Accelerating Magnetic Resonance Imaging (MRI) acquisition with deep learning and reinforcement learning

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Outlines

- Intro : MRI-data specificity, challenges and solution proposal
- Objectives
- Methodololy
- Results on different datasets
- Conclusions : Take away

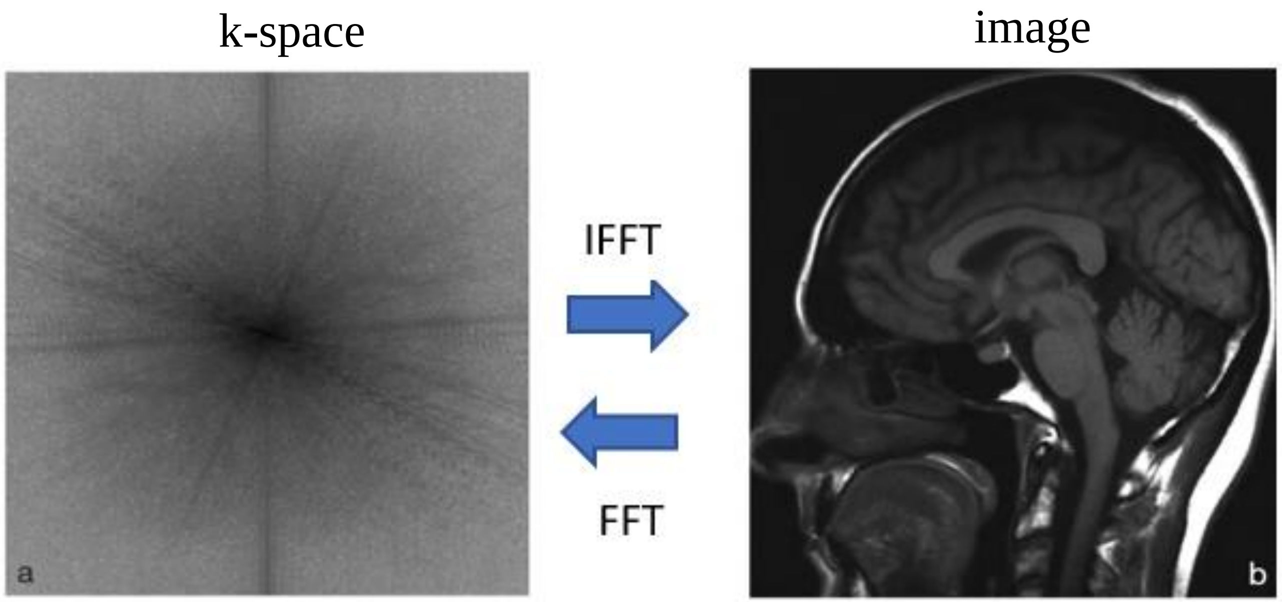
Definition : k-space

❑ **MRI is common diagnosis methods for assessing tissues structure**

- For MRI, the obtained data are not in the spatial domain, but in frequential domain : k-space

❑ **What is k-space :**

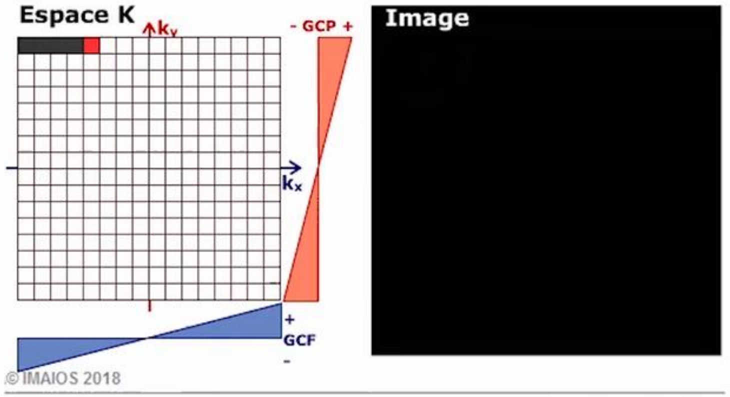
- k-space is an array of numbers representing **spatial frequencies** in the MR image



- *kx* and *ky* axes of *k*-space represent ***spatial frequencies*** in the *x*- and *y*-directions rather than positions.
- each pixel in the image maps to *every* point in *k*-space
- Each *k*-space point contains spatial frequency and phase information about *every* pixel in the final image
- The raw data are recorded by different coils ➔ channel dim

Main challenges in MRI

- ❑ Basically, line by line acquisition



Source: https://www.imaios.com/fr/e-Cours/e-MRI/Bases-physiques/Espace-K

- ❑ **Main challenges**

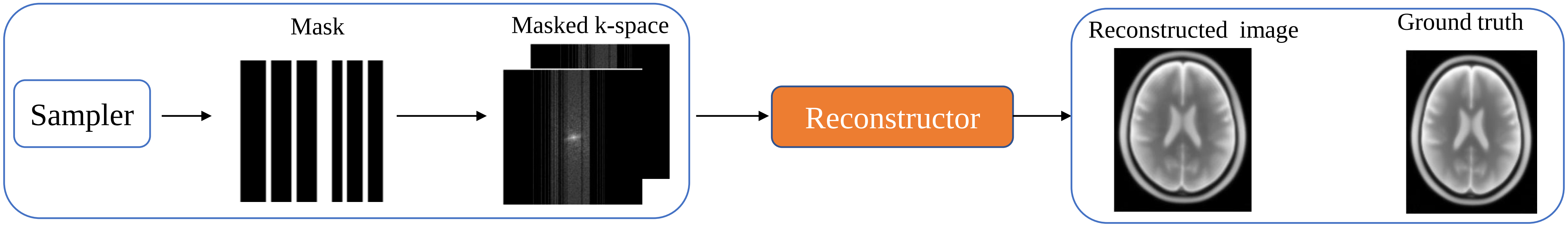
- **Long acquisition time** (about 15 min in general, and can last up to 90 minutes)
    - few exams per day to make the high cost of the machines cost-effective
    - Patient discomfort
    - Reconstruction artifacts if the patient moves in the acquisition step

How to accelerate MRI acquisition ?

Acquire less k-space measurements

Sample few parts of the k-space

Reconstruct image that preserves anatomical structure from undersampled k-space



Where to sample ?

How to reconstruct from partial data ?

- ❑ Fixed mask and non deep reconstructor : Compressed sensing (1), SENSE (2), GRAPPA (3), SPIRiT(4)

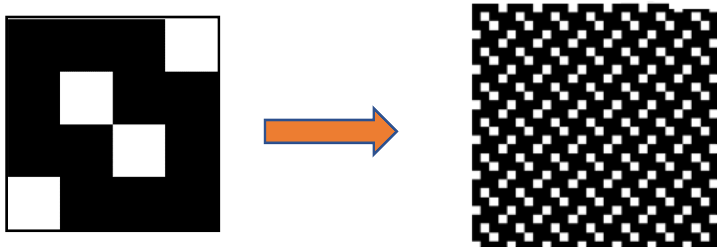
- ❑ In deep learning era :

- Given a fixed sampling mask, learn reconstructor model
- Learning jointly sampler and reconstructor :
    - Learn to generate a specific or non specific undersampling mask for each new k-space (5, 6)
    - Sequential sampler or not (7, 8)

Methodology

❑ **Objective** : Find the optimal sampling, that allows a correct reconstruction ; by considering the sampling problem as :

- **Non sequential** decision problem sequential : acquire all the desired measurements at once :
  - Learn a global mask : mask dim = Image height $\times$ Image width
  - Learn a local mask : mask dim = 4×4 , and replicate it in order to have same dimension as the global mask

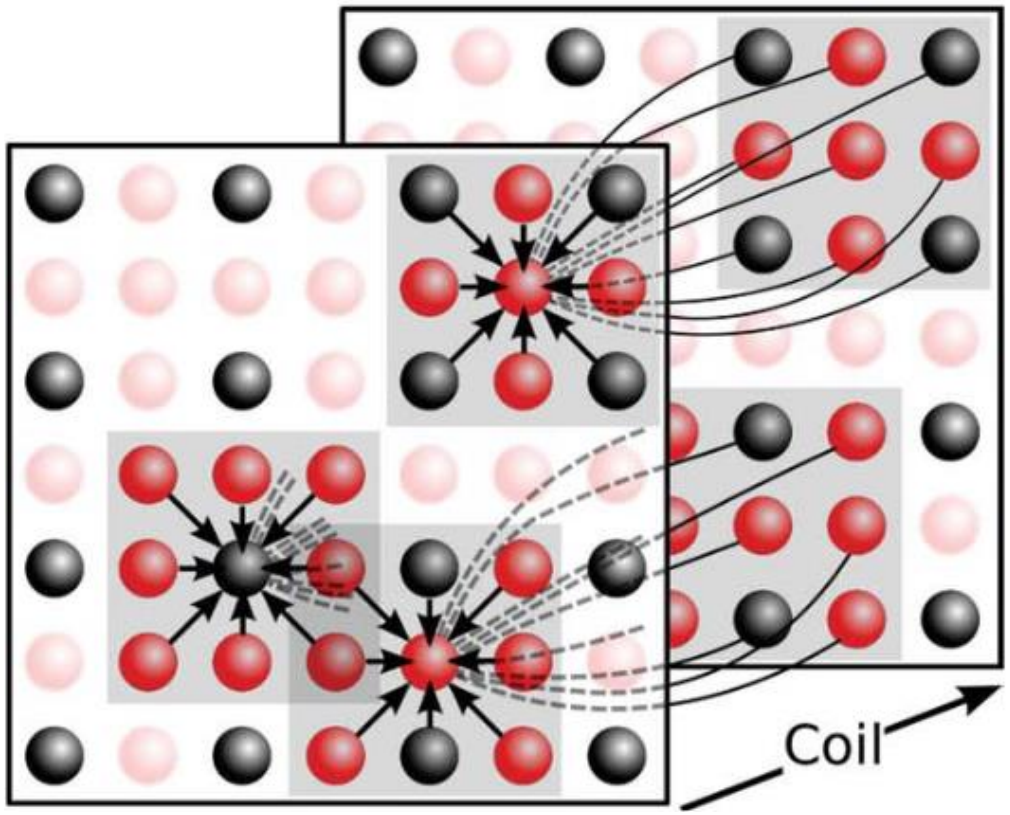


- **Sampling sequential** decision problem : determining from available measurement of k-space and what have already been acquired, the next most informative data to acquire ⇨ **Reinforcement learning**

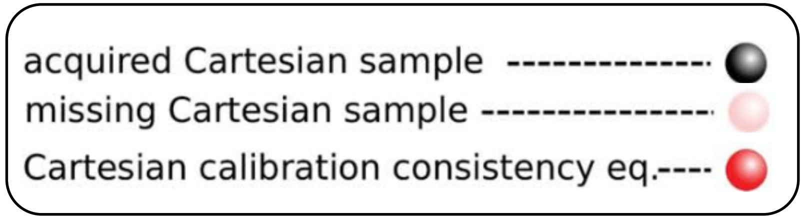
Step 1 Step 2 Step 3 Step 4

Methodology-SPIRiT for reconstruction

- SPIRiT : iterative algorithm in which in each iteration nonacquired -space values are estimated by performing a linear combination of nearby k-space values : **Calibration consistency**



- Use : convolution kernels and **impose that the center of the kernels is 0**; to avoid learning identity. The kernel size delimits the neighborhood
- Number kernels = number of coils (channels). Kernel dim = w×h×n_coils
- The kernels are estimated by fitting them on a fully acquired central region (ACS), like an auto-encoder

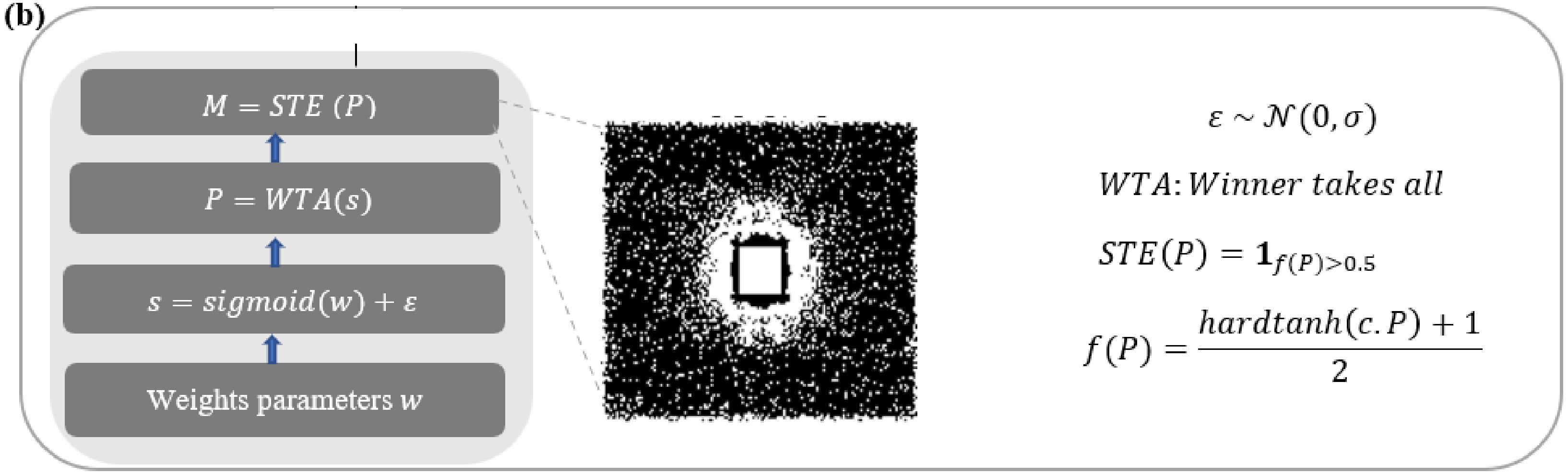


- **Data consistency :** impose the already available data in the undersampled k-space after estimation

***SPIRiT** : Iterative Self-consistent Parallel Imaging Reconstruction From Arbitrary k-Space)

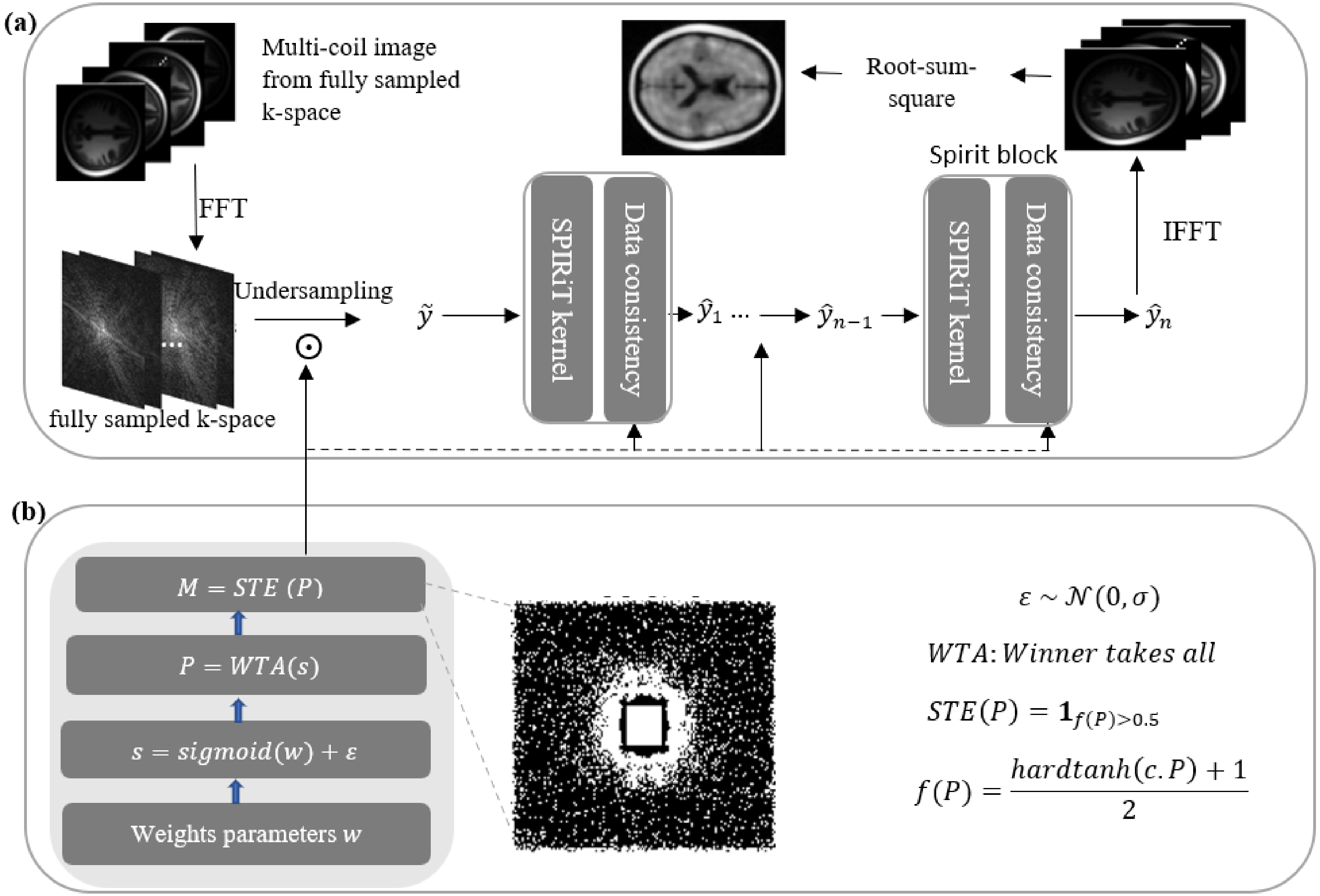
Methodology / Non-sequential model

(b)



(a) Reconstructor : stacking of n spirit blocks. **(b)** Non sequential sampler.

Methodology / Non-sequential model



- NMSE* Loss : $\frac{\sum_i ||y_i - \hat{y}_i||^2}{\sum_i ||y_i||^2}$
- Optimizer : Adam with possibly different learning rate for mask and reconstructor
- Acceleration factor R = 4, 8 ➔ take 25% or 12.5% of data

(a) Reconstructor : stacking of n spirit blocks. **(b)** Non sequential sampler.

Data & preprocessing

❑ MNIST dataset : “like MRI” but with single coil or channel

- 60,000 training images and 10,000 test images of handwritten digits
- Normalize by 255
- FFT
- Minmax scaling (more precisely, normalize by max of absolute value of real or imaginary)
- Global mask size 28×28 ; local mask size 4×4

❑ Simulated brains dataset

- Simulate 30 brains volumes (9) of size : $121 \times 121 \times 145 \times 8$ (n_slices x height x width x n_coils), each of them has different a contrast ; 24 volumes for train and 6 volumes for test.
- FFT, normalize each slice FFT by the max of its FFT module tensor
- Pick from slice 50 to 89 (~ 40 slices) : 960 slices for training, 240 for test
- Minmax scaling
- Global mask size 121×145 ; local mask size 4×4

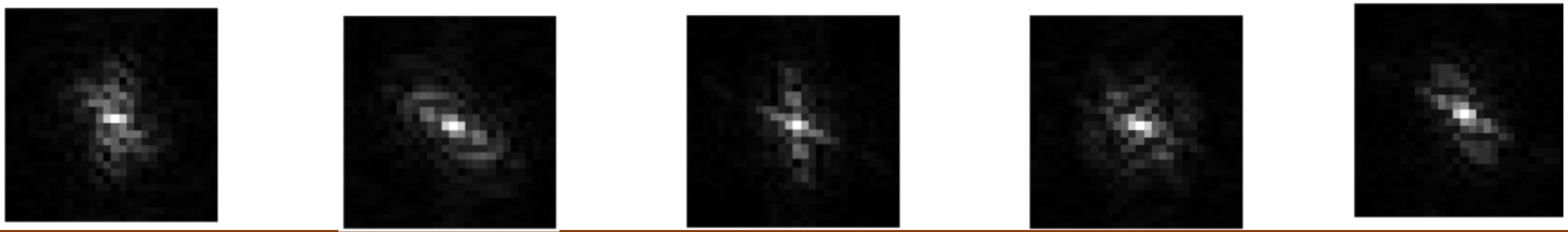
Data Visualization

- digits

- k-space

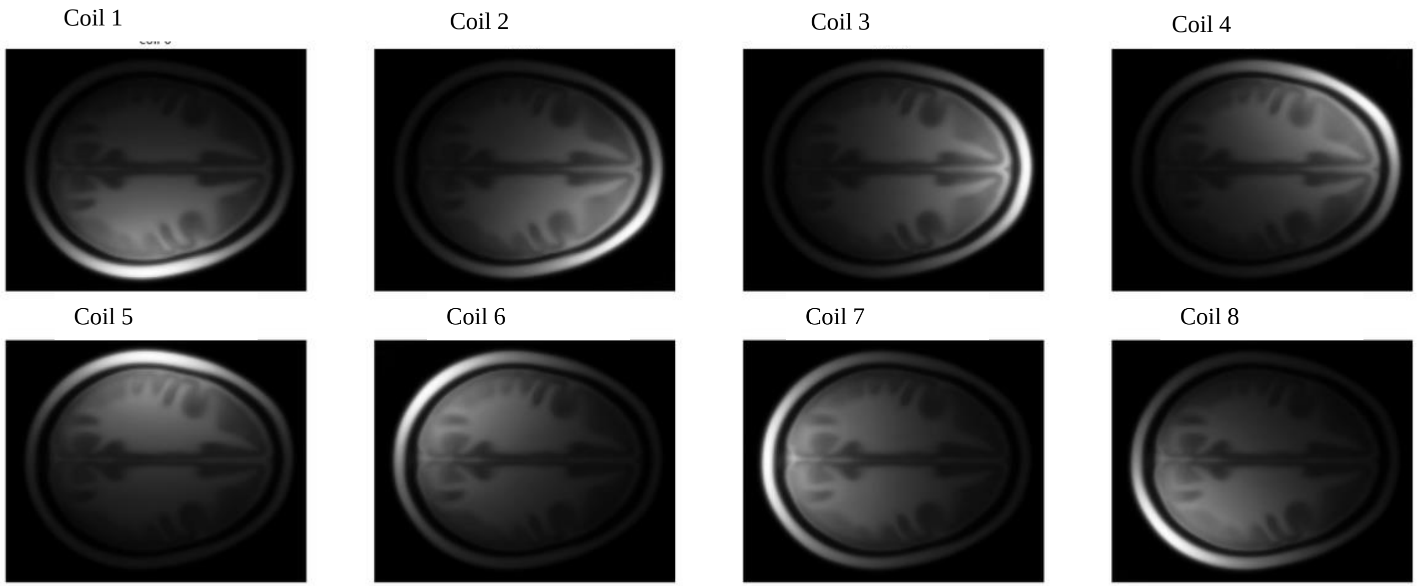
- digits

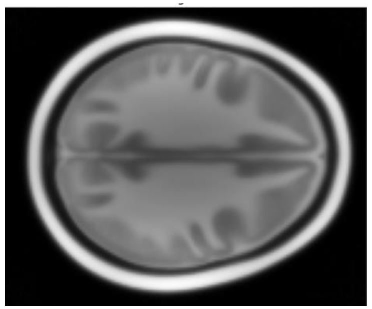
- k-space



Data Visualization

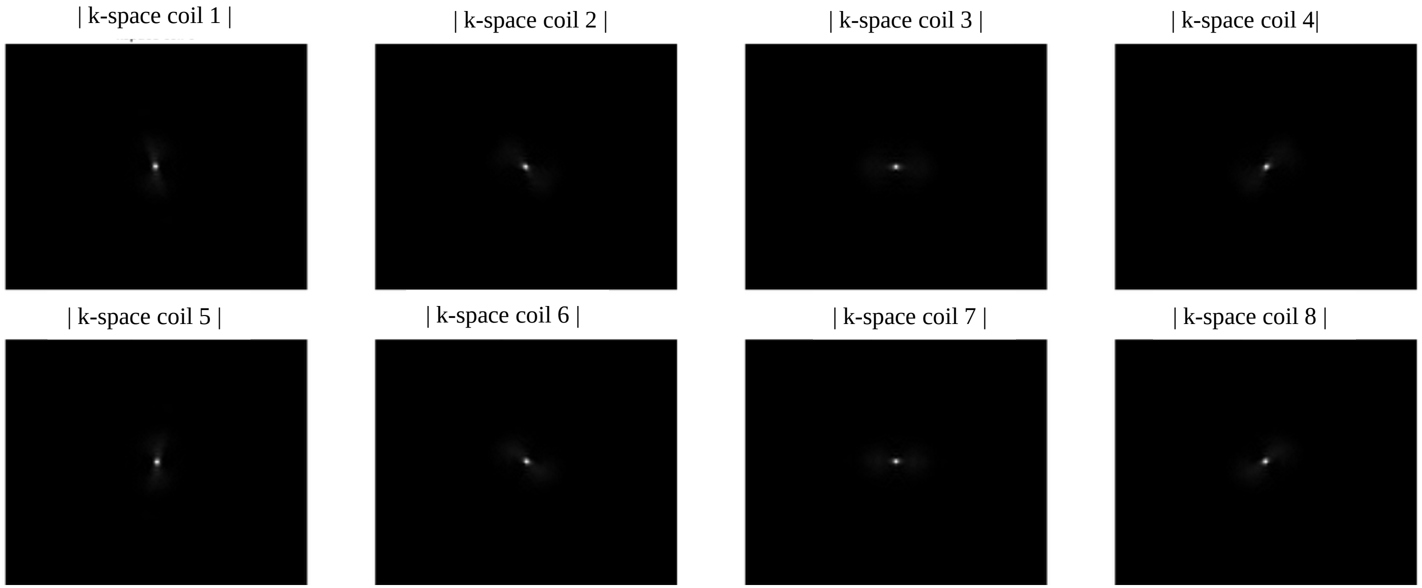
- Image





Square Root of sum of square

- | k-space |



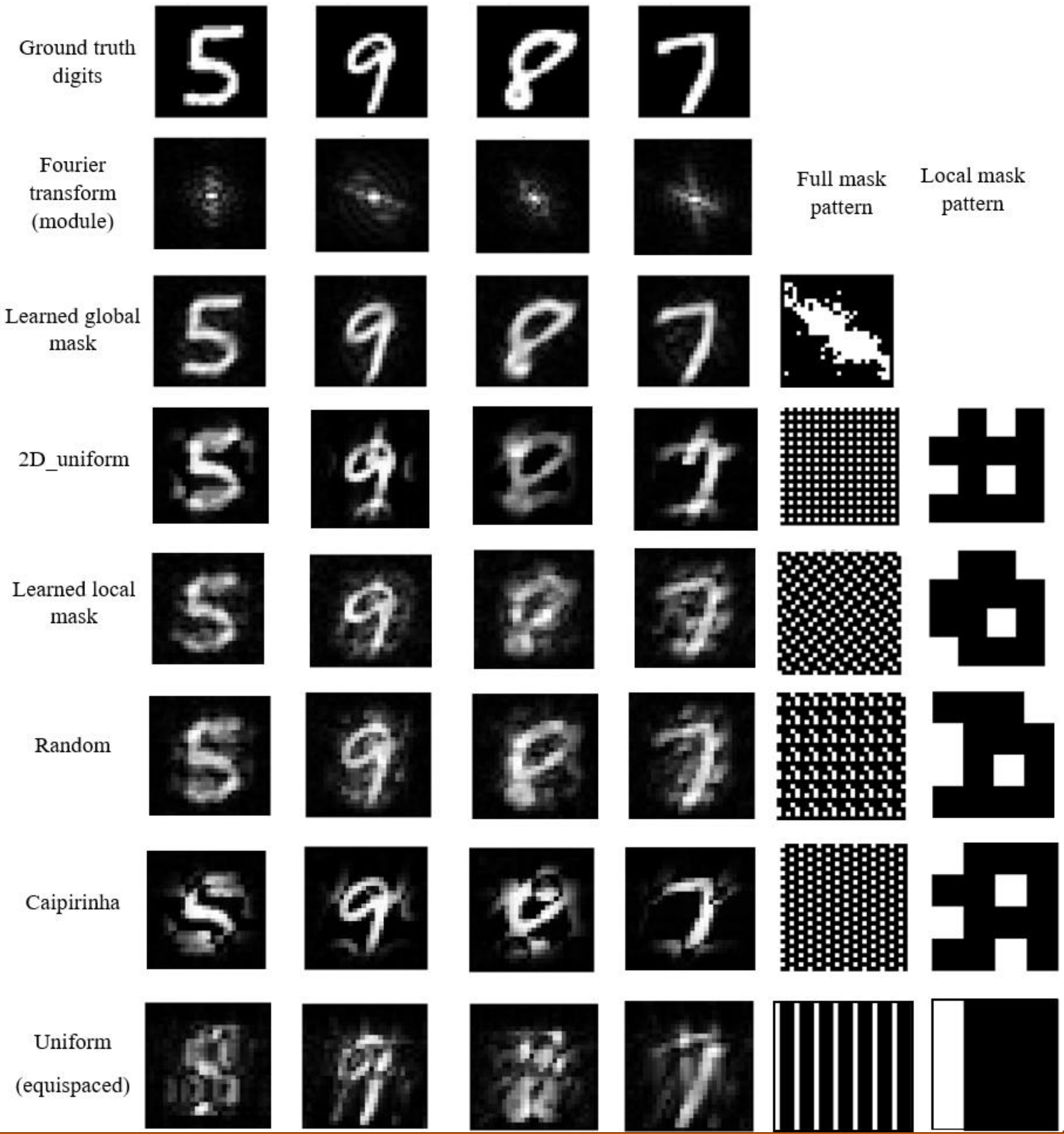
Results-MNIST / Acceleration factor R = 4

Mask	NMSE	SSIM	PSNR
Learned global mask	0.0788	0.834	20.458
2D uniform	0.2249	0.73	15.191
Learned local mask	0.259	0.677	14.766
Random	0.241	0.609	14.029
Caipirinha	0.428	0.537	11.966
Uniform	0.574	0.405	11.500

- ❑ Better reconstruction quality with learned global mask

- ❑ The global mask shape is consistent with the shape of the Fourier transform of the digits : diagonally aligned and symmetric ➔ most informative part are selected

- ❑ With local mask, we denote aliasing artefact ; except learned local mask and random (the image is noisy in theses cases



Results-MNIST / Acceleration factor R = 8

Mask	NMSE	SSIM	PSNR
Learned global mask	0.180	0.707	16.078
Learned local mask	0.434	0.396	11.524

- Again, learned global mask performs better
- Overall, for MNIST learning the full mask is more suited

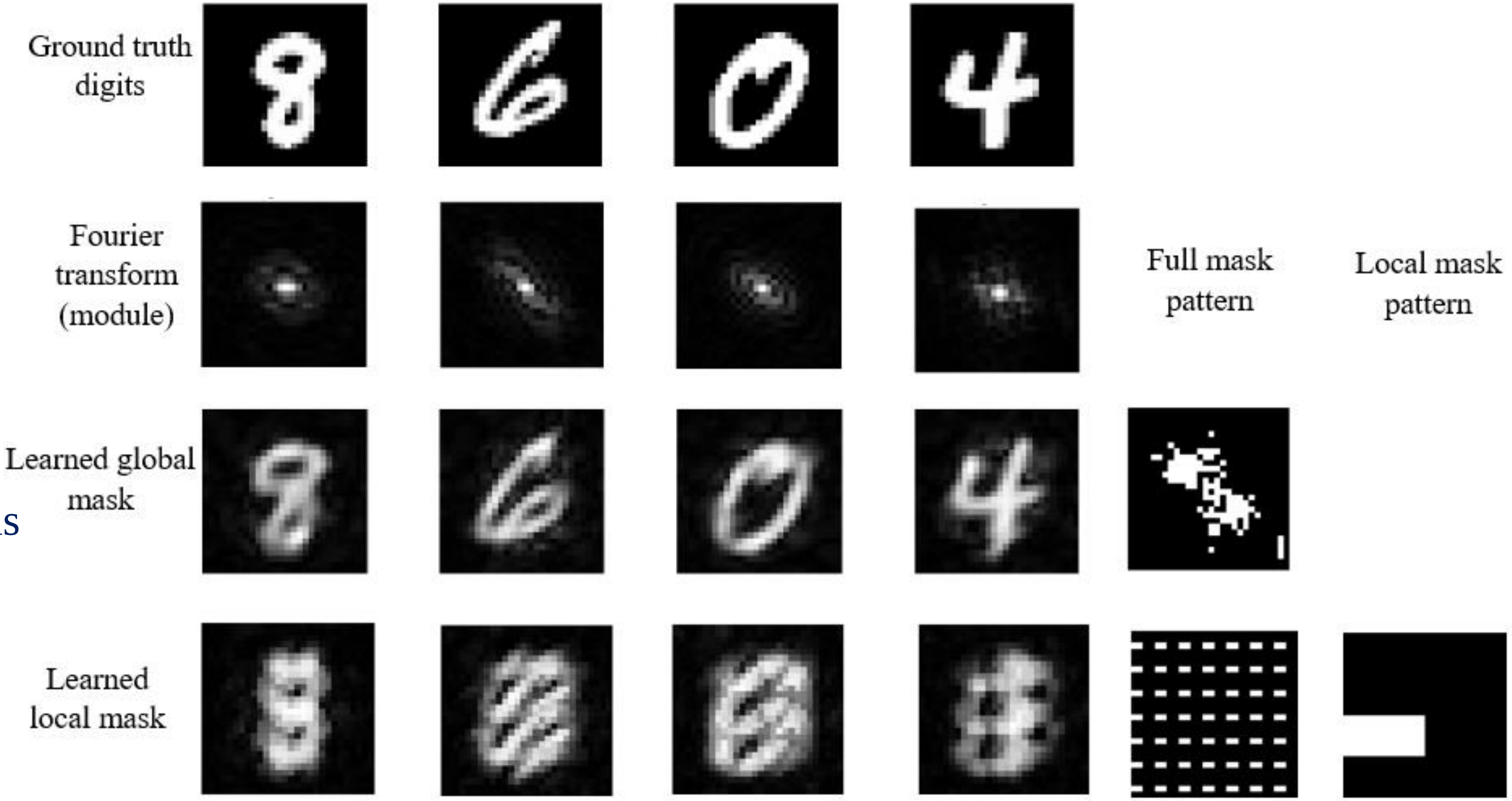
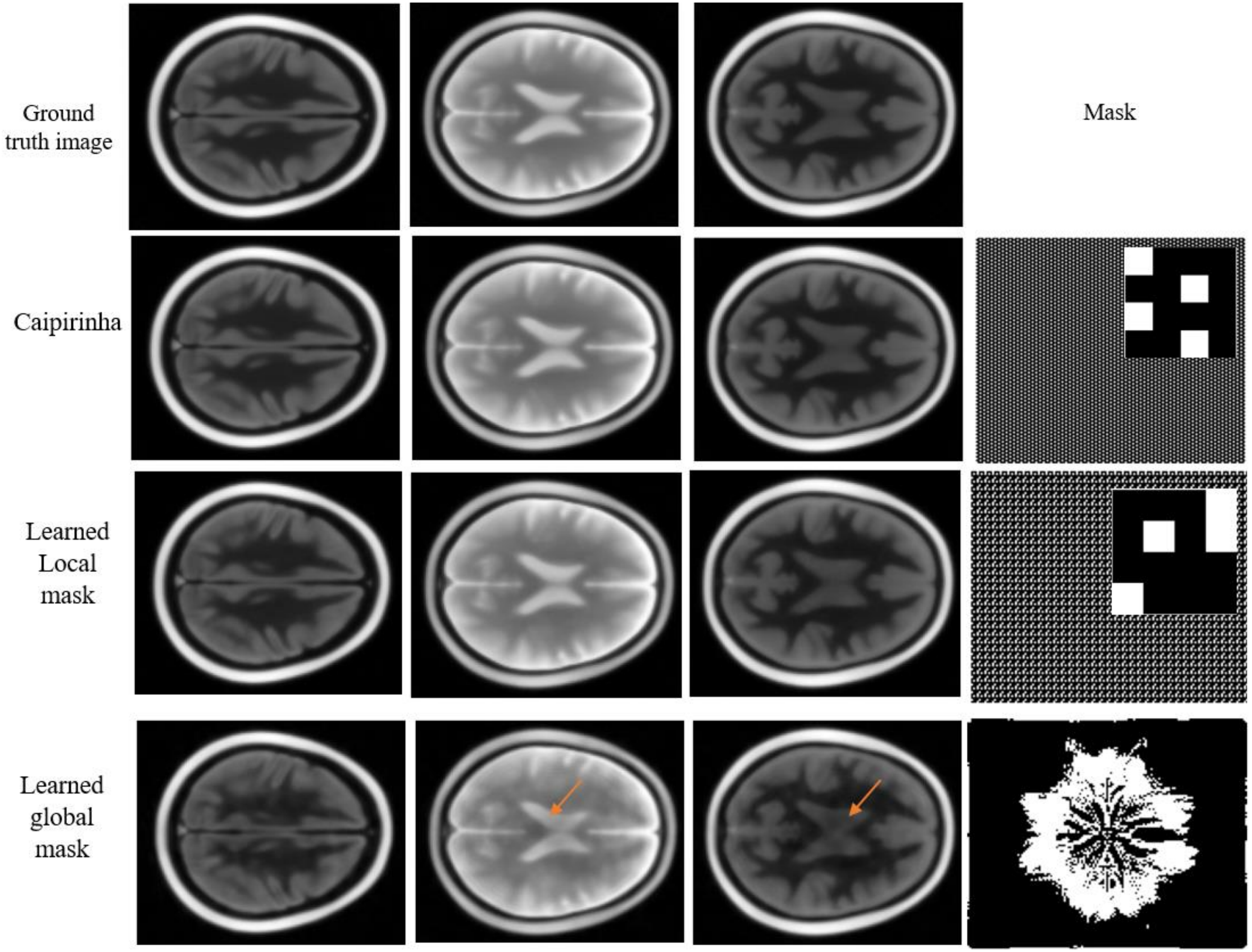


Fig 12: Global and local masks learned with the resulting reconstructions for acceleration factor R=8

Results-MRI Data / Acceleration factor R = 4

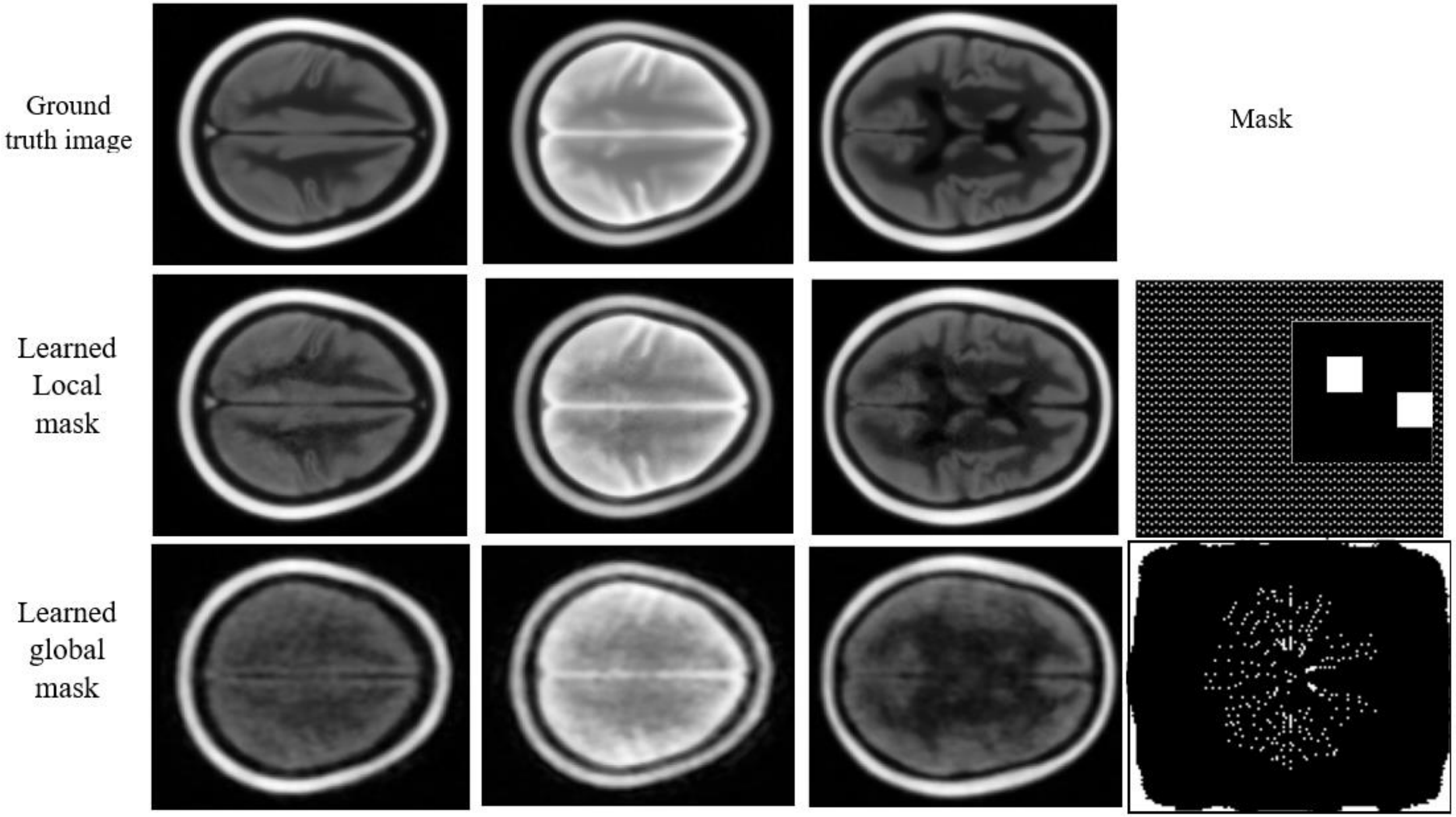
Mask	NMSE	SSIM	PSNR
Caipirinha	0.0002	0.994	52.658
Random	0.0003	0.993	50.660
Learned local mask	0.00069	0.990	45.880
2D uniform	0.00067	0.989	49.808
Uniform	0.00068	0.989	46.569
Learned global mask	0.004	0.939	36.982

- Caipirinha (10) pattern achieves the best
- Replicating local mask for this data (in their best configurations), leads to better reconstruction quality than learning the global mask
- The global mask chose frequencies (k-space points) close to the center and a little bit at the edge. This is consistent with the shape of the k-space and the coils dispositions. There are however noise in the reconstruction (orange arrows)



Results-MRI Data / Acceleration factor R = 8

Mask	NMSE	SSIM	PSNR
Learned local mask	0.002	0.965	39.806
Learned global mask	0.016	0.868	30.250



- ❑ Learned local mask perform better.
- ❑ The reconstructed images look blurry with the global mask.
- ❑ The global mask seem to select points that are close to the center, but for a reason that we ignore most of point are in the edges.
- ❑ Why thses difference of performance for the global mask ? Refine learning rate grid search, …

Take away

- Accelerate the acquisition time is a key issue in MRI, that can be addressed by acquiring less k-space measurement while having good reconstructed image quality

- In this work we proposed a model to sample k-space data and reconstruct them based of local or global sampling mask and a modified SPIRiT reconstruction model

- The result showed that reconstruction with global mask perform better of MNIST, whereas for the simulated brain data a baseline mask like Caipirinha and other local masks perform better than the global

- For some unidentified reasons, the points selected by the global mask in the case of the MRI data used , are sometimes mostly on the edge and that damages the global mask performance

- Future work, could focus on improving robustness of these results, add complementary analysis, apply to in-vivo MRI data , and propose an RL-based sampler.

Thank you !

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Appendix/Fourier Transform

- The Fourier transform of a signal gives an average of trigonometric functions of all frequencies which composed the signal.

- Consider a monochrome image (gray levels) represented by a function of two real variables, with complex values, noted u(x,y). The Fourier transform of this image is the function of two real variables and complex values defined by :

$$\boldsymbol{S(f_x, f_y) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} u(x, y)\mathbf{exp}(-i2\pi(f_x x + f_y y)dxdy}$$

- The discrete Fourier transform (DFT) associates to the matrix U a matrix V of the same dimensions, defined by :

$$V_{n,l} = \frac{1}{N_x N_y}\sum_{k=0}^{N_x-1}\sum_{m=0}^{N_y-1} U_{m,k}\exp(-i2\pi\mathrm{k}\frac{n}{N_x})\exp(-i2\pi m\frac{l}{N_y})$$

Hyperparameters used in MNIST dataset

Hyperparameters for global and local mask learning

- MASK_DIM = ([4,4] [28,28])
- ACCELERATION = (0.125 0.25)
- SPIRIT_BLOCK = (1 5 10)
- KERNEL = ([5,5] [7,7])
- STD_NOISE = (0.0175 0.03 0.05)
- LR_MASK = (1e-1 1e-2 1e-3 1e-4)
- LR_SPIRIT = (1e-2 1e-3 1e-4)

Hyperparameters for fixed local mask

- LR_OTHER=(1e-1 1e-2 1e-3 1e-4 1e-5)
- KERNEL=([5,5] [7,7])
- SPIRIT_BLOCK=(1 5 10)
- Nb random mask = 30
- Baselines masks : 2D uniform, Uniform, Capirinha

Hyperparameters used in MRI dataset

Hyperparameters for global and local mask learning

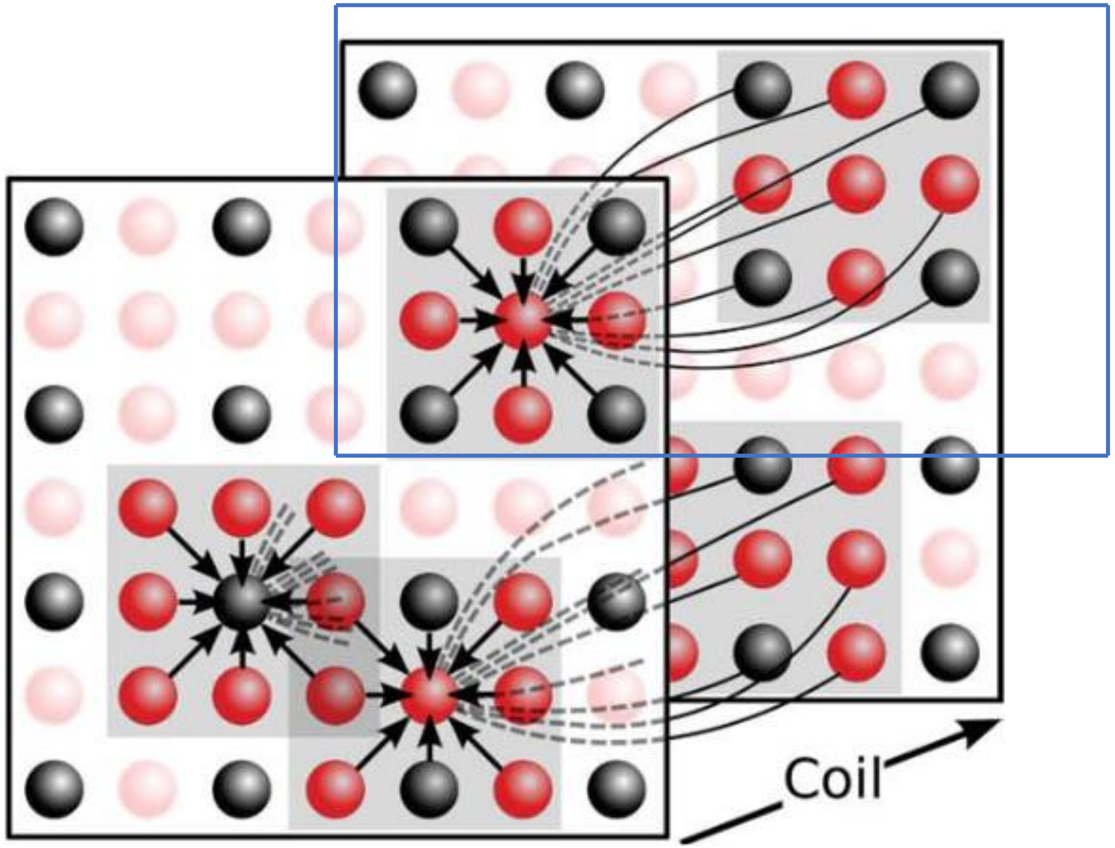
- MASK_DIM=([121,145] [4,4])
- ACCELERATION=(0.125 0.25)
- SPIRIT_BLOCK=(1 5 10)
- KERNEL=([11,11] [13,13])
- STD_NOISE=(0.0175 0.05)
- LR_MASK=(1e-2 1e-3 1e-4)
- LR_OTHER=(1e-2 1e-3 1e-4)
- ACS_TYPE=(no square)

Hyperparameters for fixed local mask

- LR_OTHER=(1e-2 1e-3 1e-4)
- KERNEL=([11,11] [13,13])
- SPIRIT_BLOCK=(1 5 10)
- ACS_TYPE=(no square)
- Nb random mask = 20
- Baselines masks : 2D uniform, Uniform, Capirinha

Methodology-SPIRiT

- SPIRiT : iterative algorithm in which in each iteration nonacquired -space values are estimated by performing a linear combination of nearby k-space values : **Calibration consistency**



$$p_5 = g_{1\,1} \times\ p_1 + g_{1\,2} \times\ p_2 + \cdots + g_{1\,18} \times p_{18}$$

$g\ a\ kernel\ of\ 3 \times 3 \times 2$ (Shift invariant)

$$p_{14} = g_{2\,1} \times\ p_1 + g_{2\,2} \times\ p_2 + \cdots + g_{2\,5} \times\ p_5 + \cdots + g_{2\,18} \times p_{18}$$

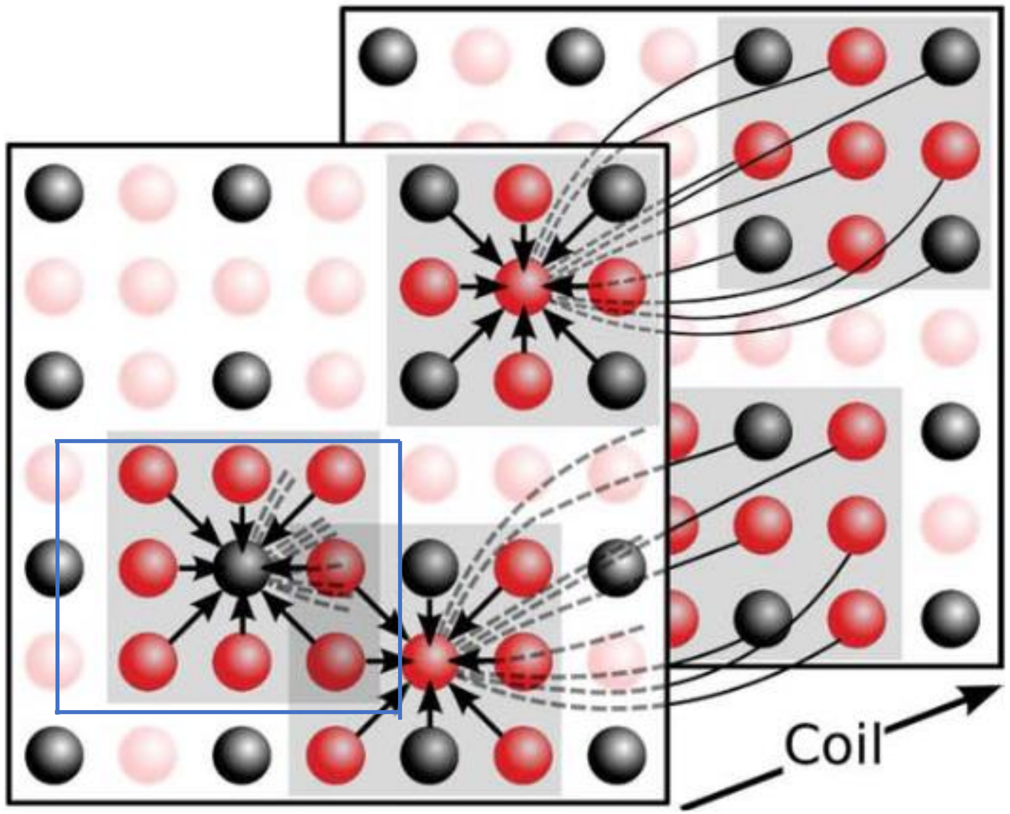
$$\hat{y}_i = \sum_{j=1}^{L} g_{ij} * \hat{y}_j$$

$$\hat{y} = G\hat{y}$$

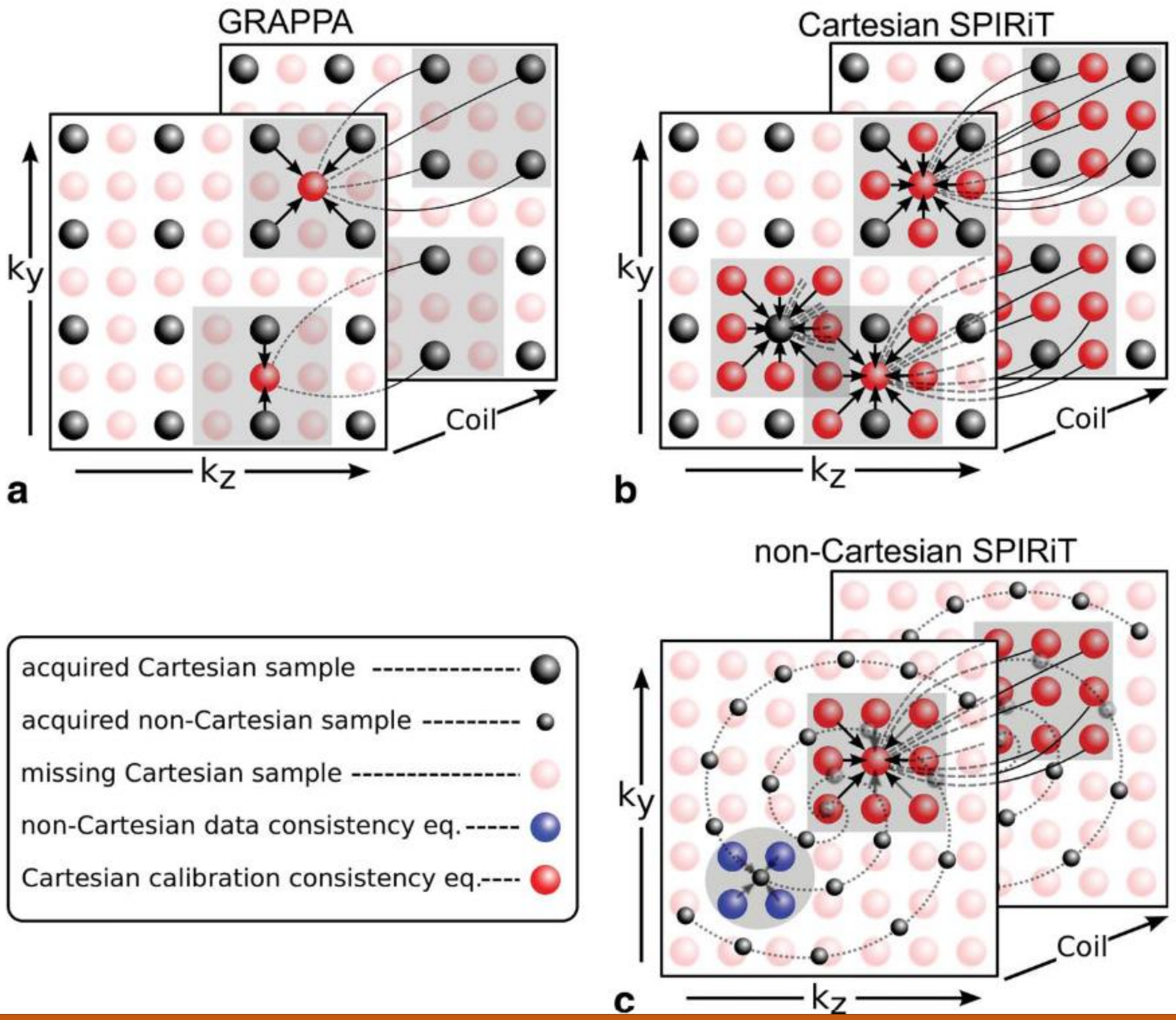
Methodology-SPIRiT

- **Data consistency :** recover the available data in the undersampled k-space after estimation

$\Rightarrow$ $\tilde{y} = D\tilde{y}$



Appendix/ SPIRiT Model



a: Traditional 2D GRAPPA. Missing k-space data are synthesized from neighboring acquired data. The synthesizing kernel depends on the specific sampling pattern in the neighborhood of the missing point. The reconstruction of a point is independent of the reconstruction
of other missing points.

b: Cartesian SPIRiT reconstruction. Three consistency equations are illustrated. The reconstruction of each point
on the grid is dependent on its entire neighborhood. The reconstruction of missing points depends on the reconstruction of other missing
points. The calibration consistency equation is independent of the sampling pattern.

c: Non-Cartesian SPIRiT. The calibration consistency equation is Cartesian (red). The acquisition data consistency relation between the Cartesian missing points and the non-Cartesian acquired
points is shown in blue. These define a large set of linear equations that is sufficient for reconstruction.

Appendix/SPIRiT Model

Solve : $\underset{x}{\operatorname{argmin}} \quad \|Dx - y\|^2 \; + \; \lambda(\epsilon)\|(G - I)x\|^2.$ With POCS : projections onto convex sets

Table 1
A POCS Algorithm for SPIRiT From Arbitrary Sampling on a Cartesian Grid

POCS SPIRiT Cartesian Reconstruction	
Inputs:	y - k-space measurements from all coils D - operator selecting acquired k-space D_c - operator selecting nonacquired k-space G - SPIRiT operator matrix obtained from calibration errToll - stopping tolerance
Outputs:	x_k - reconstructed k-space for all coils

Algorithm:	$x_0 = D^T y; k = 0$
	do {
	  $k = k + 1$
	  $x_k = Gx_{k-1}$ % calibration consistency projection
	  $x_k = D_c^T D_c x_k + D^T y$ % data acquisition consistency projection
	  $e = \|x_k - x_{k-1}\|$ % Error stopping criteria
	  $x_{k-1} = x_k$
	}while $e >$ errToll

Compressed sensing in Parallel imaging

- **Compressed sensing**

Enables reconstruction of images by using fewer k-space measurements than is possible with classical signal processing methods by enforcing suitable priors.

solve the following optimization problem:

$$\hat{\mathrm{x}} = \operatorname{argmin}_{\mathrm{x}} \frac{1}{2} \sum_i \left\| M\mathcal{F}(S_i \mathrm{x}) - \tilde{\mathrm{k}}_i \right\|^2 + \lambda \Psi(\mathrm{x})$$
$$= \operatorname{argmin}_{\mathrm{x}} \frac{1}{2} \left\| A(\mathrm{x}) - \tilde{\mathrm{k}} \right\|^2 + \lambda \Psi(\mathrm{x}),$$

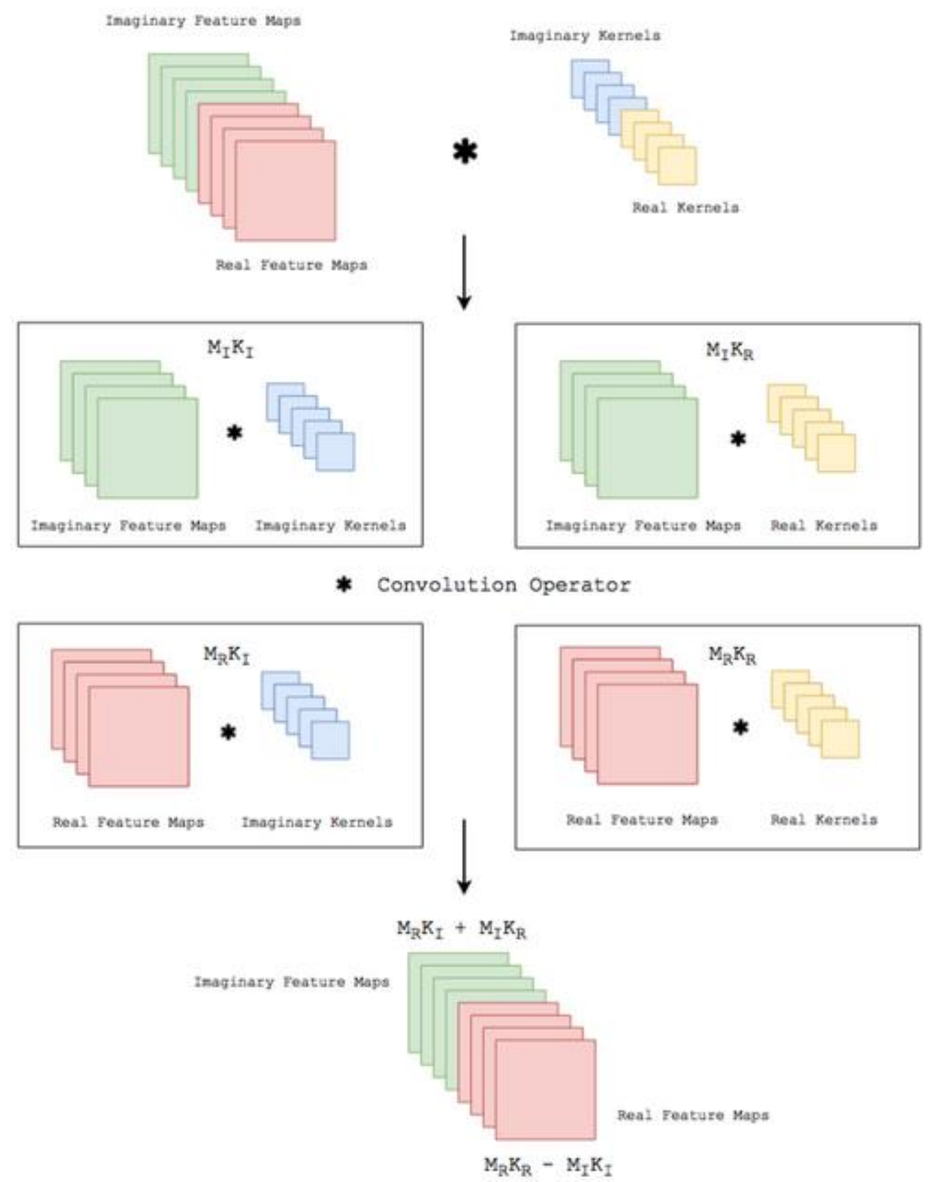
- A is the linear forward operator that multiplies by the sensitivity maps, applies 2D Fourier transform and then under-samples the data

- $\tilde{k}$ is the vector of masked k-space data from all coils
- Solved iteratively with gradient descent method $\mathrm{x}^{t+1} = \mathrm{x}^t - \eta^t \left(A^*(A(\mathrm{x}) - \tilde{\mathrm{k}}) + \lambda \Phi(\mathrm{x}^t) \right)$

- And $\Phi(\mathrm{x})$ is the gradient of Ψ which is a regularization function that enforces a sparsity constraint

https://arxiv.org/abs/2004.06688 , section 2.2

Appendix/Complex Convolution



$$M' = K * M = (M_{\Re} + iM_{\Im}) * (K_{\Re} + iK_{\Im})$$

$$M' = \{M_{\Re} * K_{\Re} - M_{\Im} * K_{\Im}\} + i\{M_{\Re} * K_{\Im} + M_{\Im} * K_{\Re}\}$$