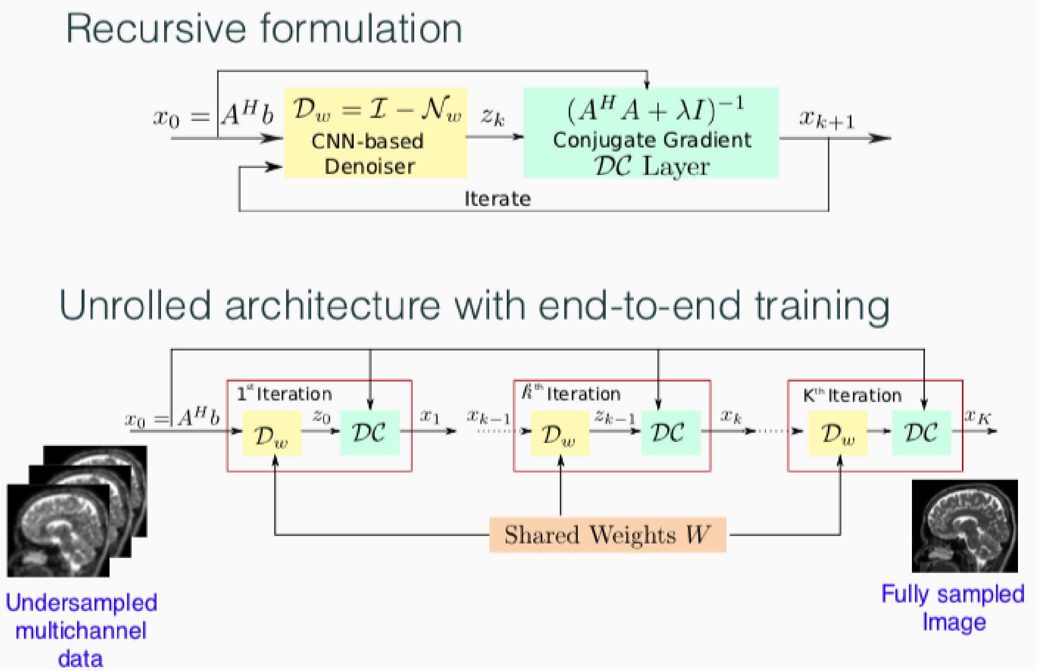
Increased complexity



Eo et al., (2018)

Unrolled optimization





Require less data for training

Involve potentially inefficient conventional image encoding operators

Aggarwal et al., (2018)

Self-/un- supervised DL models

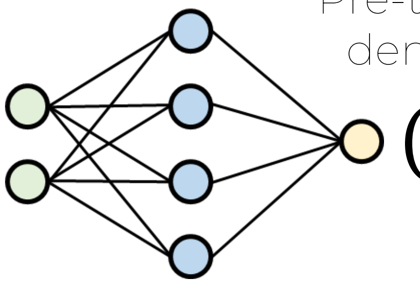
Ground truth image not available → can compute loss both in measurement space only

In the limit case of $N_{train} = 1$, training is performed during reconstruction itself

- Example: PnP reconstruction

Pre-trained
denoiser

$$\hat{x} = \text{argmin}_x \|F(x) - y\|_2^2 +$$



$$(x)$$

DeepMR framework

PREDATOR project

Aim 1:

- Development of an open-source framework for development of advanced qMR reconstruction
- Acquisition of high-quality data for Deep Learning based qMR reconstruction

python™ GitHub PyTorch zenodo

Aim 2:

- Application to real-world MR acquisition (healthy + patients), either retrospectively on previously acquired data (MR Fingerprinting) and prospectively (QSM)

Aim 3:

- Implement on-line reconstruction on MR scanner
- Measure scalability of the algorithms on low-end hardware (consumer-level PCs, single-board computers) for low-income countries

DeepMR framework

I/O

- Raw data loading
- Dicom Export

Linear Operators

- FFT
- NUFFT
- Wavelet Transform
- ...

Regularization Operators

- L1 Wavelet
- Total Variation
- Local Low Rank
- PnP denoisers
- ...

Solvers

- Gradient Method
- Conjugate Gradient
- ADMM
- ...

Parametric-mapping

- Pytorch-based EPG simulator (T1, T2, MT, chemical exchange, slice profile...)
- NN-based inference

NN-utils

- Pre-defined architectures
- Utils as data-loaders, schedulers...

DeepMR framework

I/O

- Raw data loading
- Dicom Export

Linear Operators

- FFT
- NUFFT
- Wavelet Transform
- ...

Proximal Operators

- L1 Wavelet
- Total Variation
- Local Low Rank
- ...

Solvers

- Gradient Method
- Conjugate Gradient
- ADMM
- ...

Parametric-mapping

- Pytorch-based EPG simulator (T1, T2, MT, chemical exchange, slice profile...)
- NN-based inference

NN-utils

- Pre-defined architectures
- Utils as data-loaders, schedulers...

DeepMR framework

I/O

- Raw data loading
- Dicom Export

Linear Operators

- FFT
- NUFFT
- Wavelet Transform
- …

Proximal Operators

- L1 Wavelet
- Total Variation
- Local Low Rank
- …

Solvers

- Gradient Method
- Conjugate Gradient
- ADMM
- …

Parametric-mapping

- Pytorch-based EPG simulator (T1, T2, MT, chemical exchange, slice profile…)
- NN-based inference

NN-utils

- Pre-defined architectures
- Utils as data-loaders, schedulers…

Efficient Bloch simulator

Efficient Bloch simulator

Pytorch implementation based on Extended Phase Graphs formalism

- Effect of RF pulse and spin relaxation is represented by matrix-matrix product operations
- Effect of gradient is represented in the Fourier space as a shift between different (discrete) states representing different dephasing orders

Efficient Bloch simulator

Pytorch implementation based on Extended Phase Graphs formalism

- Effect of RF pulse and spin relaxation is represented by matrix-matrix product operations
- Effect of gradient is represented in the fourier space as a shift between different (discrete) states representing different dephasing orders

Features:

- Include all main MR related parameters (relaxation, diffusion, chemical exchange, magnetization transfer, system imperfections)
- Highly parallelized (both on CPU and GPU)
- Supports gradient calculation via forward automatic differentiation (enable backpropagation in NN training, efficient parameter fitting and optimization of acquisition parameters)

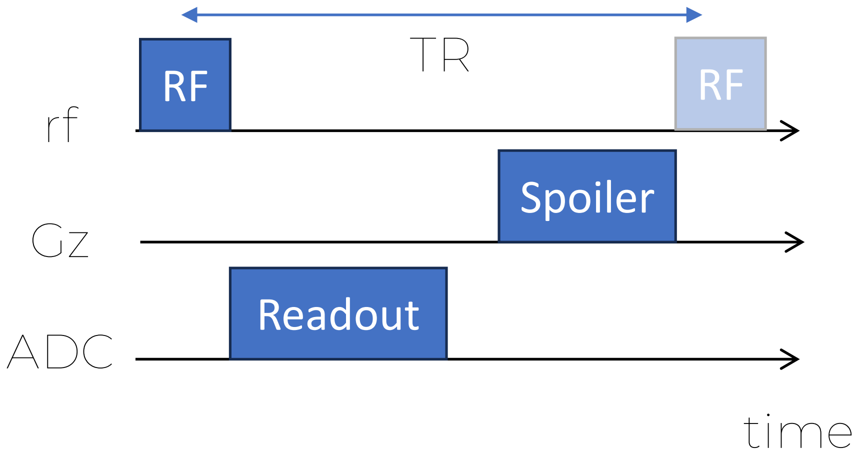
Efficient Bloch simulator

Validation:

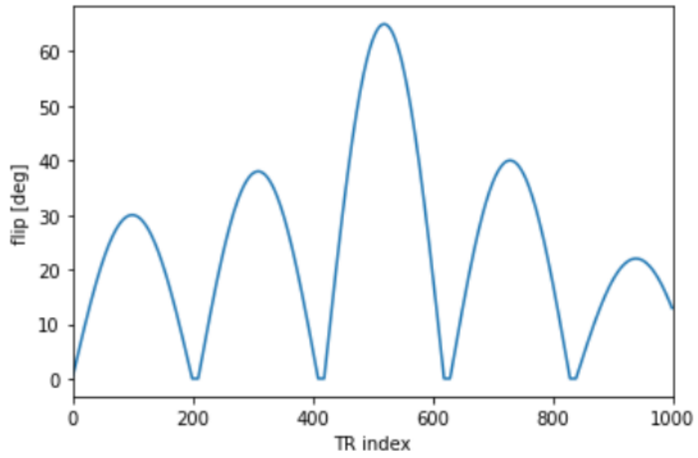
- Acquisition: Variable Flip Angle unbalanced SSFP with 1000 echoes (TR=8.5ms)
- Virtual Object: Three representative tissues:
    - White Matter (T1=500ms; T2=70ms)
    - Gray Matter(T1=833ms; T2=83ms)
    - CSF (T1=2569ms; T2=329ms)

Benchmark: comparison of computations time against *sycomore* (state-of-the-art C++ implementation) on a batch of tissue species of size 65536

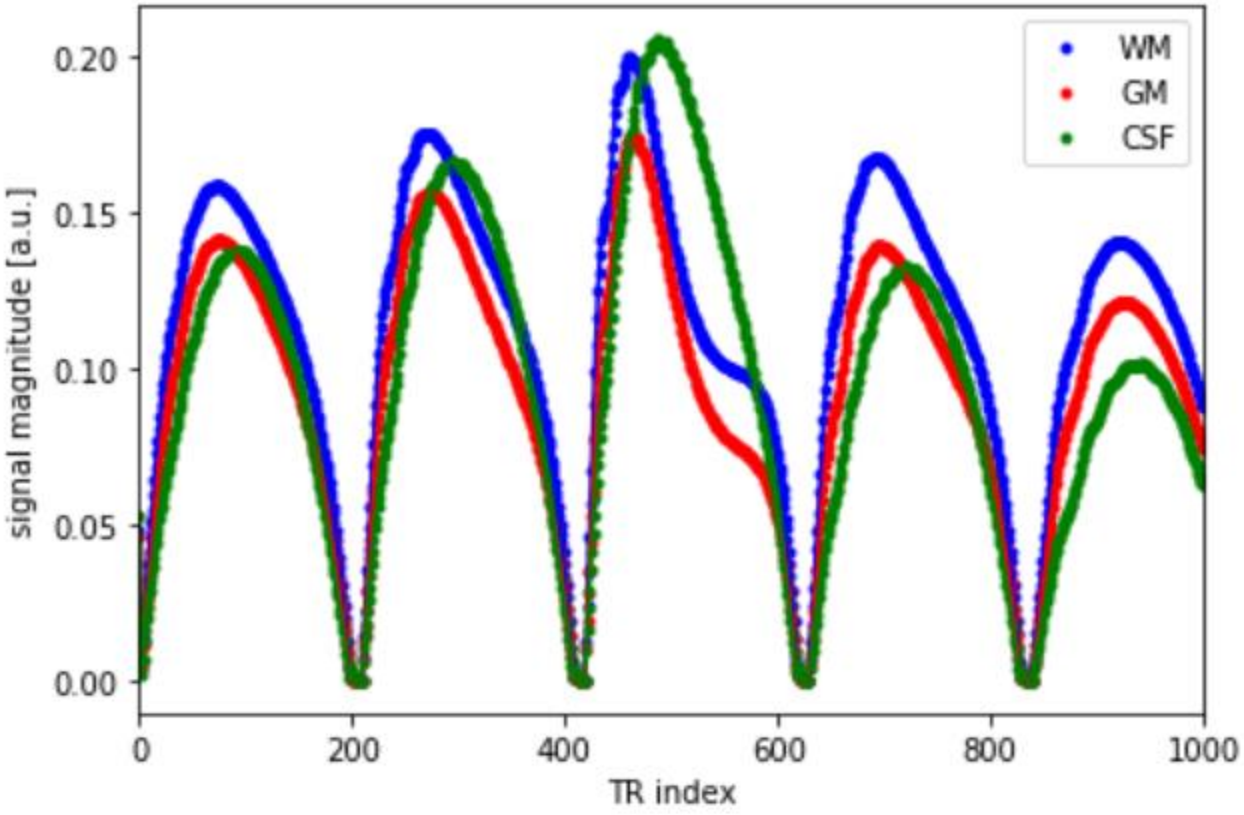
Sequence scheme



Flip angle variation



Efficient Bloch simulator

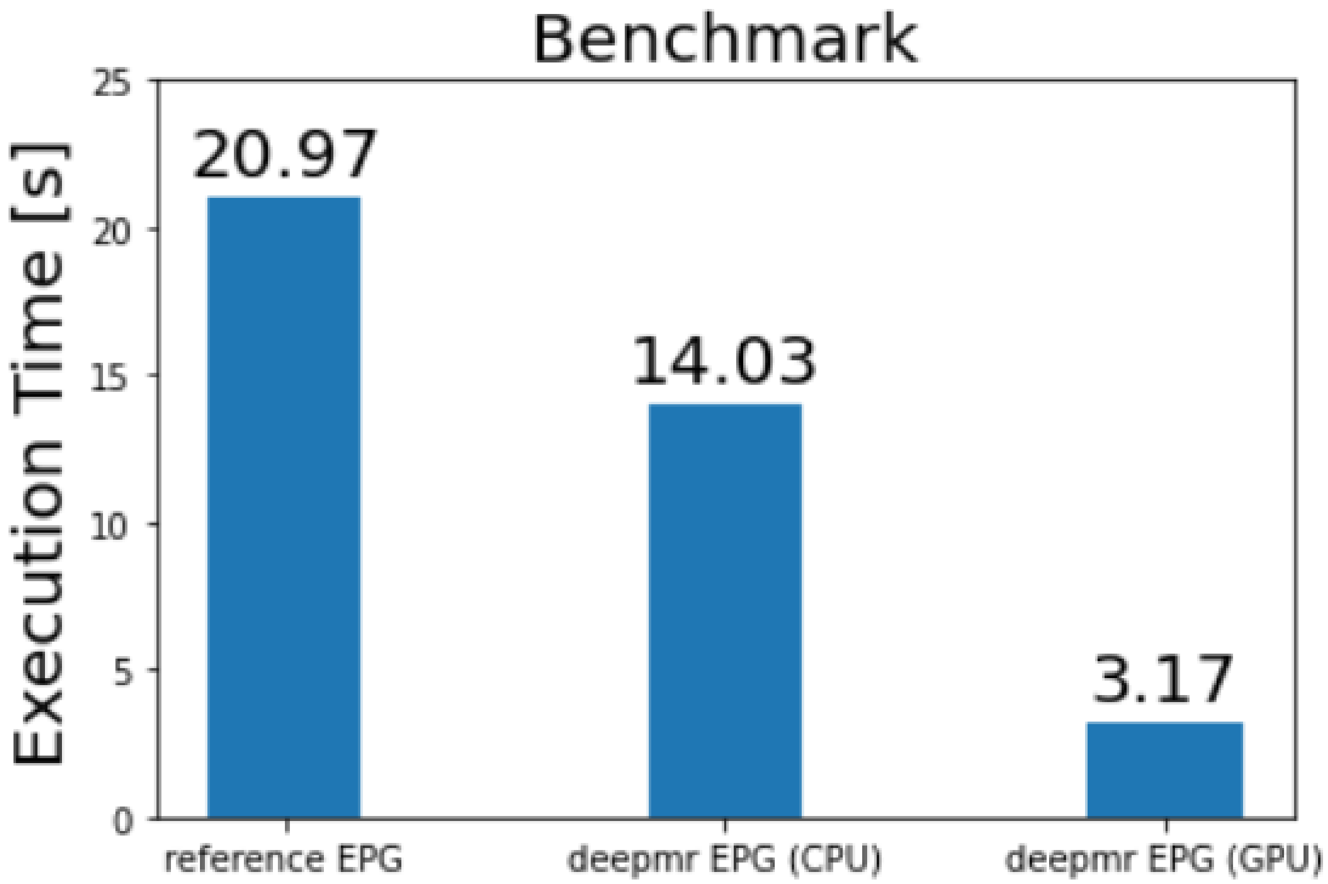


No differences compared to the reference implementation

- : reference implementation

\- : deepmr implementation

Efficient Bloch simulator



Up to one-order of magnitude of speed-up
(on GPU)

Efficient encoding operator

Efficient encoding operator

$$y = PFM(x) + n$$

P: sampling operator
F: Fourier Transform
M: Bloch response

PF: Non-Uniform Sparse FFT

Efficient encoding operator

$$y = PFM(x) + n$$

P: sampling operator
F: Fourier Transform
M: Bloch response

PF: Non-Uniform Sparse FFT

Efficient encoding operator

P: sampling operator
F: Fourier Transform
M: Bloch response
PF: Non-Uniform Sparse FFT

$$y = PFM(x) + n$$

M is often replaced with a projection on a linear subspace for speedup

→ jointly perform P, F and M!

Efficient encoding operator

$$y = PFM(x) + n$$

M is often replaced with a projection on a linear subspace for speedup

→ jointly perform P, F and M!

Implementation: Pytorch + Numba

- Can operate both on CPU and GPU
- Efficient backpropagation noticing that, for linear operators, backward pass is equivalent to adjoint operator

Efficient encoding operator

Validation:

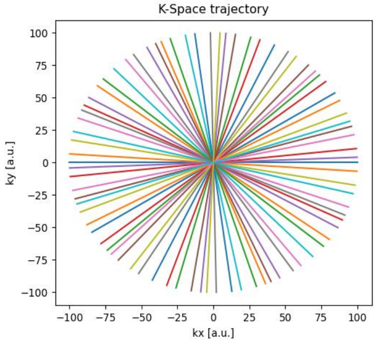
- Acquisition: Fast Spin-Echo with 1000 echoes and golden-angle incremented 2D radial sampling (100 spokes / echo)
- Virtual Object: Shepp-Logan phantom with three regions:
  - White Matter (T2=70ms)
  - Gray Matter(T2=83ms)
  - CSF (T2=329ms)
- Basis determination: SVD of an ensemble of 300 signal evolution (T2:1 – 329ms)
- K-Space data: calculated via forward NUFFT from *torchkbnufft*

Benchmark: comparison of both forward and adjoint NUFFT computations time against *torchkbnufft* implementation

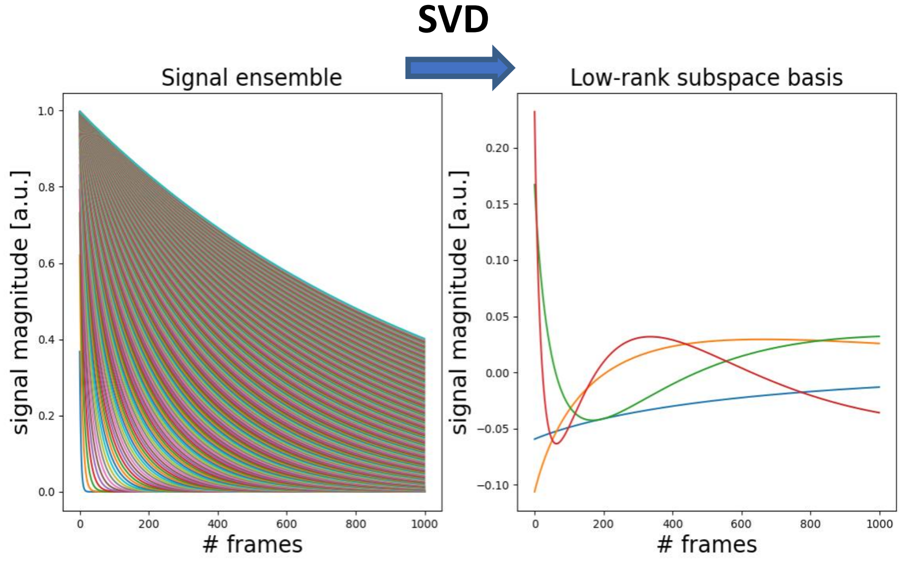
Signal equation

$$S(TE) = \exp(-\frac{TE}{T2})$$

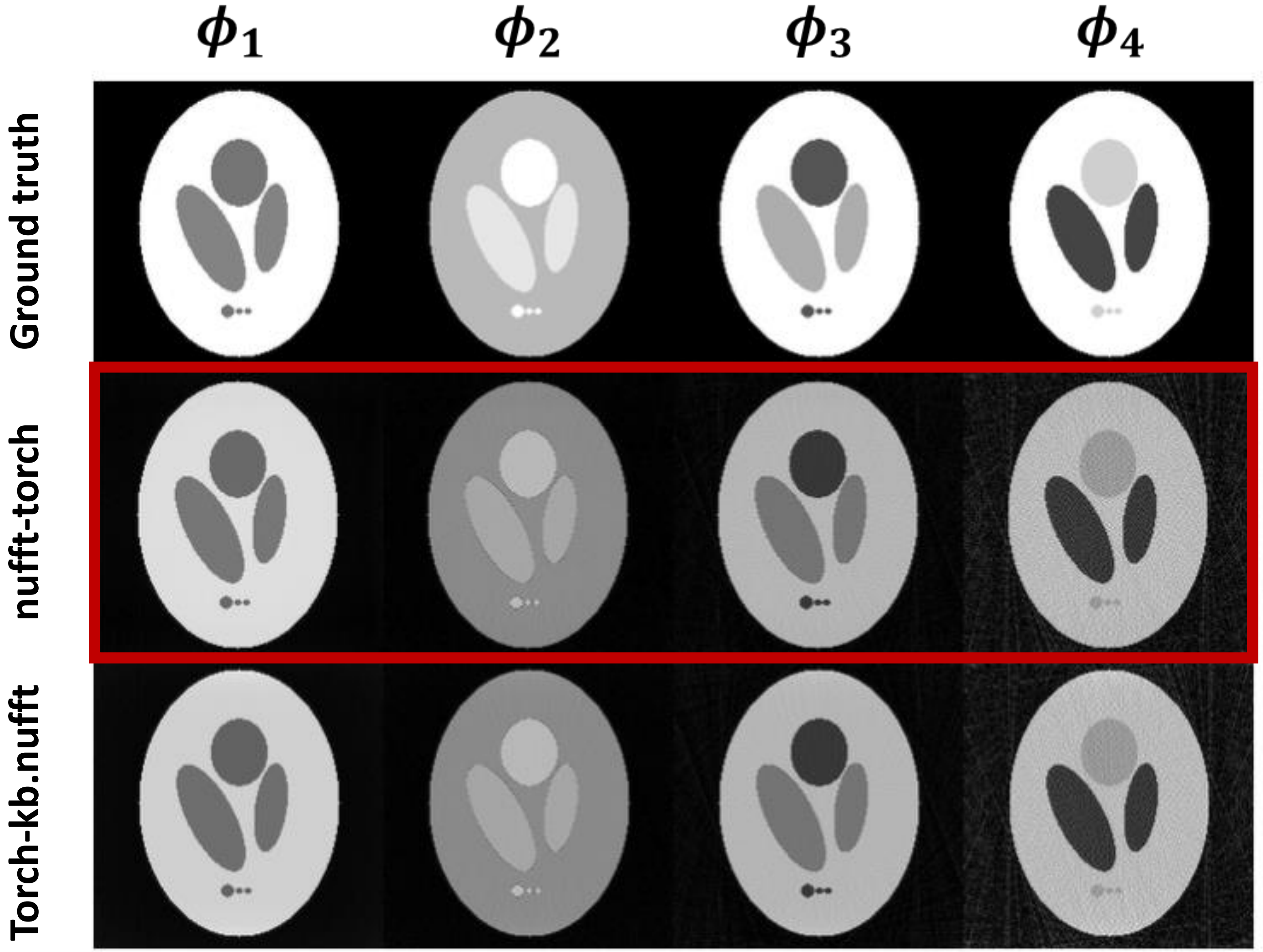
Trajectory



Basis determination

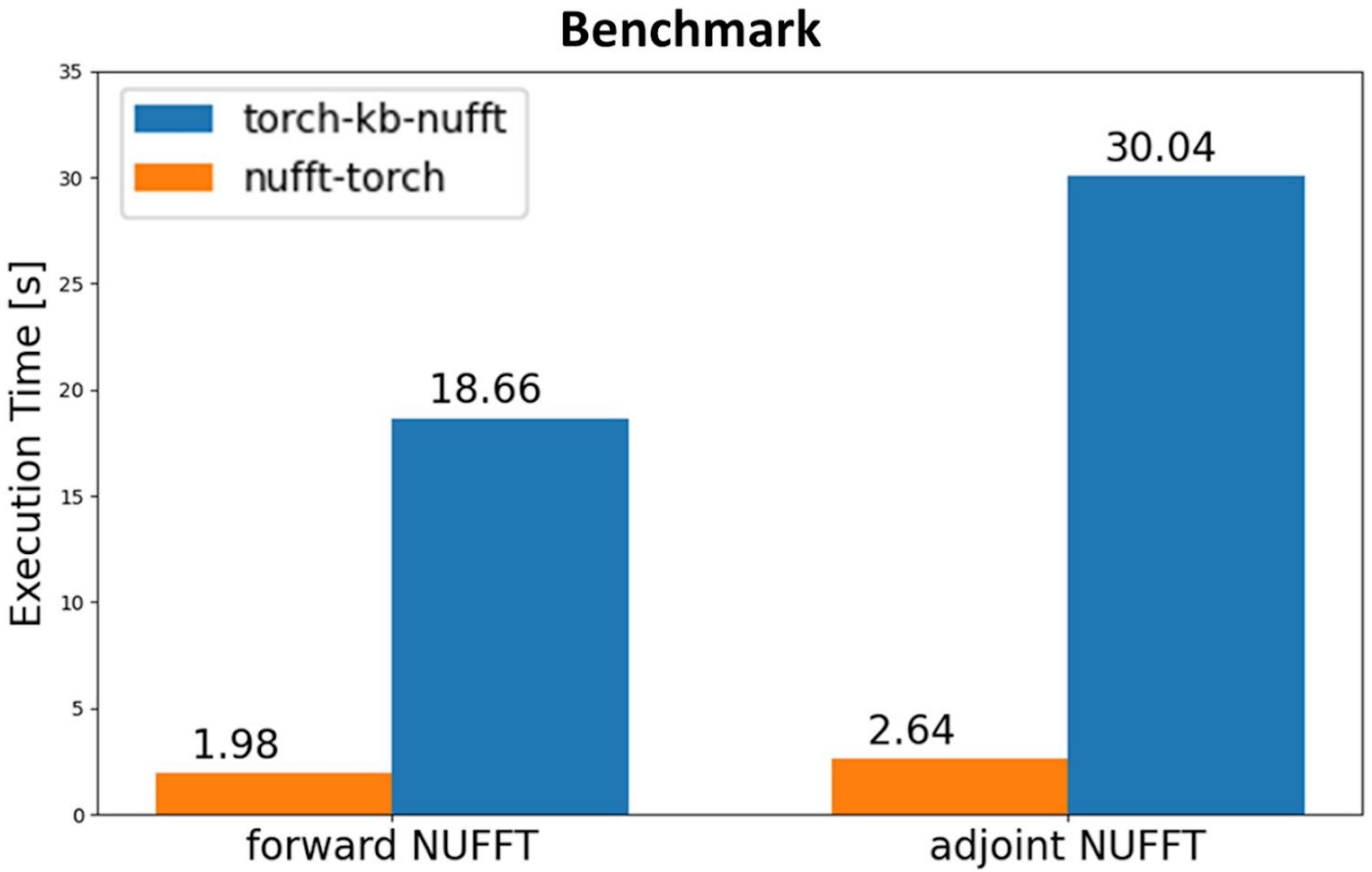


Efficient encoding operator



No differences compared to the reference implementation

Efficient encoding operator



One order of magnitude of speed-up compared to the reference implementation

qMR database creation

qMR database creation

M2. Creation of training qMRI database of healthy volunteers (31 Dec 2023): Generation of sub-millimetric T1, T2, T2*/susceptibility maps of at least 10 subjects.

Protocol

Sequence Type	Parameter	FA [deg]	RF phase inc [deg]	TE [ms]	TR [ms]	FoV [mm]	Resolution [mm]	Acceleration factor	Scan Time [min:sec]
SPGR	T1	3, 11, 28	quadratic	3.3	8.5	224x224x160	0.8 iso	4	9:06
bSSFP	T2	10, 20, 30, 35	0, 180	2	4	224x224x160	0.8 iso	4	6:00
ME-GRE	T2*, B0, QSM	15	quadratic	3.9, 8.5, 13.1, 17.7	30	224x224x160	0.8 iso	4	5:06

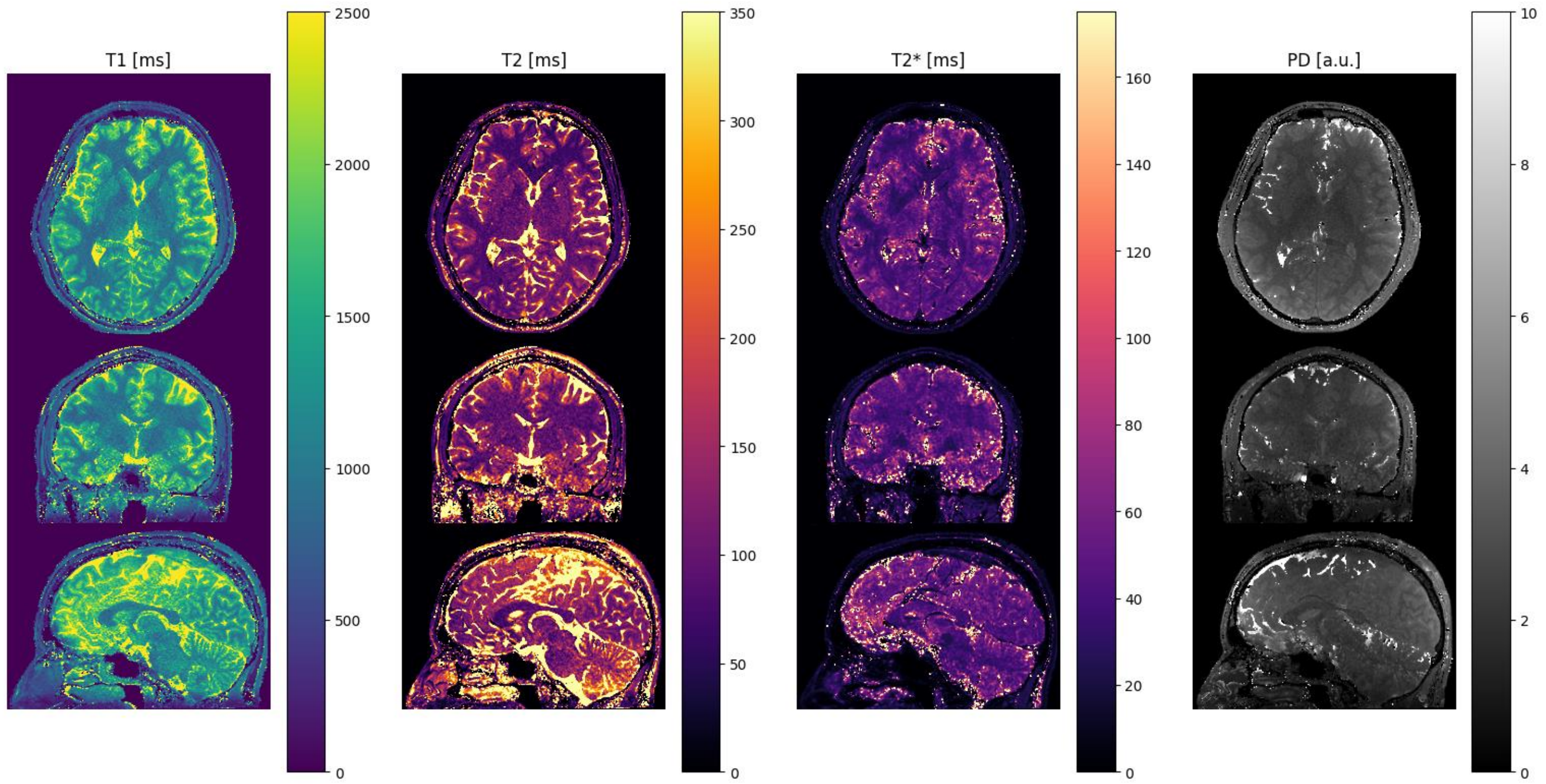
Protocol also include a B1+ calibration scan (Bloch-Siegert) (whole-brain, 4x4x5 mm^3 resolution)

Dataset

- 1 healthy volunteer (Male, 34 years old)

qMR database creation

M2. Creation of training qMRI database of healthy volunteers (31 Dec 2023): Generation of sub-millimetric T1, T2, T2*/susceptibility maps of at least 10 subjects.



Good geometrical quality and reasonable quantification.

To-Do: improve accuracy and precision of fitting

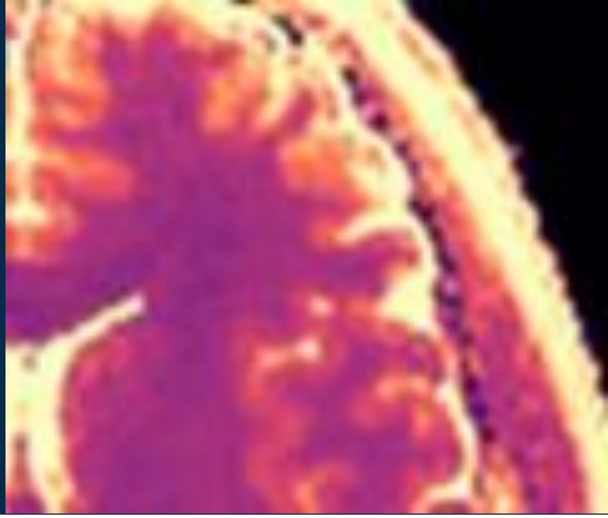
Conclusions

- AI-based approaches have great potential in accelerating MR acquisition and reconstruction

- The DeepMR framework will contribute to the field providing easy-to-use, extensible and efficient tools to develop novel reconstruction approaches

Pisa
October 16 2023

Thank you for your attention!



INFN

IRCCS FONDAZIONE STELLA MARIS

IMAGO7