Gerstner Sloan Kettering
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Magnetic Resonance Imaging

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Agenda

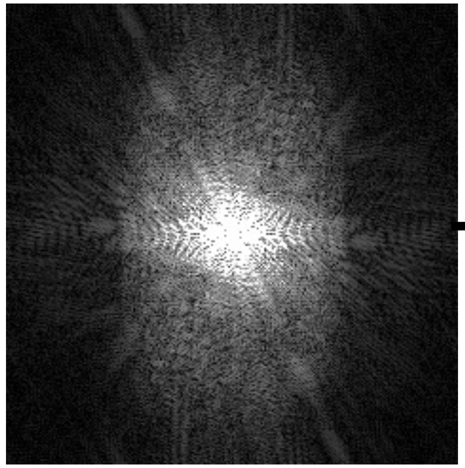
- Imaging with magnetic field gradients
  - k-space
- Pulse sequences
  - Gradient-echo, spin-echo
- Image reconstruction: k-space undersampling
- Parallel imaging, compressed sensing, deep learning
- MR fingerprinting: quantitative imaging
- Experiment in Matlab & Python: accelerated brain MRI

MRI

scanner

acquisition

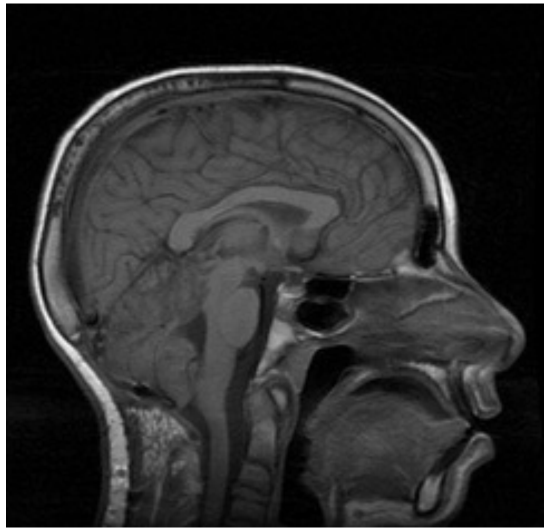
raw data

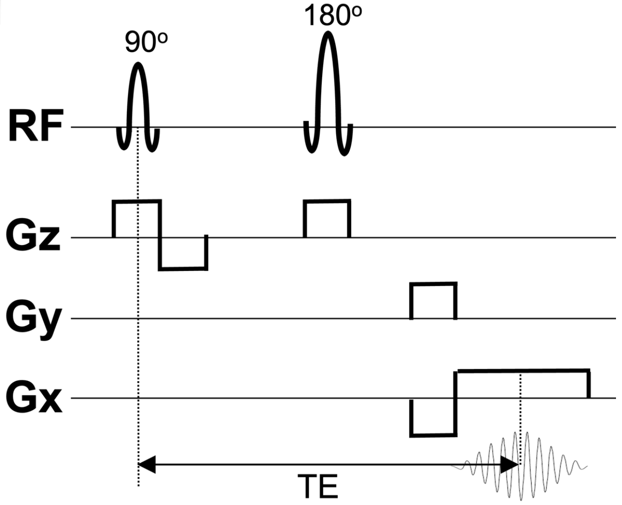


k-space

reconstruction

image





pulse sequence

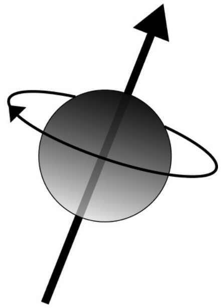
algorithm

Data acquisition

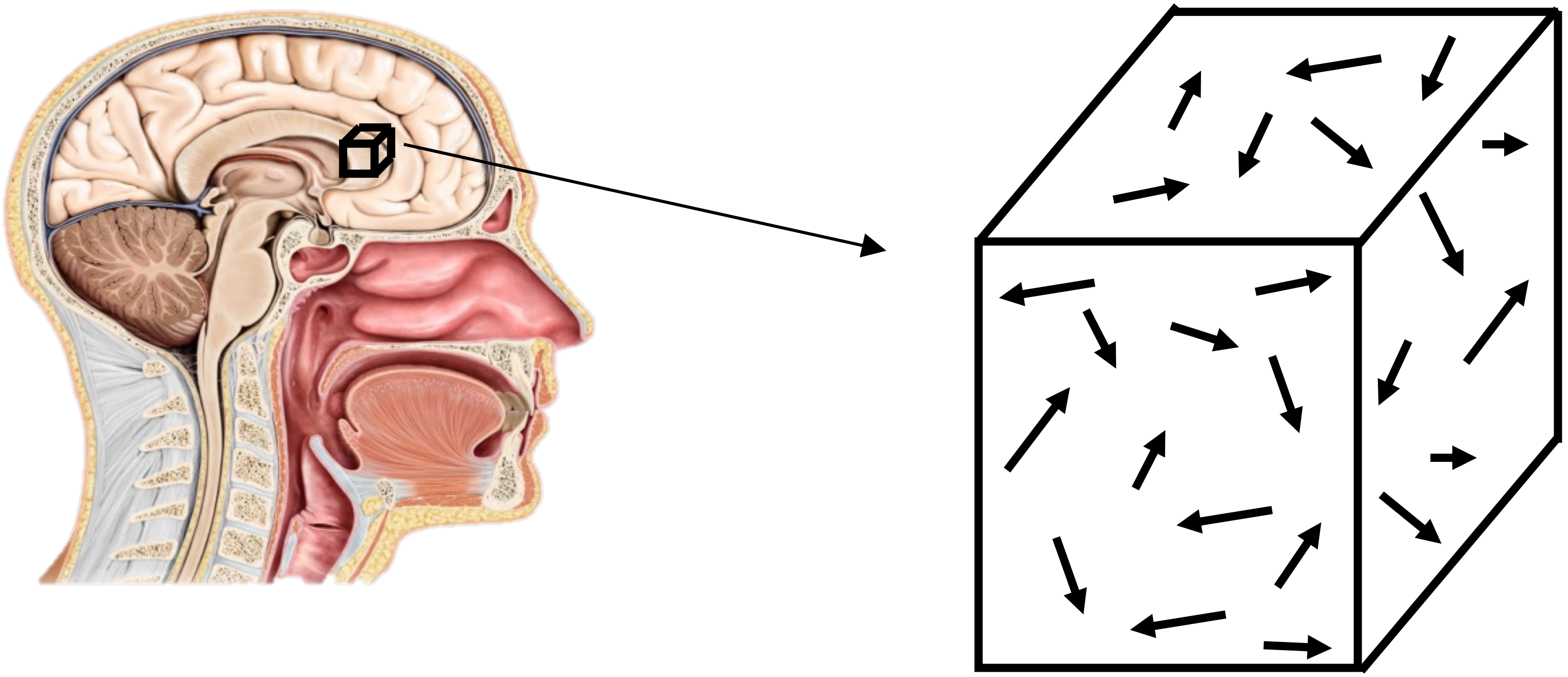
Gradients, k-space and pulse sequences

Protons and spins

- **The nucleus of the hydrogen atom (proton) has a magnetic momentum (spin)**

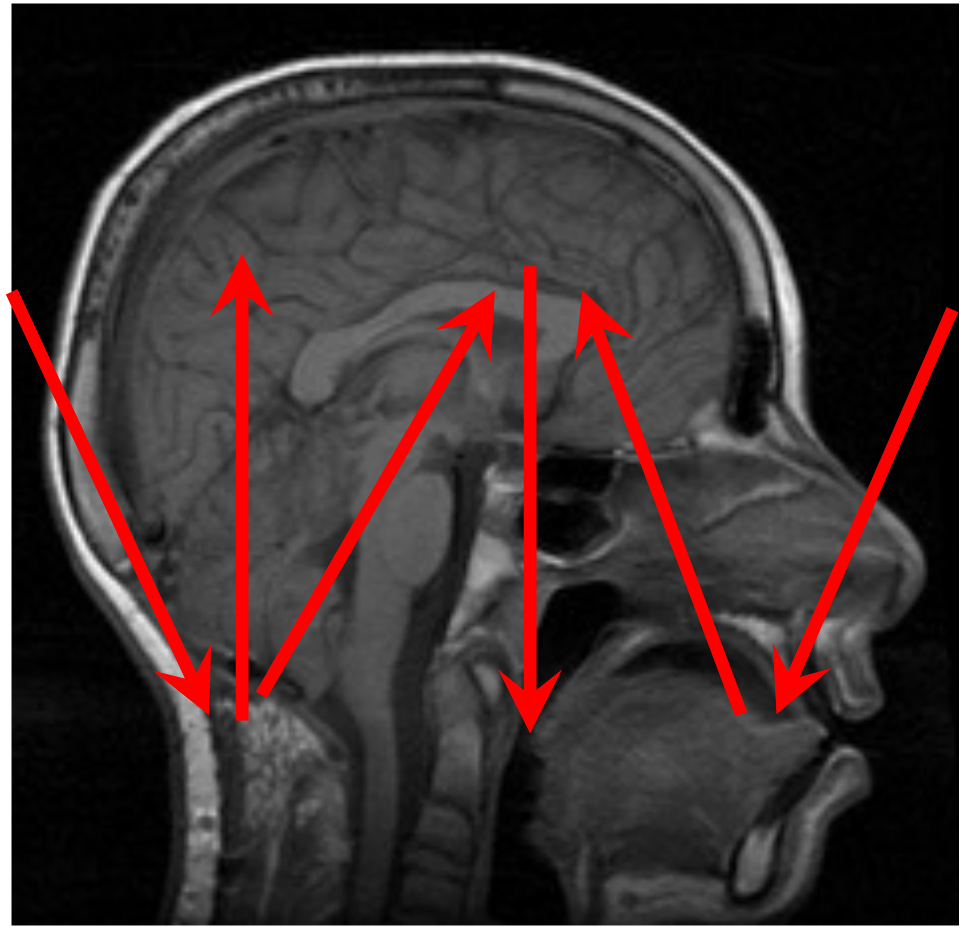


- **Proton = tiny rotating magnet**



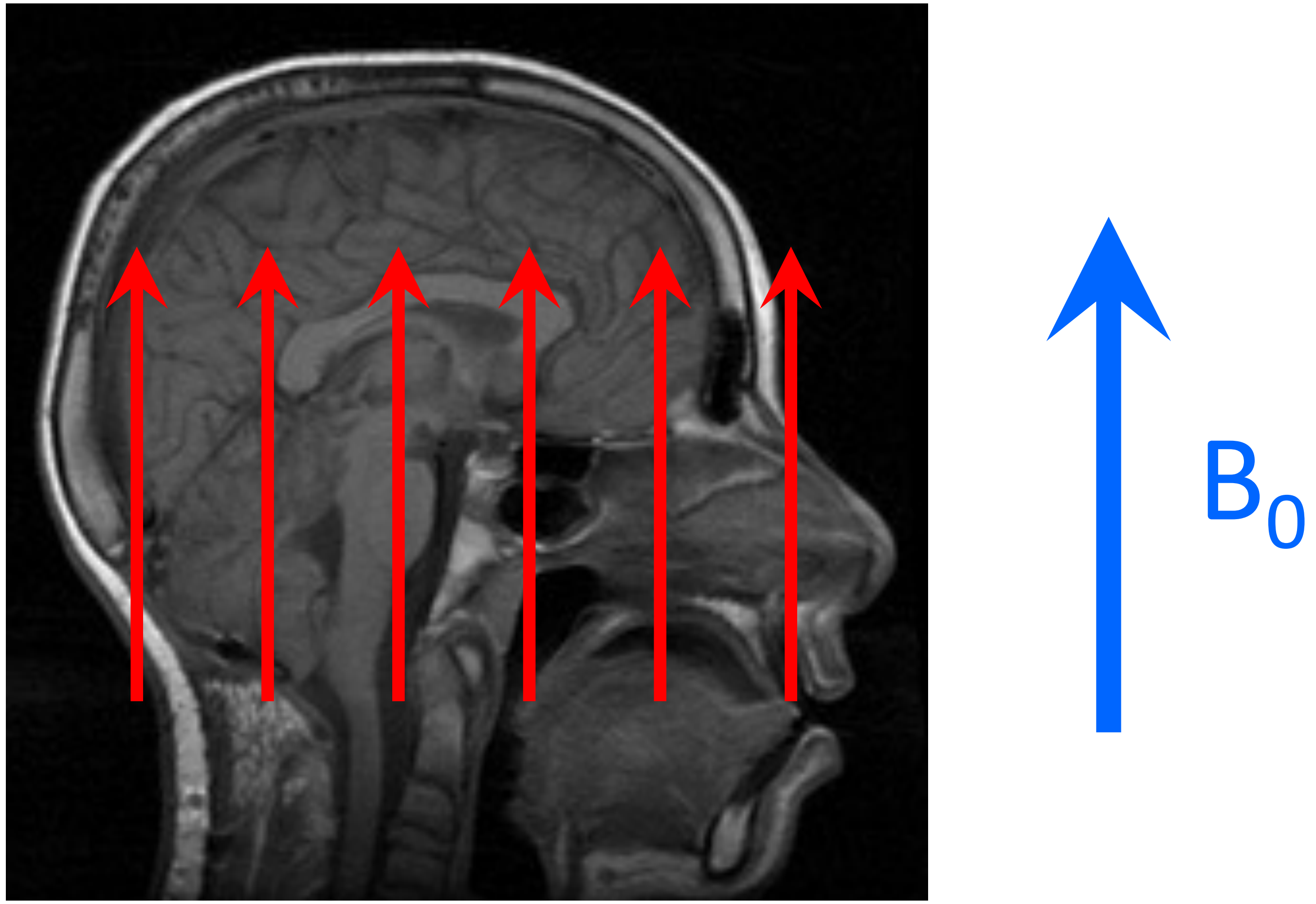
Polarization and magnetization

- **Spins are randomly oriented (no net magnetization)**



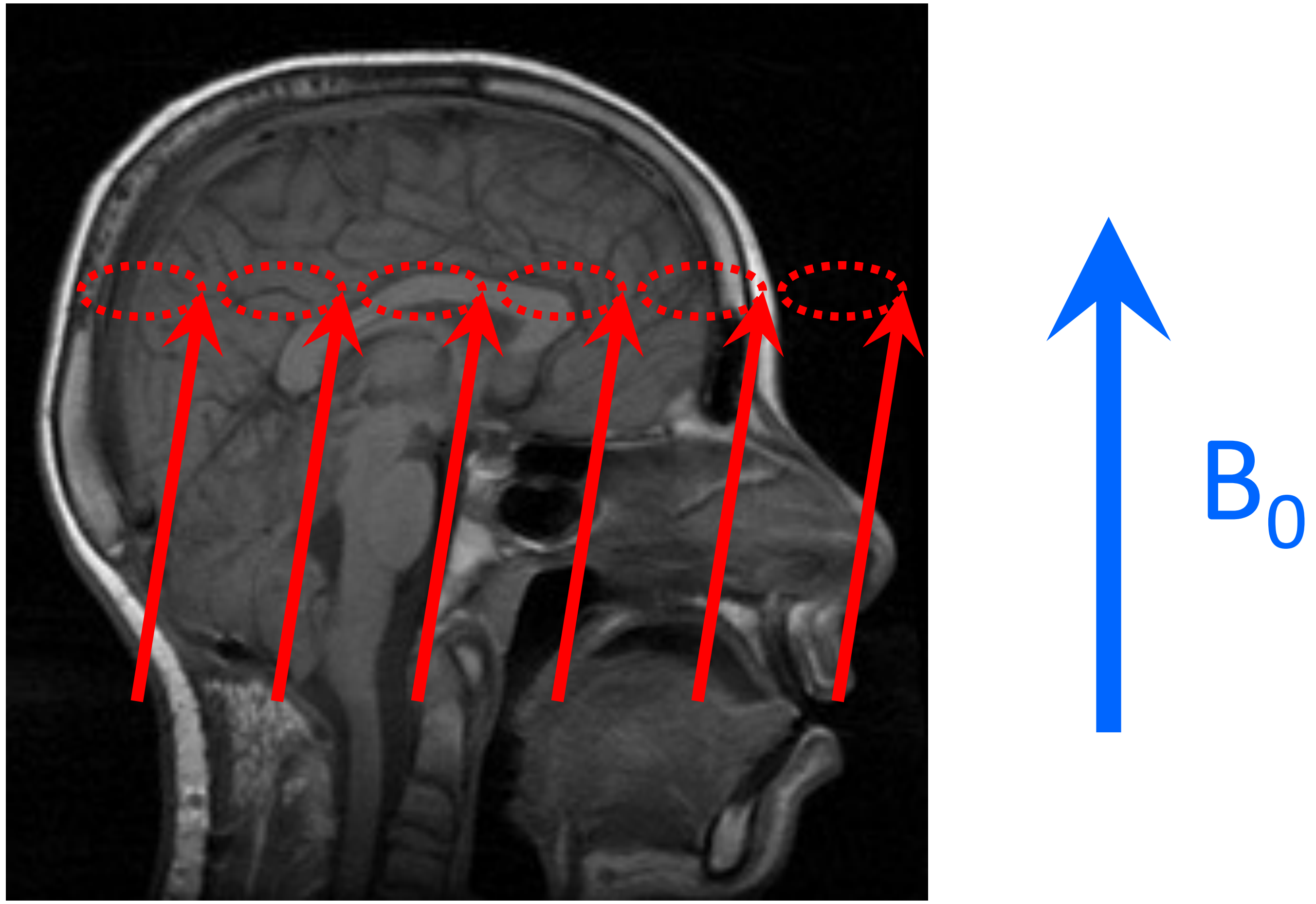
Polarization and magnetization

- **Spins are aligned by a strong magnetic field**
  - **magnetization**



Magnetic resonance

- **Precession proportional to the magnetic field strength**



$$f_0 = \gamma B_0$$

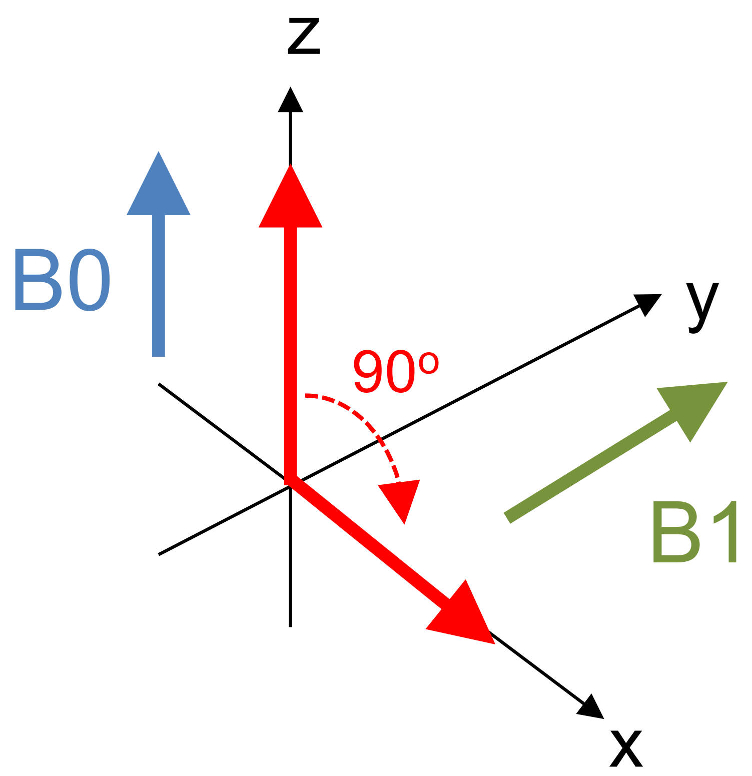
Magnetic resonance

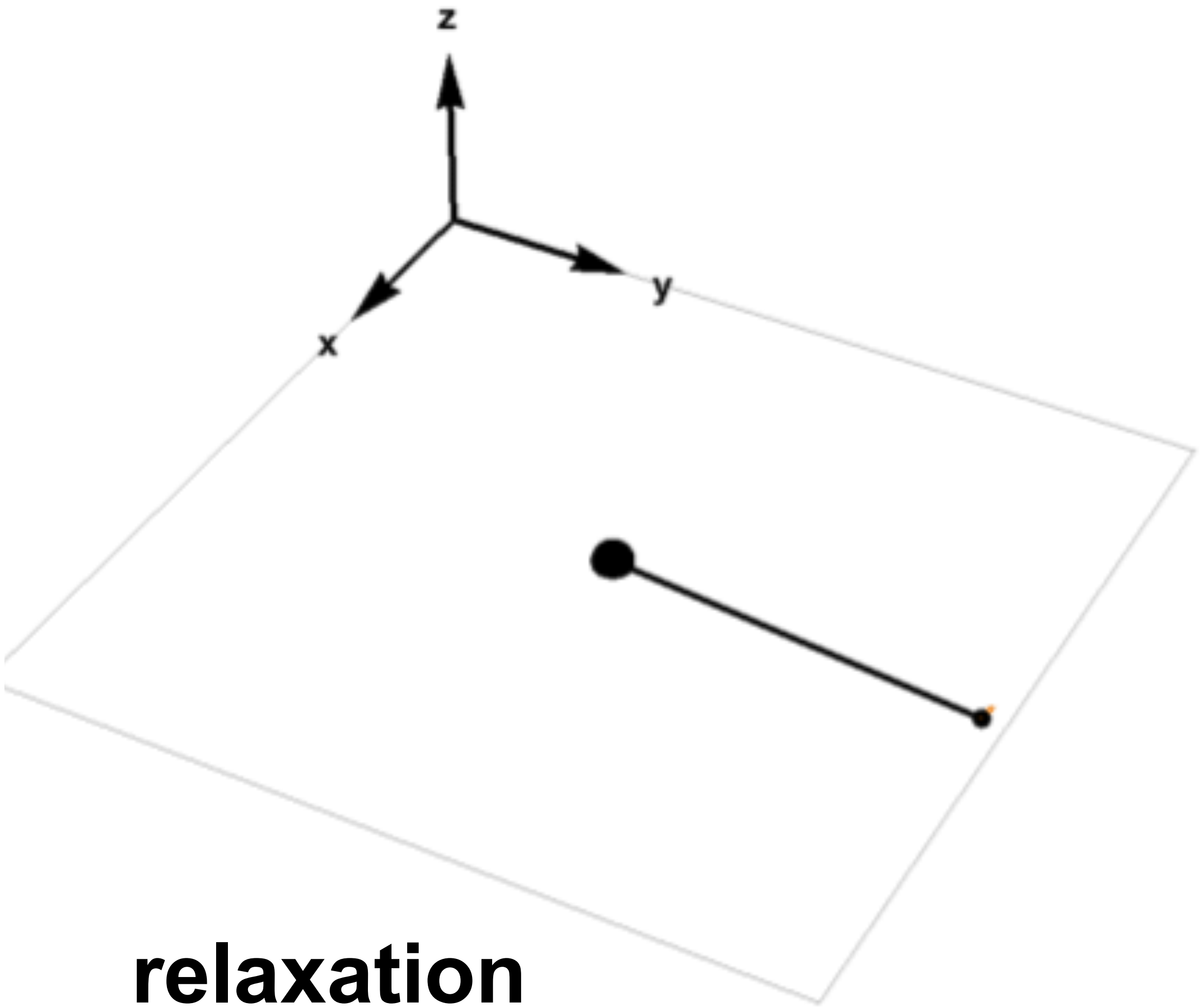
- $\gamma = 42.58\ MHz/T$ **(gyromagnetic ratio for ^{1}H)**

- $\boldsymbol{f_0}$ **= 63.9 MHz (1.5T)**
  = 127.74 MHz (3T)

RF excitation (B1)

- **Displacing the spins from equilibrium**
- **Produce a detectable magnetization**

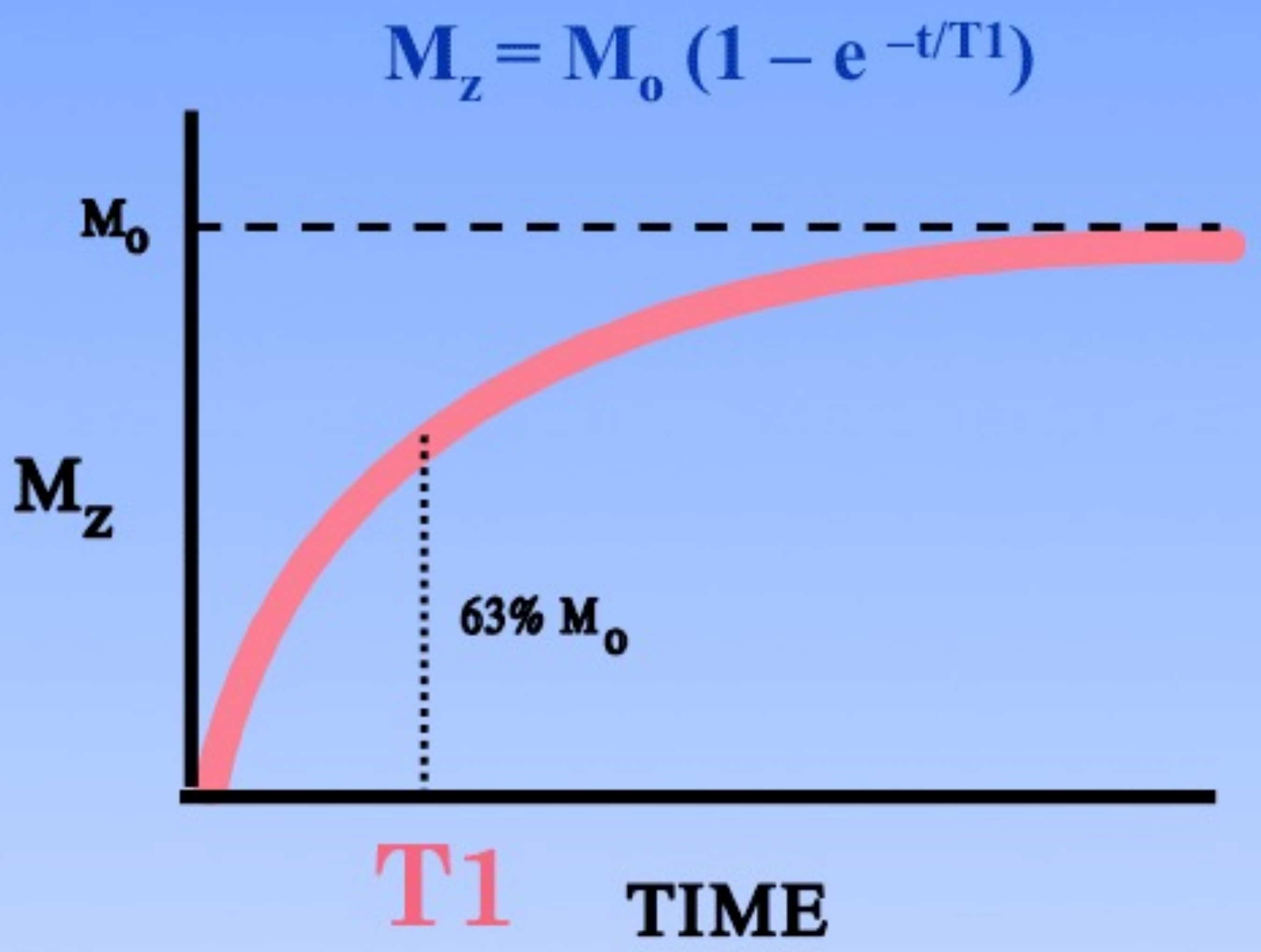




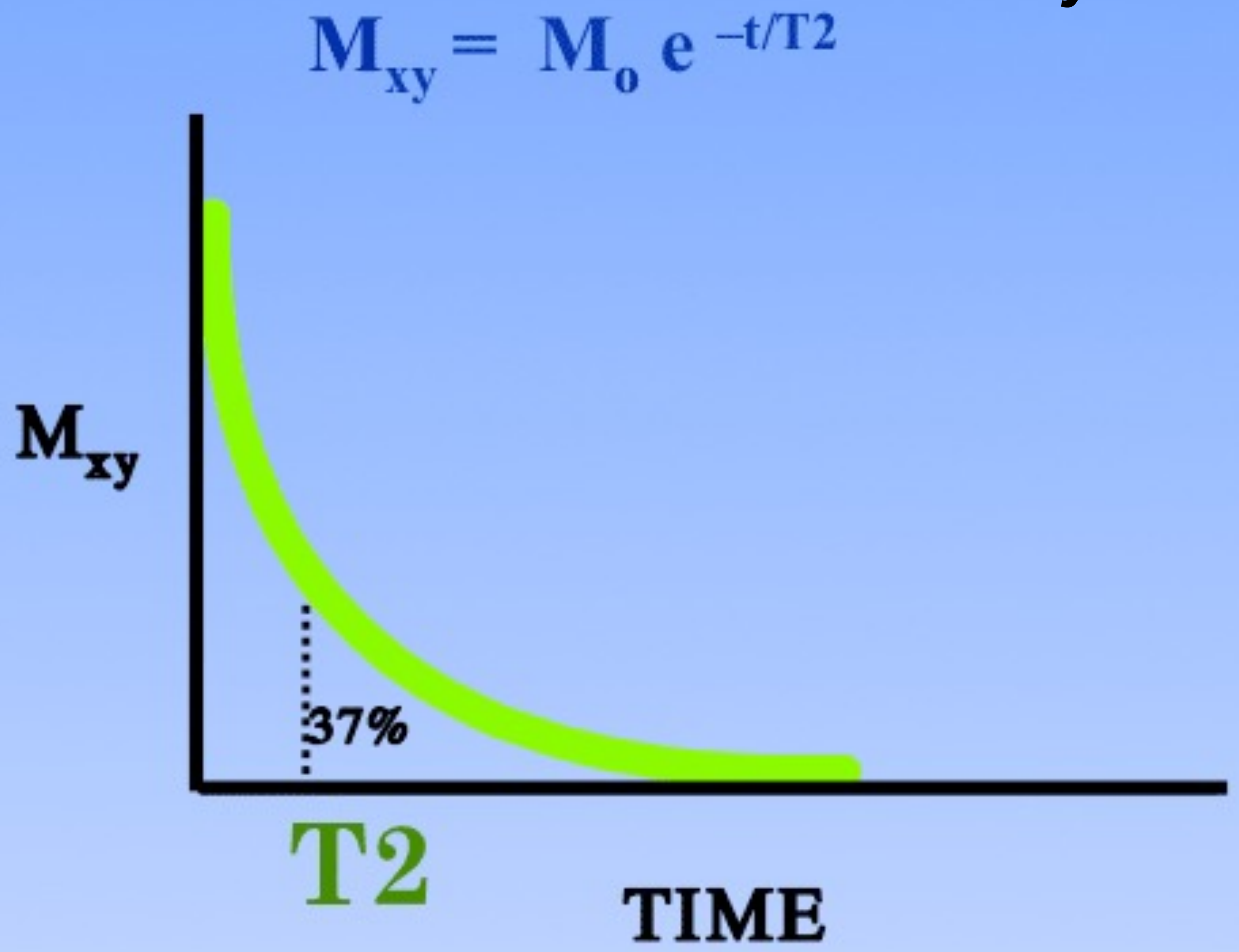
relaxation

Relaxation (T1, T2)

T1: recovery of M_z



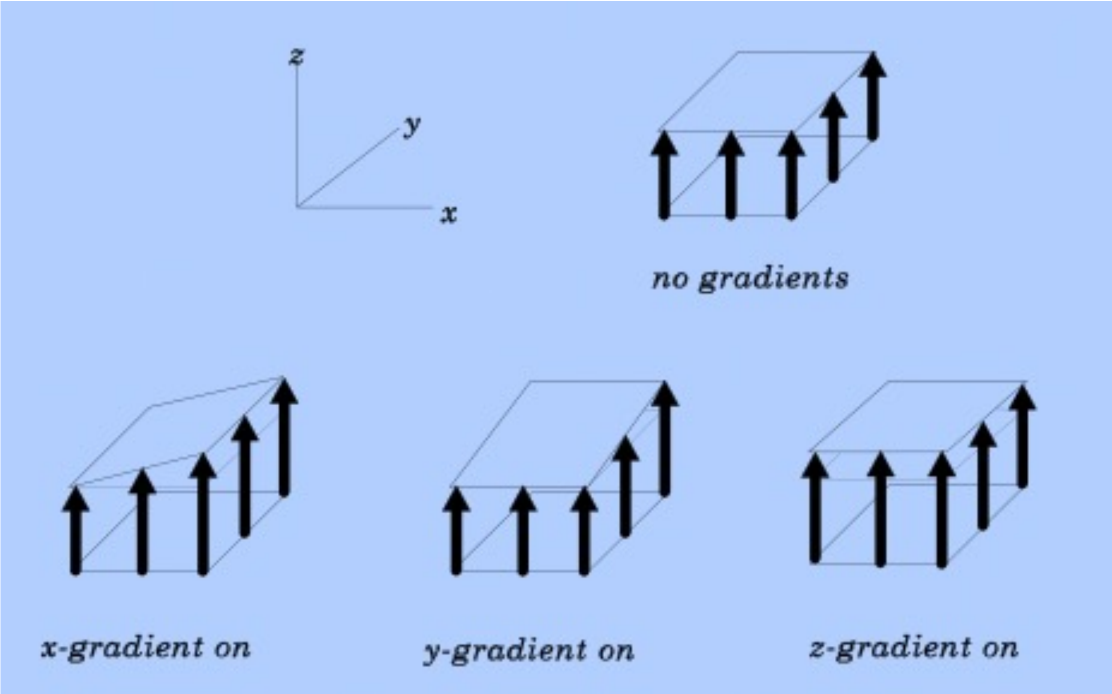
T2: decay of M_x and M_y

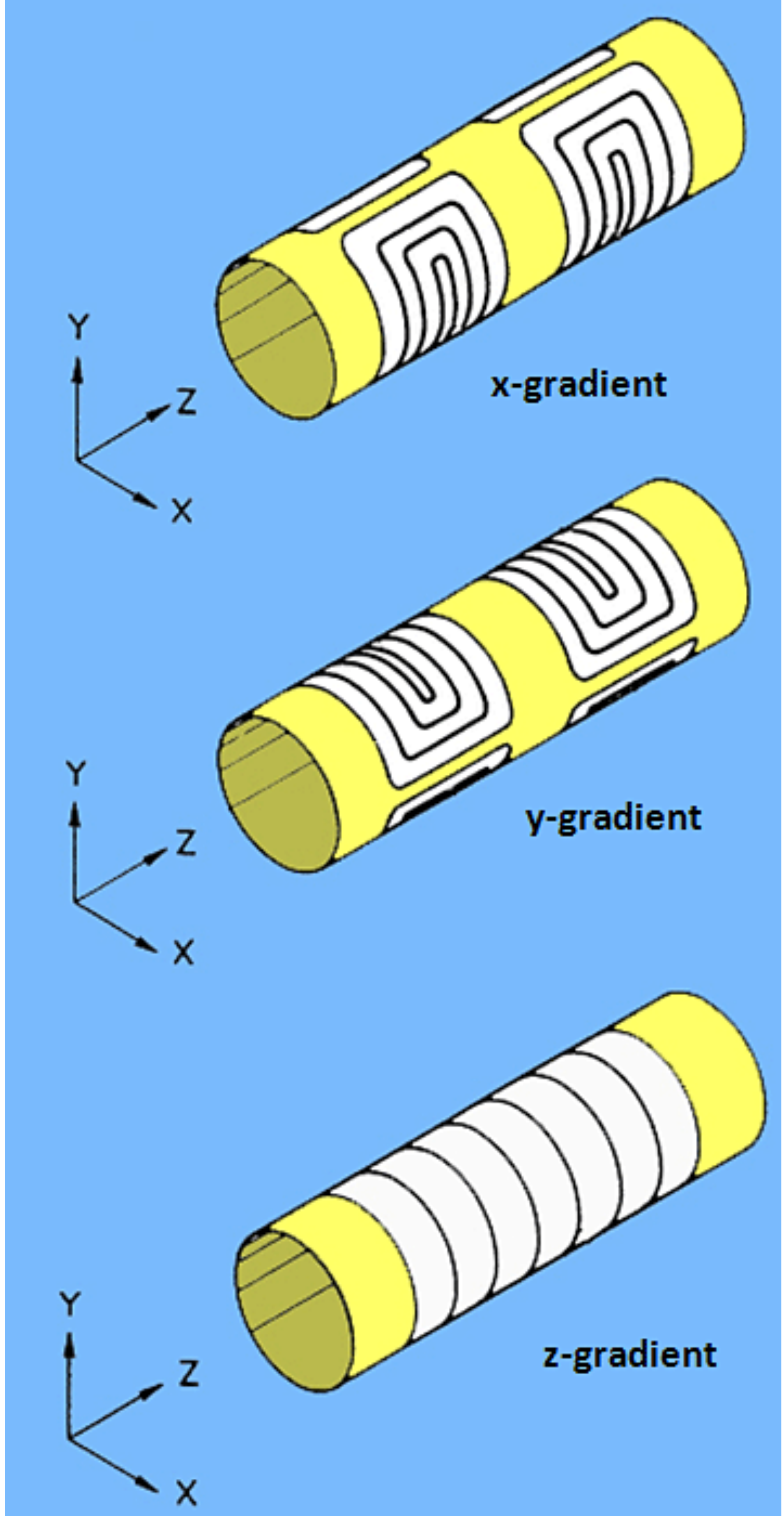


Imaging

- **Magnetic field gradients**
  - **Spatially-varying magnetic fields**

$$B(x, y, z) = B0 + G_x x + G_y y + G_z z$$





Signal equation

- **After B0 demodulation, only magnetic field gradients contribute to the MR signal:**

$$S(t) = \int_{\boldsymbol{r}} M(\boldsymbol{r}) e^{i2\pi\gamma \int_0^t \boldsymbol{G}(\tau)d\tau \cdot \boldsymbol{r}} d\boldsymbol{r}$$

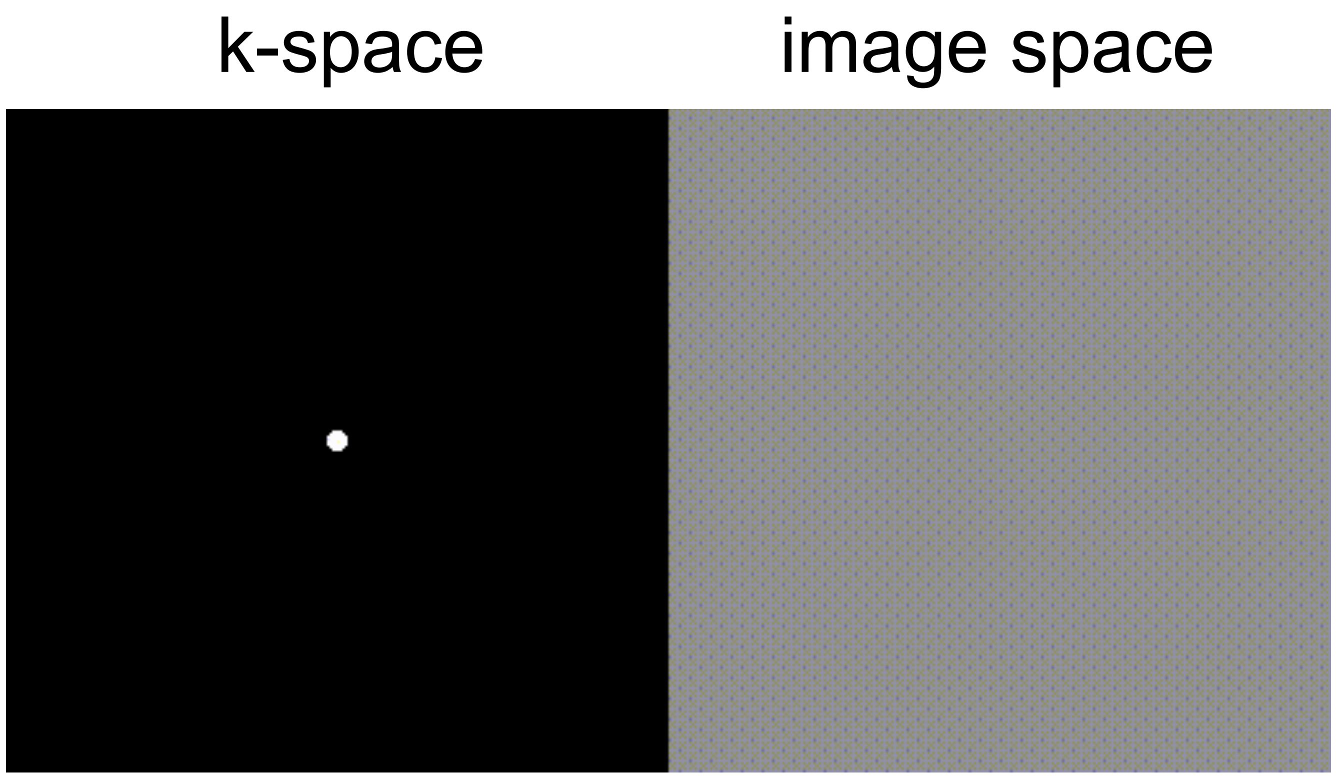
  – **Defining:** $\boldsymbol{k}(t) = \gamma \int_0^t \boldsymbol{G}(\tau)d\tau$ **(k-space)**

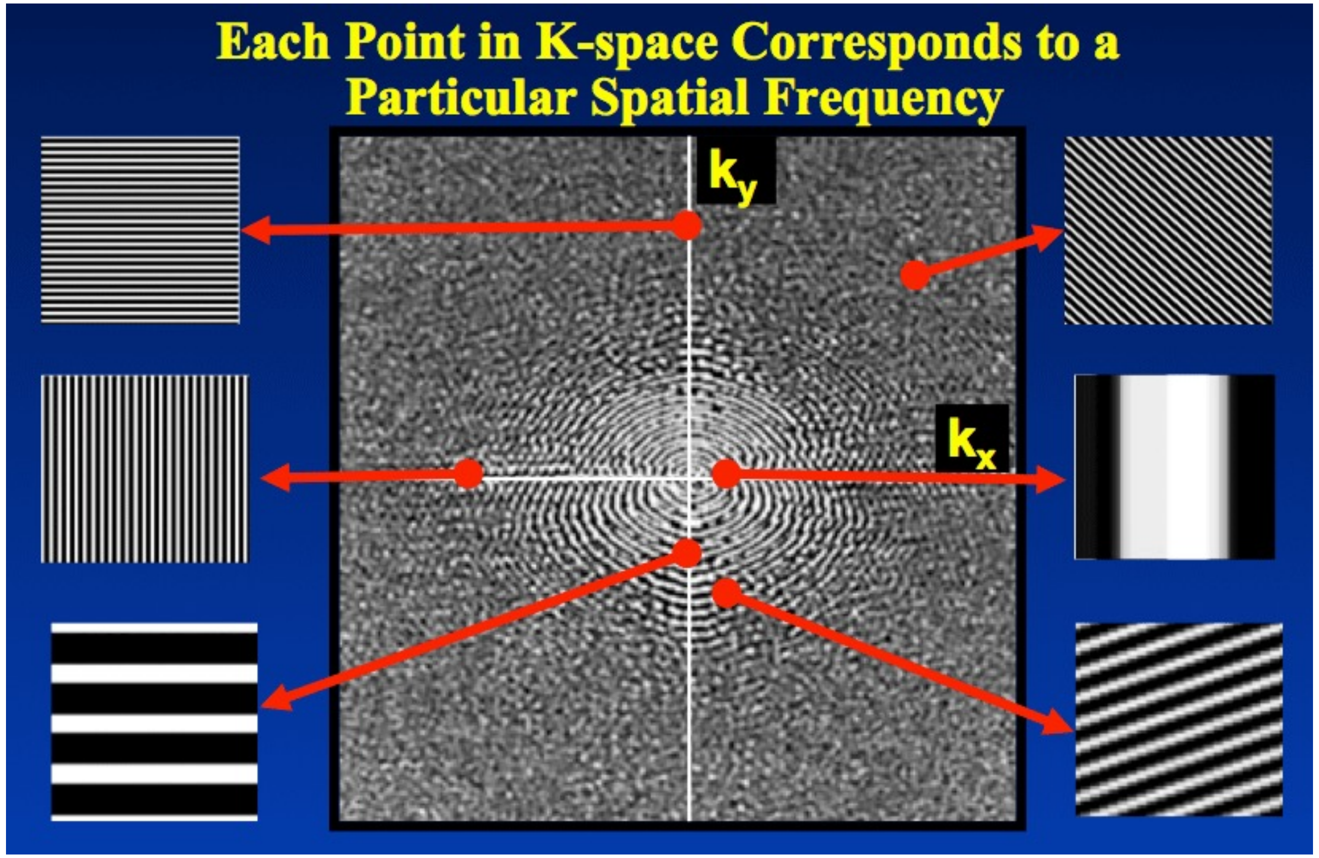
$$s(t) = \int_{\boldsymbol{r}} M(\boldsymbol{r}) e^{i2\pi\boldsymbol{k}(t)\cdot\boldsymbol{r}} d\boldsymbol{r}$$

Fourier transform of $M(\boldsymbol{r})$

k-space

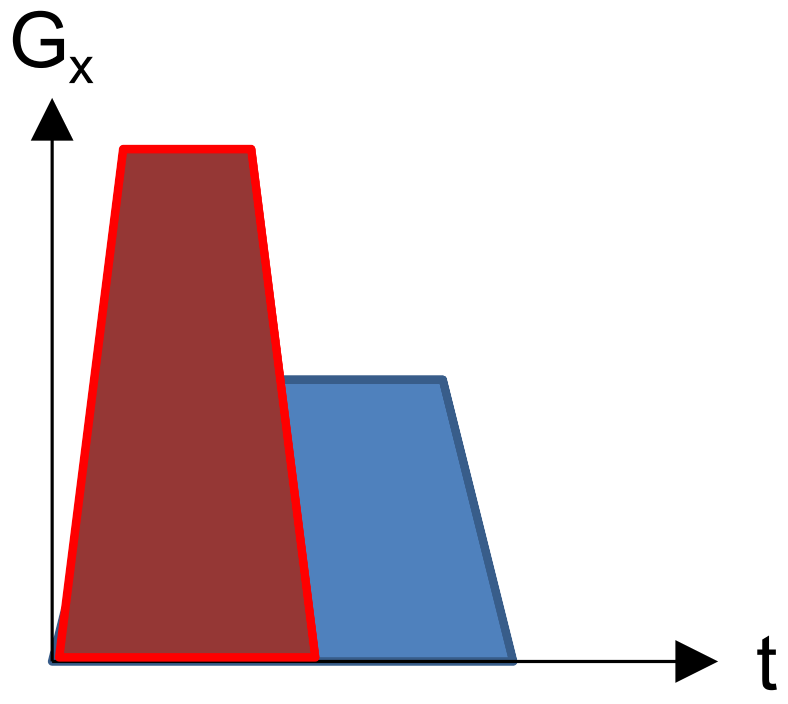
- **Space of spatial frequencies**

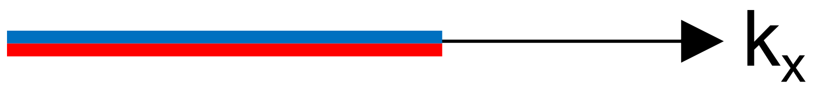




k-space

- **Gradient moment** $$k(t) = \gamma \int_0^t G(\tau) d\tau$$



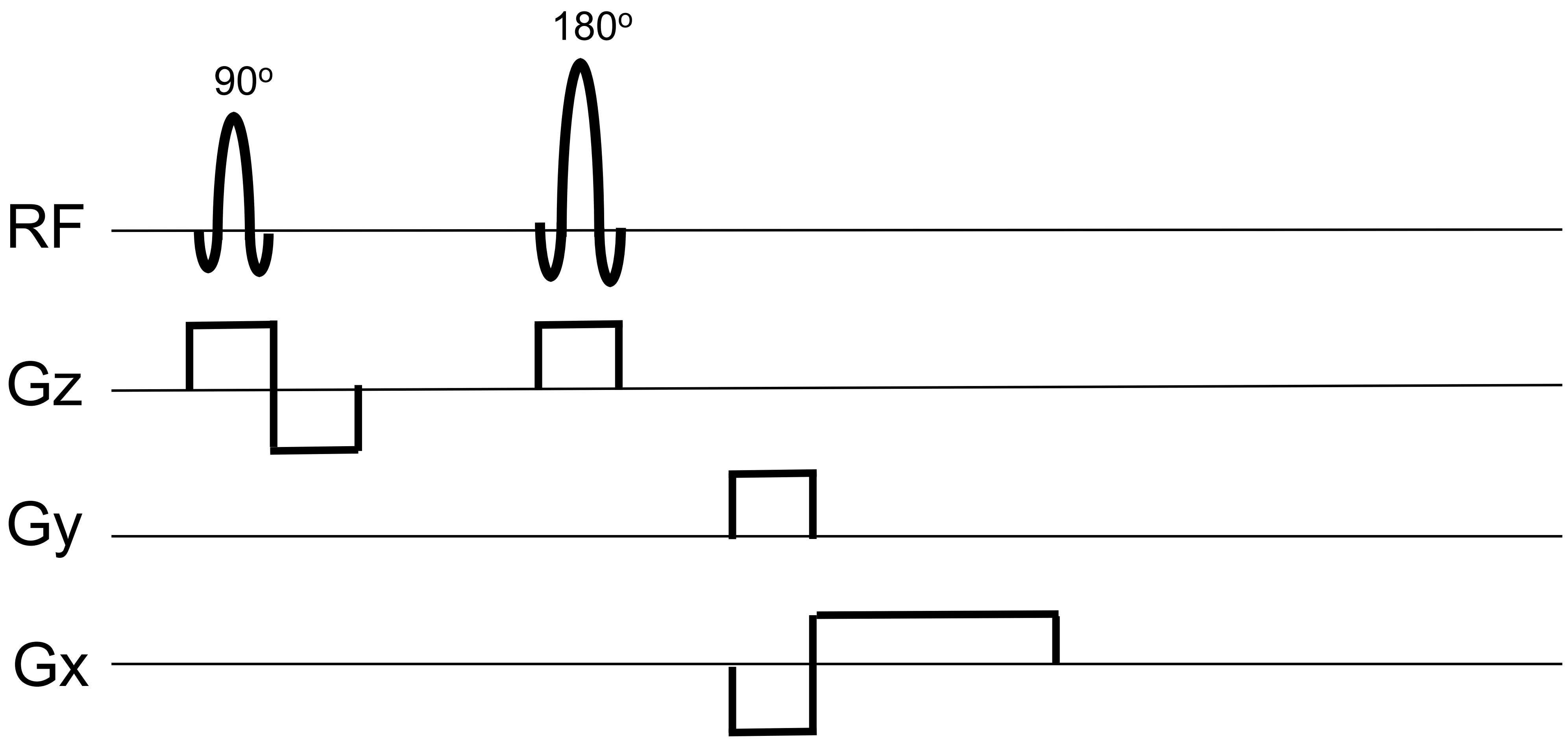


scan time = T

scan time = T/2

Pulse sequence

- **Diagram of the temporal waveforms used for the RF (B1) and gradient (Gx, Gy and Gz) pulses**



Pulse sequence

- **Program to acquire MRI data**
  - Write source code
  - Compile source code
  - Run compiled code on the scanner

ksgre: GRE sequence (2D/3D)

Data Structures

```
struct KSGRE_SEQUENCE
```

Macros

```
#define KSGRE_MINHNOVER 16
#define KSGRE_DEFAULT_SSI_TIME 200 /* which may allow us to use the same SSI for other sequence modules too */
#define KSGRE_DEFAULT_SSI_TIME_SSFP 100
#define KSGRE_INIT_SEQUENCE
```

Functions

```
STATUS cvinit (void)
STATUS cveval (void)
STATUS my_cveval (void)
STATUS cvcheck (void)
STATUS predownload (void)
STATUS pulsegen (void)
STATUS mps2 (void)
STATUS aps2 (void)
STATUS scan (void)
       abstract ("GRE [KSFoundation]")
       psdname ("ksgre")
STATUS ksgre_pg (int start_time)
   int ksgre_scan_coreslice (const SCAN_INFO *slice_pos, int dabslice, int shot, int exc)
   int ksgre_scan_coreslice_nargs (const SCAN_INFO *slice_pos, int dabslice, int nargs, void **args)
   int ksgre_scan_sliceloop (int slperpass, int passindx, int shot, int exc)
   int ksgre_eval_ssitime ()
  void ksgre_init_imagingoptions (void)
STATUS ksgre_init_UI (void)
STATUS ksgre_eval_UI ()
STATUS ksgre_eval_setupobjects ()
STATUS ksgre_eval_TErange ()
STATUS ksgre_eval_inversion (KS_SEQ_COLLECTION *seqcollection)
STATUS ksgre_eval_tr (KS_SEQ_COLLECTION *seqcollection)
STATUS ksgre_eval_scantime ()
STATUS ksgre_check ()
STATUS ksgre_predownload_plot (KS_SEQ_COLLECTION *seqcollection)
STATUS ksgre_predownload_setrecon ()
 float ksgre_scan_phase (int counter)
STATUS ksgre_scan_init (void)
STATUS ksgre_scan_prescanloop (int nloops, int dda)
```

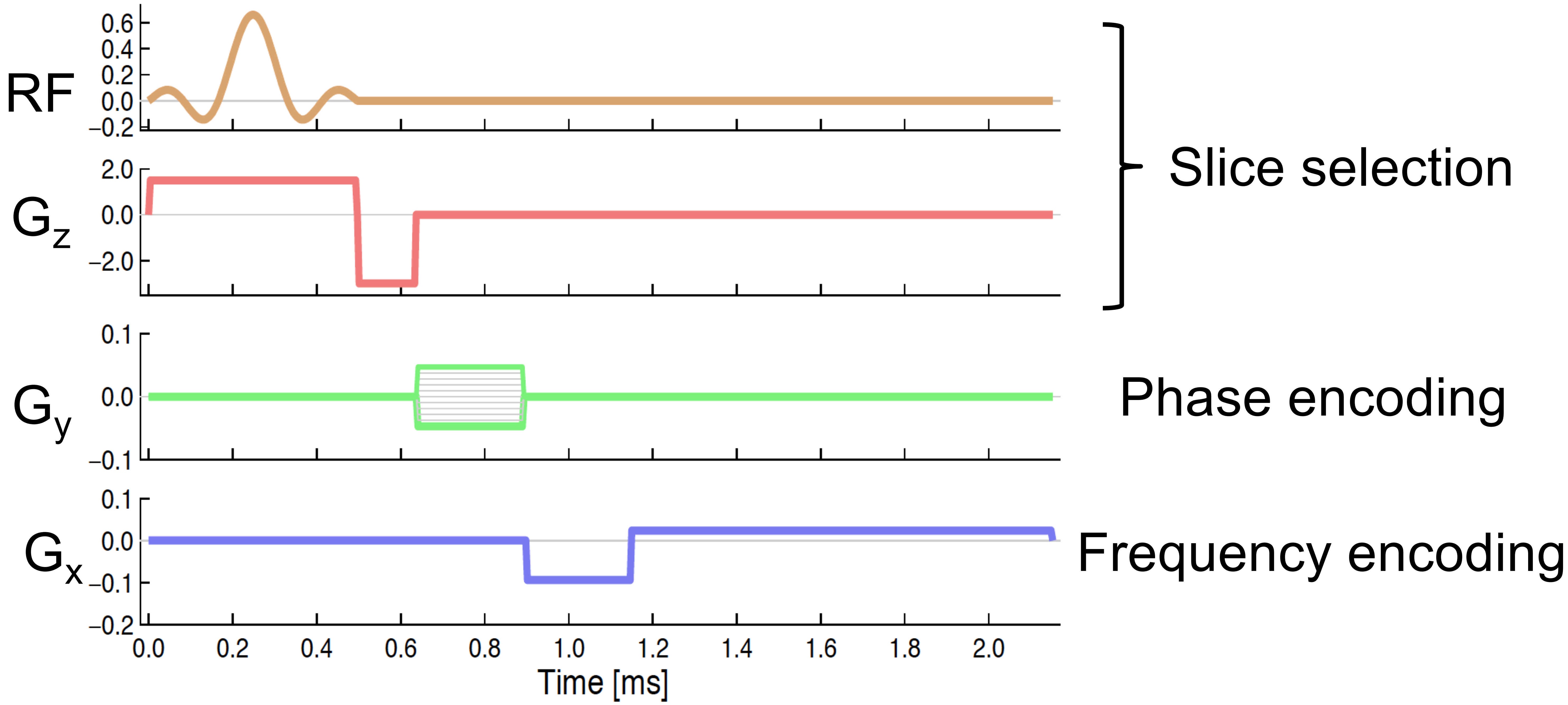
Variables

```
KS_SEQ_COLLECTION seqcollection
            float ksgre_excthickness = 0
            float ksgre_gscalerfexc = 0.9
              int ksgre_slicecheck = 0 with {0, 1, 0, VIS, "move readout to z axis for slice thickness test",}
            float ksgre_spoilerarea = 1500.0 with {0.0, 10000.0, 1500.0, VIS, "ksgre spoiler gradient area",}
```

Imaging techniques

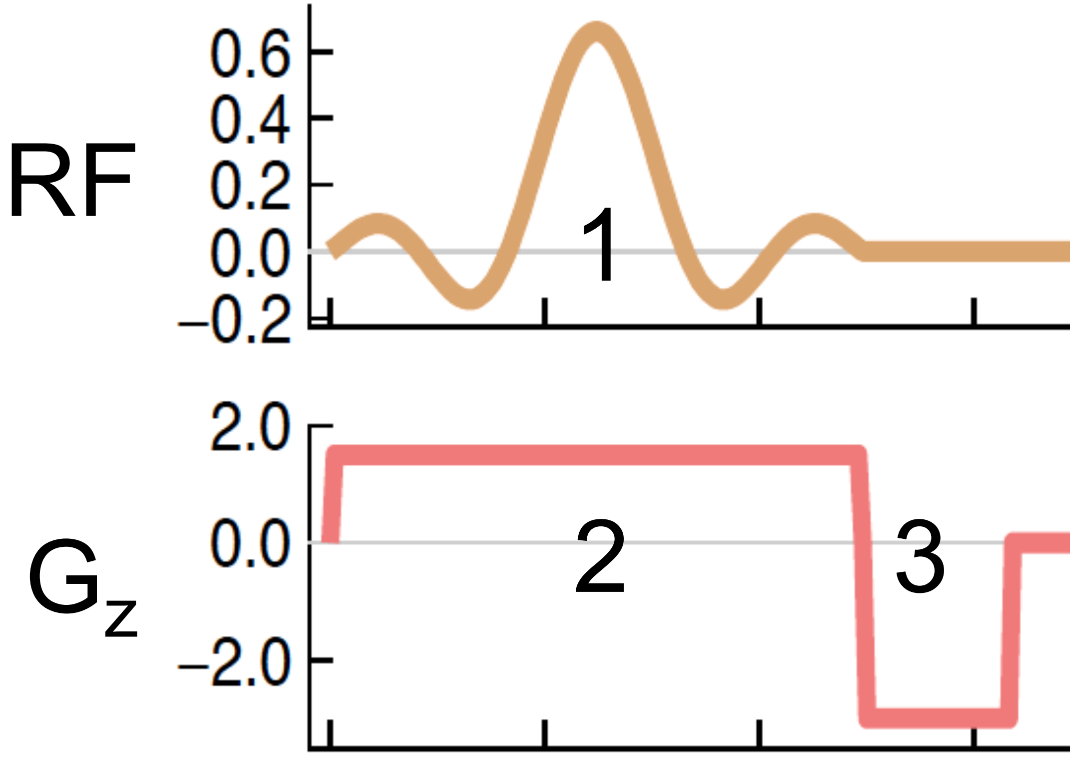
- Slice-selective excitation (z)
- Phase encoding (y)
- Frequency encoding (x)

2D Fourier encoding (Cartesian k-space encoding)



Slice selection

- **a.k.a. slice-selective excitation**
- **Combination of a RF pulse and a gradient**



1 – RF pulse

2 – Slice selection gradient

$$\Delta f = \gamma G_z \Delta z$$

3 – Slice refocusing gradient

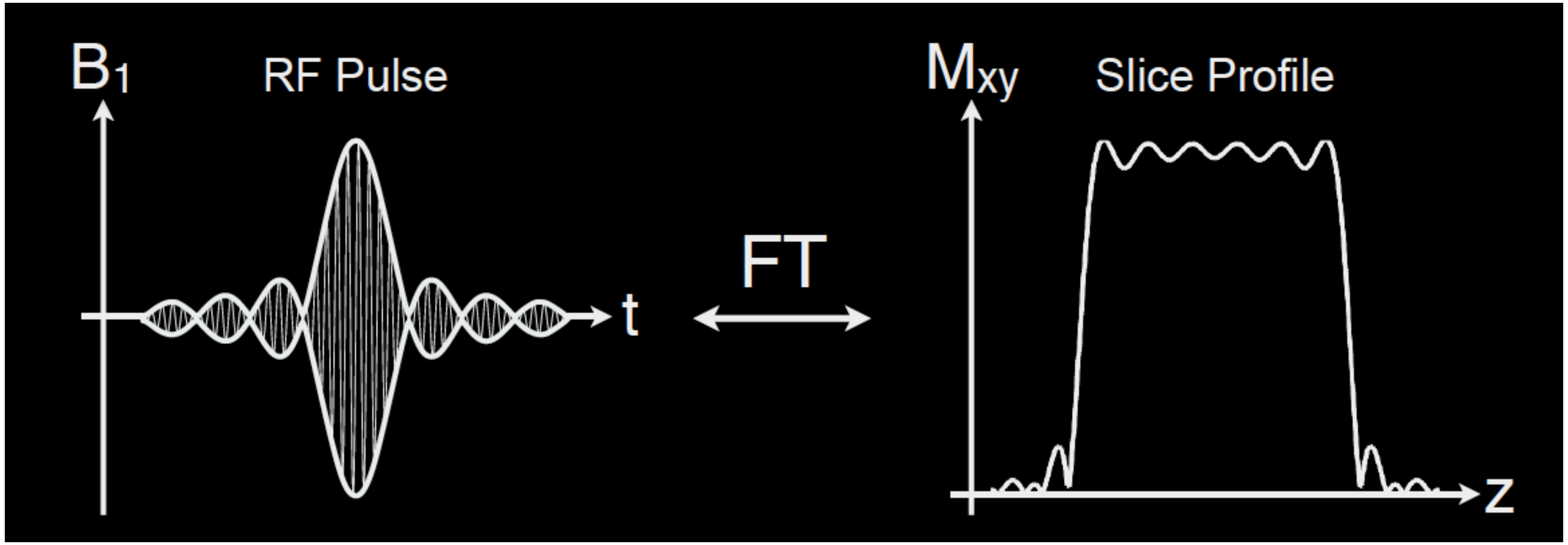
More information at https://mriquestions.com/slice-selective-excitation.html

RF pulses

- **Center frequency and bandwidth matched to the slice frequencies**

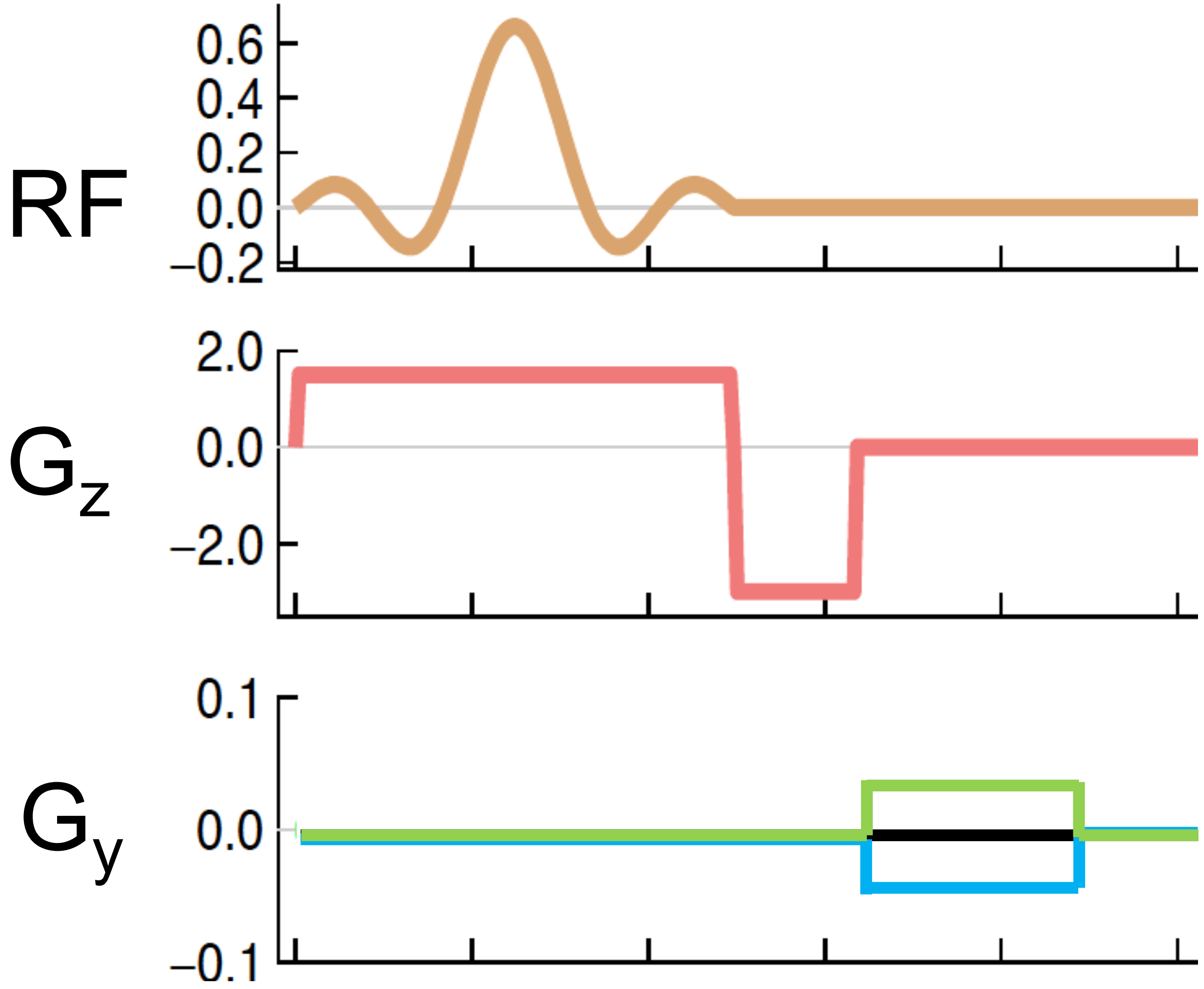
$$\Delta f = \gamma G_z \Delta z$$

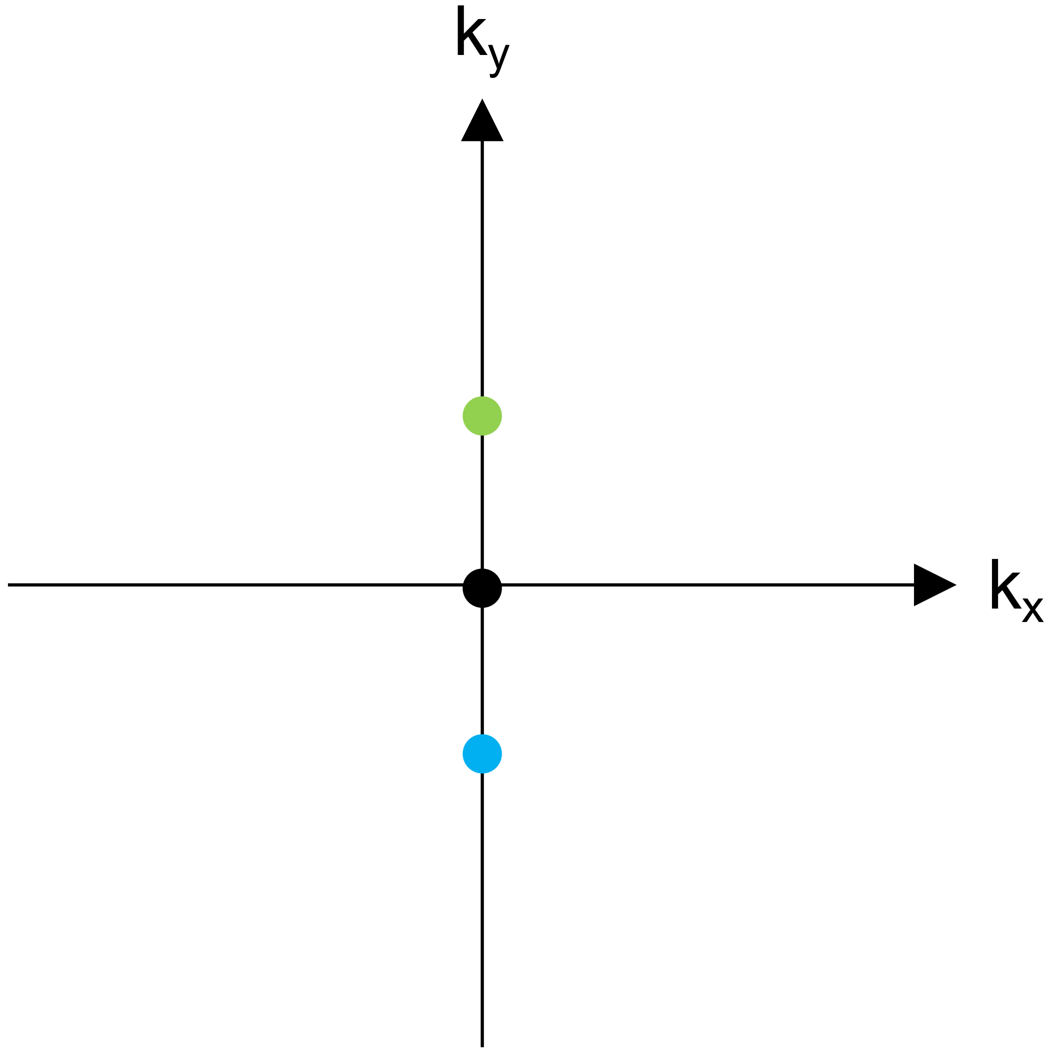
- **Slice profile = FT of the envelope**
  - **Ideal RF pulse: sinc function, square slice profile, too long in practice**



Phase encoding

- **Select one k_y position**

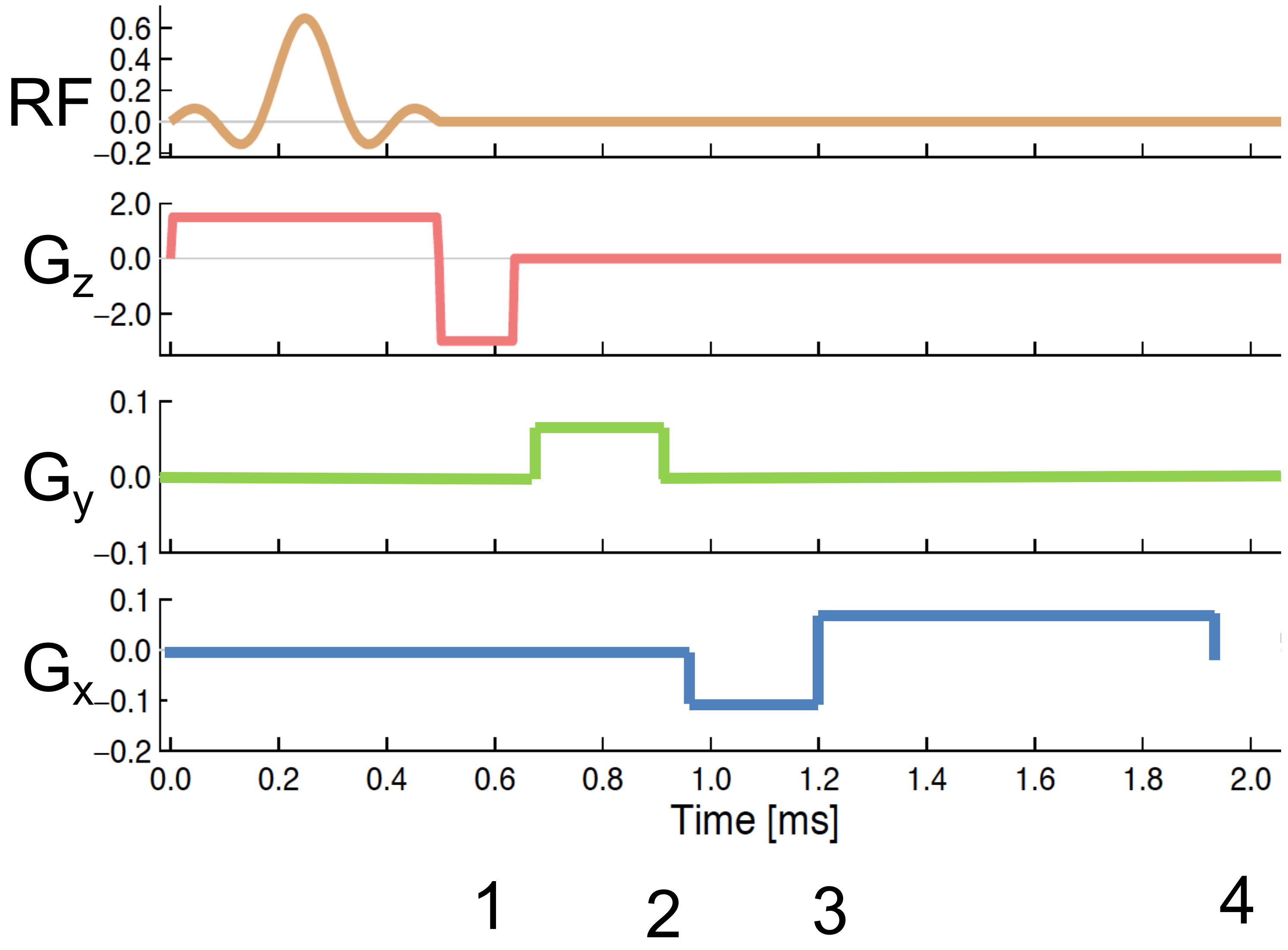


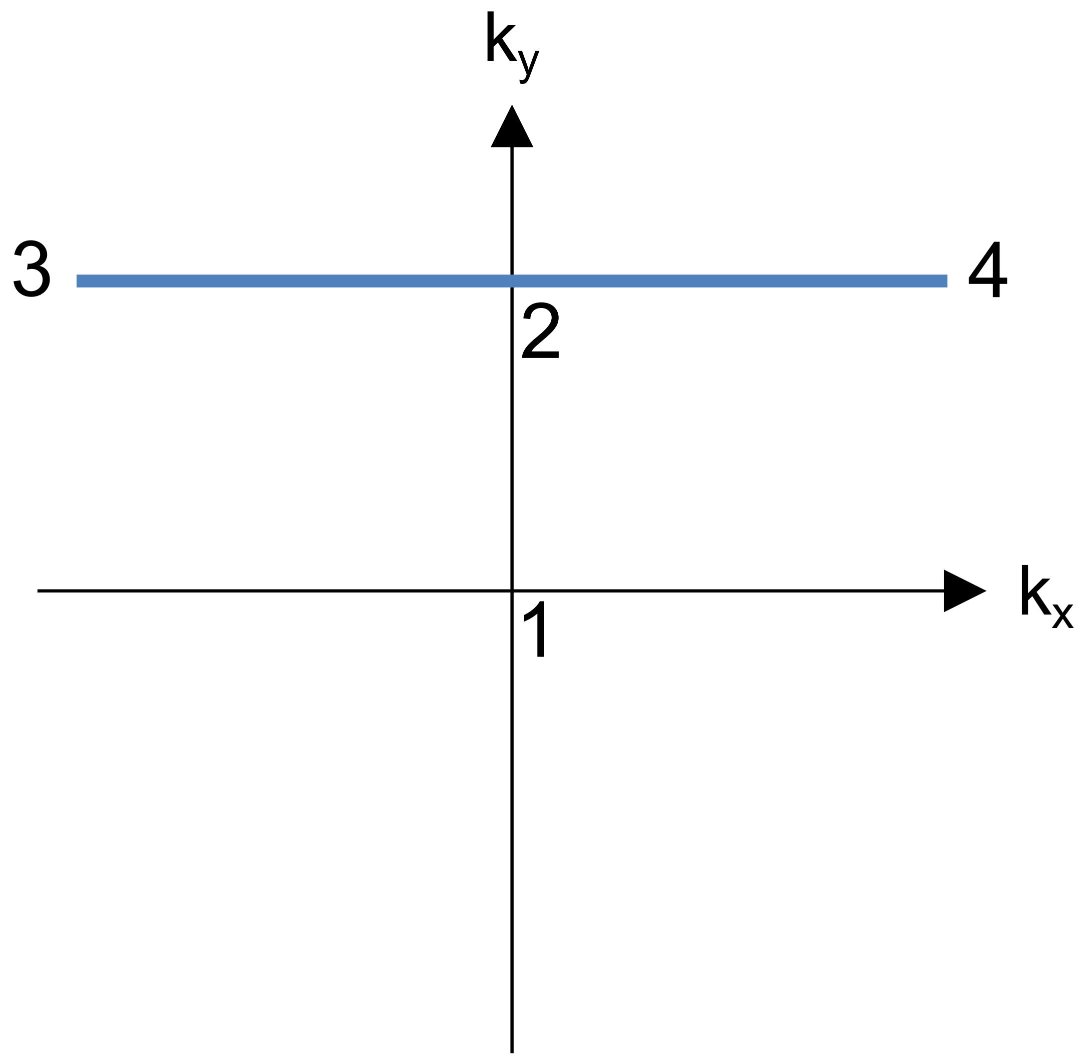


linear accumulation of phase

Frequency encoding

- **Traverse a k_x line**



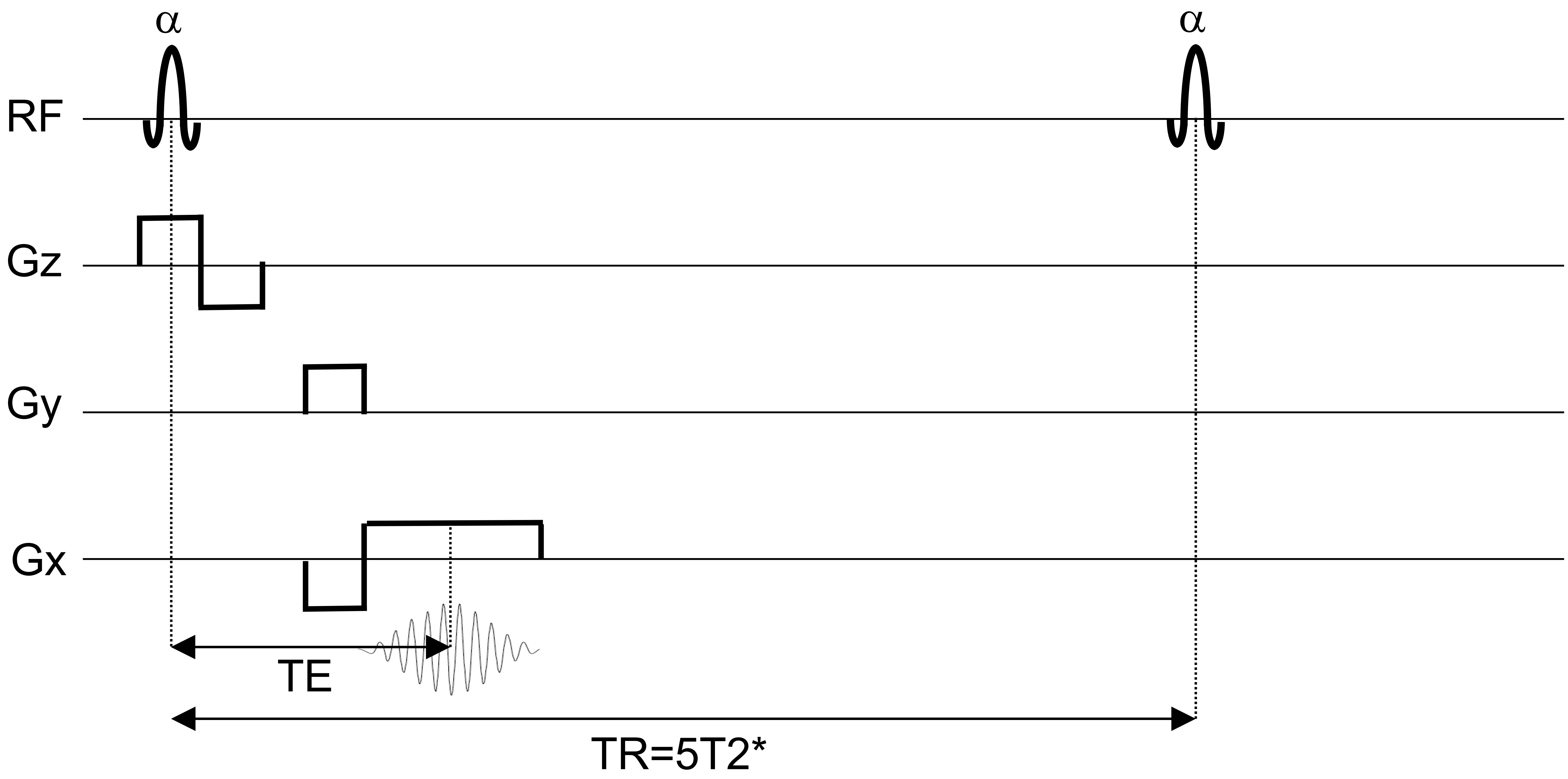


linear accumulation of frequency

Gradient echo sequences

- Gradient echo sequences use a combination of one RF pulse and gradients to produce an echo
  - No refocusing 180º RF pulse
- Each excitation samples a line in k-space
- The flip angle can be lower than 90º, which enables to reduce the repetition time (TR) and thus scan time
  - Higher flip angles increase T1 weighting
  - Lower flip angles increase T2* weighting

Gradient echo sequence

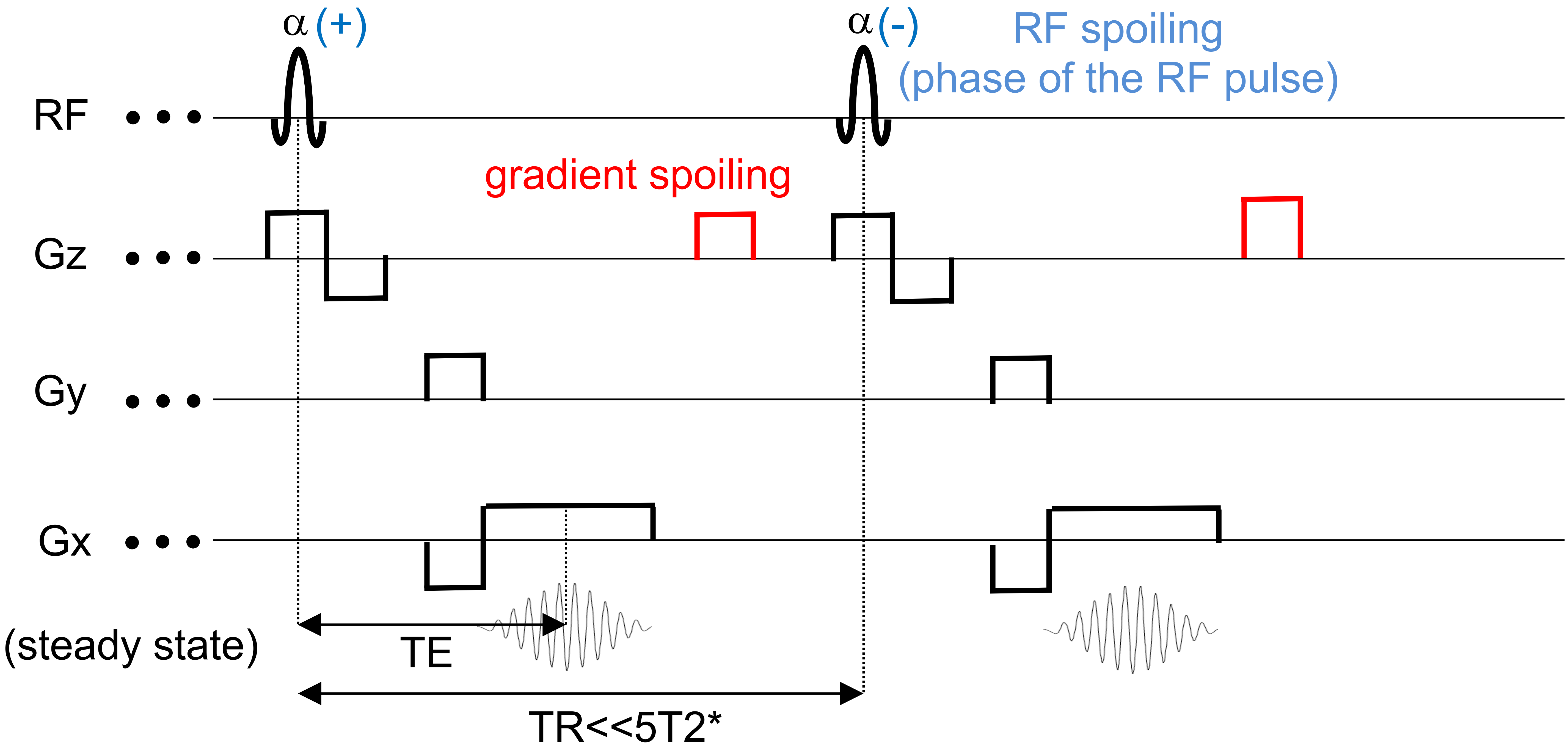


Spoiling

- ***Spoiling*** refers to the elimination of the transverse component of the magnetization before the next RF pulse in a gradient echo sequence
- The implicit spoiling mechanism is to have a TR of 5T2*, which limits the applicability of gradient echo sequences
- There are two main spoiling mechanisms to have a short TR:
  - Gradient spoiling: a slice-selective gradient with a different amplitude
  - RF spoiling: change the phase of the RF pulse

More information at https://mriquestions.com/spoiling---what-and-how.html

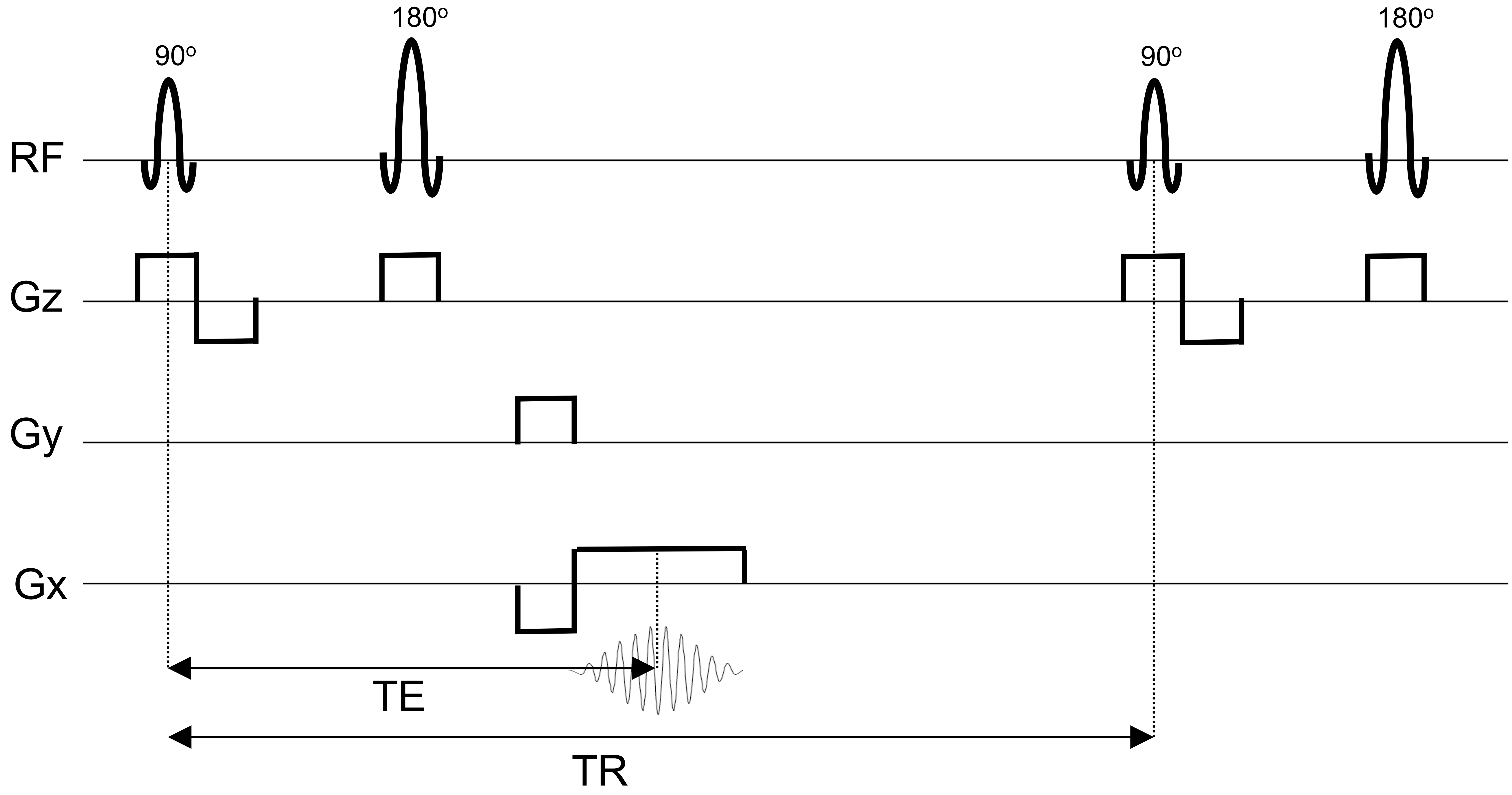
Spoiled gradient echo sequence



Spin echo sequences

- The spin echo sequence uses a 90º excitation pulse, 180º refocusing pulse at TE/2 and signal reading centered at TE. This series is repeated for each TR. With each repetition, a k-space line is filled, thanks to a different phase encoding.
- The 180º refocusing pulse compensates for the magnetic field heterogeneities to obtain an echo that is weighted in T2 and not in T2*.

Spin echo sequence



Contrast

$$S = S_0\left(1 - e^{-\frac{TR}{T1}}\right) e^{-\frac{TE}{T2}}$$

TR

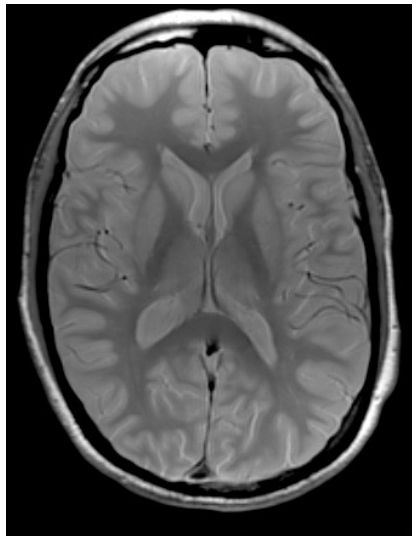
TE

S=0

Short TR, short TE

- Incomplete recovery
- Minimal signal decay

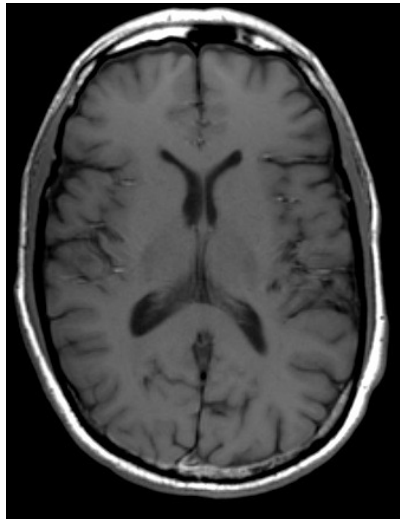
T1 weighting



Long TR, short TE

- Full recovery
- Minimal signal decay

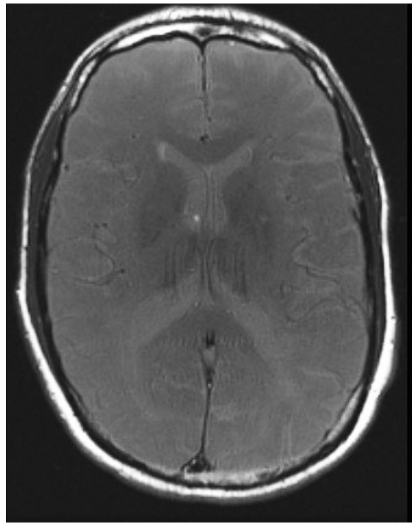
Proton density weighting



Short TR, long TE

- Incomplete recovery
- Signal decay

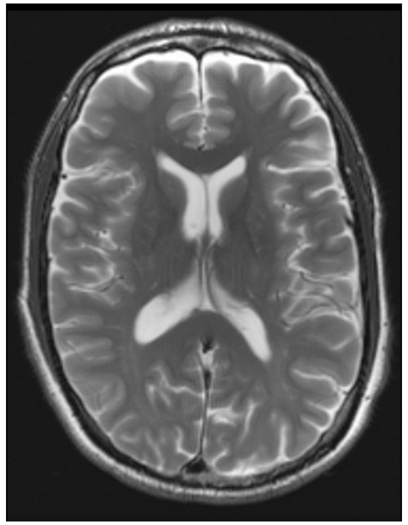
Mixed weighting (not used)



Long TR, long TE

- Full recovery
- Signal decay

T2 weighting

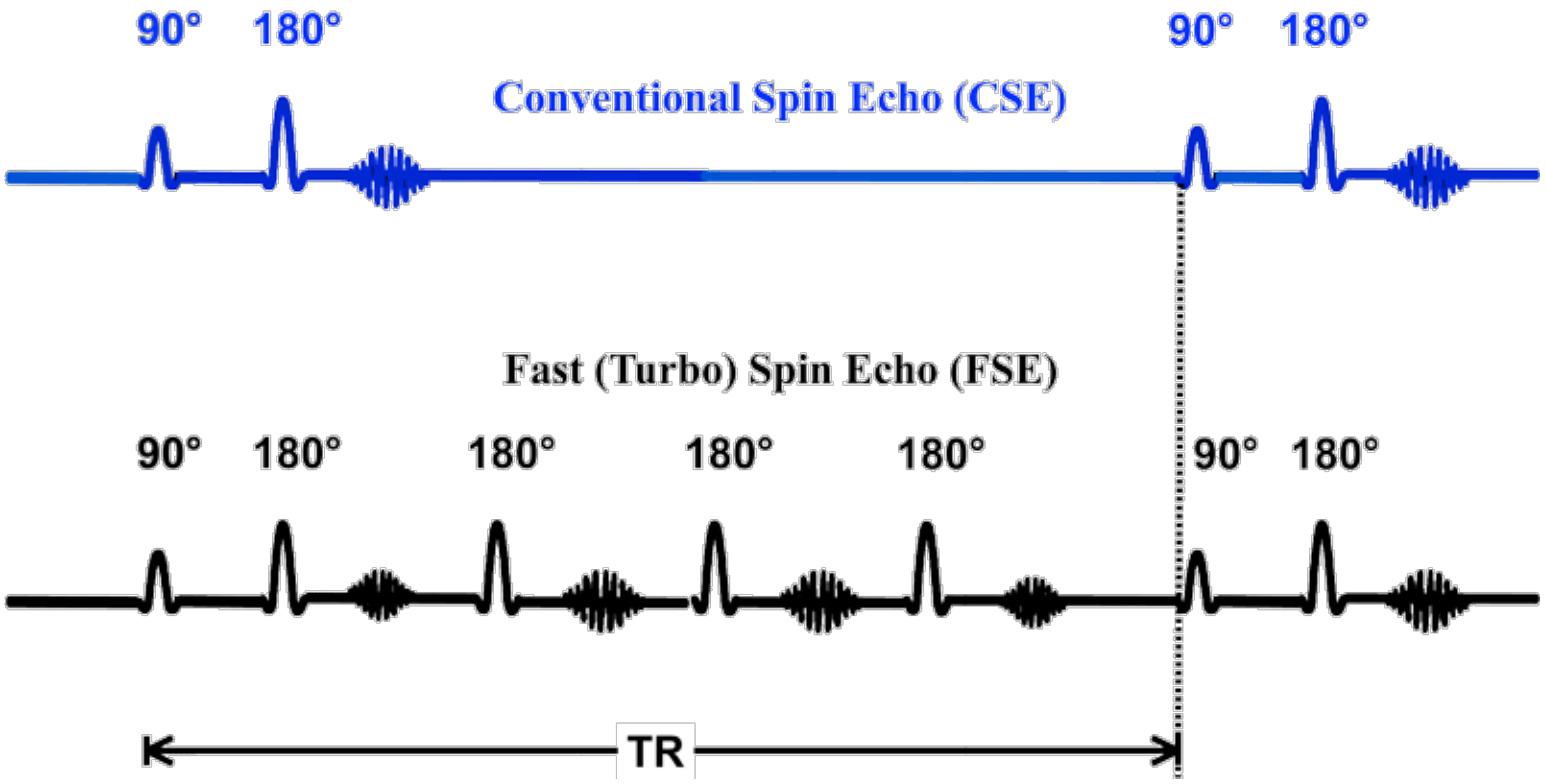


S=0 (very long TE)

Turbo Spin Echo (TSE) or Fast Spin Echo (FSE)

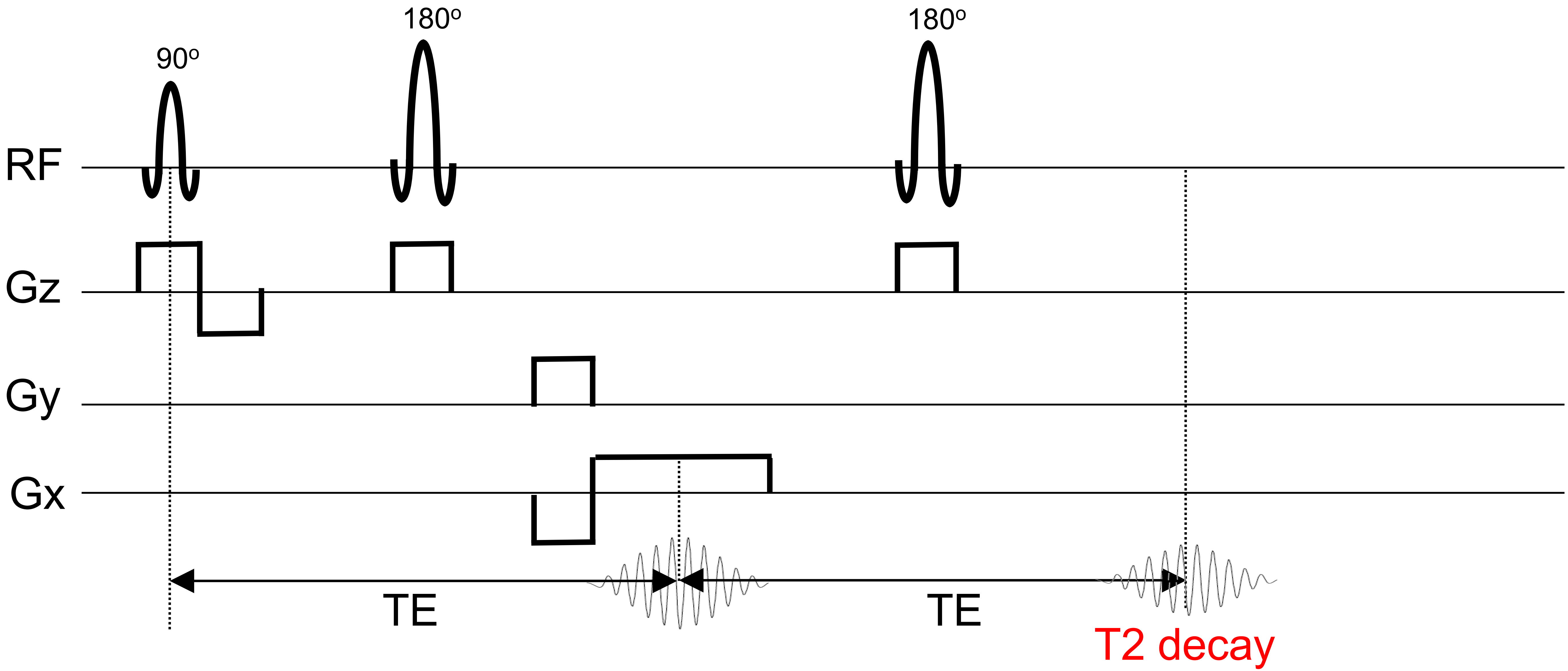
- Fast spin echo (FSE) imaging, also known as Turbo spin echo (TSE) imaging, are commercial implementations of the RARE (Rapid Acquisition with Relaxation Enhancement) technique originally described by Hennig et al in 1986.
- FSE uses one 90^o pulse followed by a series of 180^o pulses. Phase encoding is applied for each 180^o pulse such that multiple k-space lines can be acquired for each TR (echo train), which reduces the total acquisition time
- FSE is one of the workhorse sequences in modern MRI

Turbo Spin Echo (TSE) or Fast Spin Echo (FSE)



Turbo Spin Echo (TSE) or Fast Spin Echo (FSE)

- **The signal for each echo in the train is modulated by T2**
- **Long echo trains can result in blurring due to T2 decay**



Test your knowledge: True or False

- **Gradient echo sequences do not require an RF pulse to form an echo**

FALSE

Every MRI sequence, including gradient echo sequences, require a RF pulse to flip the spins and generate a signal.

Test your knowledge: True or False

- **Fat (short T1) appears bright on T1-weighted images and dark on T2-weighted images**

TRUE

Fat has a short T1, which allows it to recover signal quickly, appearing bright on T1-weighted images, and has a short T2, which causes it to lose signal quickly, appearing darker on T2-weighted images compared to water.

Test your knowledge: True or False

- **Spin echo has a shorter echo time (TE) than gradient echo**

FALSE

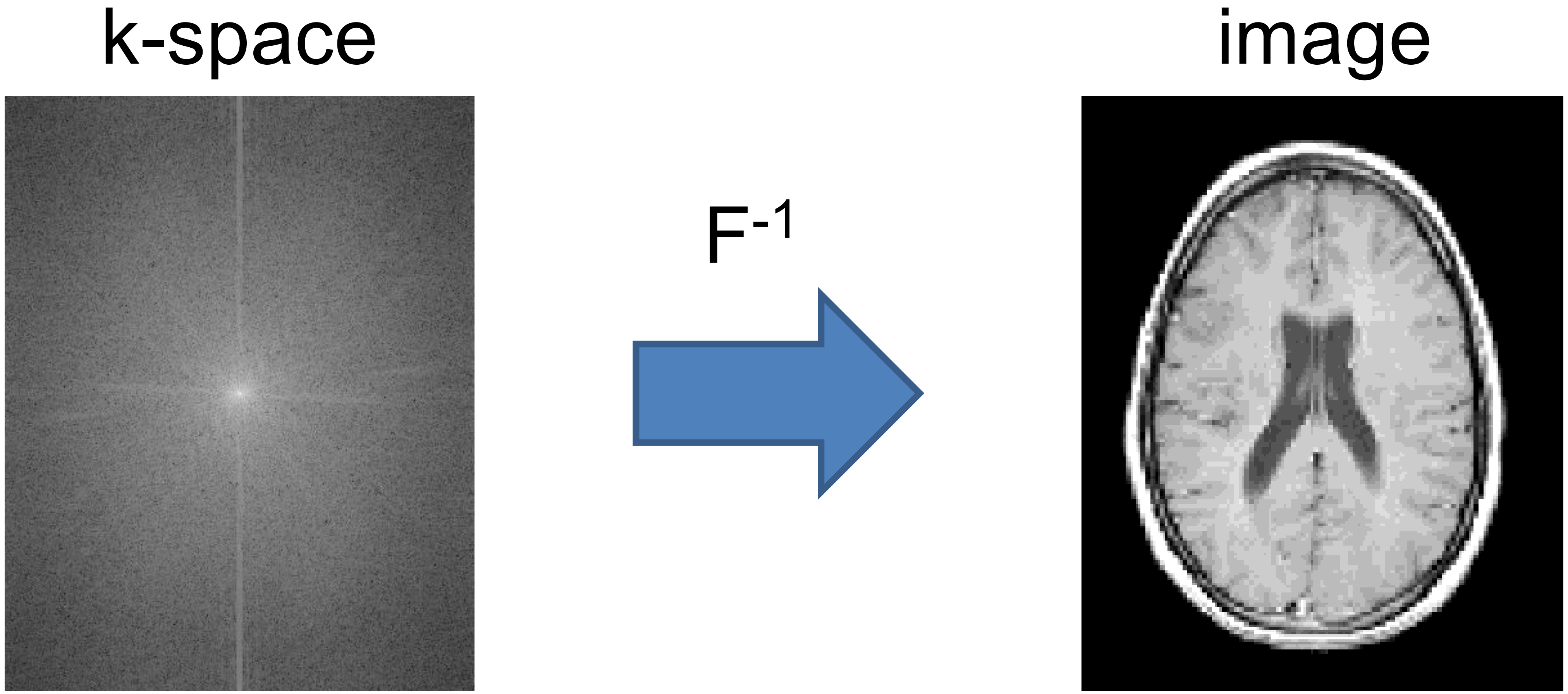
Spin echo sequences require a longer TE because they must wait for the 180° pulse to refocus the spins, and this process takes more time compared to the use of a refocusing gradient.

Image reconstruction

Fourier, parallel imaging, compressed sensing, deep learning

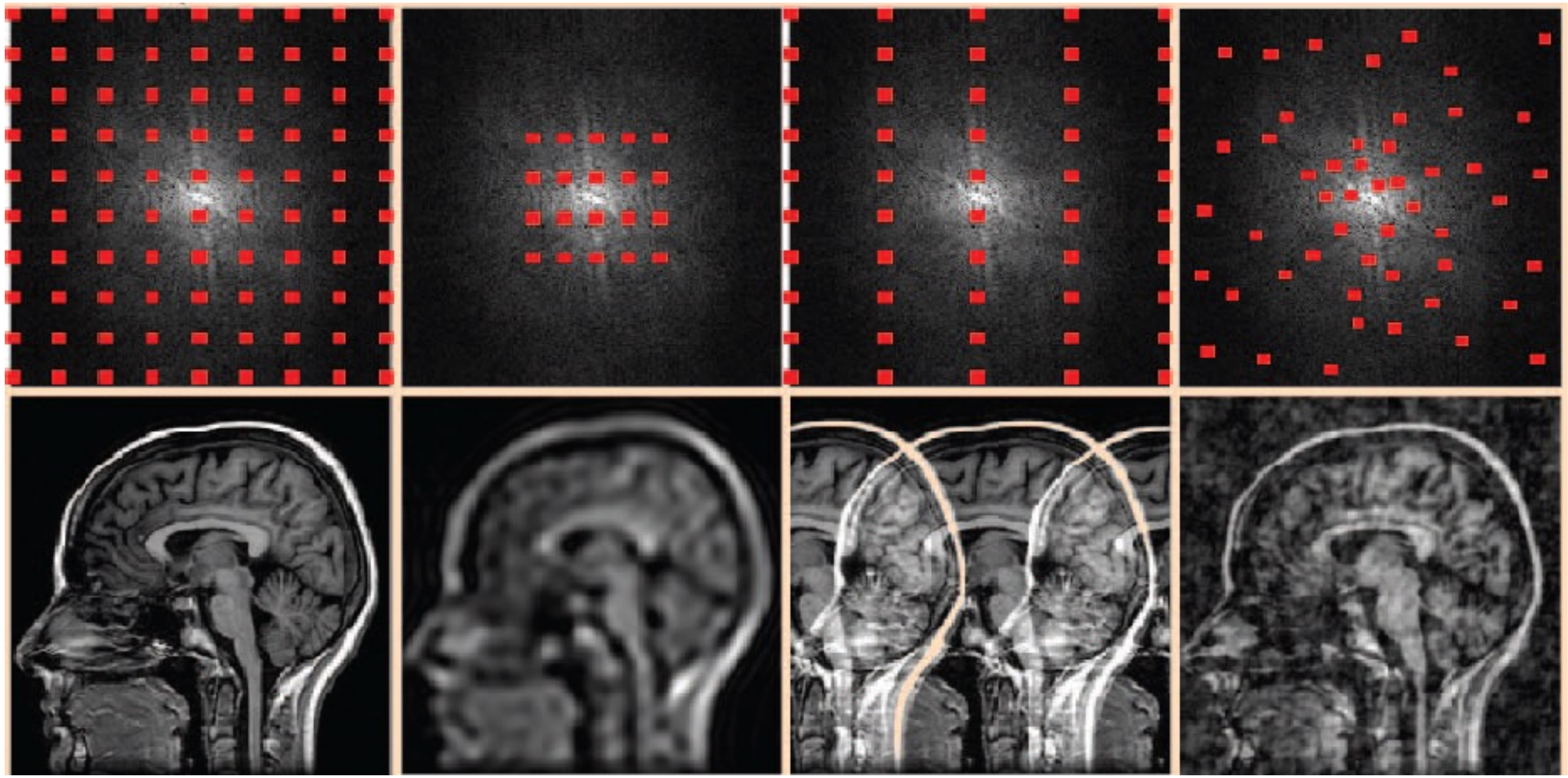
Image reconstruction

- **Turn acquired k-space data into an image**
- **Inverse Fourier transform**



k-space undersampling = acceleration

- **Reduce the number of k-space points**

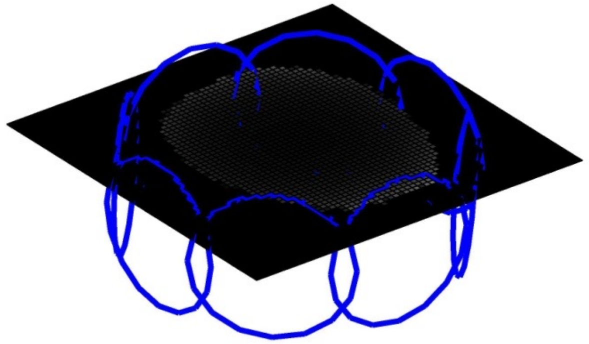


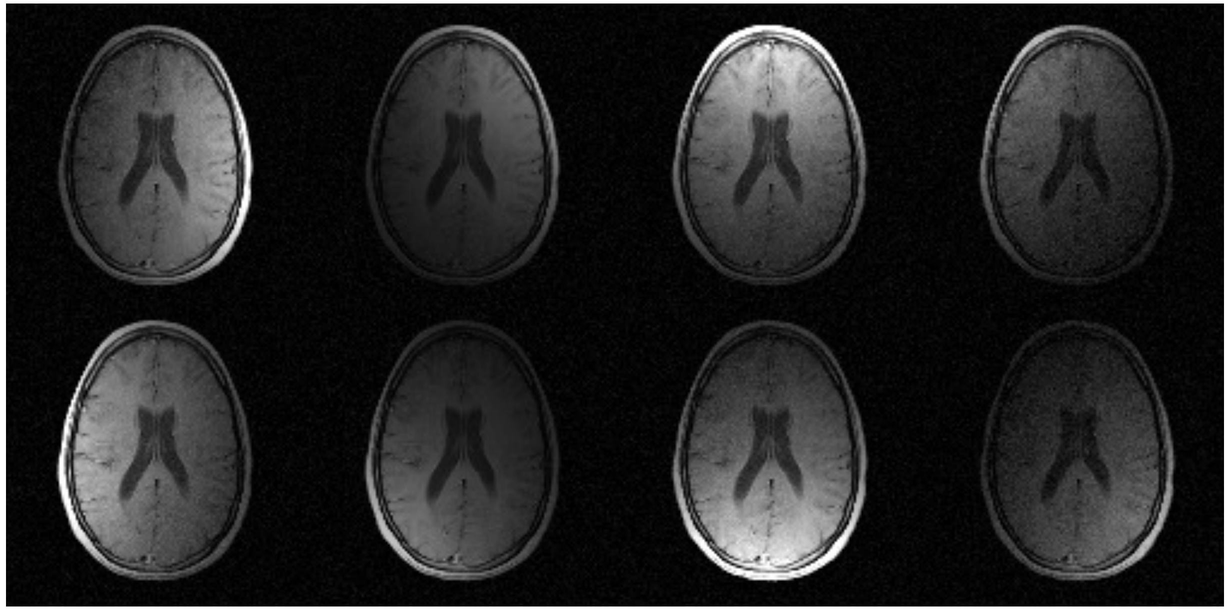
k-space undersampling = acceleration

- **Reconstruction: fill-in k-space or unalias images**
- **Parallel imaging:** Multiple coils
- **Compressed sensing:** Image compressibility
- **Deep learning:** Neural network learning

Parallel imaging

- **Multiple receiver coils with different spatial sensitivities**





$$y_i(r) = m(r)c_i(r)$$

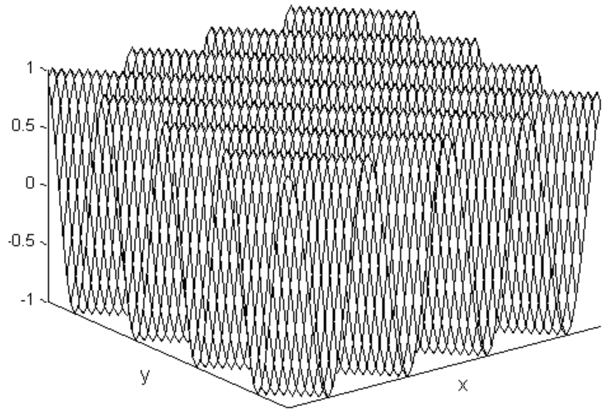
- **Uniform k-space undersampling**
- **Matrix inverse (linear)**

Sodickson DK, Manning WJ. Magn Reson Med. 1997; 38: 591-603
Pruessmann KP et al. Magn Reson Med 1999; 42: 952-962

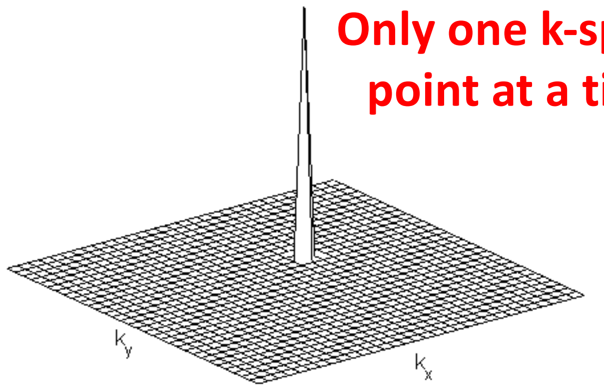
Gradient + coil-sensitivity encoding

Image space | **k-space**

Gradient encoding only

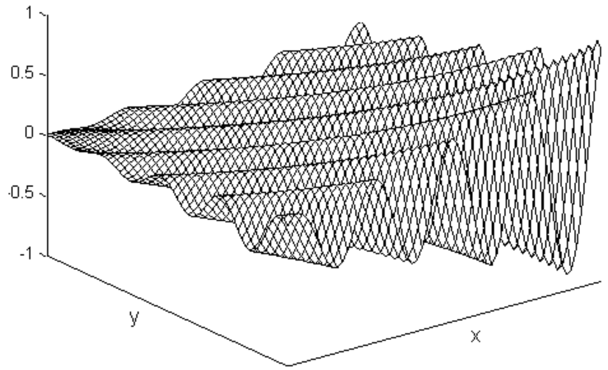


FT

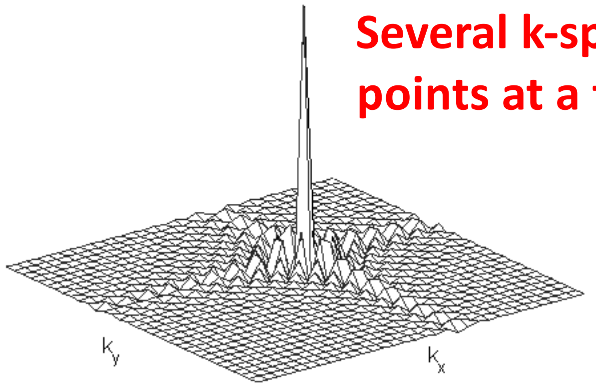


Only one k-space point at a time

Gradient + Coil sensitivity



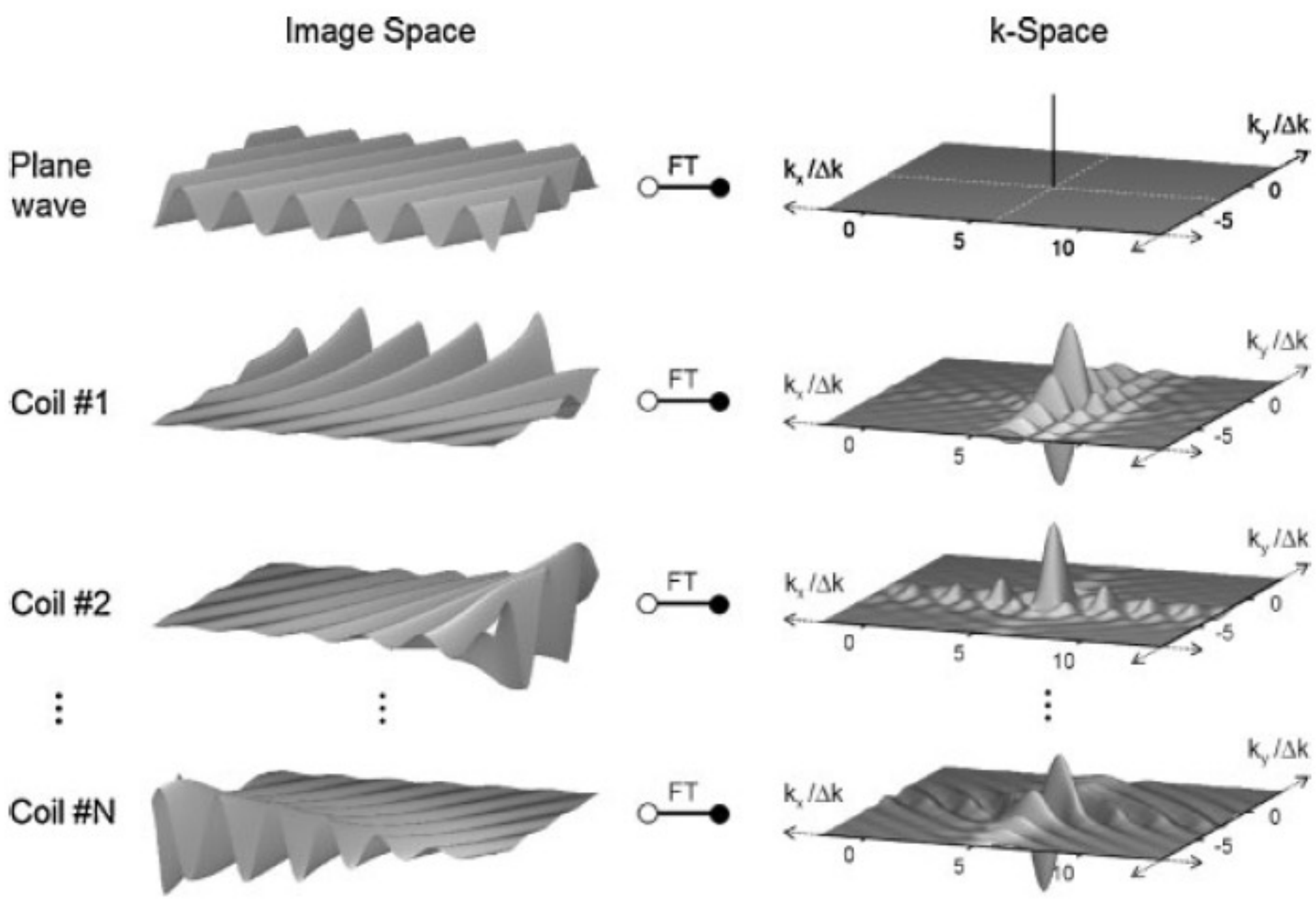
FT



Several k-space points at a time

Gradient + coil-sensitivity encoding

- **Effective k-space oversampling**



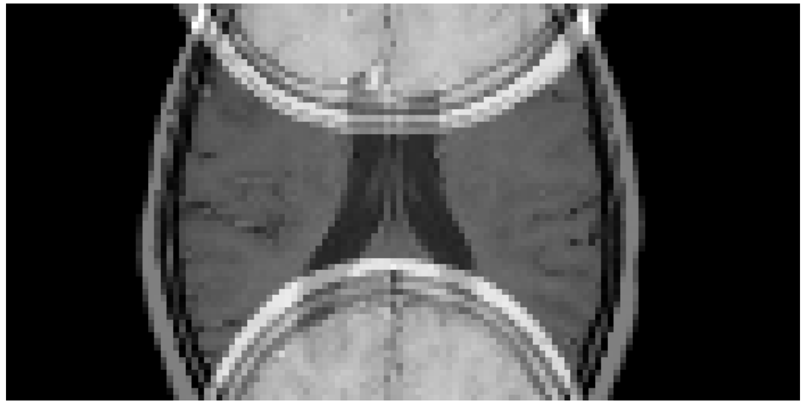
Parallel imaging reconstruction

- Image domain
  - Unfold aliased images
  - SENSE

- k-space
  - Estimate missing k-space points
  - Interpolation
  - SMASH, GRAPPA

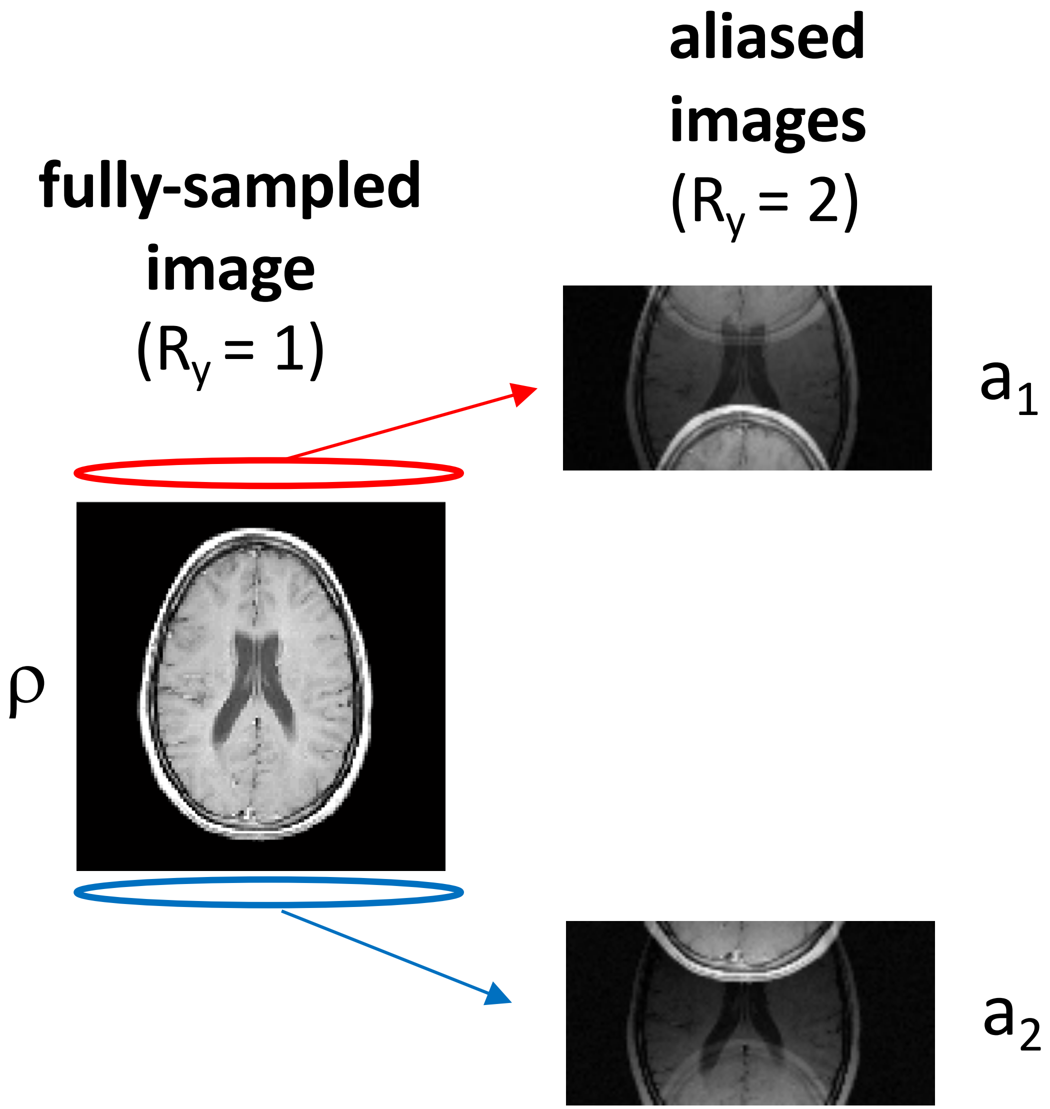
SENSE reconstruction

- Image domain
  - FOV is reduced by R
  - Each point in the aliased image is a combination of R points from the fully-sampled image



SENSE reconstruction

- **Encoding equation (linear model: matrix)**



$$\begin{bmatrix} a_1(r) \\ a_2(r) \end{bmatrix} = \begin{bmatrix} c_1(r) & c_1\left(r+\frac{W_y}{2}\right) \\ c_2(r) & c_2\left(r+\frac{W_y}{2}\right) \end{bmatrix} \begin{bmatrix} \rho(r) \\ \rho(r+\frac{W_y}{2}) \end{bmatrix}$$

a **E** **ρ**

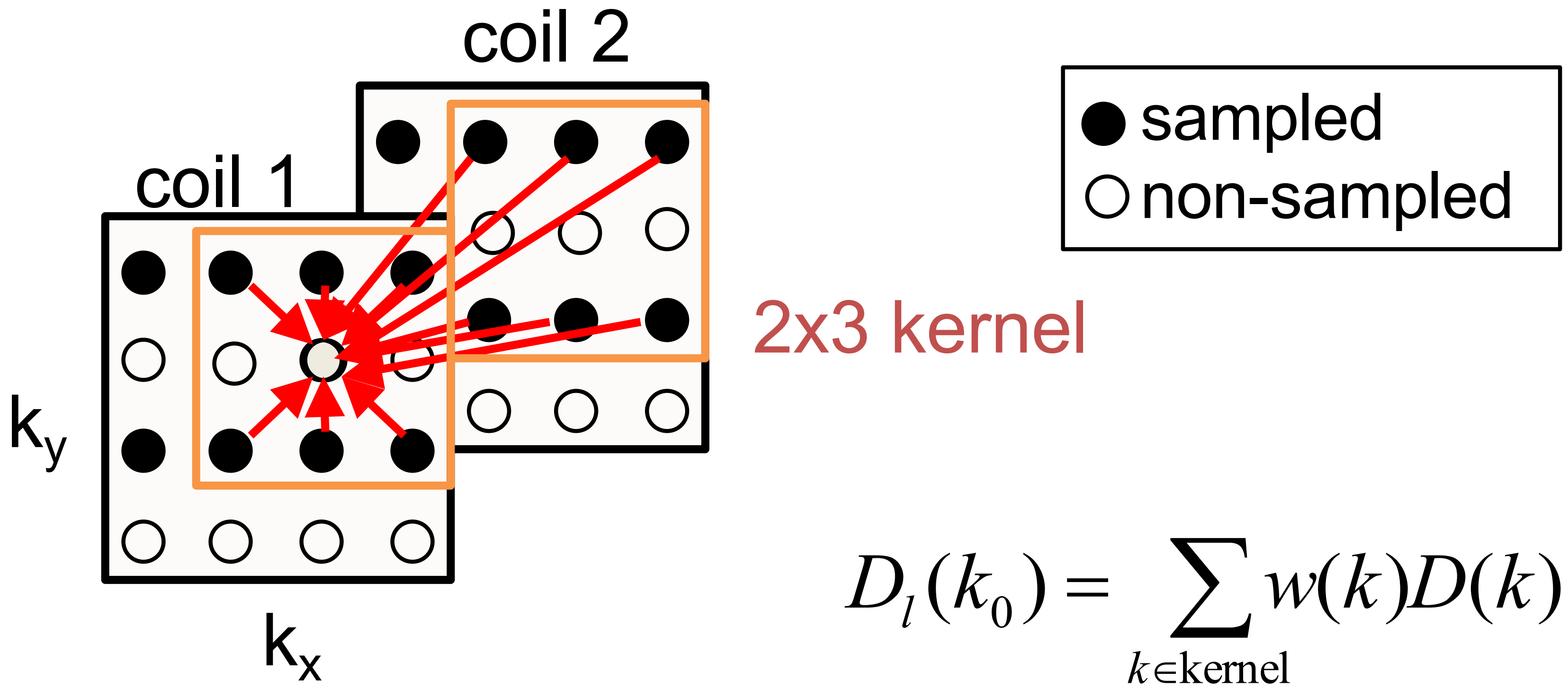
SENSE reconstruction

- Inverse of the encoding equation
  - Undersampling factor < number of coils
  - Pseudoinverse of E

$$\hat{\boldsymbol{\rho}} = \left(\mathbf{E}^H \mathbf{E}\right)^{-1} \mathbf{E}^H \mathbf{a}$$

GRAPPA

- **Coil-by-coil k-space reconstruction**
- **Linear combination of k-space neighbors from all coils**



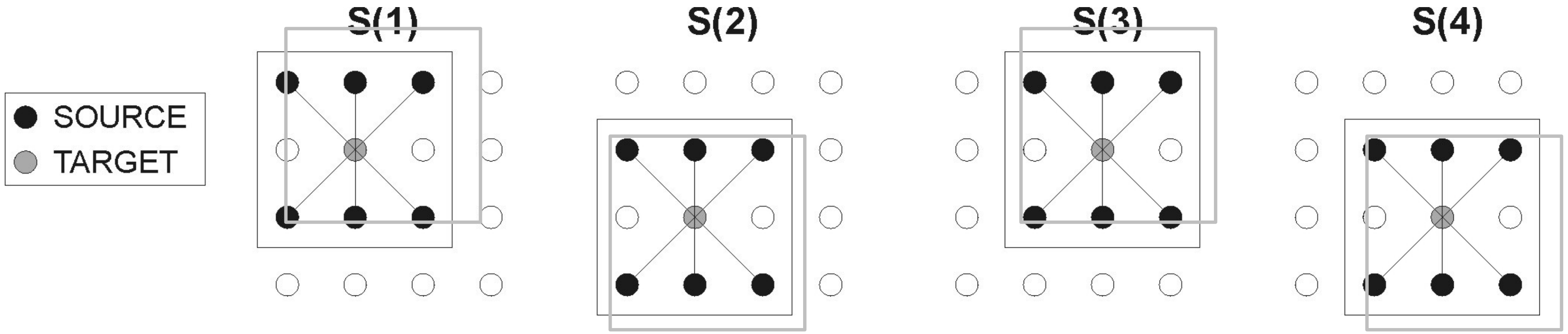
$$D_l(k_0) = \sum_{k \in \text{kernel}} w(k) D(k)$$

Griswold MA et al. Magn Reson Med 2002; 47: 1202-10

GRAPPA

- **Reconstruction weights (GRAPPA kernel)**

ACS: 4x4 matrix
kernel size: 2x3
R_y=2



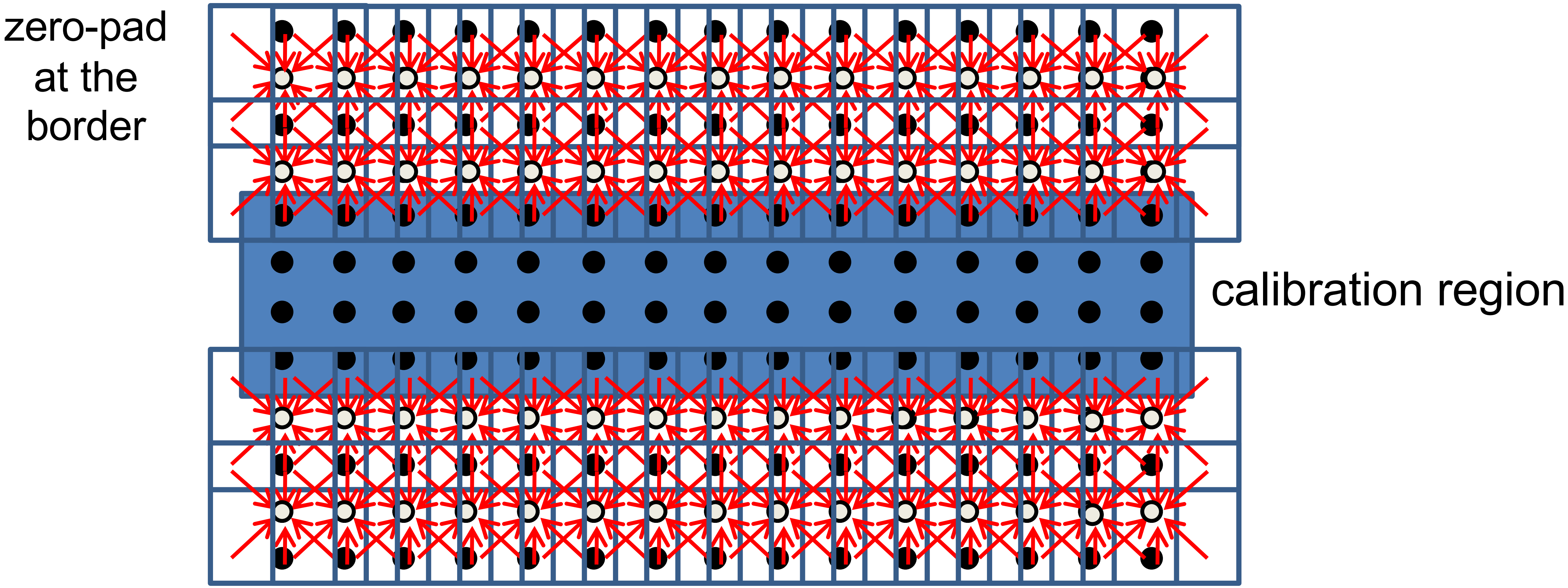
Calibration model: $\mathbf{T} = \mathbf{S}\mathbf{w}$

S: source matrix ($N_b \times K_{size}N_c$)
T: target matrix ($N_b \times N_c$)

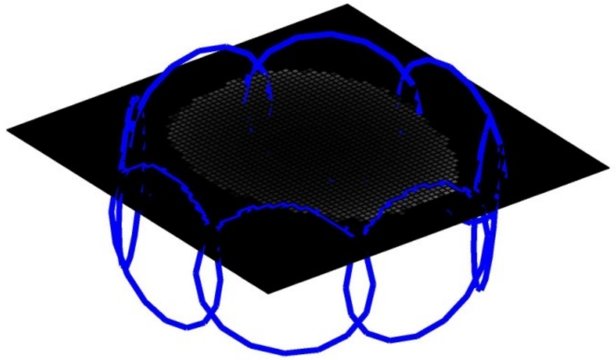
Invert to get the weights: $\mathbf{w} = (\mathbf{S}^H\mathbf{S})^{-1}\mathbf{S}^H\mathbf{T}$ ($N_b \times K_{size}N_c$)

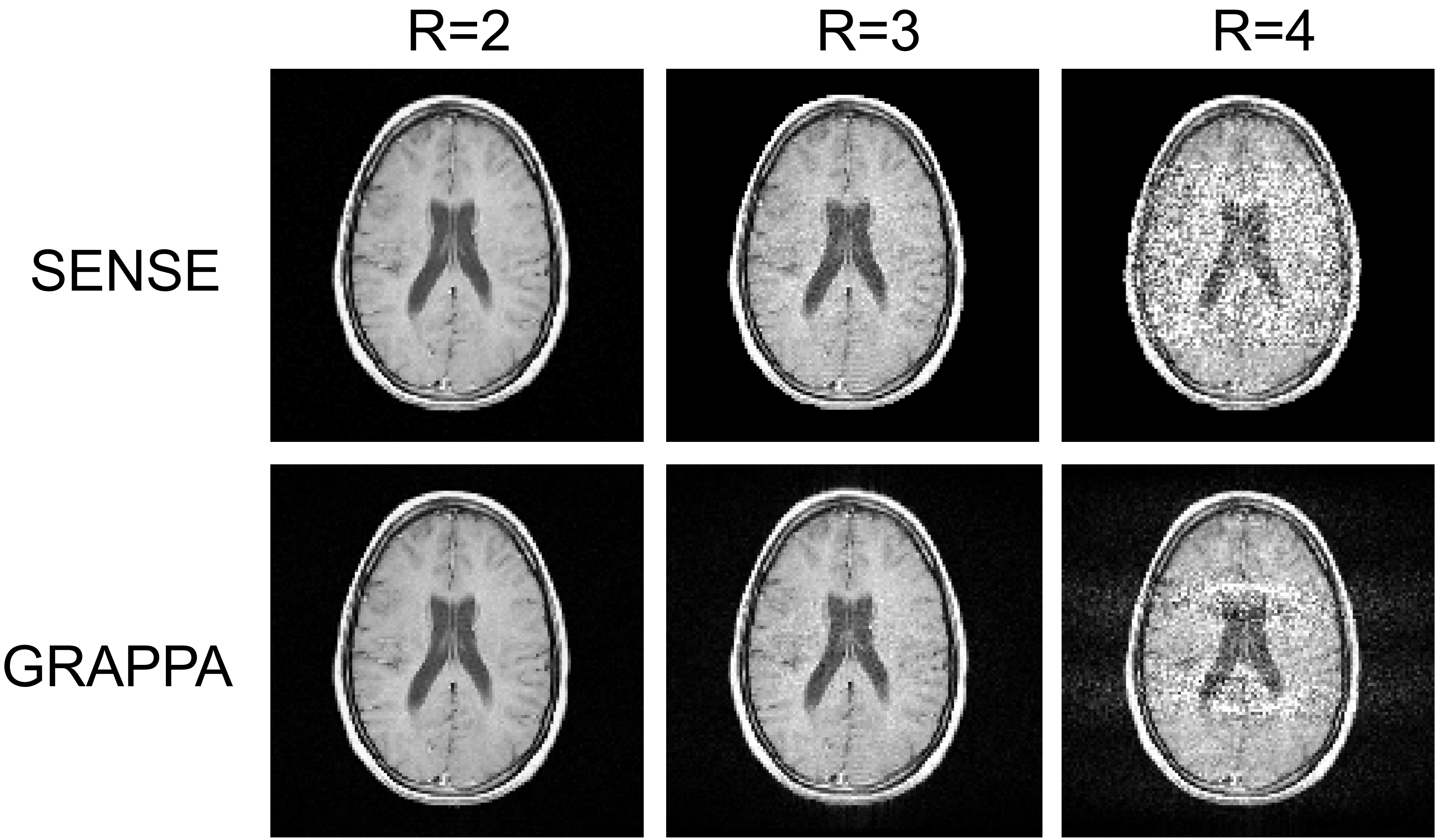
GRAPPA algorithm

- Compute GRAPPA weights from calibration data
- Compute missing k-space data (coil-by-coil reconstruction)
- Inverse FFT to each coil individual coil images and coil combination



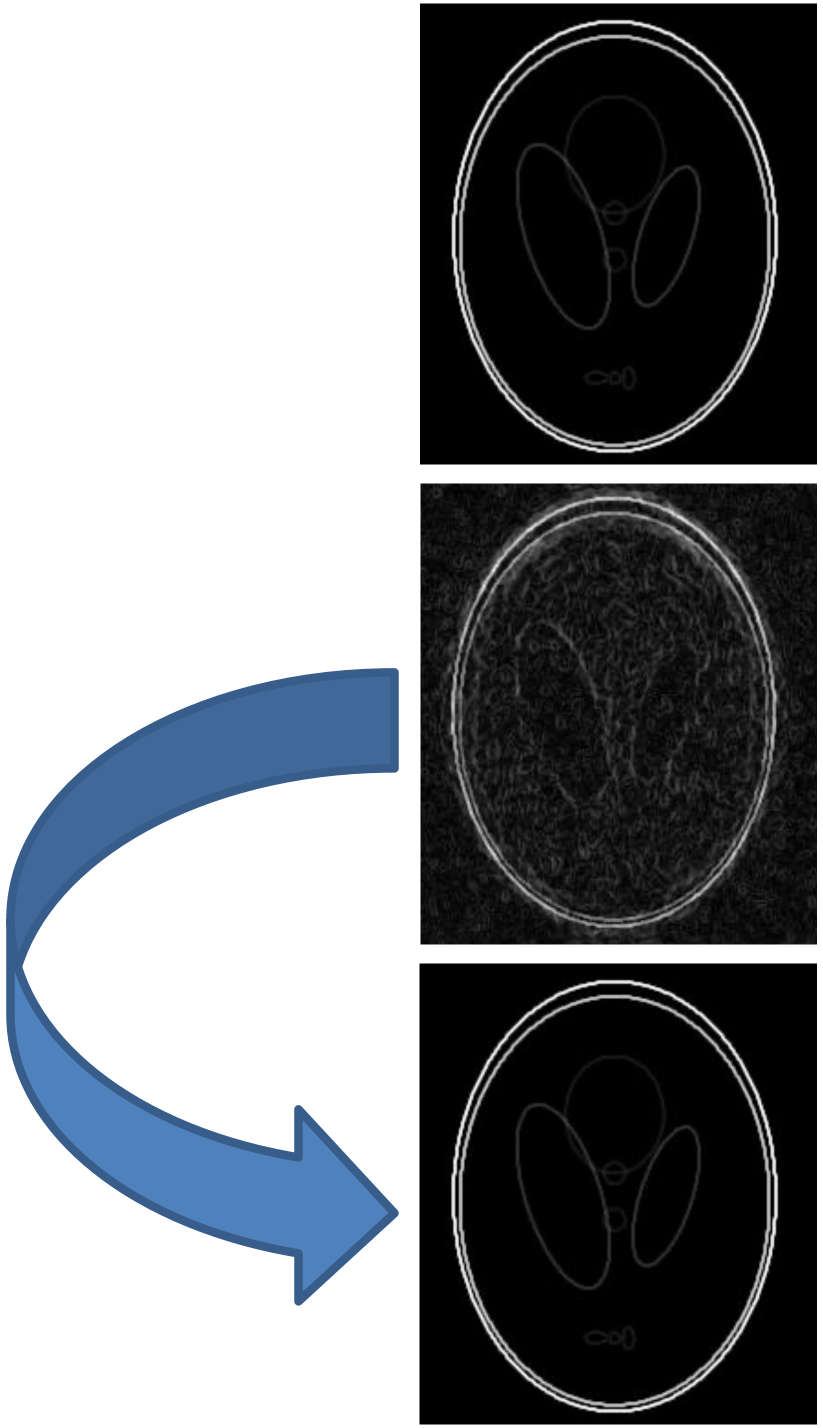
Reconstruction examples





Compressed sensing

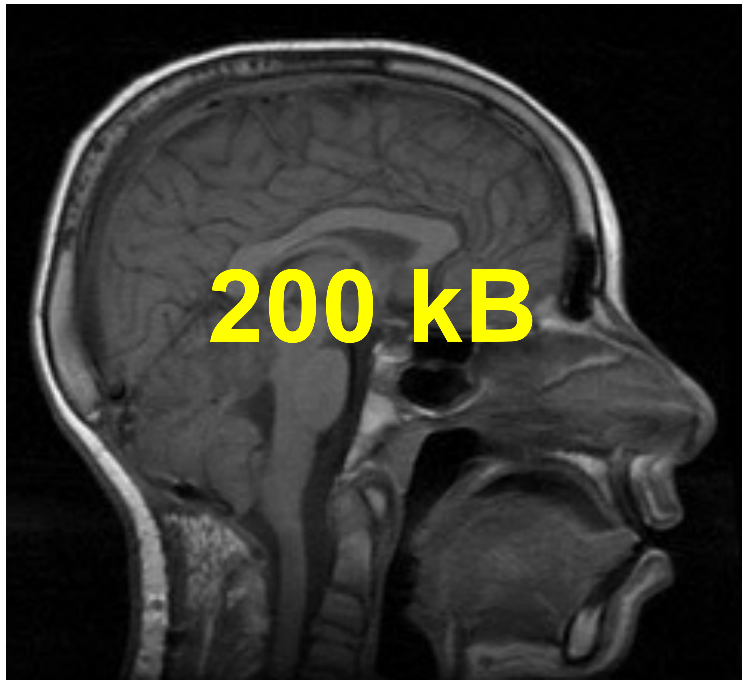
- Compressibility/sparsity
- Incoherence
- Non-linear reconstruction



Medical images are compressible

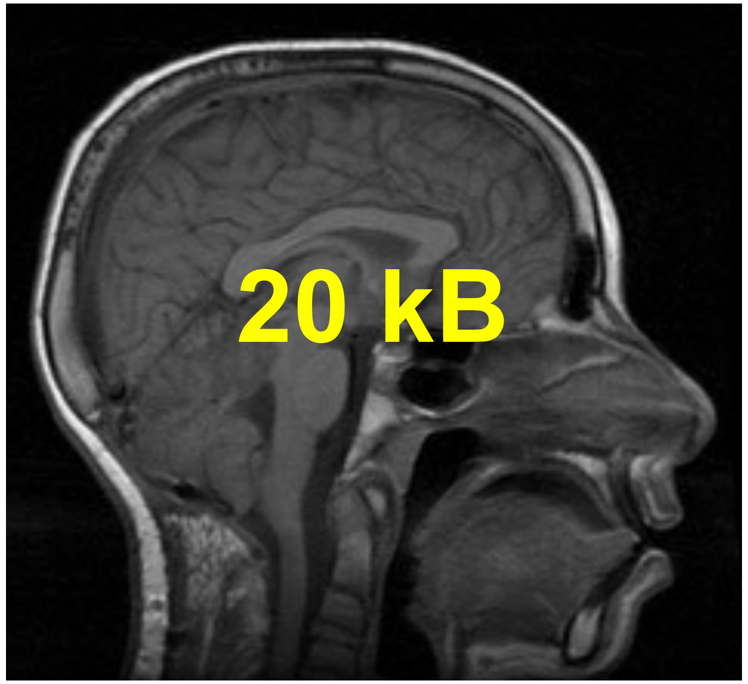
- **Information < number of pixels**

raw



JPEG

compressed

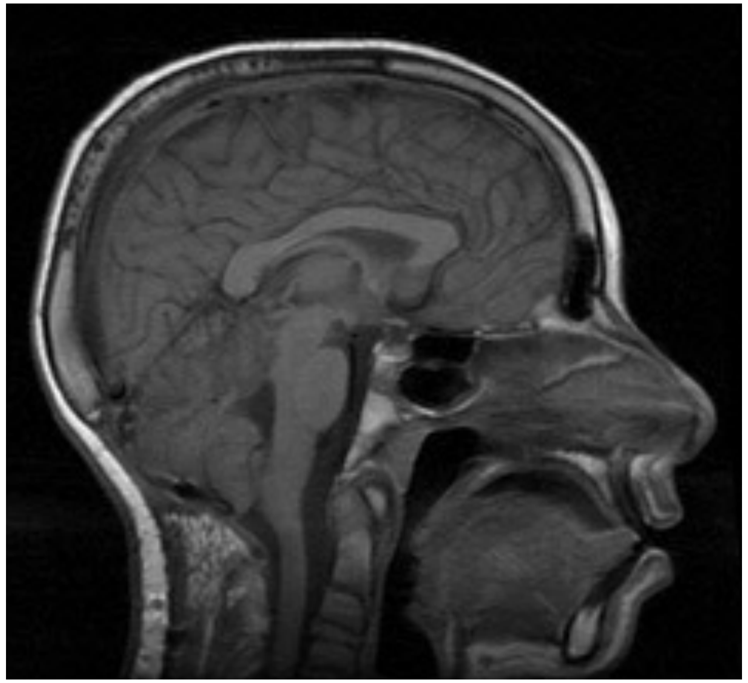


10% of the data → true information

90% of the data → 

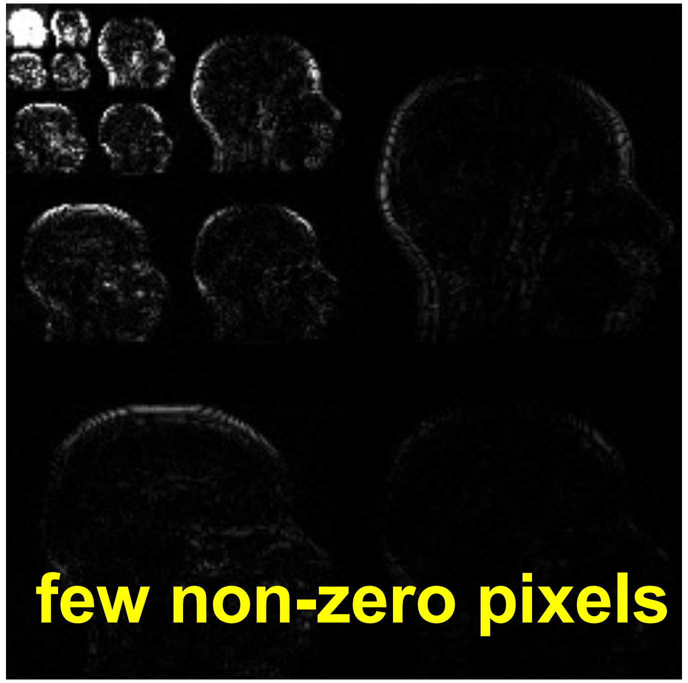
Medical images are compressible

- **Sparsity is the key**



sparsifying transform

wavelets
(JPEG2000 standard)



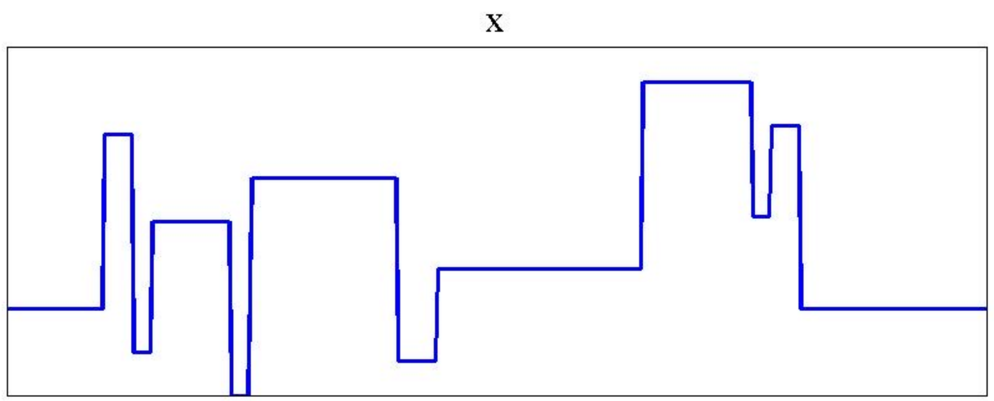
Sparsifying transforms

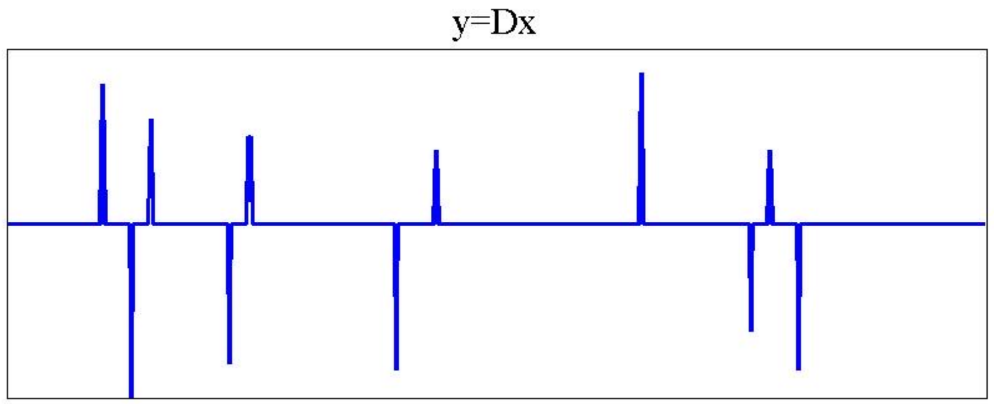
- **Finite differences**

$$y(n) = x(n) - x(n-1)$$

In matrix form : $y = Dx$

$$D = \begin{bmatrix} 1 & -1 & & \\ & 1 & -1 & \\ & & 1 & -1 \end{bmatrix}$$



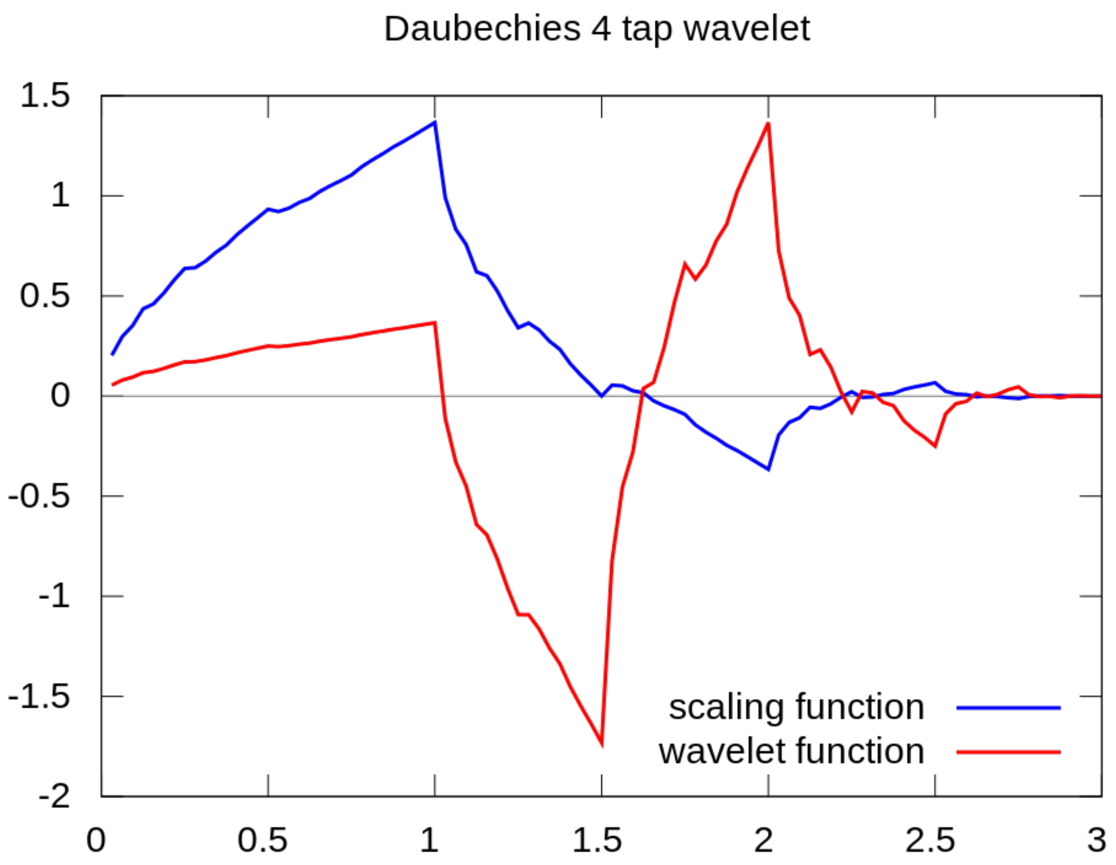


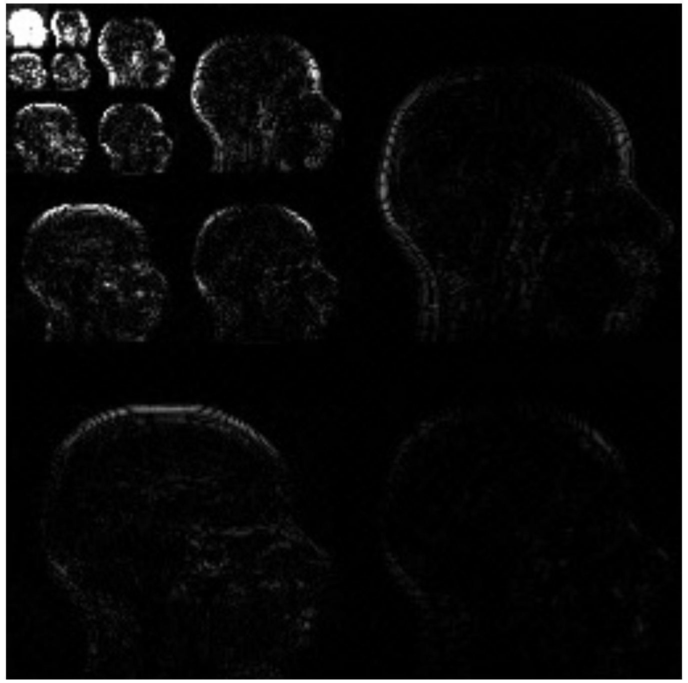
- Total variation

$$TV(x) = \sum_{n=2}^{N} |x(n) - x(n-1)| \quad \Rightarrow \quad \min TV(x) = \min \|Dx\|_1$$

Sparsifying transforms

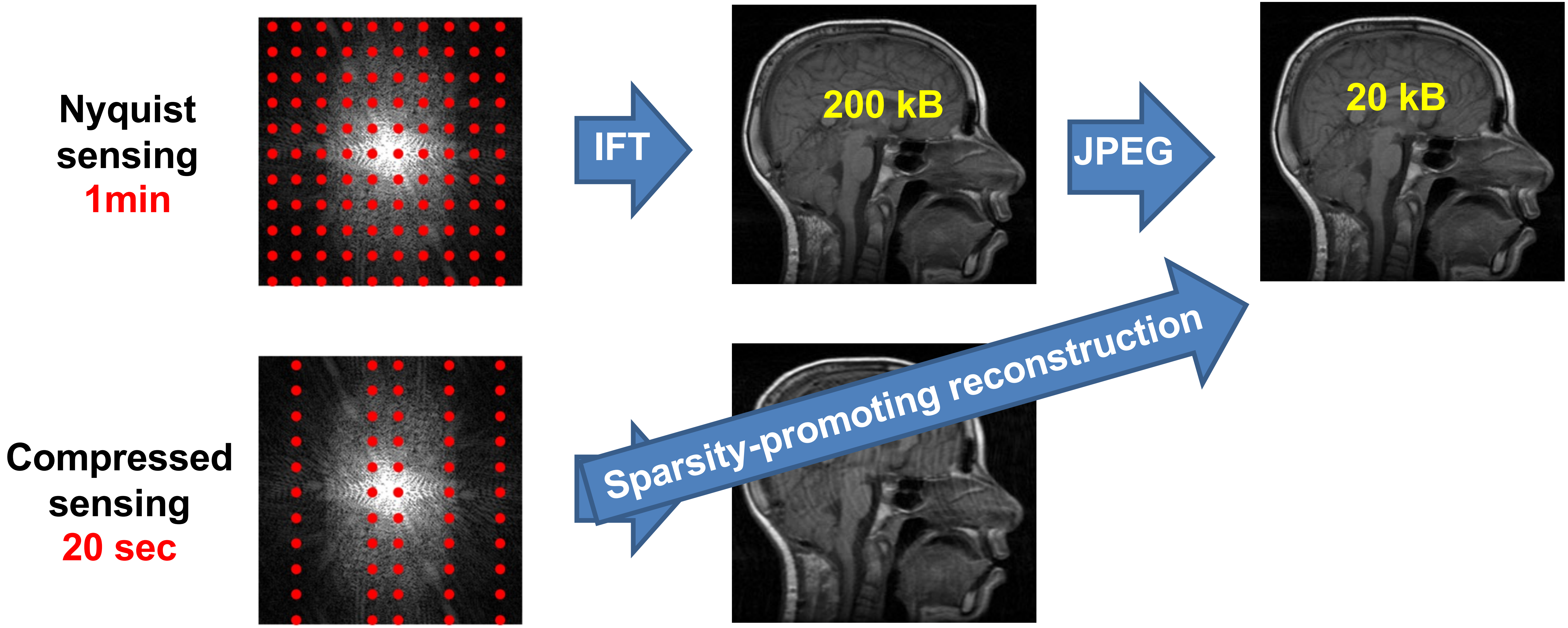
- **Wavelets**
  - **Space-frequency localization**
  - **More efficient than Fourier transform to represent discontinuities**





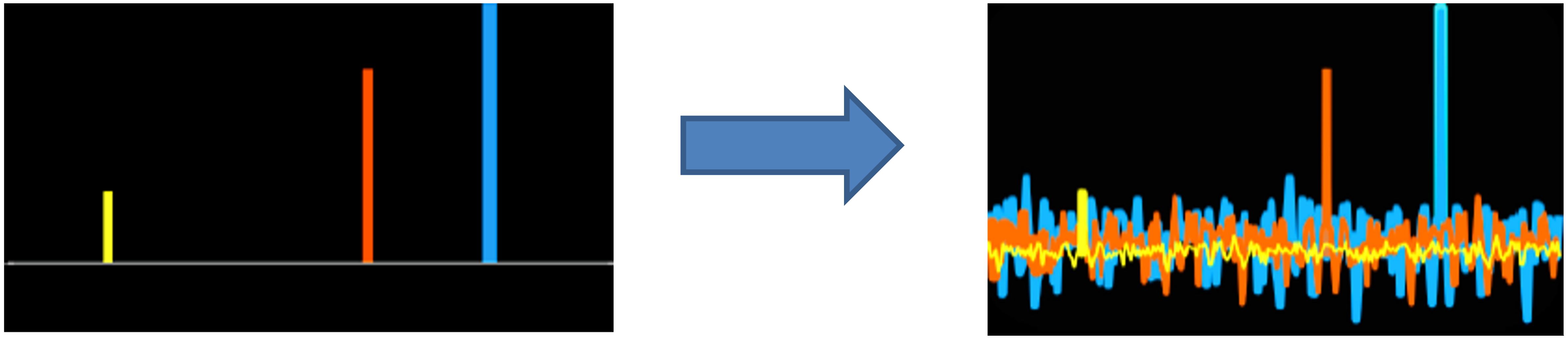
Compressed sensing

- **Exploit compressibility/sparsity to reduce k-space data**



How to sample k-space to exploit image sparsity?

- **Incoherence**
  - Aliasing artifacts should not replicate image features
  - Aliasing artifacts should look like noise

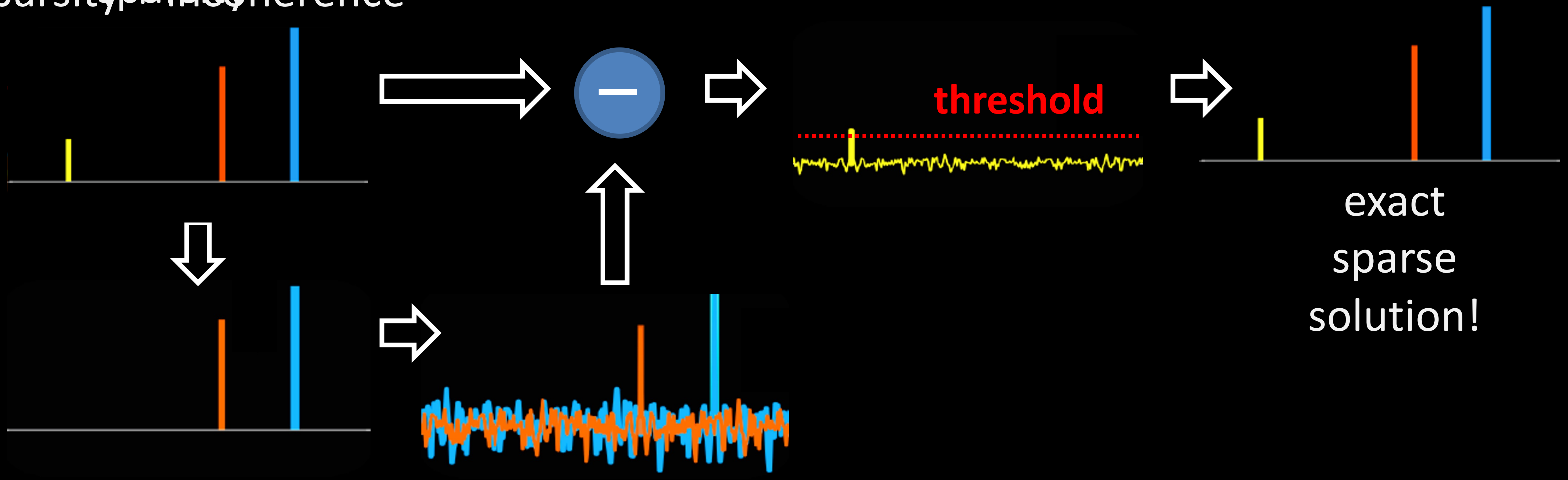


How to reconstruct to exploit image sparsity?

- **Sparse reconstruction**

sparsity + incoherence

sparsity



Iterative thresholding algorithm

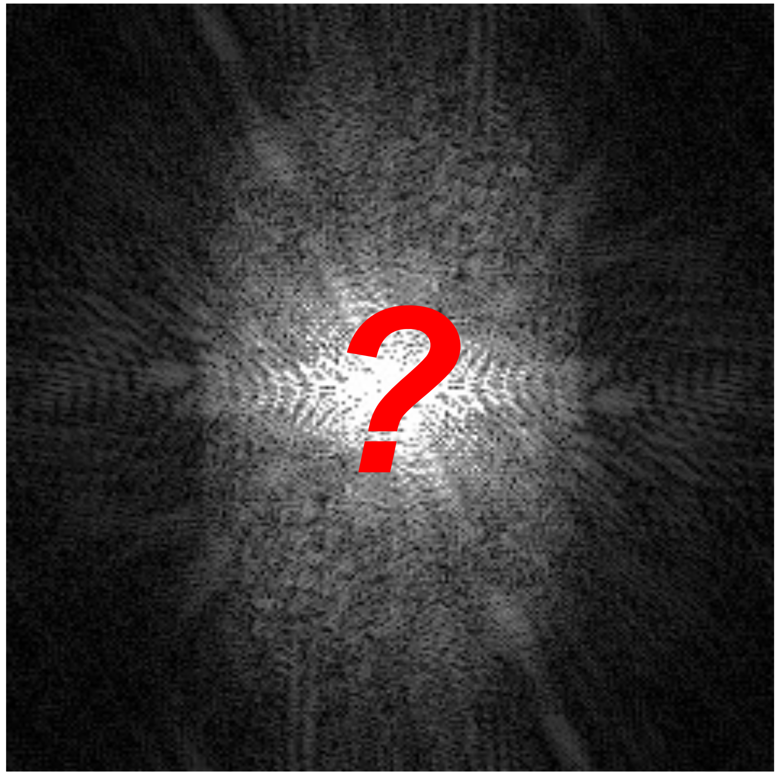
Incoherent k-space sampling

- **Knee image example**

fully-sampled image

sparse representation

k-space sampling



Incoherent k-space sampling

- **Uniform k-space undersampling**

k-space

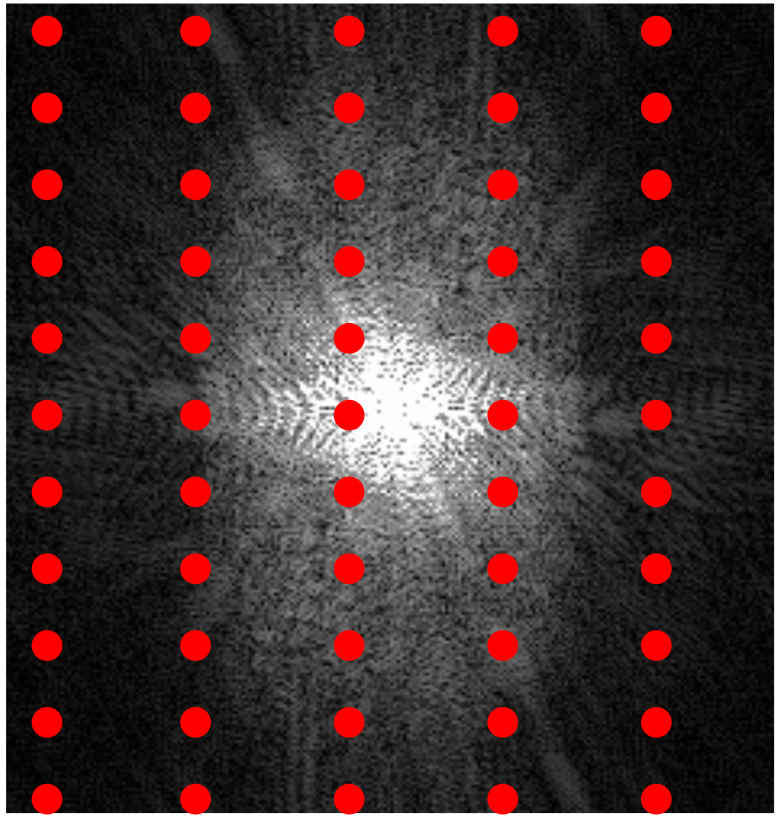
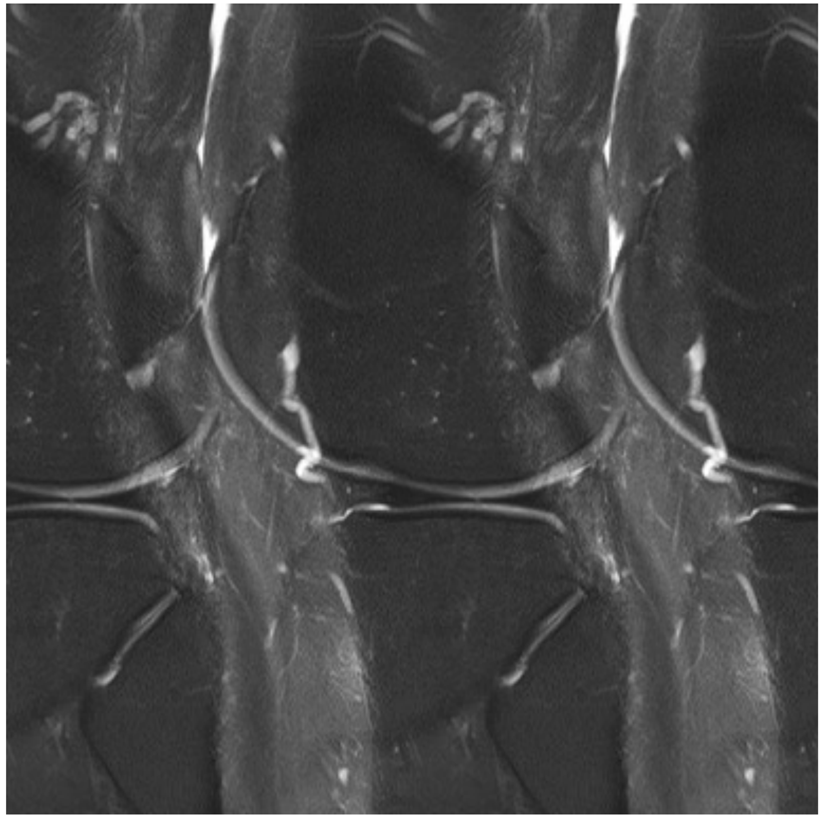
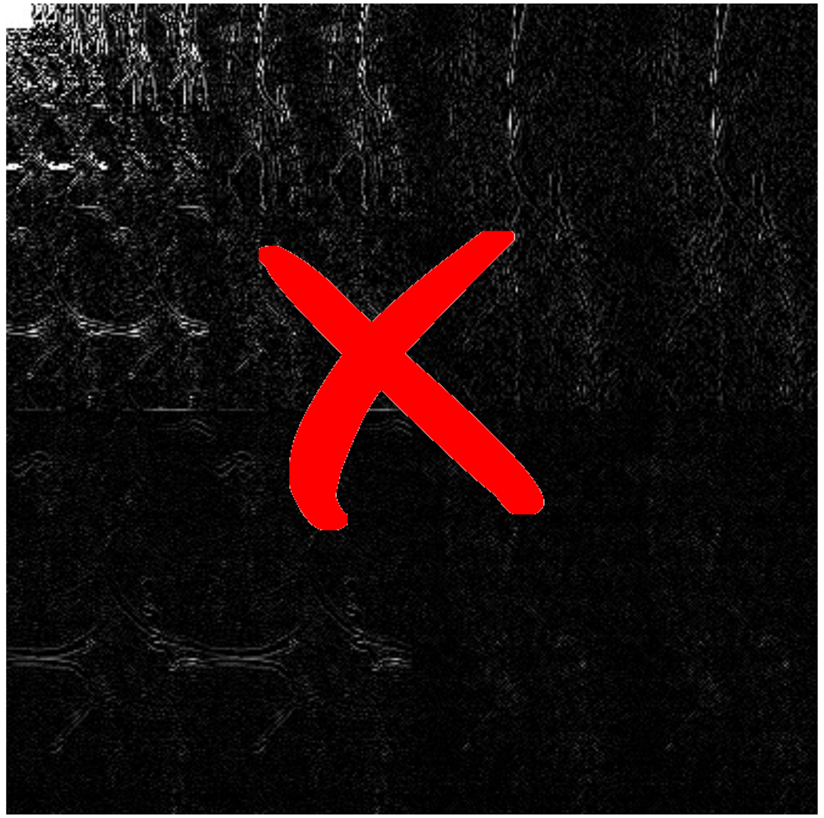


image space



transform space

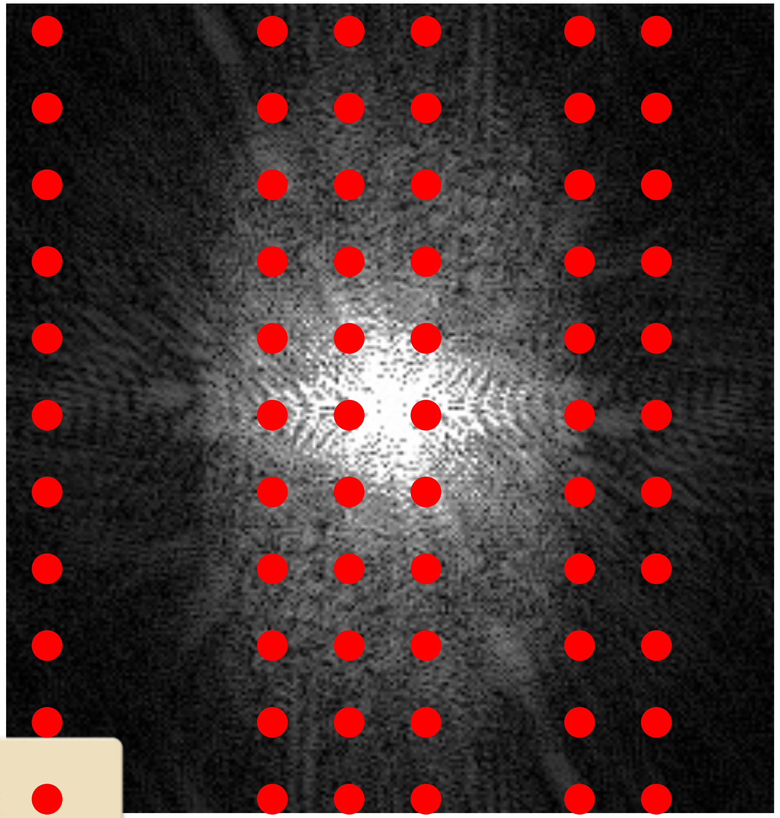


sparsity is lost

Incoherent k-space sampling

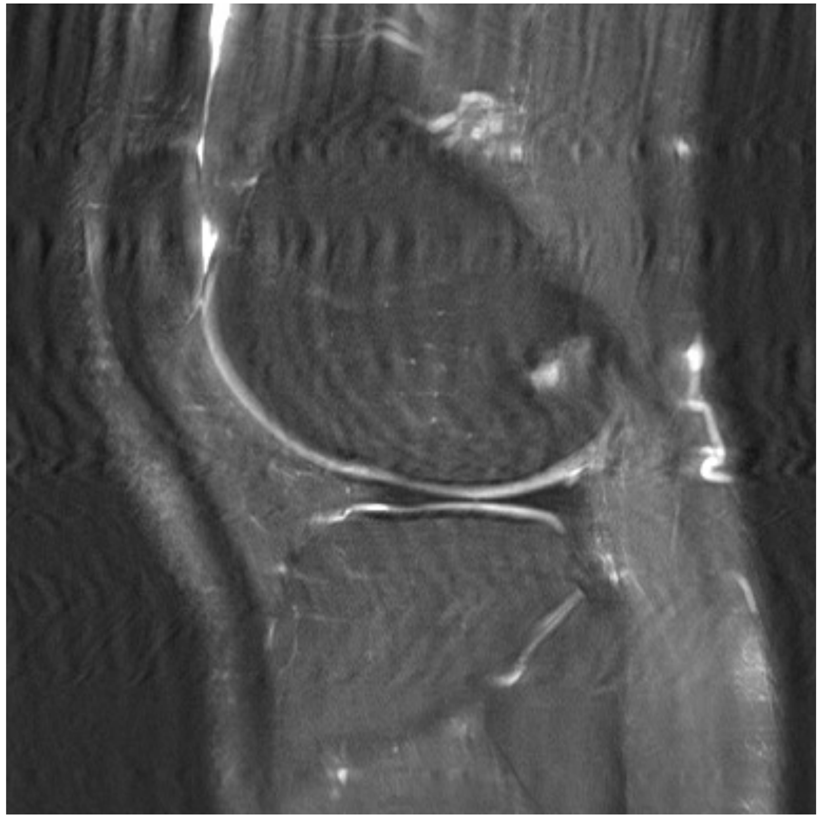
- **Non-uniform k-space undersampling**

k-space

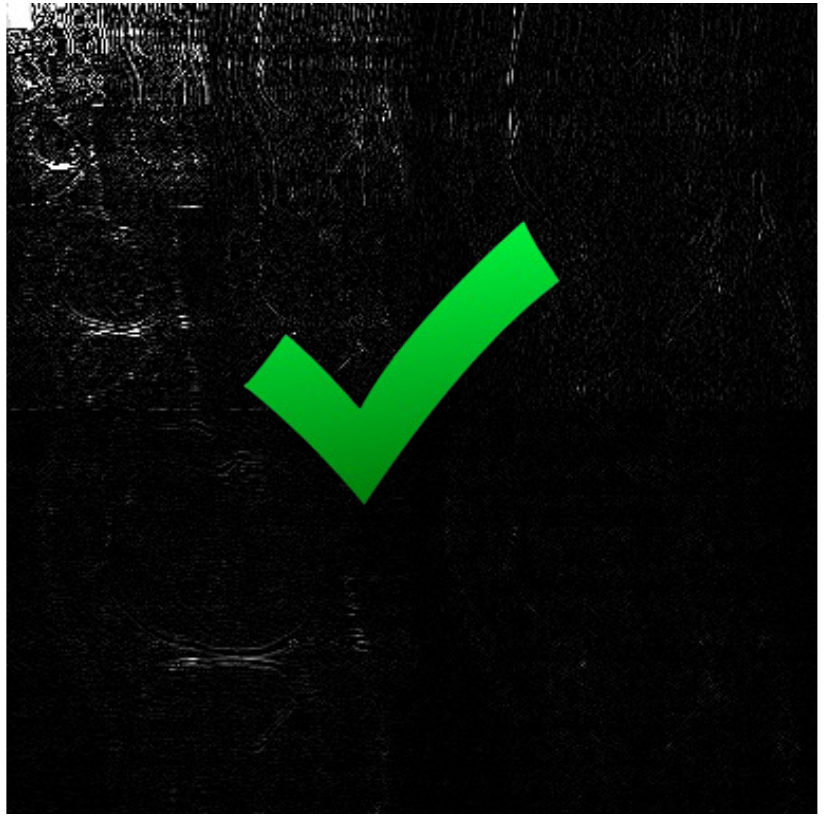


random

image space



transform space



sparsity is preserved

Inherent incoherence in non-Cartesian sampling

- **Radial sampling**

k-space

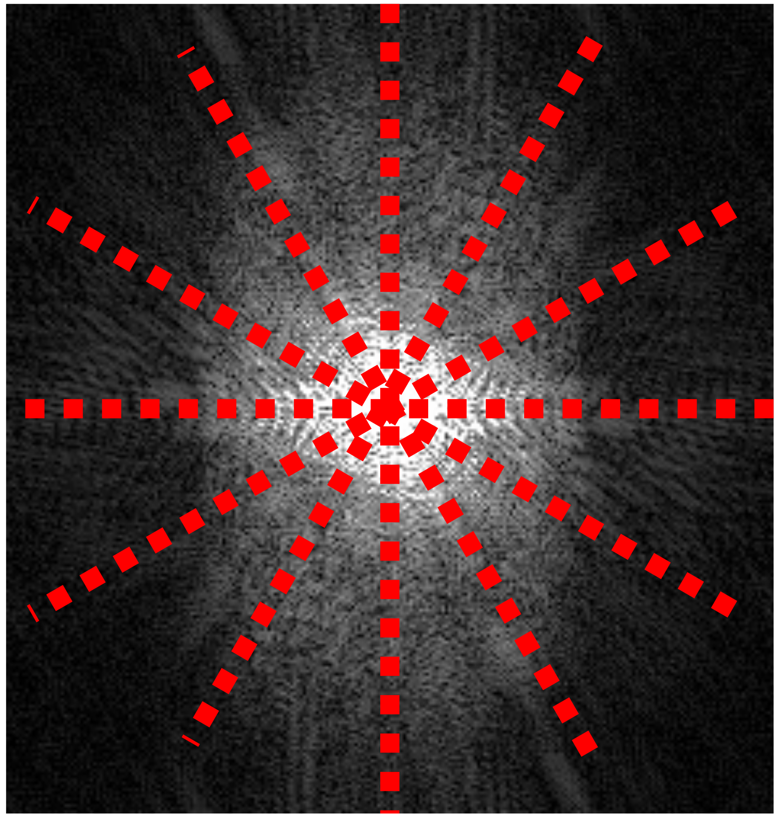
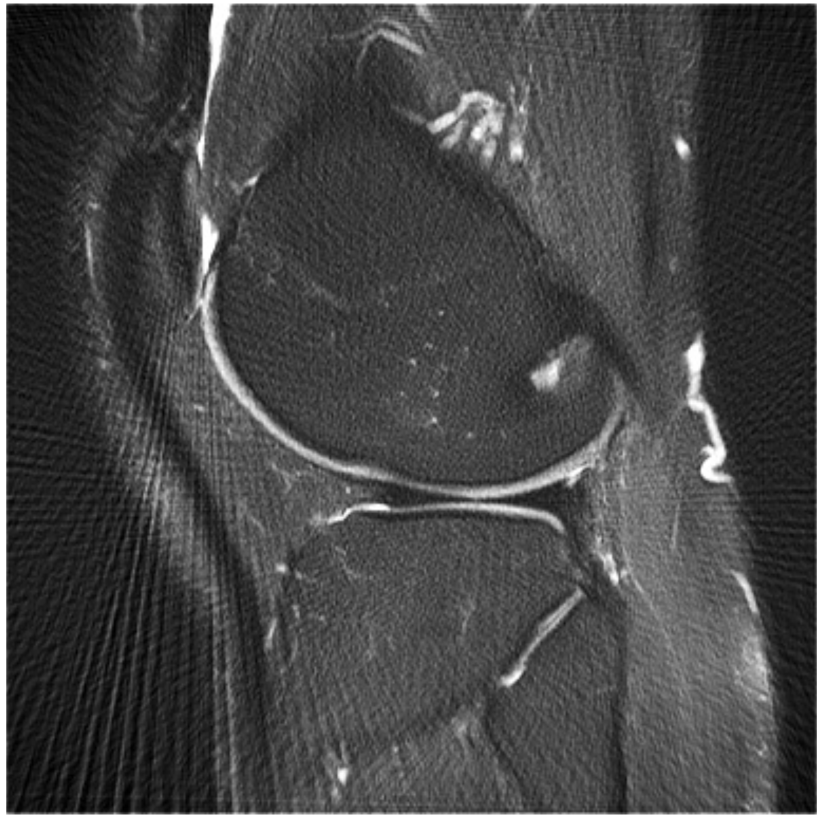
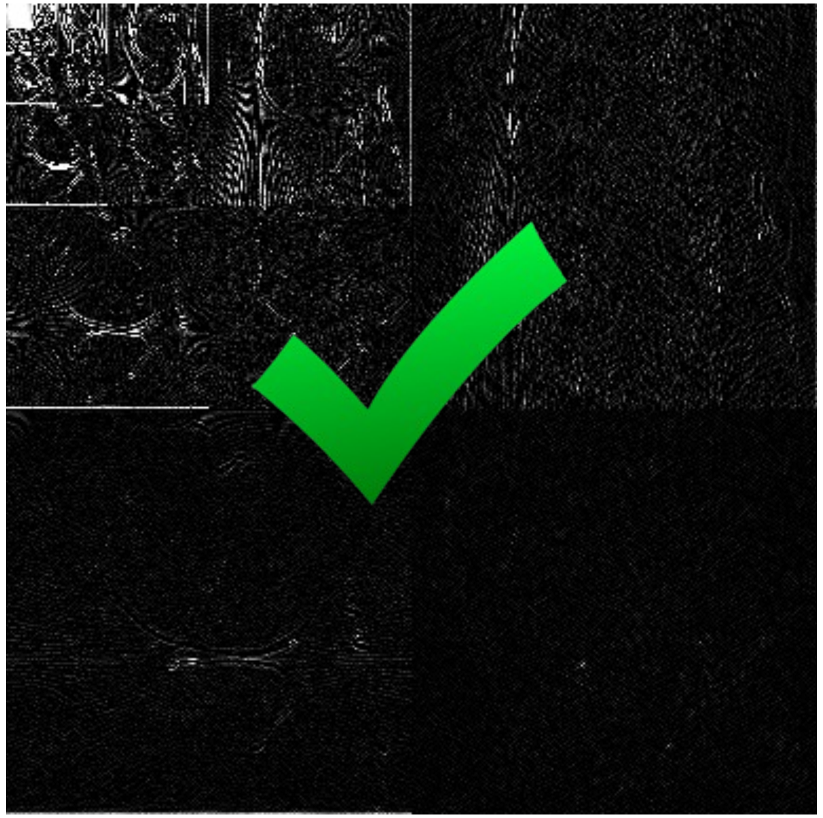


image space



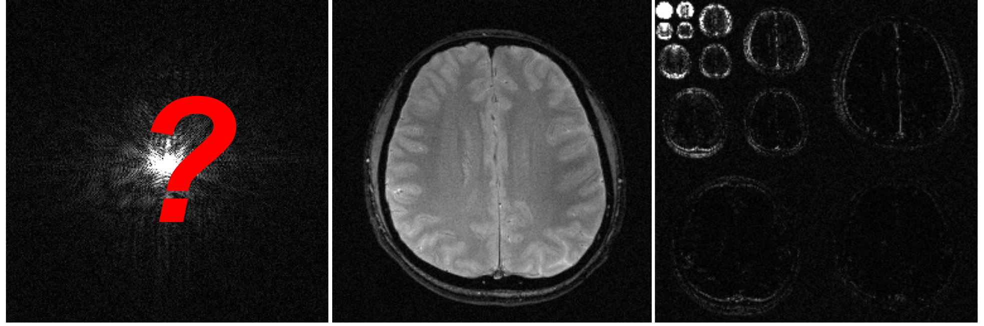
transform space

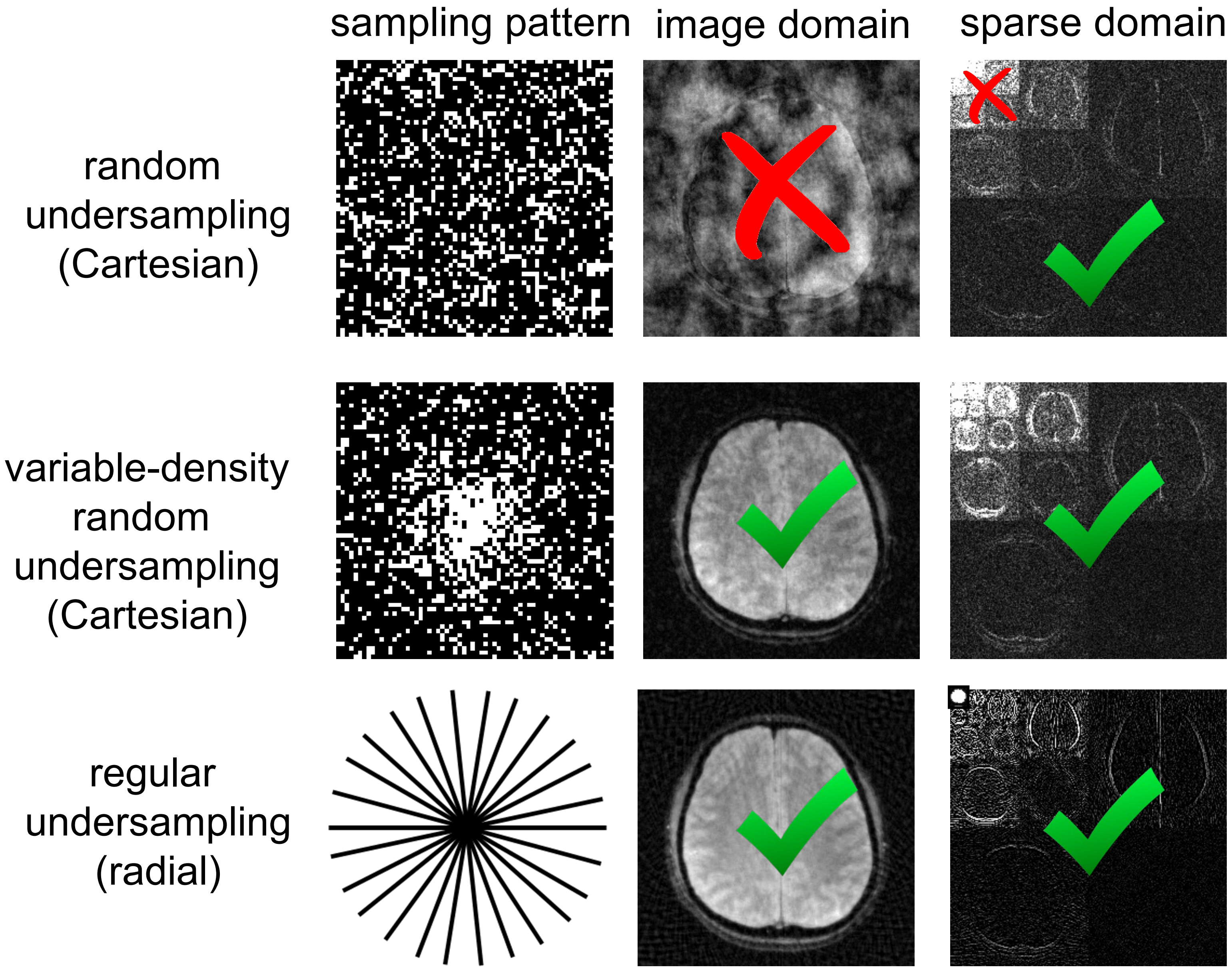


sparsity is preserved

Incoherent sampling patterns

- **What are the best samples?**





Sparse reconstruction

- **Optimization problem, iterative algorithm**
- **Acquisition model:** $d = Em$

d: k-space data
E: undersampled Fourier transform
m: image to reconstruct

$$\min_{\mathbf{m}} \|\mathbf{Em} - \mathbf{d}\|_2^2 + \lambda \|\mathbf{Tm}\|_1$$

- **T: sparsifying transform**
- **λ: regularization parameter**
  - **Trade-off between sparsity (l1-norm term) and data consistency (l2-norm term)**

Sparse reconstruction using iterative soft-thresholding

inputs: E, d, T, λ

initial solution: $m_0 = E^* d$

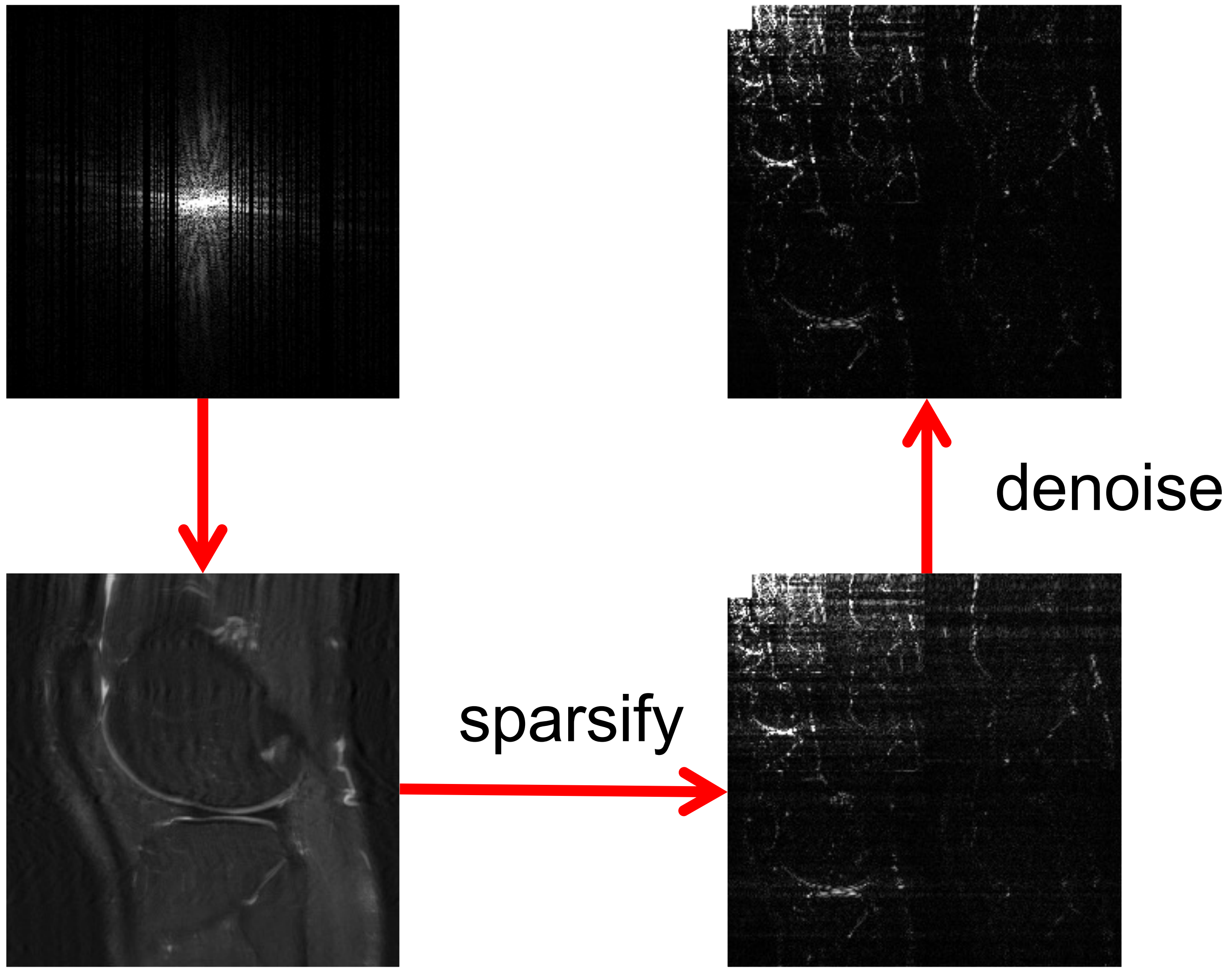
for each iteration *k*

enforce sparsity: $m_k = T^*\left(Soft(Tm_{k-1}, \lambda)\right)$

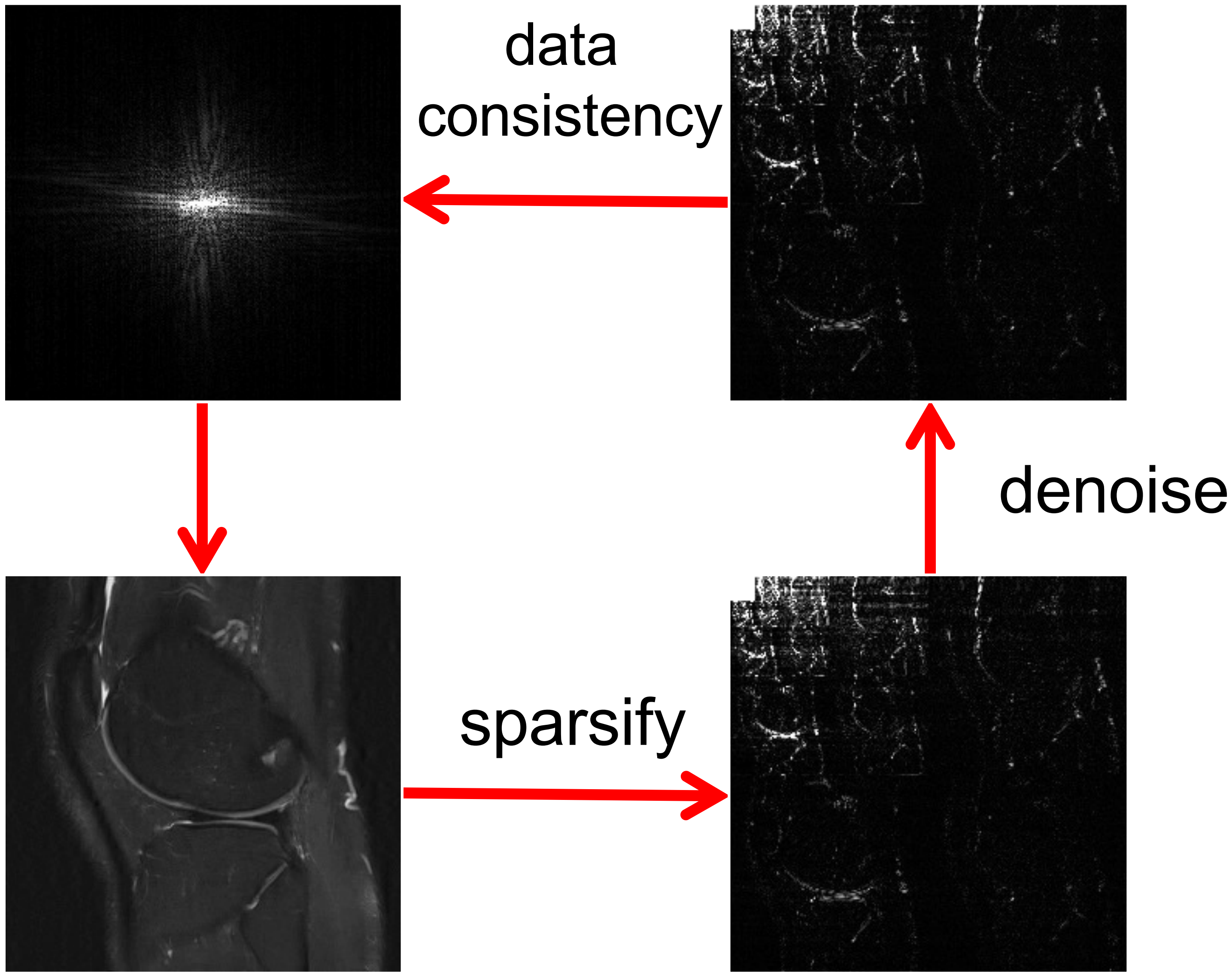
enforce data consistency: $m_k = m_k - E^*(Em_k - d)$

end for

Sparse reconstruction using iterative soft-thresholding

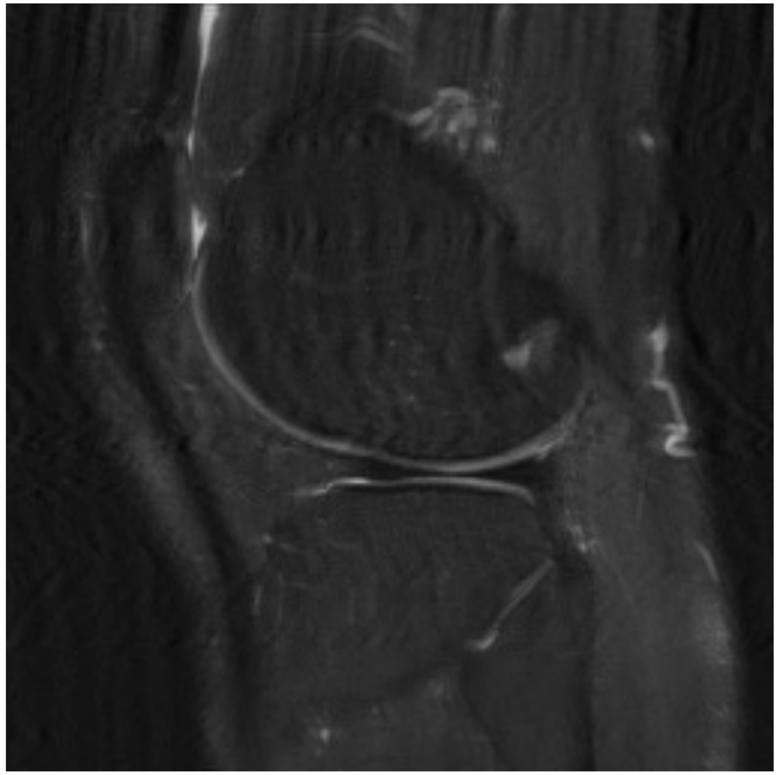


Sparse reconstruction using iterative soft-thresholding



Sparse reconstruction using iterative soft-thresholding

initial solution

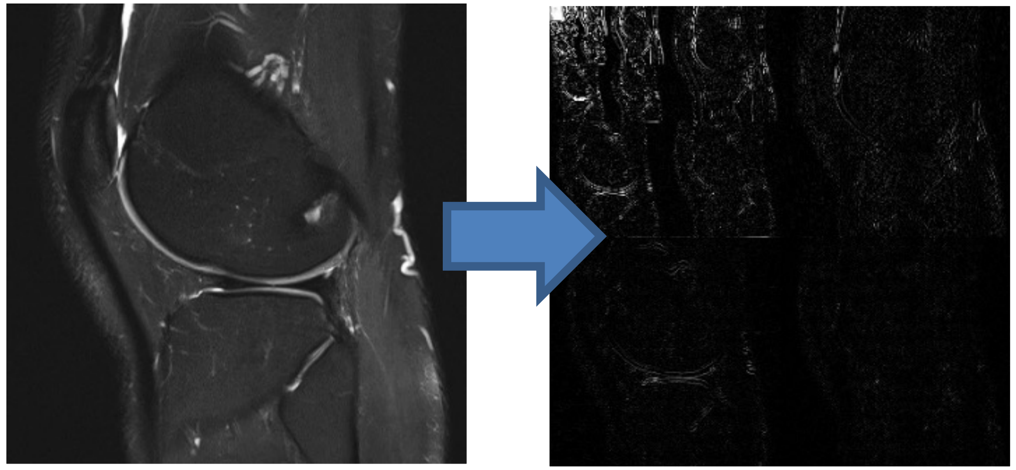


after 40 iterations

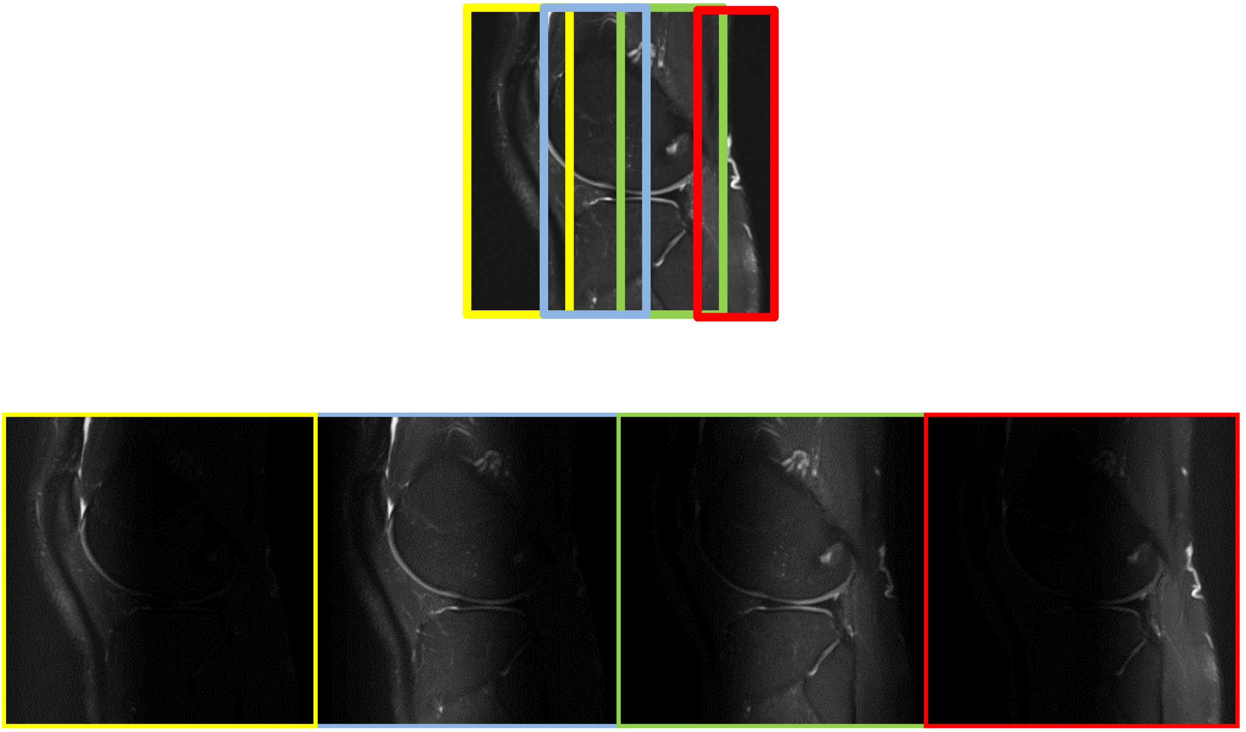
Combination of compressed sensing and parallel imaging

- **Complementary sources of information**

sparsity

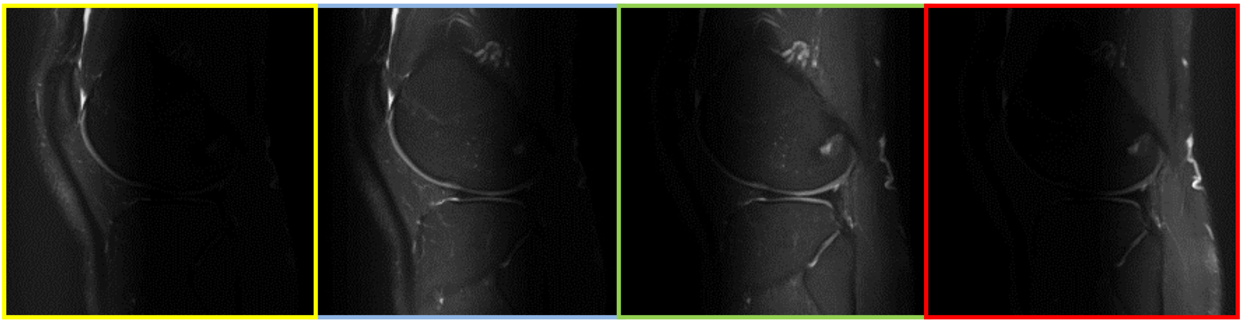


coil sensitivity encoding



Combination of compressed sensing and parallel imaging

- **Joint sparsity rather than coil-by-coil sparsity**
  - **New definition of sparsity**
  - **Exploit inter-coil correlations**



$x = [x_1, x_2, x_3, x_4]$

(1) joint l_1-norm: $$\|\mathbf{x}_{MF}\|_1 = \sum_{p=1}^{Np} \left| \sum_{l=1}^{Nc} \frac{c_l^*(p) x_l(p)}{|c_l(p)|^2} \right|$$

(2) l_1-l_2-norm: $$\|\mathbf{x}\|_{1,2} = \|x_{SOS}\|_1 = \sum_{p=1}^{Np} \left(\sum_{l=1}^{Nc} |x_l(p)|^2 \right)^{1/2}$$

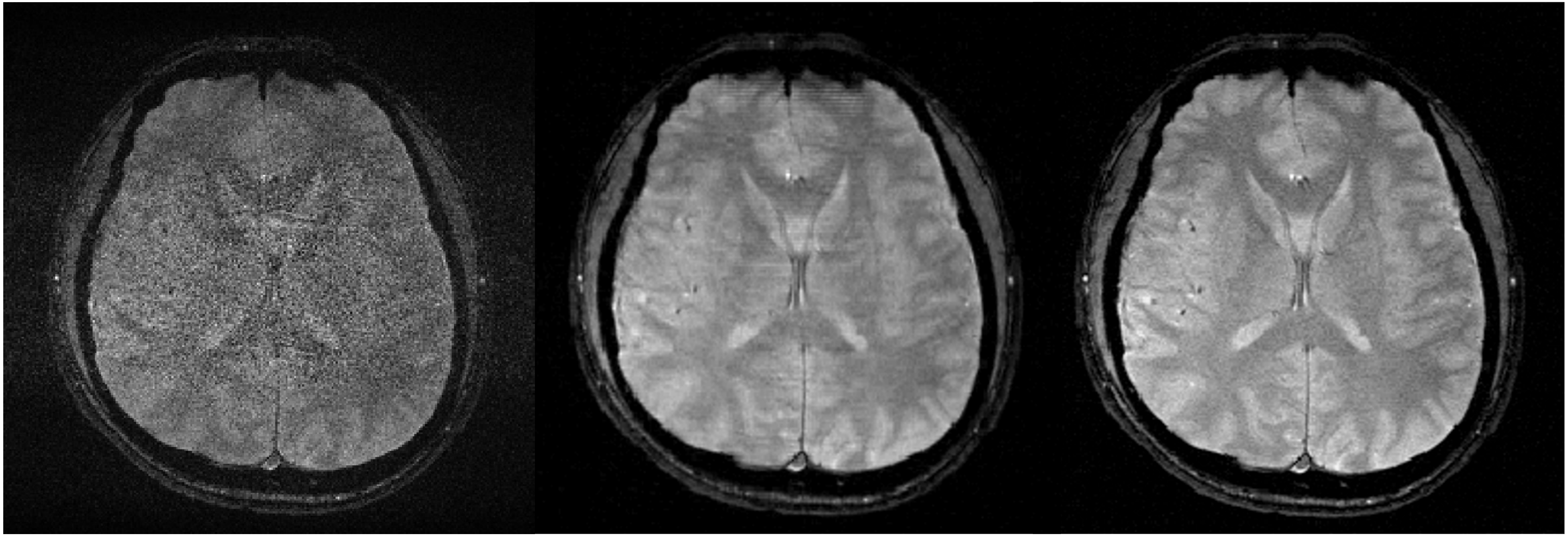
(1) Otazo R et al. ISMRM 2009, 378; MRM 2010

(2) Lustig M et al. ISMRM 2009, 379; MRM 2010

SPARSE-SENSE

- **4-fold acceleration**

GRAPPA | Coil-by-coil CS | SPARSE-SENSE

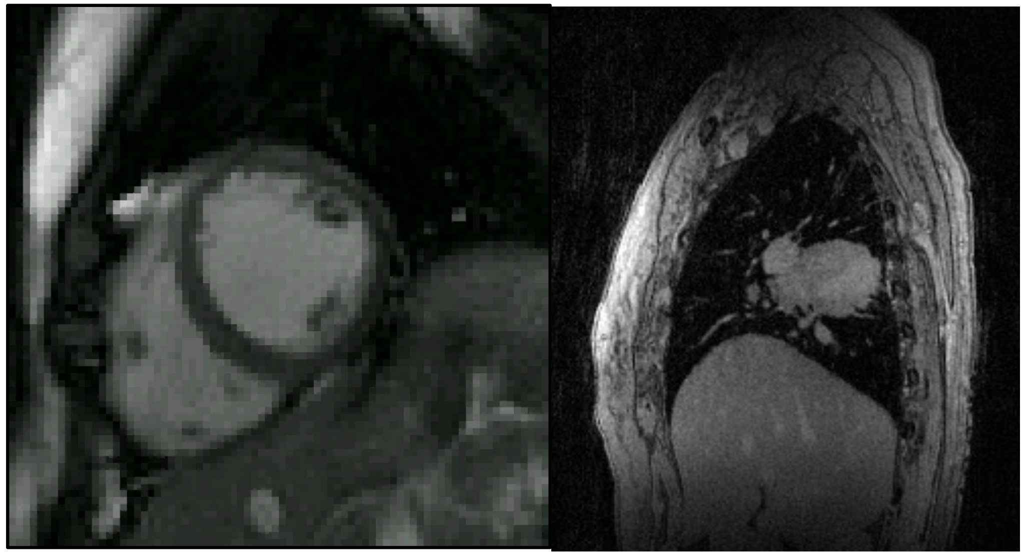


Otazo R et al. ISMRM 2009, 378

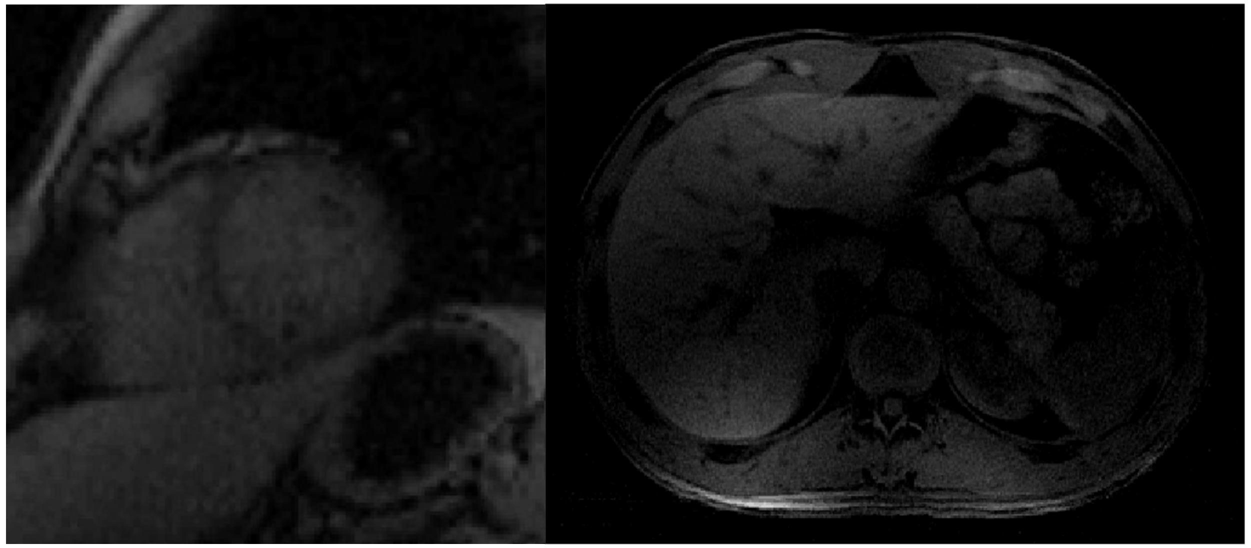
Dynamic MRI

- **Time-series of images**
- **Video**
- **Physiological information**

motion

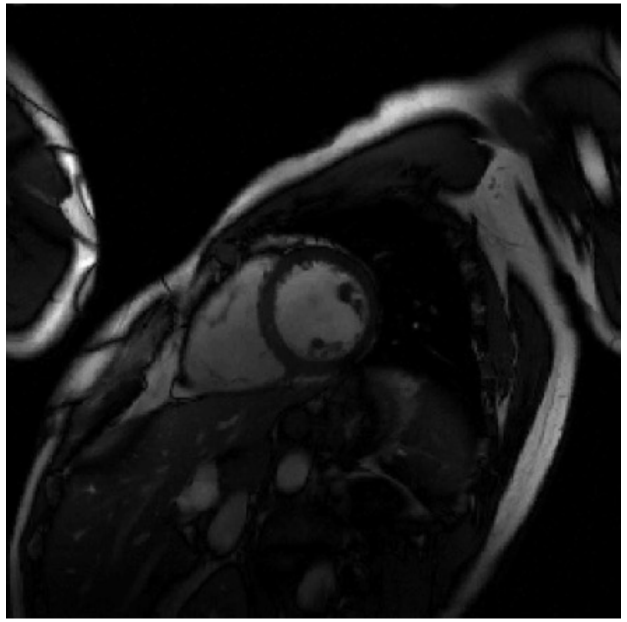


contrast agent
- gadolinium-based: T1 reduction

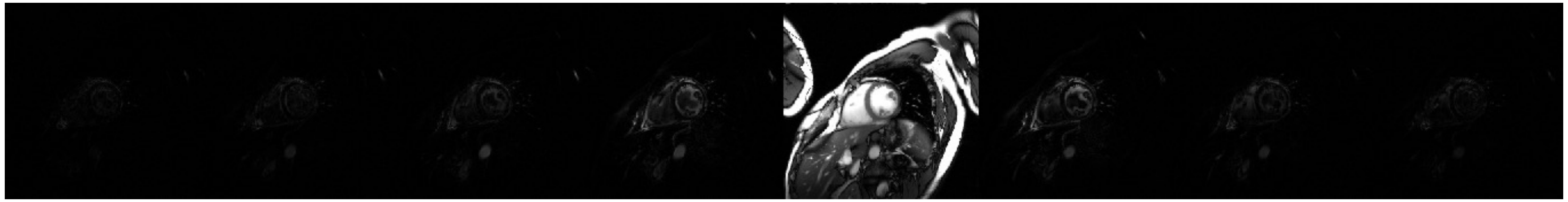


Temporal compressed sensing

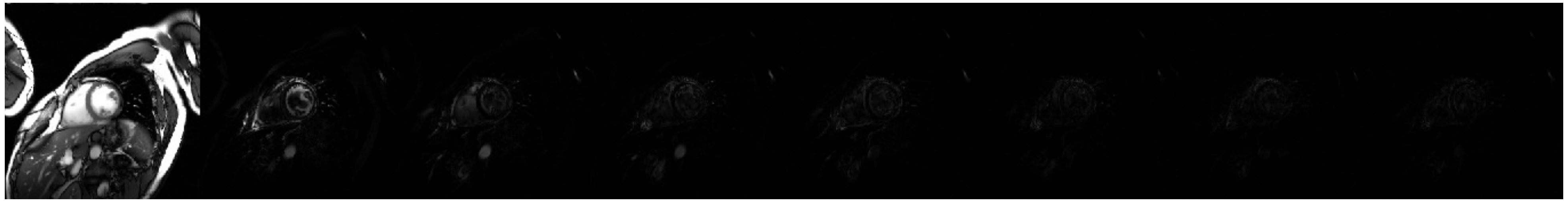
- **Temporal sparsity**
  - **Videos are more compressible than images**



Temporal FFT

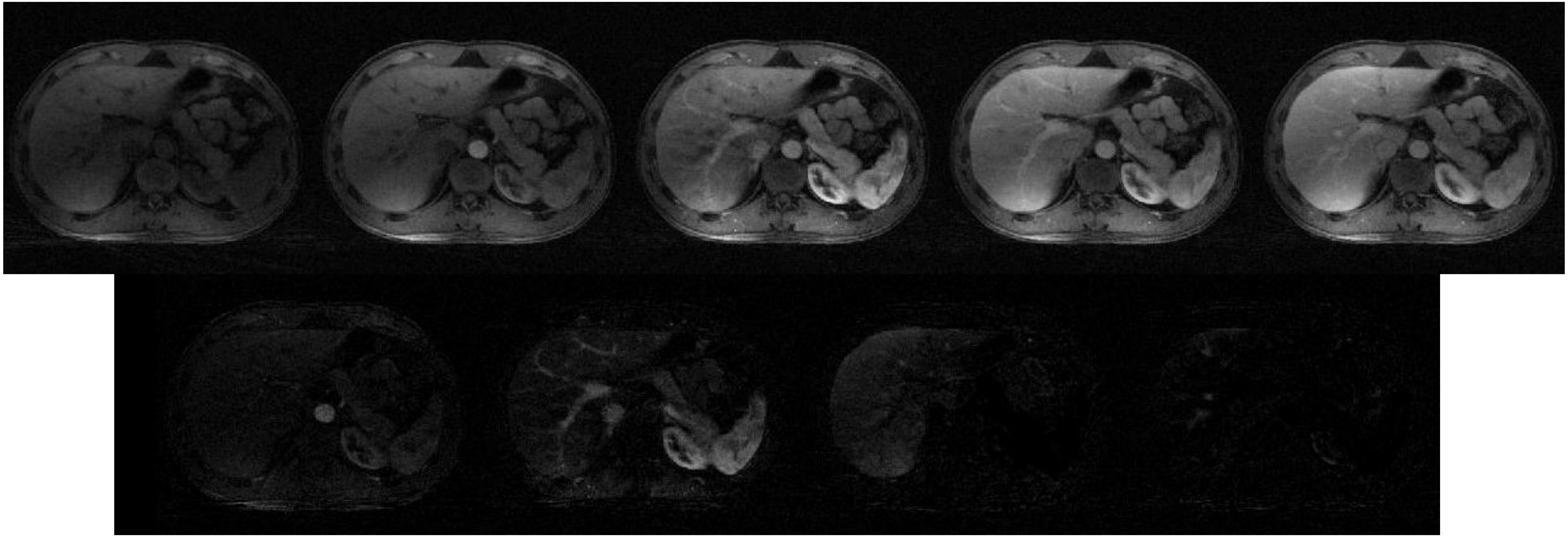


Temporal PCA



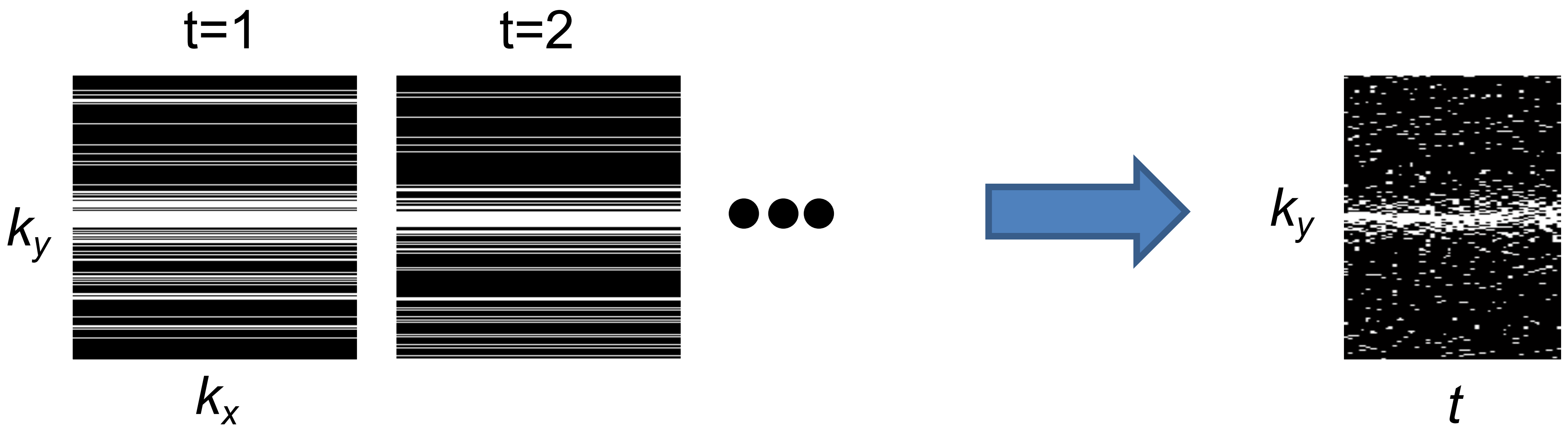
Temporal compressed sensing

- **Temporal sparsity**
  - **Difference between consecutive frames is sparse**



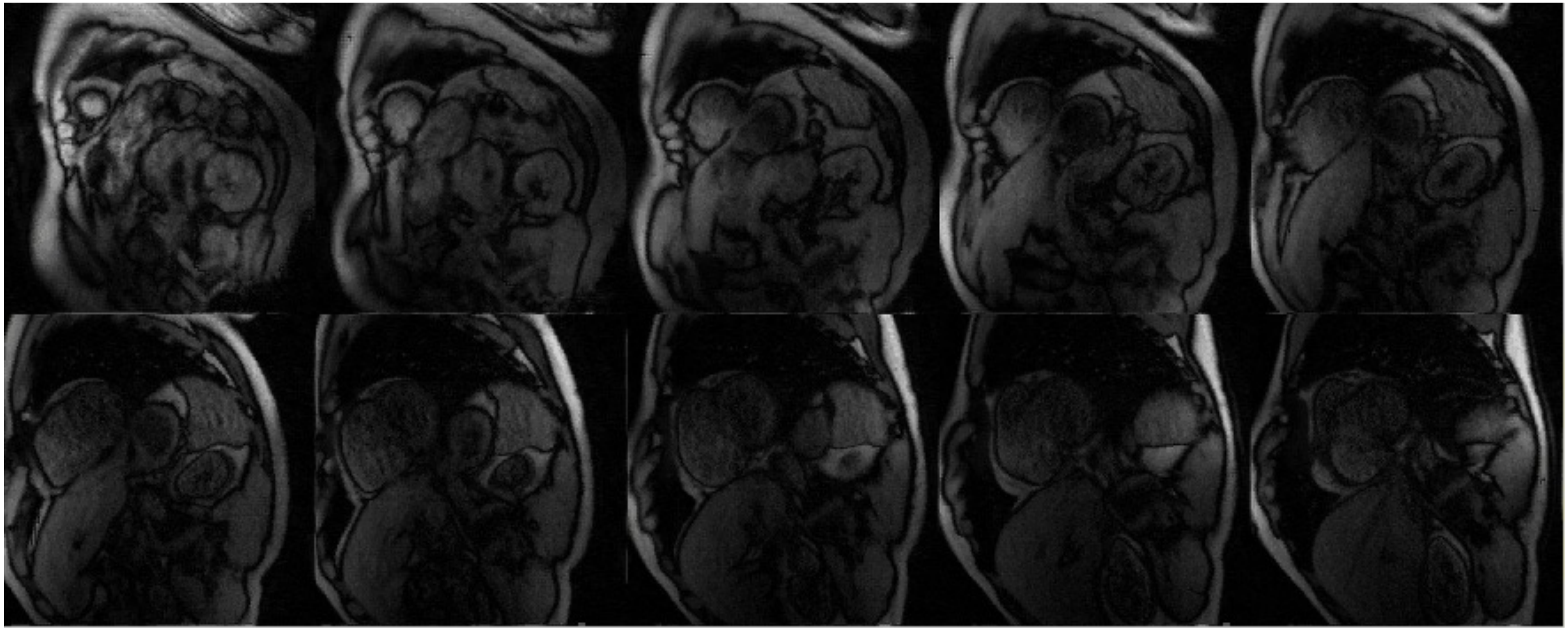
Temporal compressed sensing

- **Temporal incoherence**
  - **Different irregular k-space sampling pattern for each time point**
    - **Random Cartesian**



k-t SPARSE-SENSE

- **Cardiac perfusion (video of contrast enhancement)**
  - **8-fold acceleration, 10 slices per heartbeat**
  - **Temporal res. = 60 ms/slice, spatial res. = 1.7x1.7x3 mm^3**

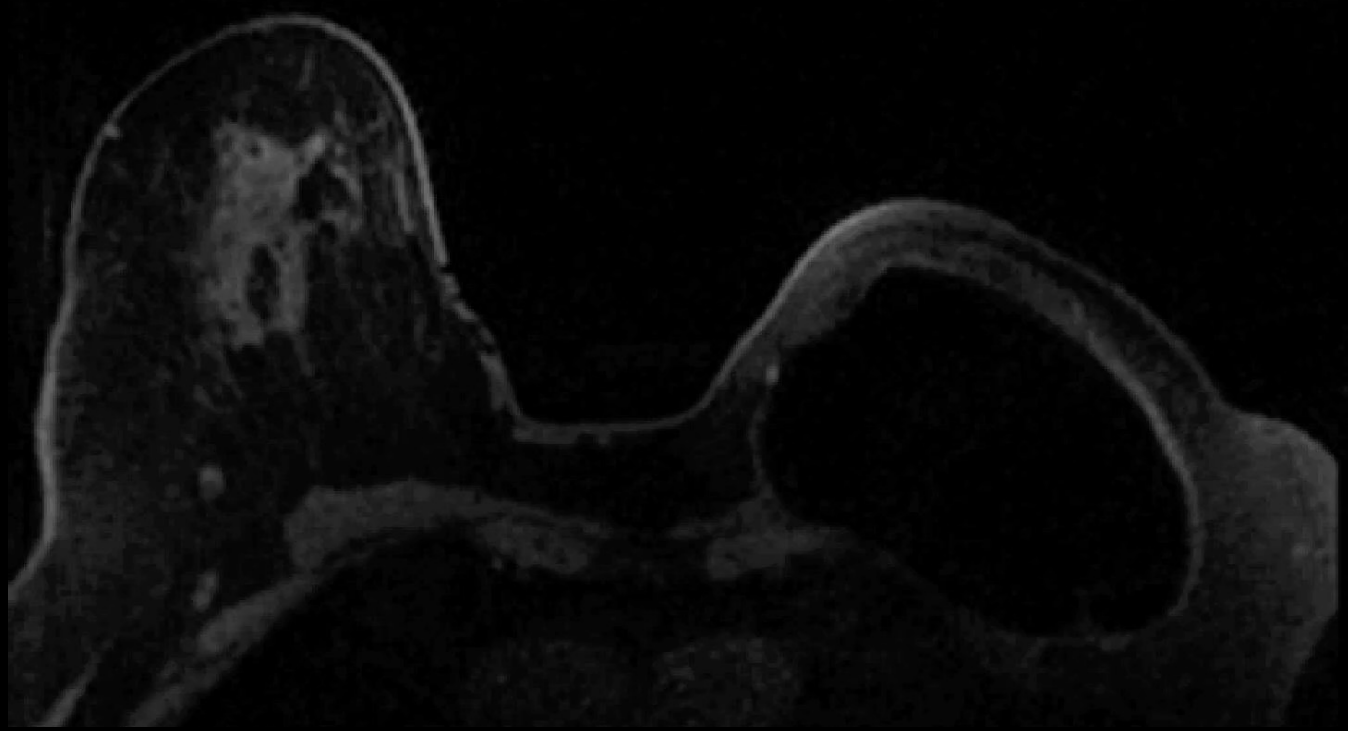


Otazo R et al. MRM 2010

GRASP: radial compressed sensing

- **Dynamic contrast enhanced imaging**
- **Isotropic spatial resolution = 1.6 mm^3**
- **Temporal resolution = 5 seconds**

78-year-old woman with stage T1c invasive ductal carcinoma

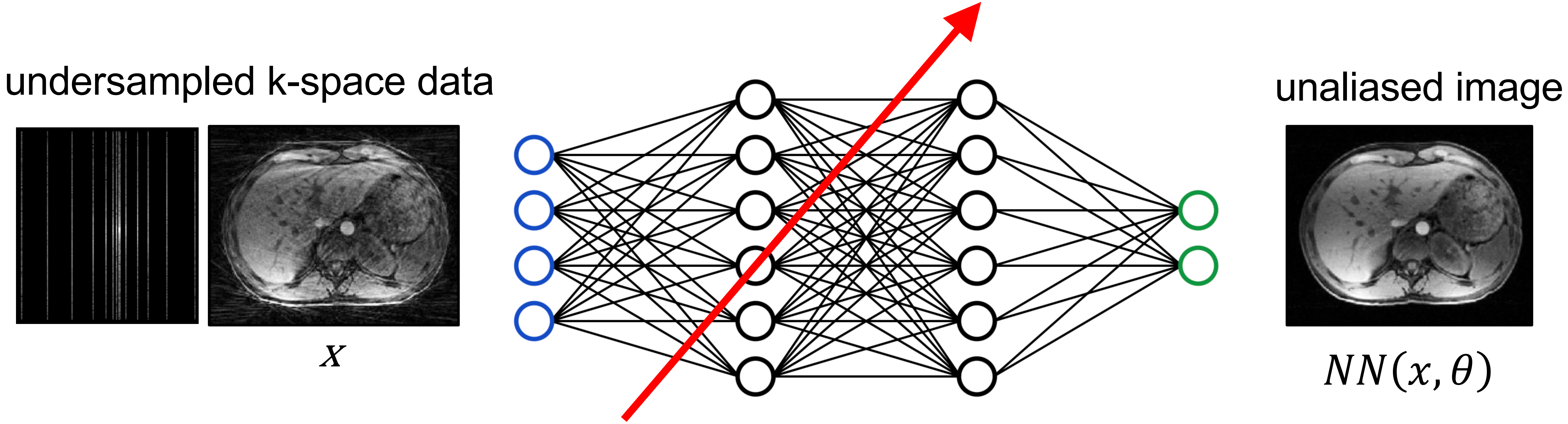


acquired axial orientation

reformatted sagittal

Deep learning MRI reconstruction

- **Neural network for reconstruction for undersampled k-space data**

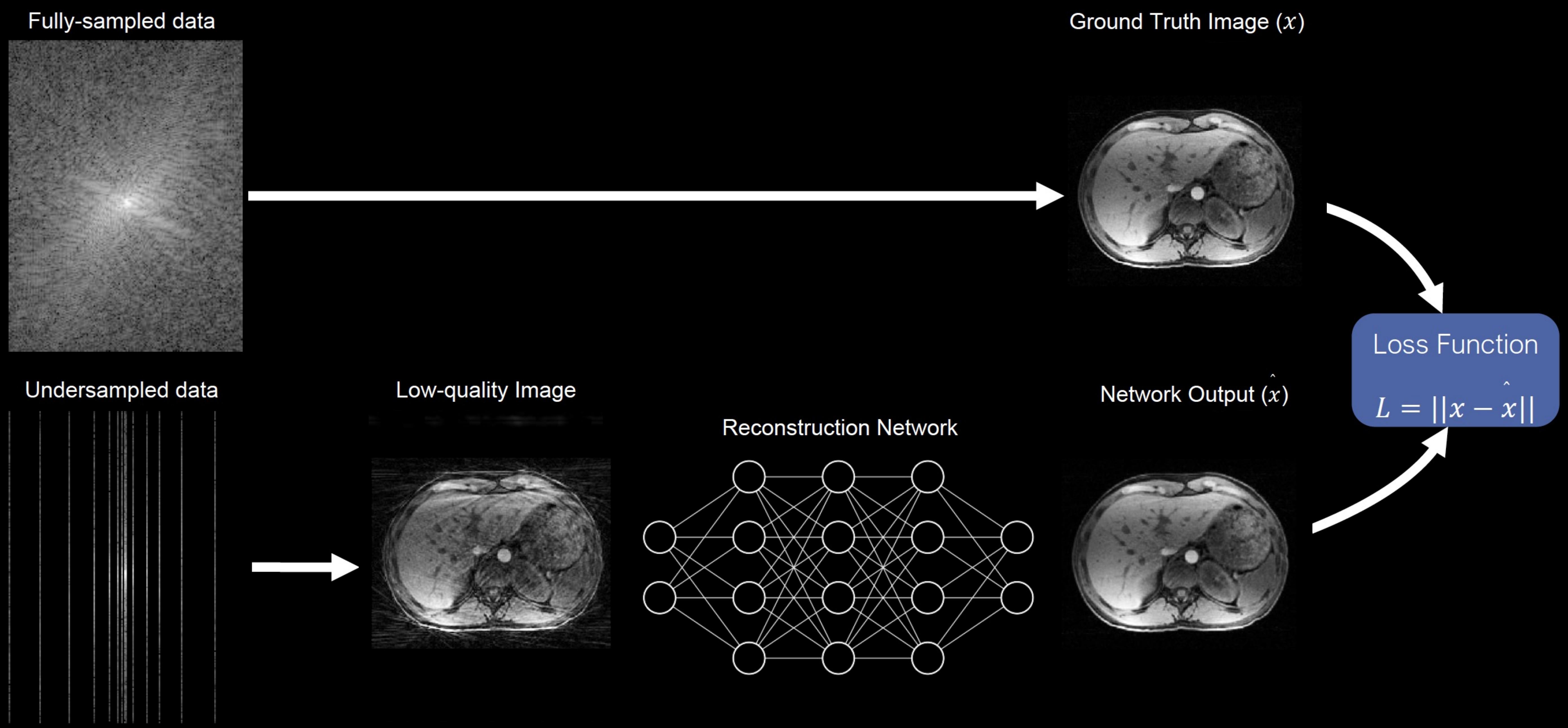


learning: compute network parameters to minimize loss function

$$L(\theta) = \sum_i \|NN(x_i, \theta_i) - y_i\|$$

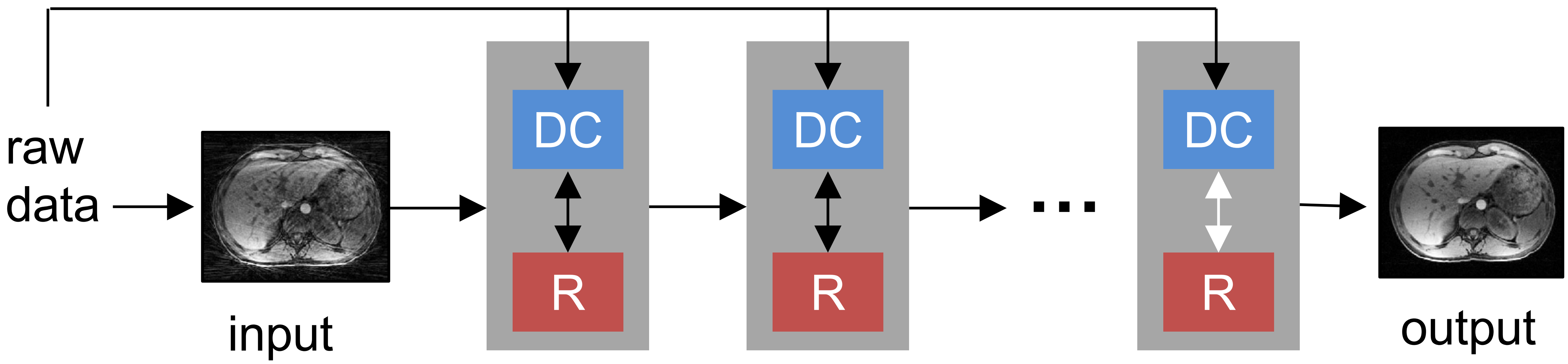
y: training target
i: index for training cases

Supervised learning with fully-sampled k-space data



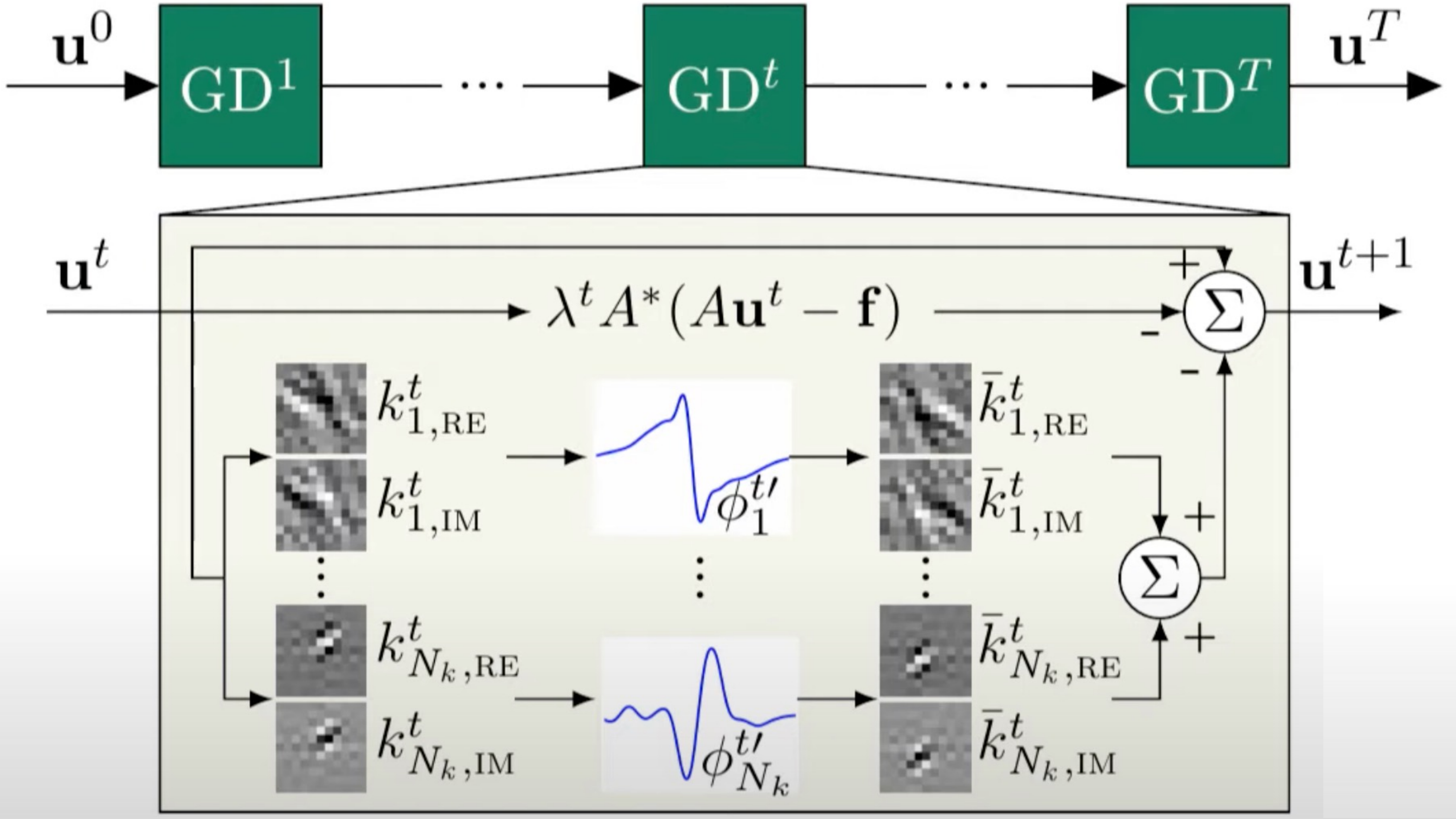
Unrolled network

- **Unroll compressed sensing iterations**
  - **Fixed data consistency (DC)**
  - **Trainable regularization (R)**



Variational network

- **Gradient descent algorithm as a network**



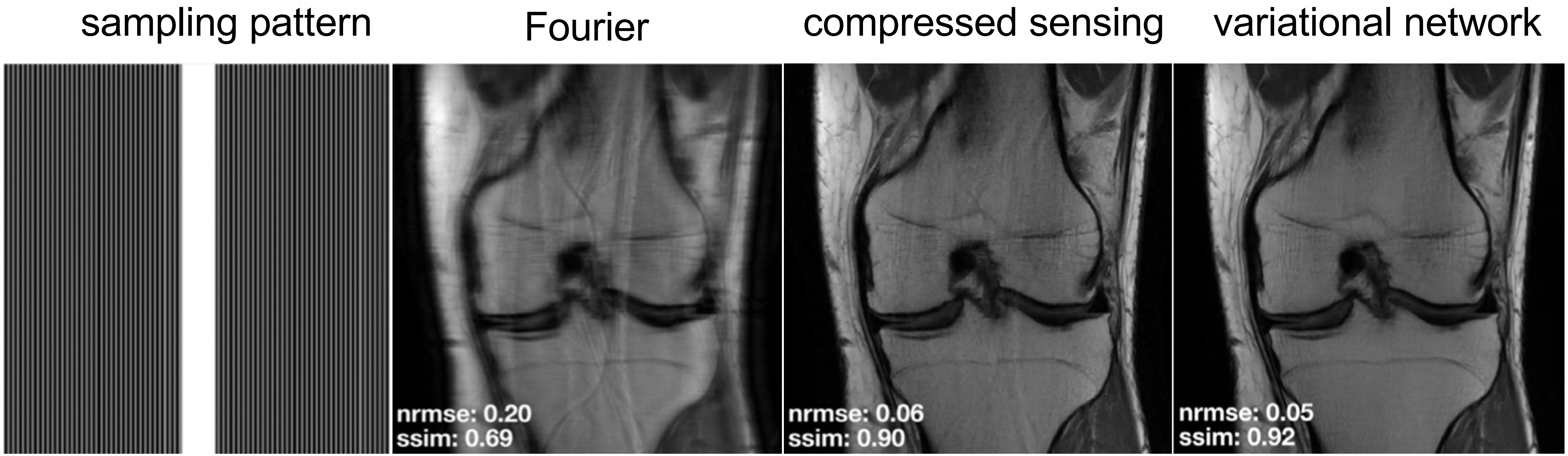
$$u^{t+1} = u^t - \sum_{i=1}^{N_k} (K_i^t)^\top \phi_i^{t\prime}(K_i^t u^t) - \lambda^t A^*(Au^t - f)$$

A: acquisition model

Hammernik K et al. MRM 2017

Variational network

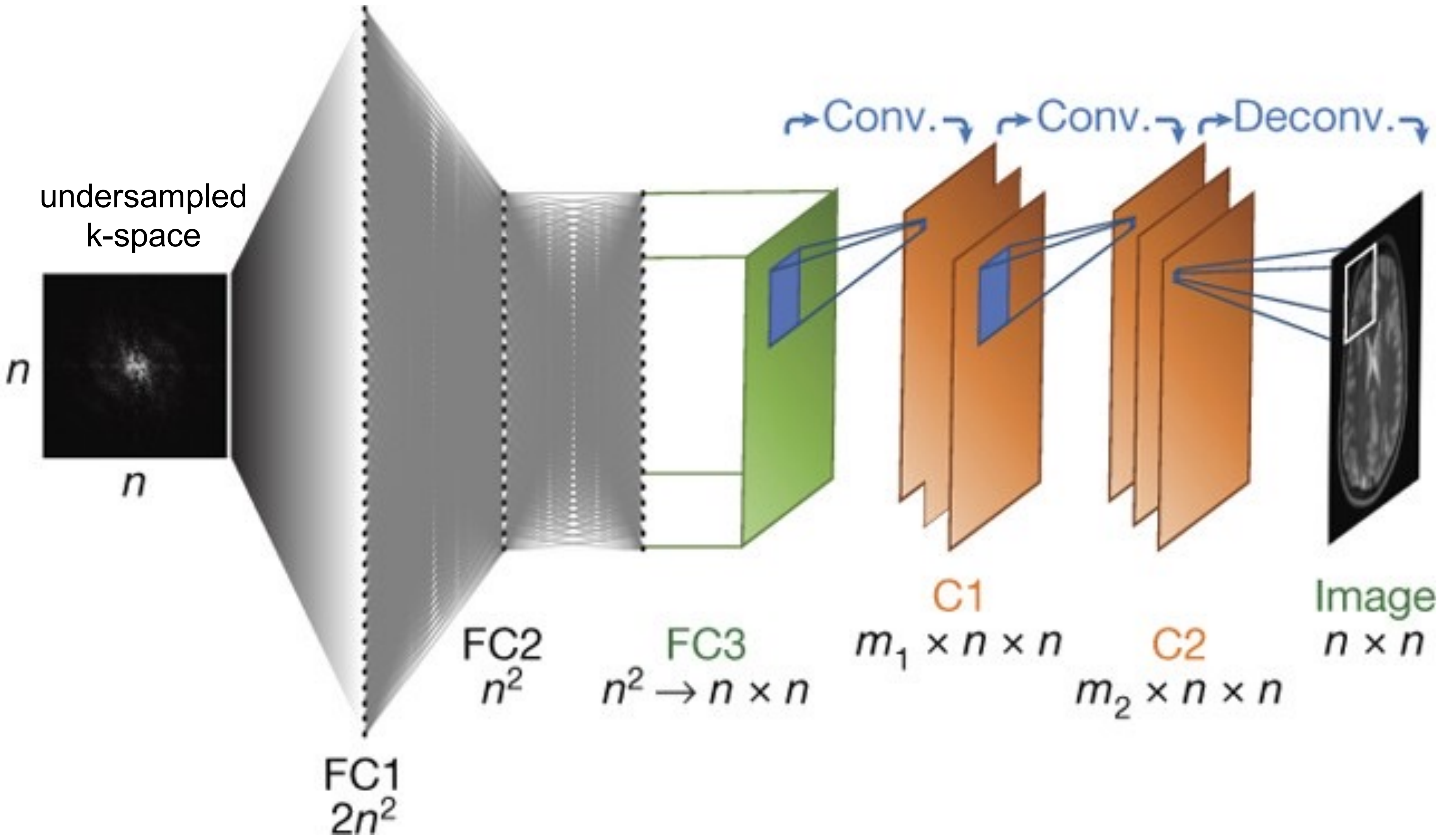
- **4-fold acceleration**



Hammernik K et al. MRM 2017

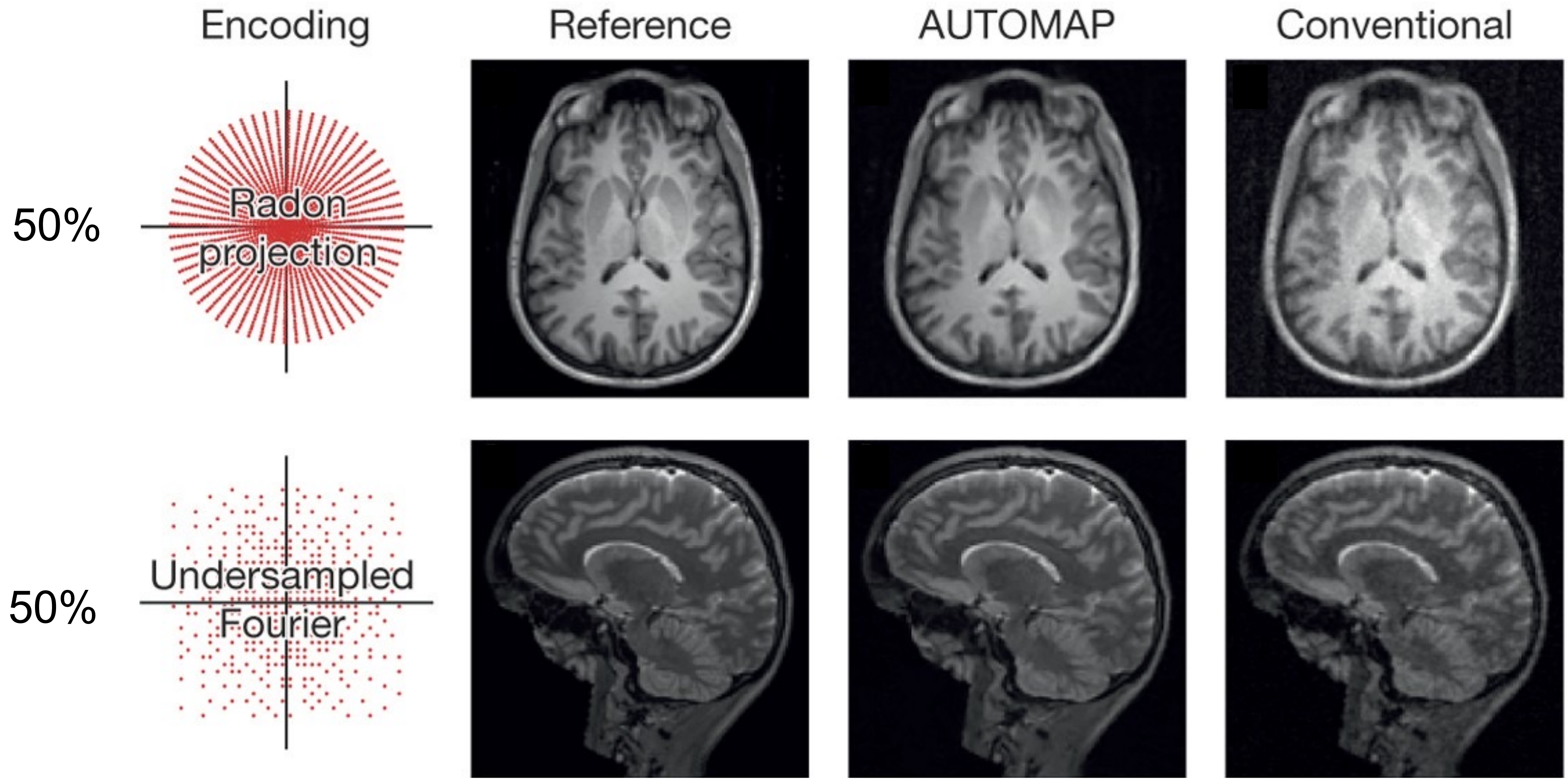
AUTOMAP: self-consistent network

- **Fully-connected + convolutional layers**
  - **Low-dimensional manifold learning**



Zhu B et al. Nature 2018

AUTOMAP



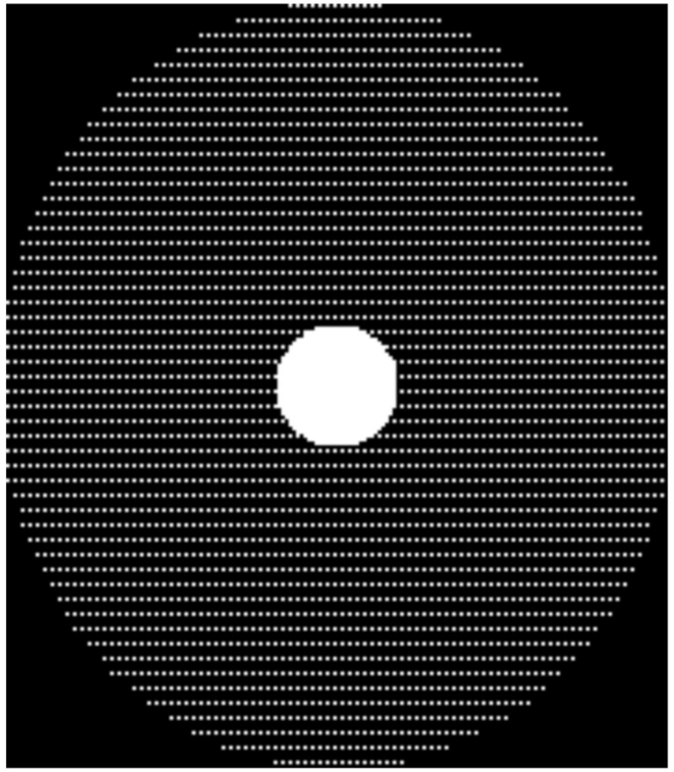
Zhu B et al. Nature 2018

Modular network for 3D MRI with 2D acceleration

- **Brain MRI: k_y-k_z acceleration (coronal), axial image evaluation**

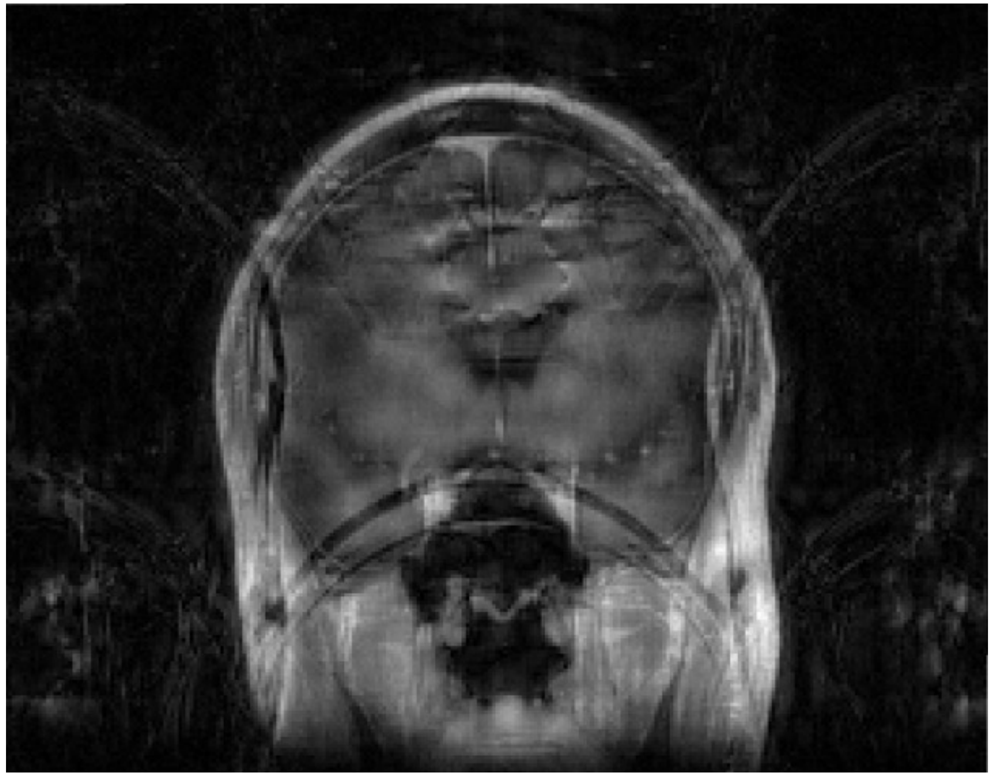
8-fold acceleration

k_y

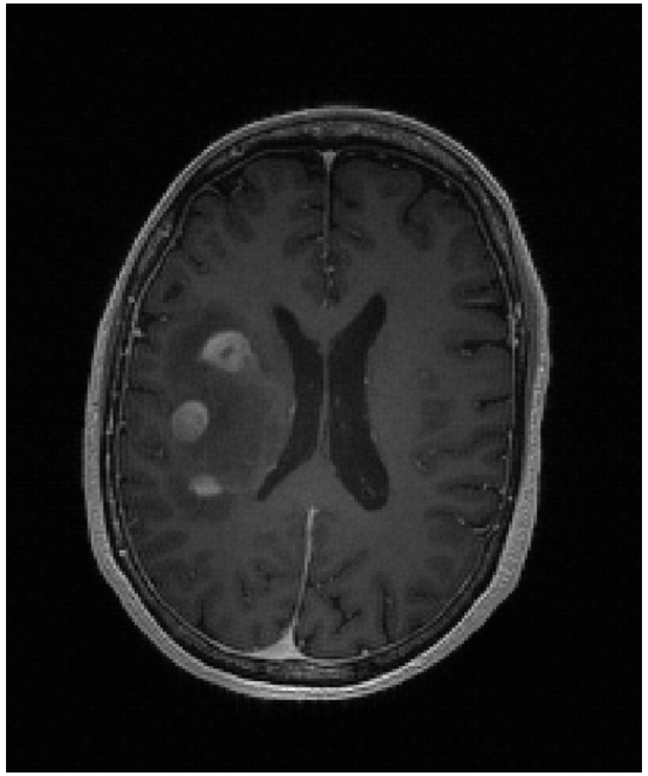


k_z

coronal image

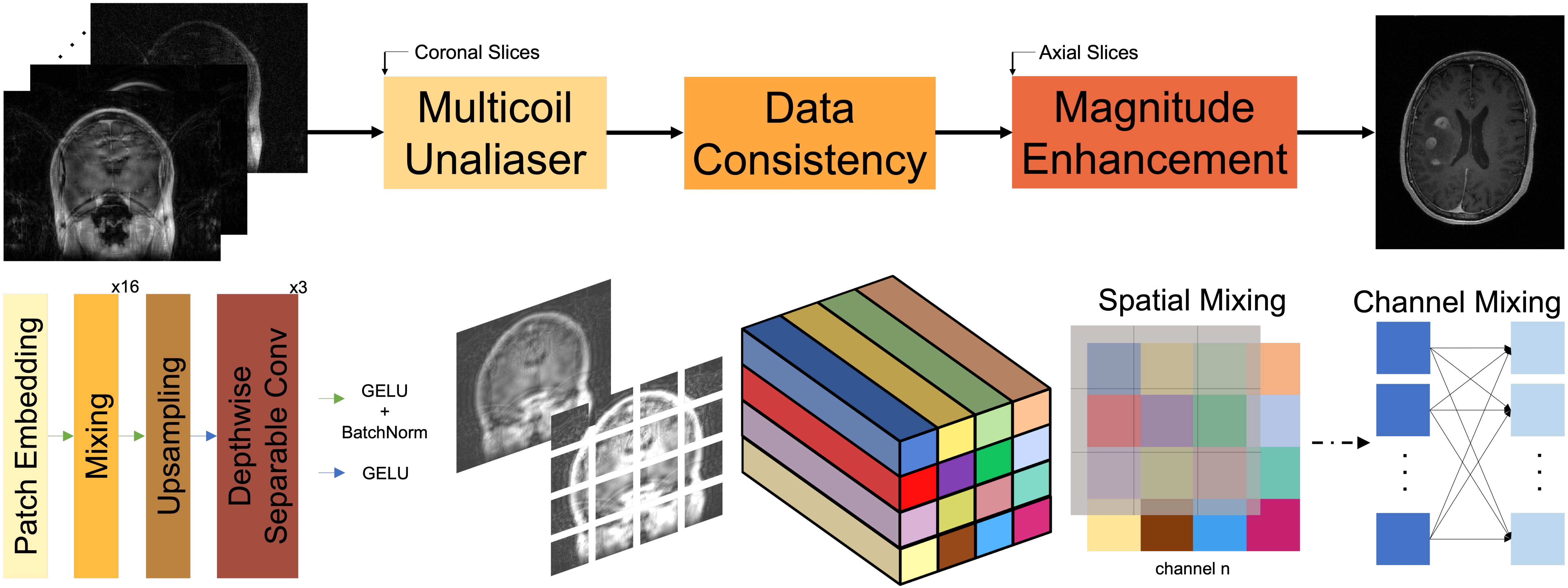


axial image

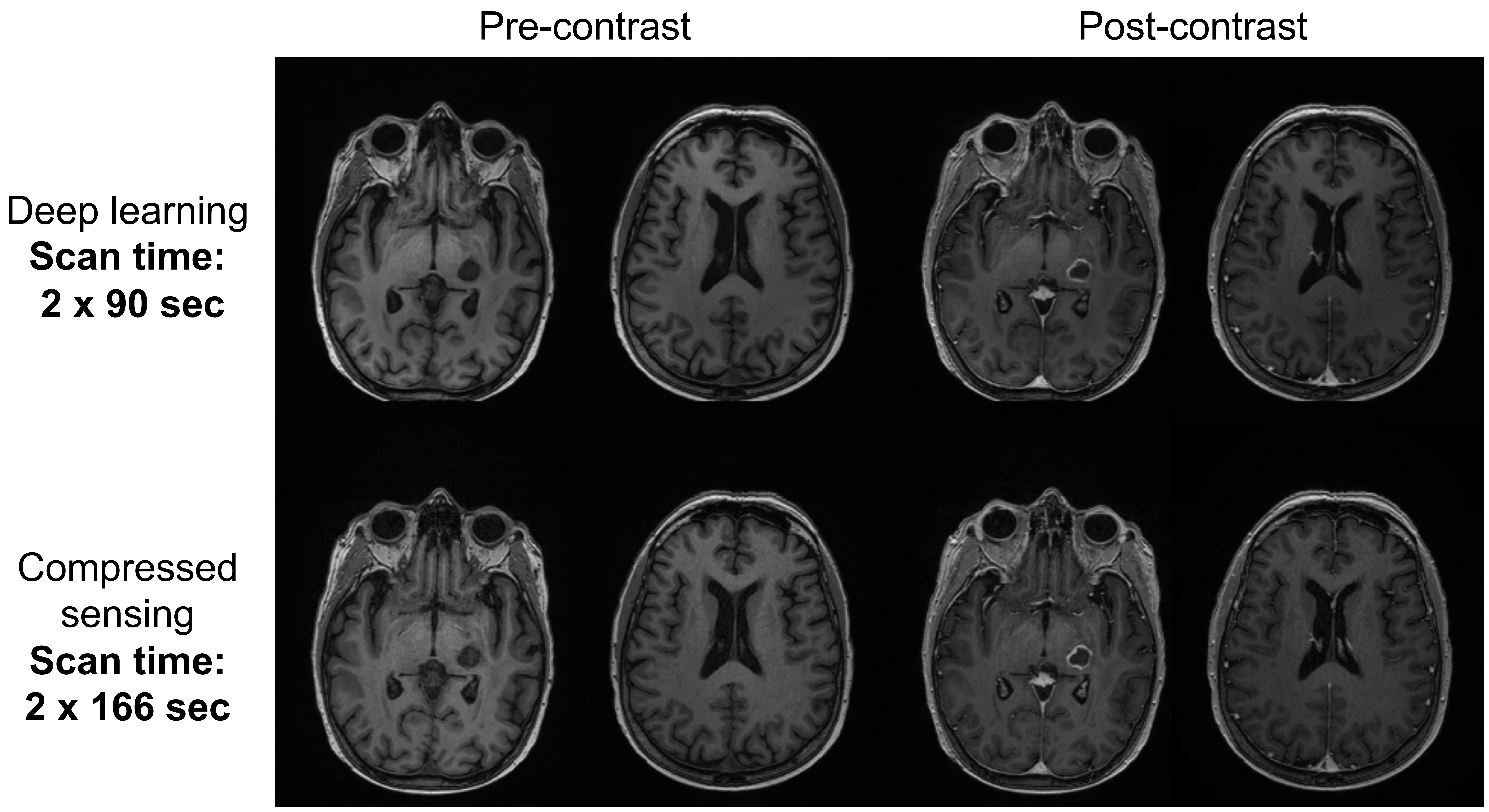


Mekhanik A et al. ISMRM 2022

Modular network for 3D MRI with 2D acceleration

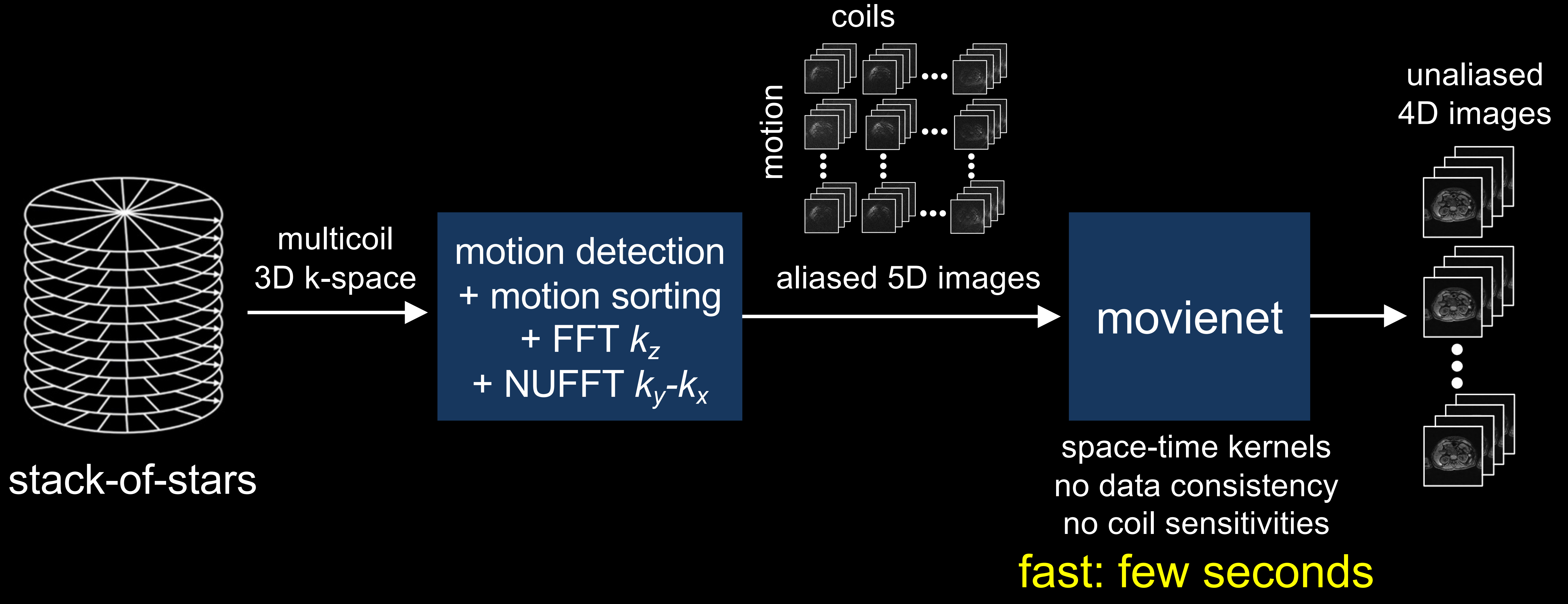


Mekhanik A et al. ISMRM 2022


Pre-contrast
Post-contrast
Deep learning
Scan time:
2 x 90 sec
Compressed sensing
Scan time:
2 x 166 sec

movienet

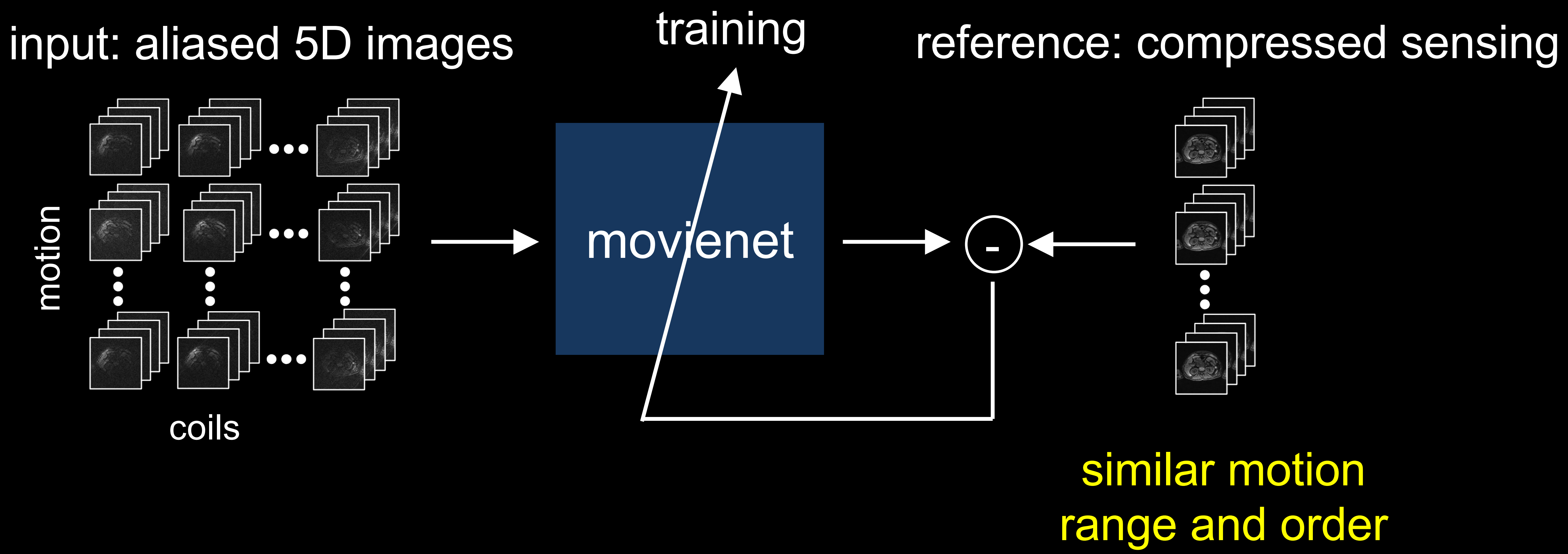
- **Fast 4D reconstruction without data consistency**



Murray V et al. MRM 2023

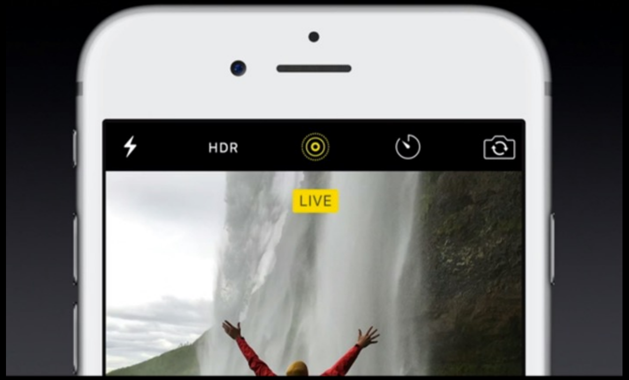
Motion consistency instead of data consistency

- **Preserve motion range and order of motion states in the input**



Motion-tolerant MRI with movienet

- Scan time = 1 minute
- movienet with 4 motion states
- Live mode picture



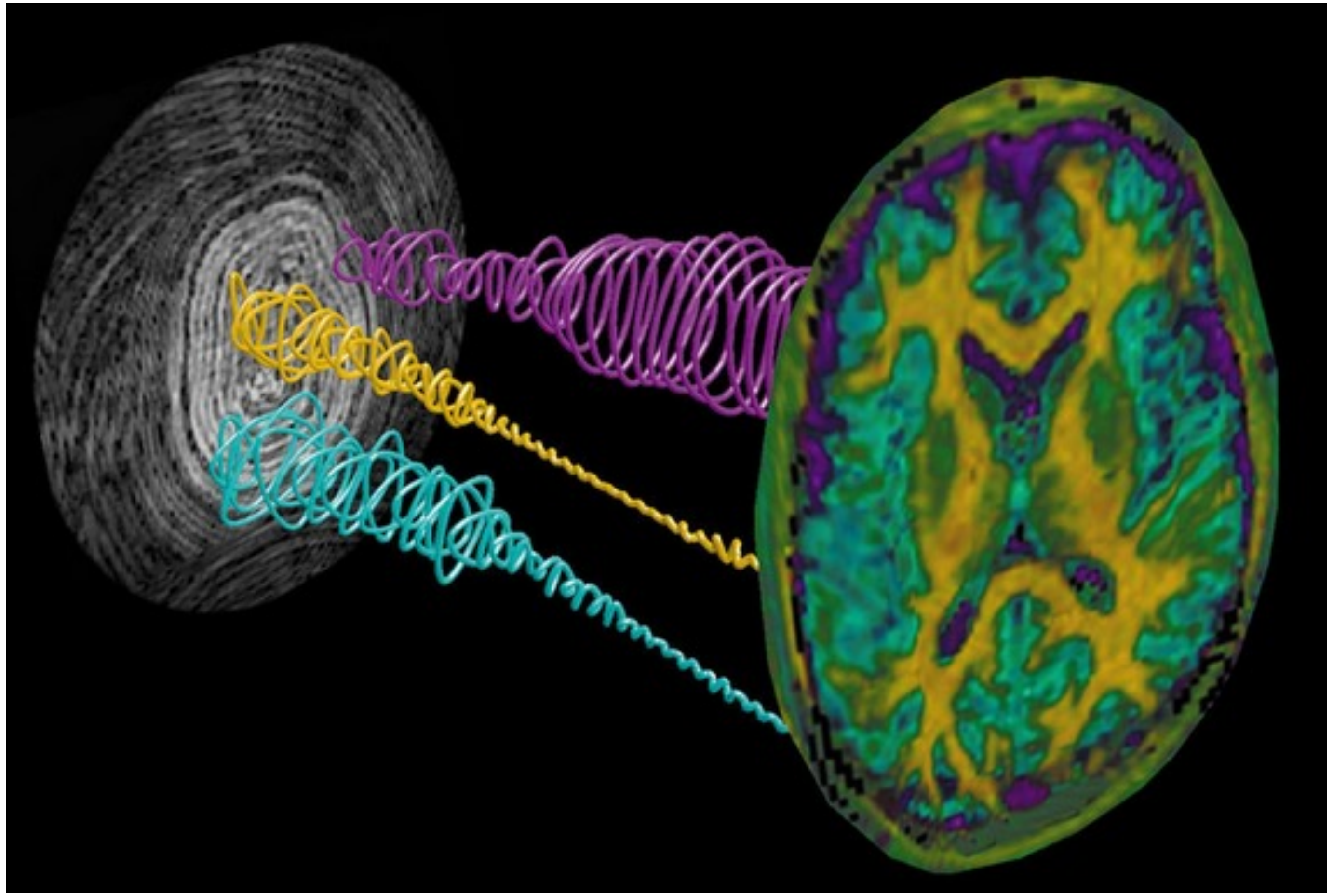
conventional (3D)

movienet (4D)

patient with
kidney cyst

MR fingerprinting

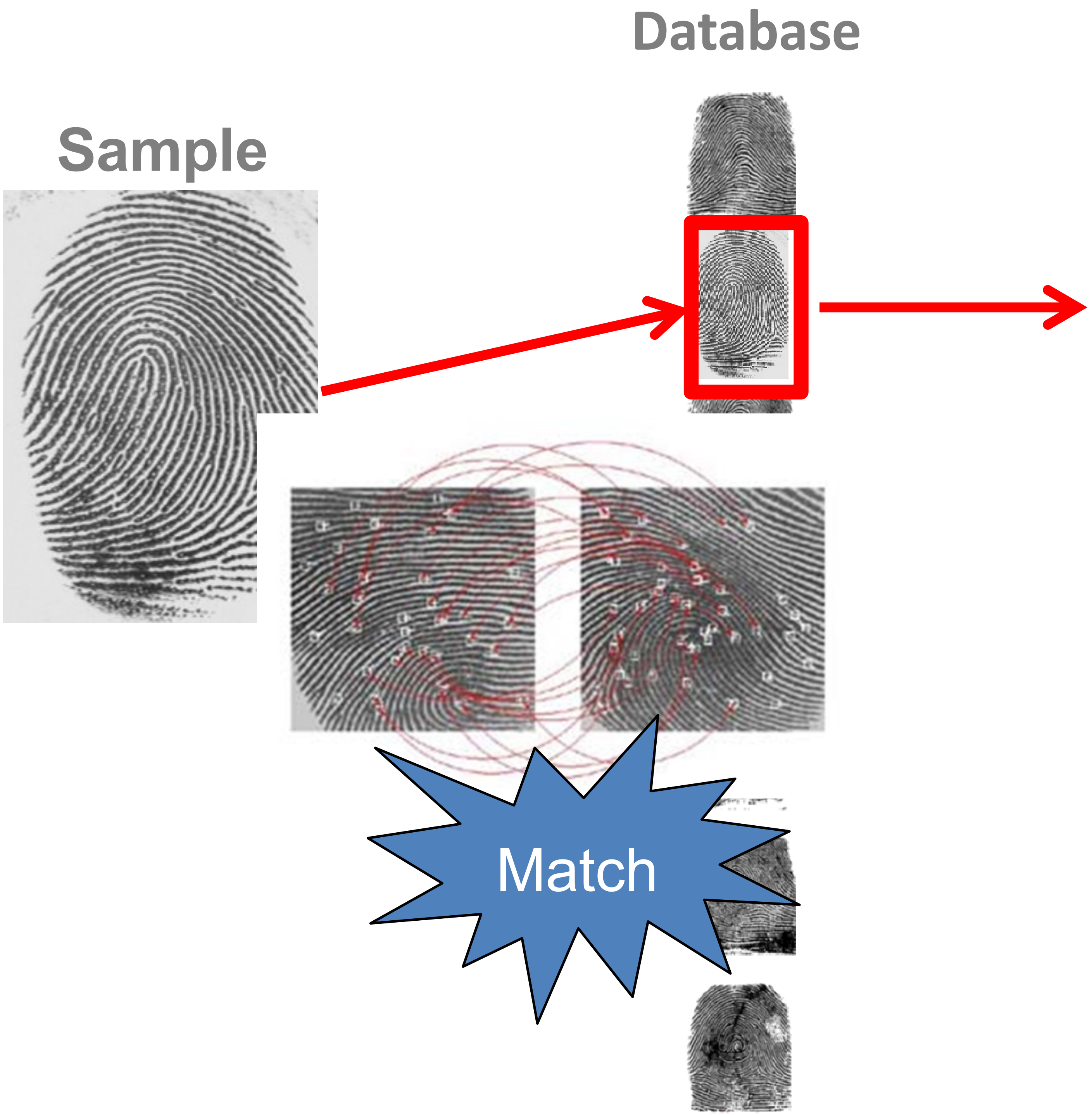
- **Fast quantitative mapping of tissue parameters**
  - **T1, T2, PD**
  - **Diffusion**
  - **pH level**



- **Different types of tissue have unique MR signal evolutions**

Ma D et al. Nature 2013

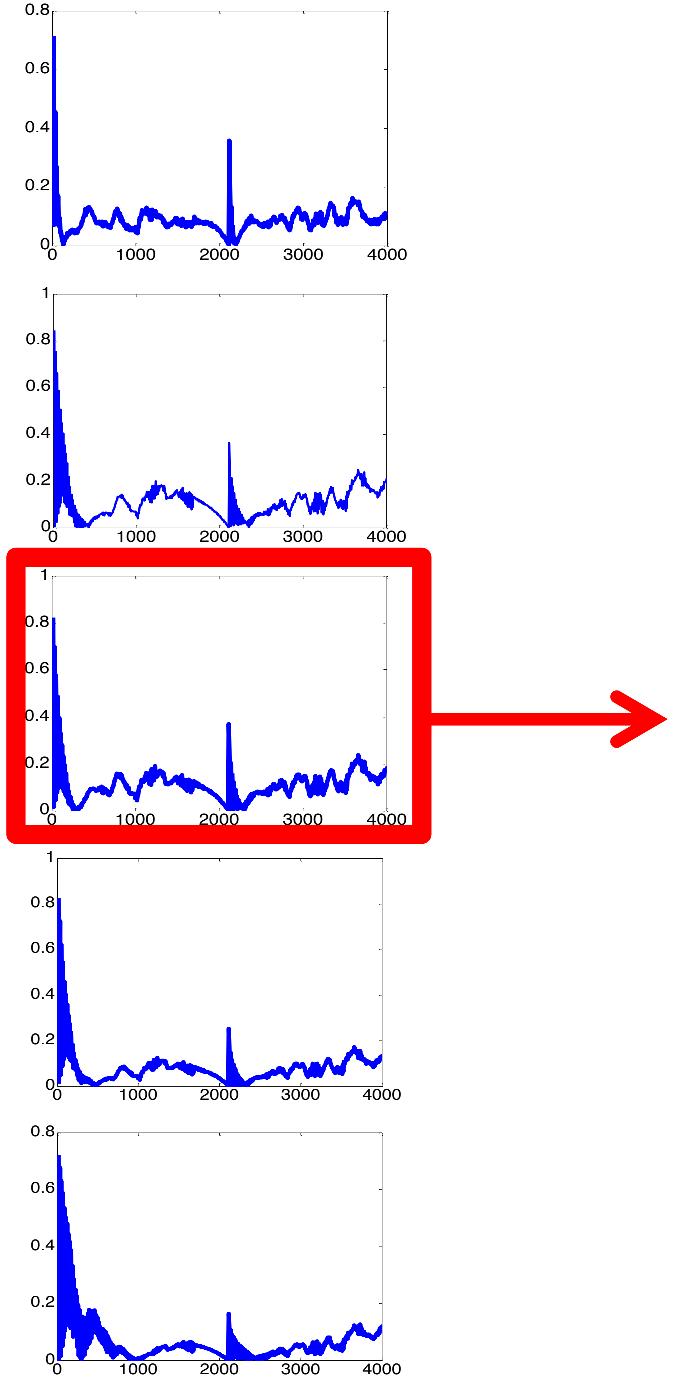
Fingerprint identification system



Name
Phone number
Address
…
…

MR fingerprinting

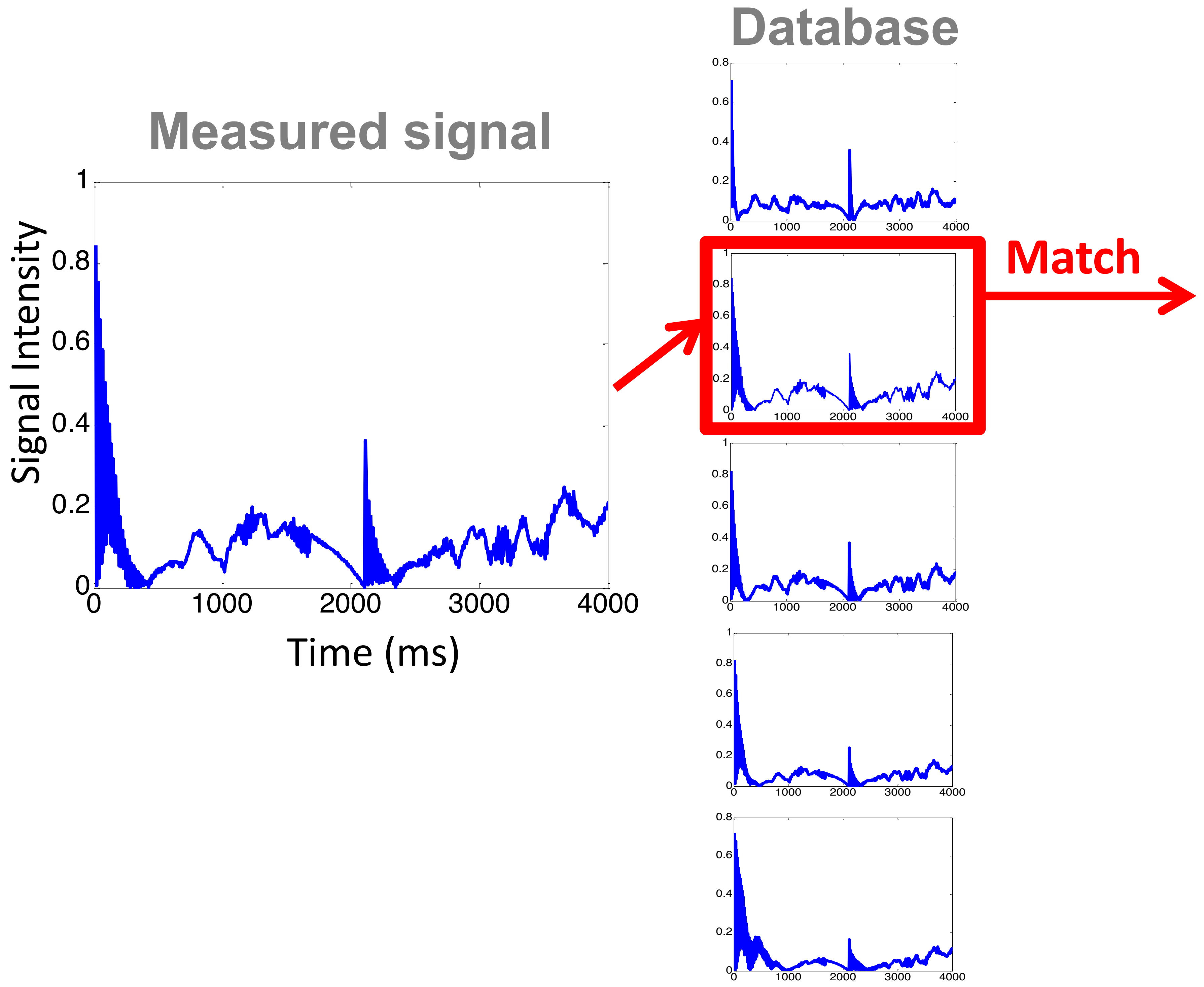
Database



Bloch simulation for given:

T1
T2
M0
Diffusion
Off-resonance
B1 field
…
…

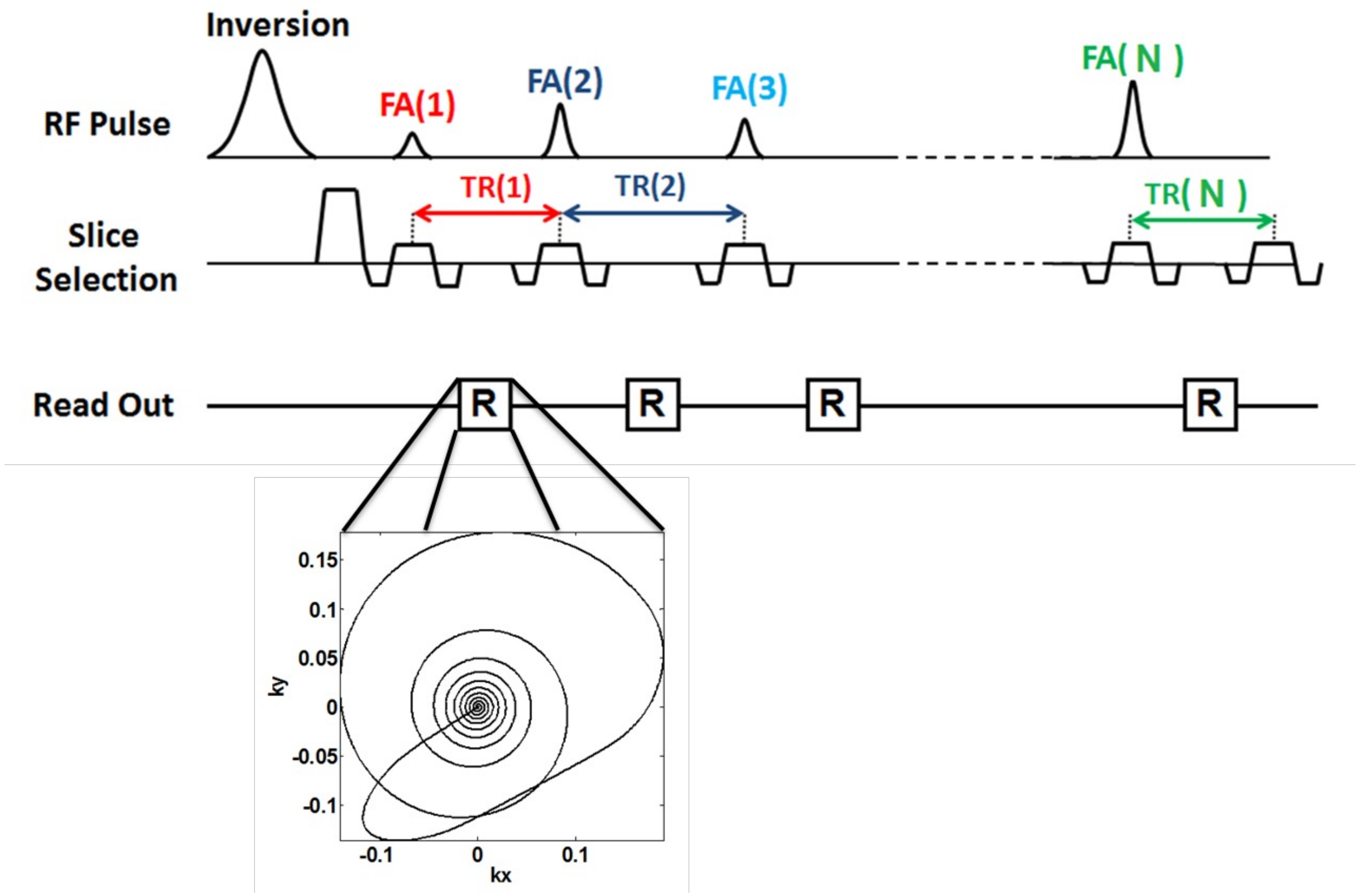
MR fingerprinting



T1
T2
M0
Diffusion
Off-resonance
B1 field
…
…

MR fingerprinting acquisition

- Series of highly-undersampled data
- Each frame has mixed contrast
  - Different FA and TR



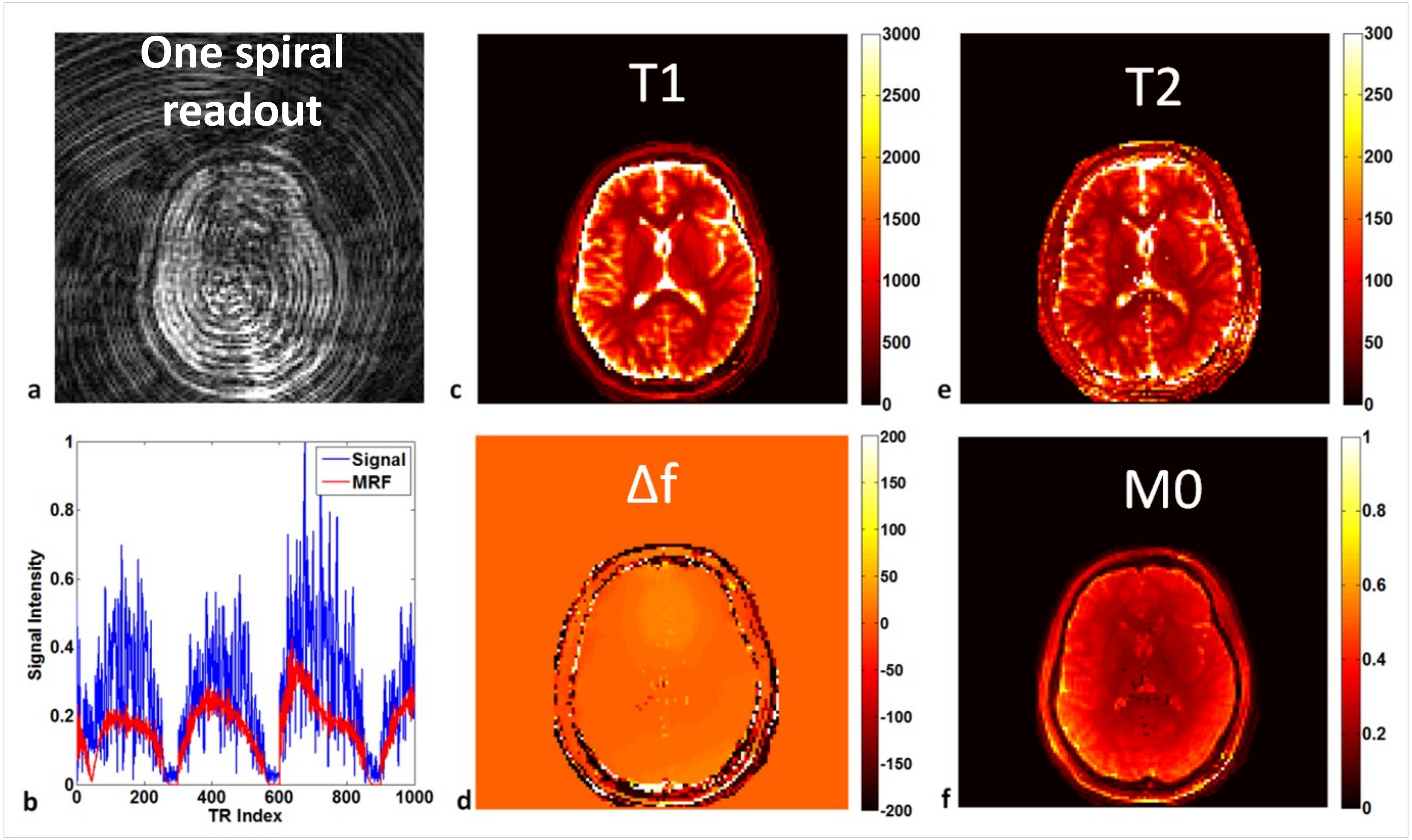
MR fingerprinting reconstruction

- **Database entry that yields highest correlation with the input temporal signal**

$$i(r) = \arg\max_{i} \langle d_i, s(r) \rangle$$

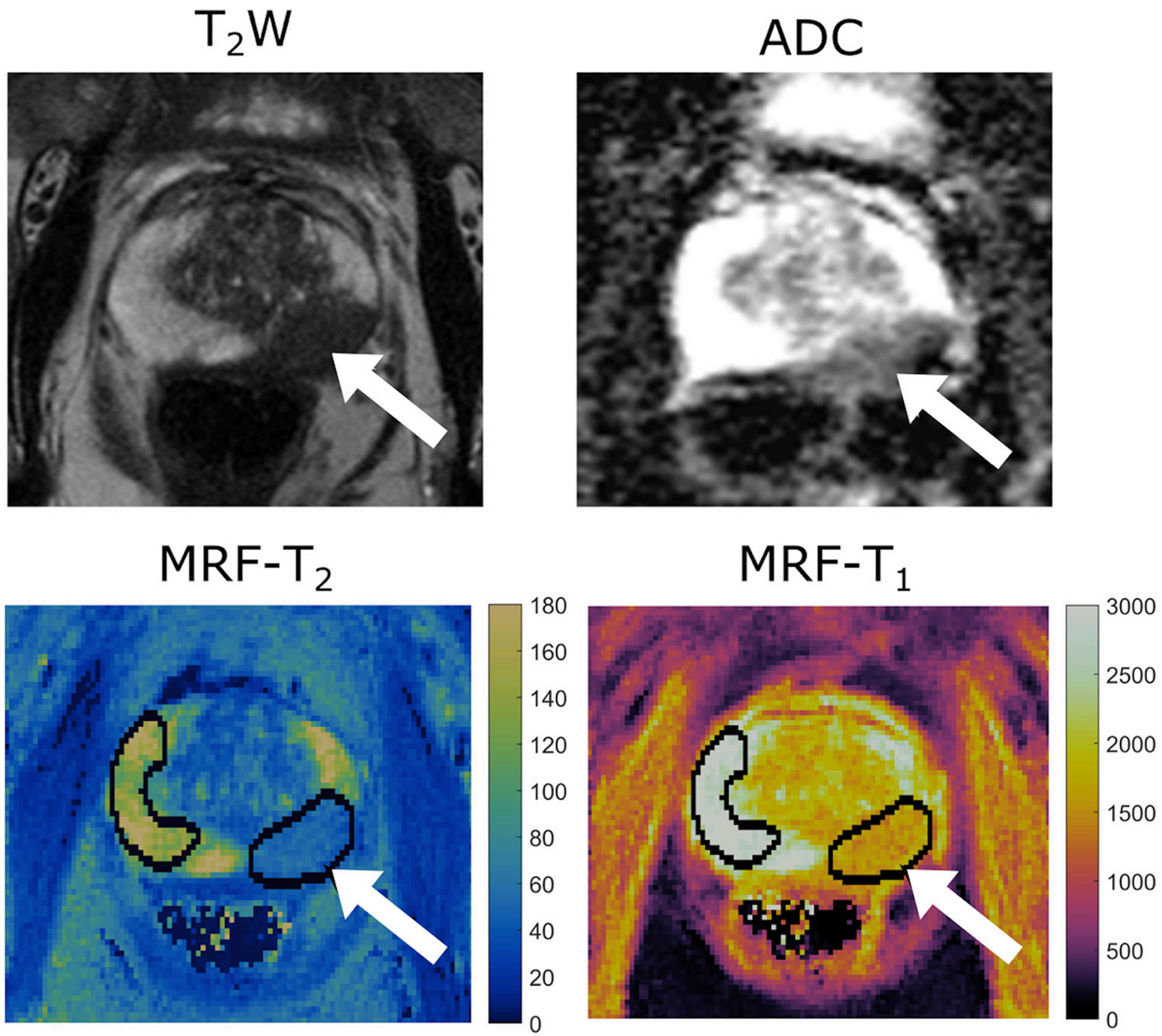
$i(r)$: database index for pixel *r*
d_i : *i*-th database element
$s(r)$: temporal signal for pixel *r*

MR fingerprinting in the brain



1,000 time frames, scan time = 12.3 seconds

MR fingerprinting of prostate cancer

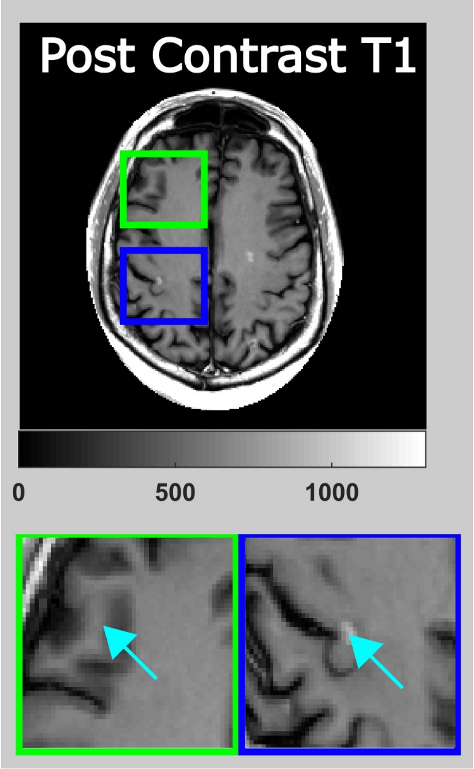


Lo W-C et al. MAGMA 2023

Metabolic MR fingerprinting (CEST-MRF)

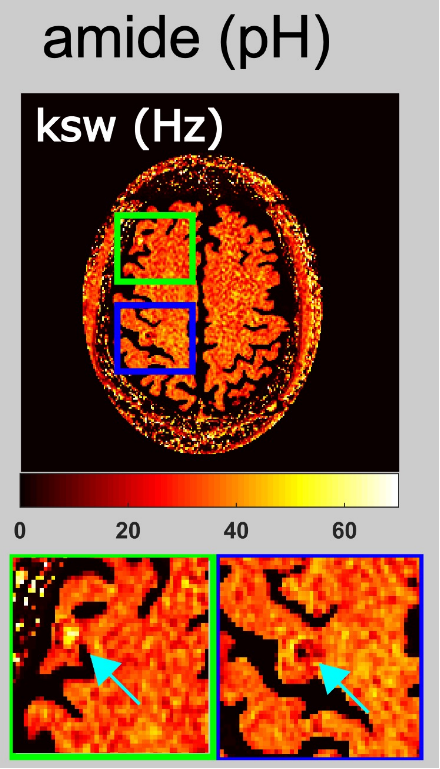
- **New contrast beyond T1 and T2 mapping: pH level of tumors**
- **Improved diagnosis and treatment monitoring of brain tumors**

Standard



Non-visible in standard MRI

CEST-MRF



Cohen O et al. NMR in Biomed 2023

Review paper on compressed sensing

Compressed Sensing MRI

[A look at how CS can improve on current imaging techniques]

[Michael Lustig,
David L. Donoho,
Juan M. Santos, and
John M. Pauly]

Compressed sensing (CS) aims to reconstruct signals and images from significantly fewer measurements than were traditionally thought necessary. Magnetic resonance imaging (MRI) is an essential medical imaging tool with an inherently slow data acquisition process. Applying CS to MRI offers potentially significant scan time reductions, with benefits for patients and health care economics.

Questions

- What are the factors that limit the speed of conventional MRI using magnetic field gradients?
  - Gradient performance: amplitude and slew-rate
    - Physical: power increases with the cube of the acceleration factor
    - Physiological: peripheral nerve stimulation due to fast gradient switching

Questions

- **What are the main ingredients for compressed sensing?**
  - **Sparsity: image representation**
  - **Incoherence: k-space undersampling pattern**
  - **Non-linear reconstruction: promote sparsity**

Questions

- **Why is MRI a good candidate for application of compressed sensing?**
  - **Images are compressible (in general)**
  - **Acquisition is in a transform domain (facilitates incoherence)**
    - **Software change to undersample k-space**

Questions

- Is random k-space sampling the only way to achieve incoherence?
  - No, regular undersampling of non-Cartesian k-space trajectories will also result in incoherence

Questions

- **Can you apply compressed sensing to accelerate the acquisition of dynamic MRI (videos)? Discuss the main differences with respect to acceleration of anatomical images**

  - **Yes, in fact videos are more compressible than images and therefore higher accelerations should be expected for dynamic imaging. The main differences would be to have a sparsifying transform that exploits temporal correlations and to change the k-space undersampling pattern for each time point to have spatial and temporal incoherence**

- **Hands-on exercise: compressed sensing in Matlab**

- **Homework: deep learning reconstruction**