Motion in MRI

Challenges, Strategies & Quality Evaluation

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BIC-ISMRM Ed Talks
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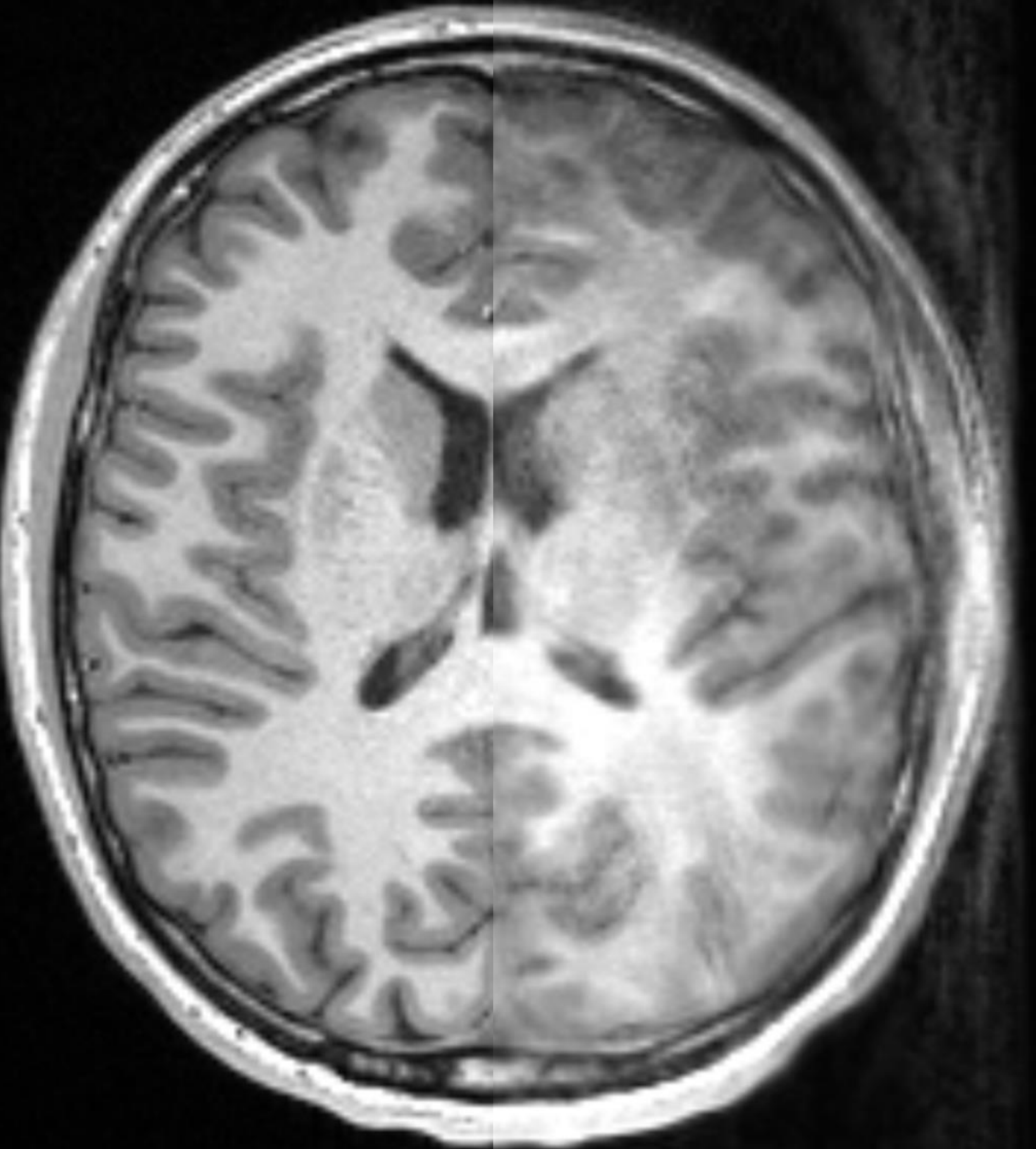


Outline

1a) Challenges

Motion types

Motion in k-space

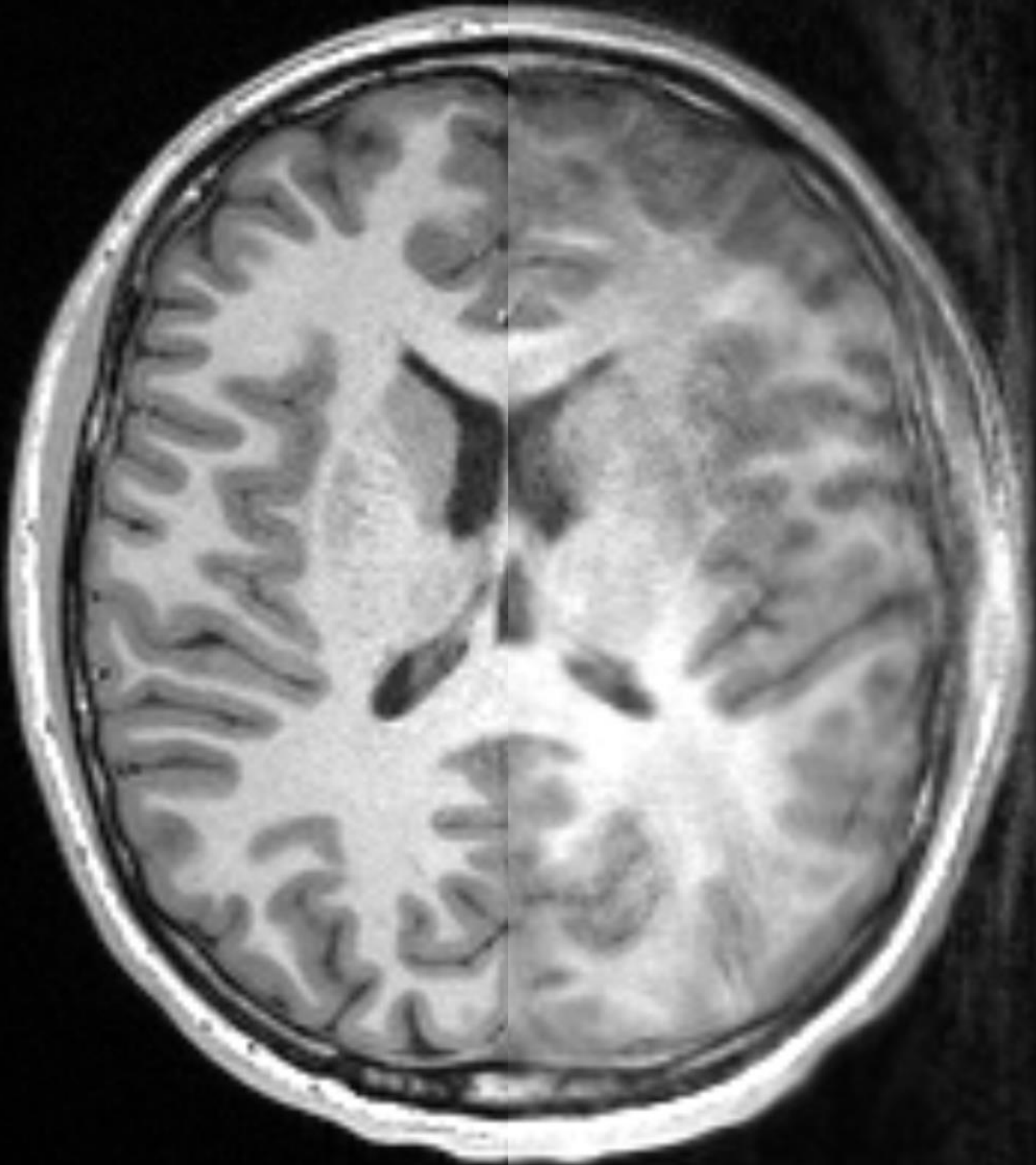
1b) Strategies

Motion estimation

Prospective vs. retrospective

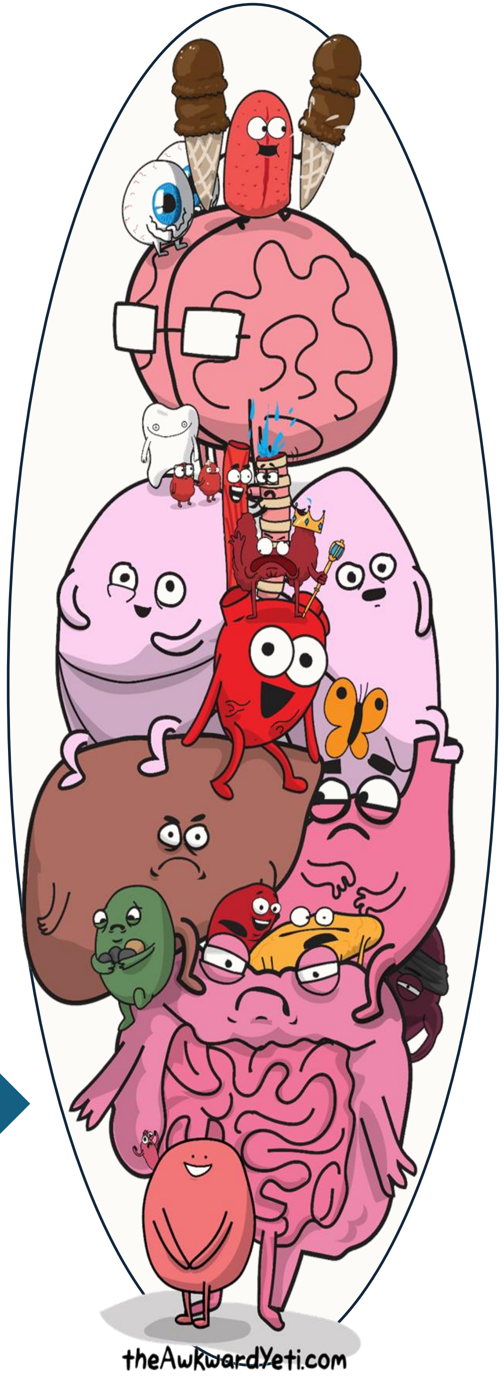
Learning-based correction

2) Image Quality Evaluation



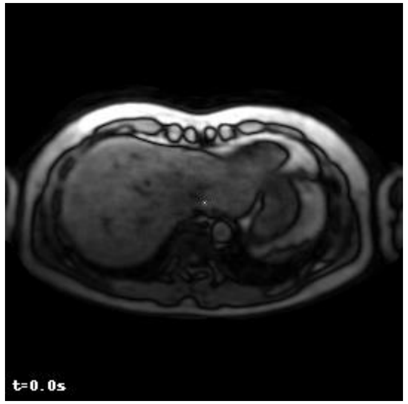
Motion in different body parts
Gastrointestinal

- **What**: digestive system
- **How**: peristalsis, random
- **Extent**: depending on subject, digestion status

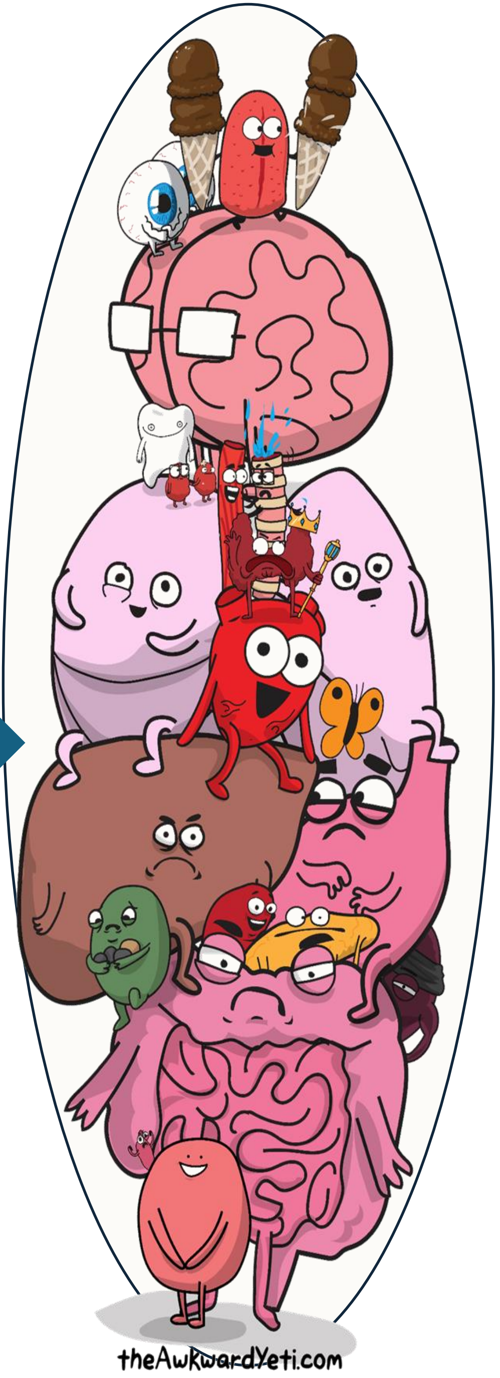


Slide Courtesy by Laura Bortolotti (with adaptions)
Alshammari et al. Neurogastroenterol. Motil. (2023), de Jonge et al. Br J Radiol (2018)

Motion in different body parts
Abdomen/Torso

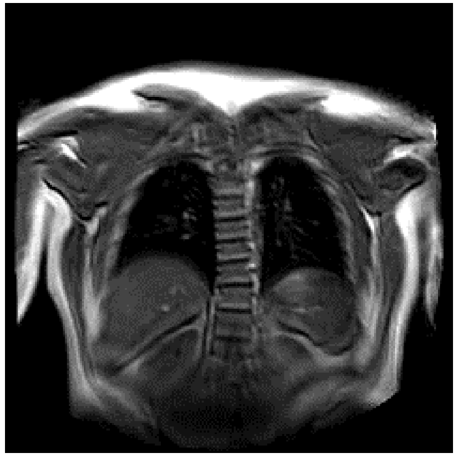


- **What**: involuntary body motion
- **How**: periodic (respiration) and random (reflex actions and postural adjustments)
- **Extent**: depending on subject and position

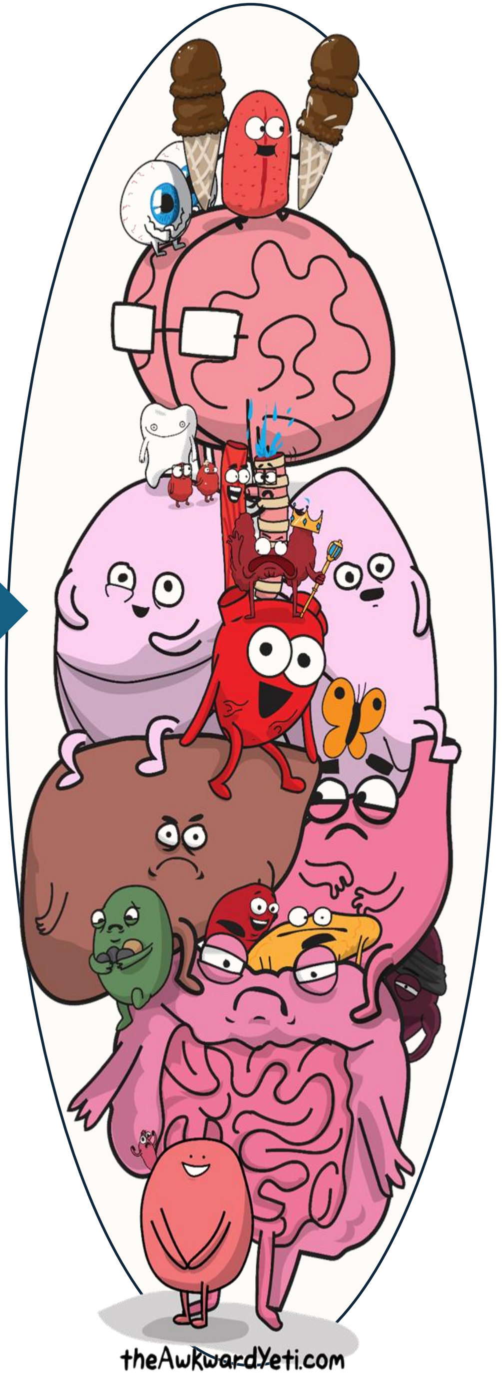


Slide Courtesy by Laura Bortolotti (with adaptions)
Bortolotti et al. ISMRM (2023), Spieker et al. arXiv (2025)

Motion in different body parts
Upper abdominal organs



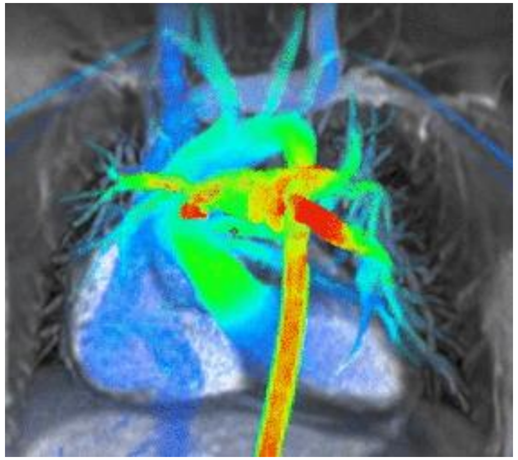
- **What**: diaphragm/lung motion
- **How**: periodic (respiration)
- **Extent**: highly depending on subject



Slide Courtesy by Laura Bortolotti (with adaptions)
Peggs et al. ISMRM (2024)

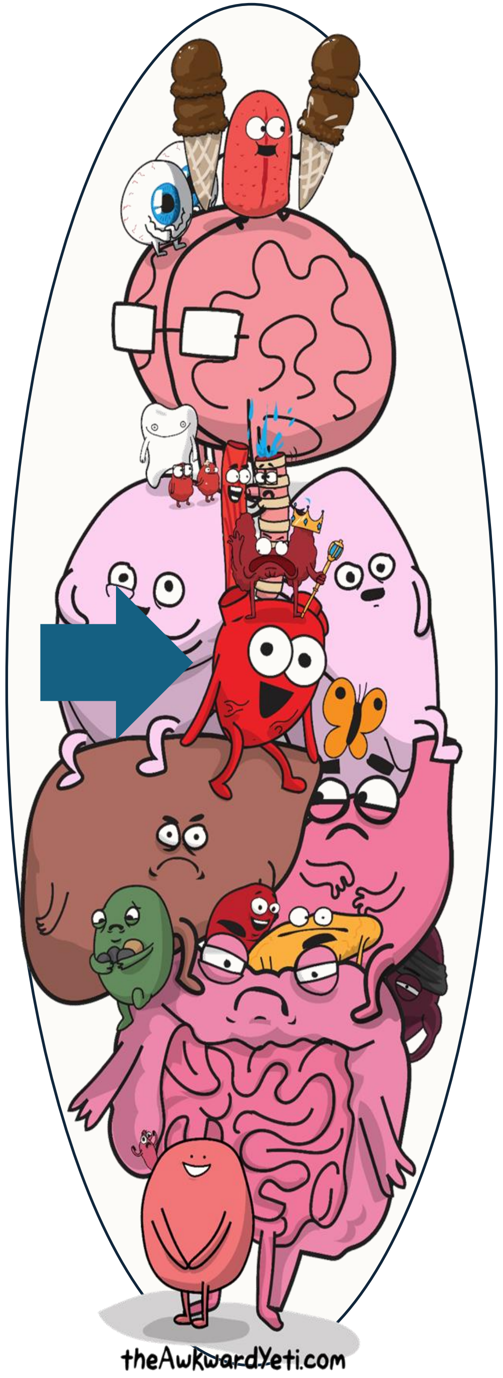
Motion in different body parts

Heart



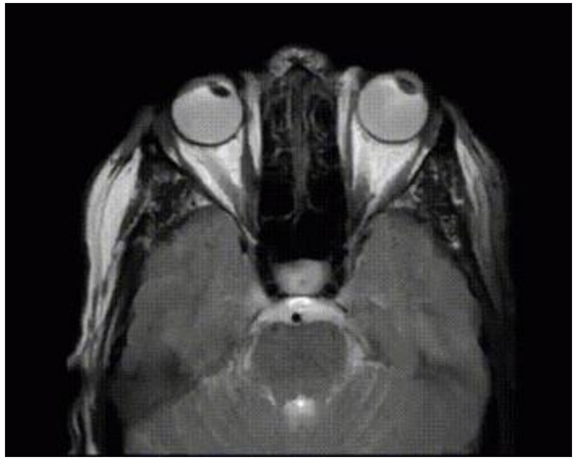
- **What**: Muscle contractions
- **How**: periodic (heartbeat)
- **Extent**: ~cm

Slide Courtesy by Laura Bortolotti (with adaptions)
Campbell-Washburn et al. JMRI (2017), Rashid et al. JMRI (2023)
https://commons.wikimedia.org/wiki/File:Cardiac_MRI_flow.gif



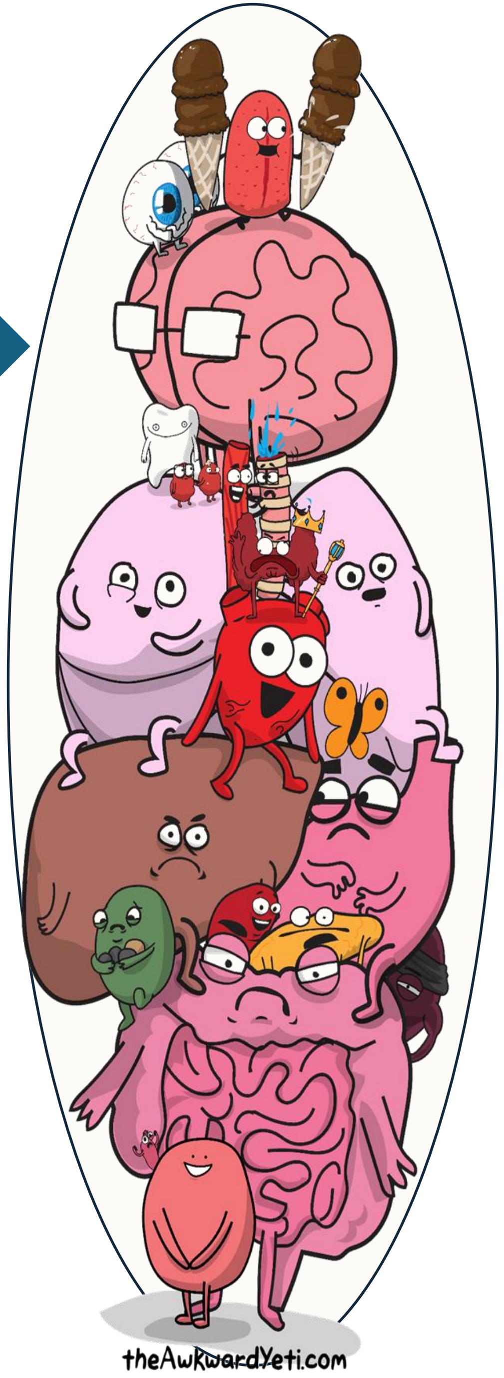
Motion in different body parts

Head and brain



- **What**: Rigid-body motion of the head
- **How**: random, mostly z-translation and x-rotation
- **Extent**: subject-dependent, up to 15 cm

Slide Courtesy by Laura Bortolotti (with adaptions)
Kirchner et al. et al. Eneuro (2022), Godenschweger et al. PMB (2016), Eichhorn et al. Front. Radiol. (2021)
“Singing in the MRI with Tyley Ross” (https://m.youtube.com/watch?v=J3TwTb-T044)



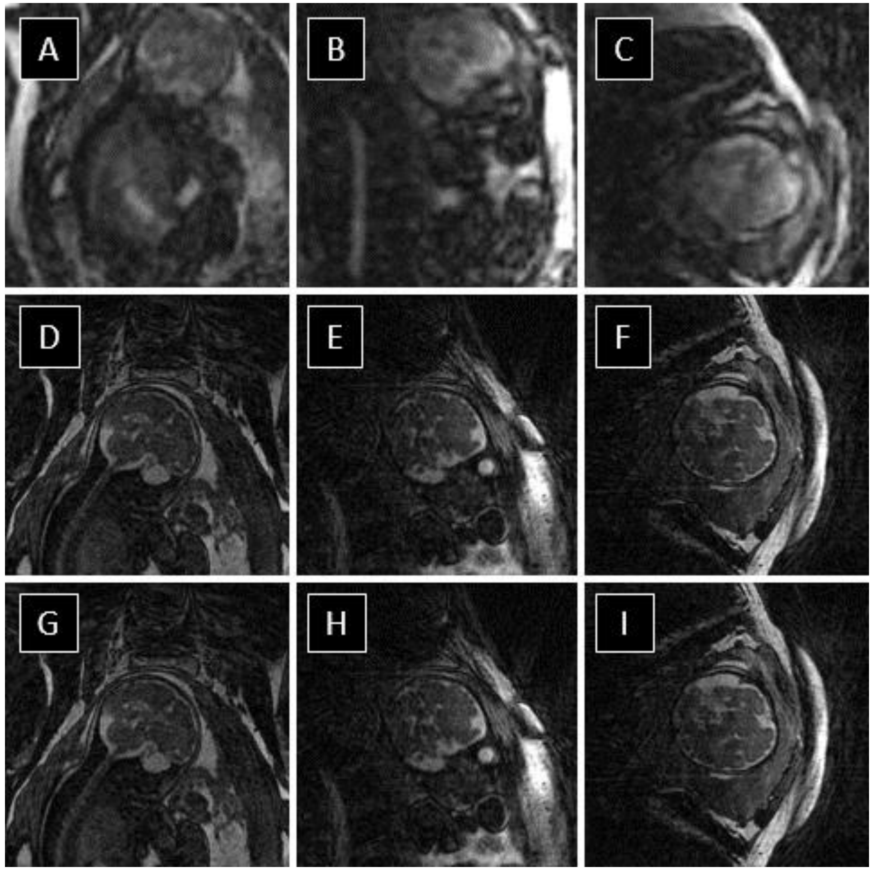
Motion in different body parts

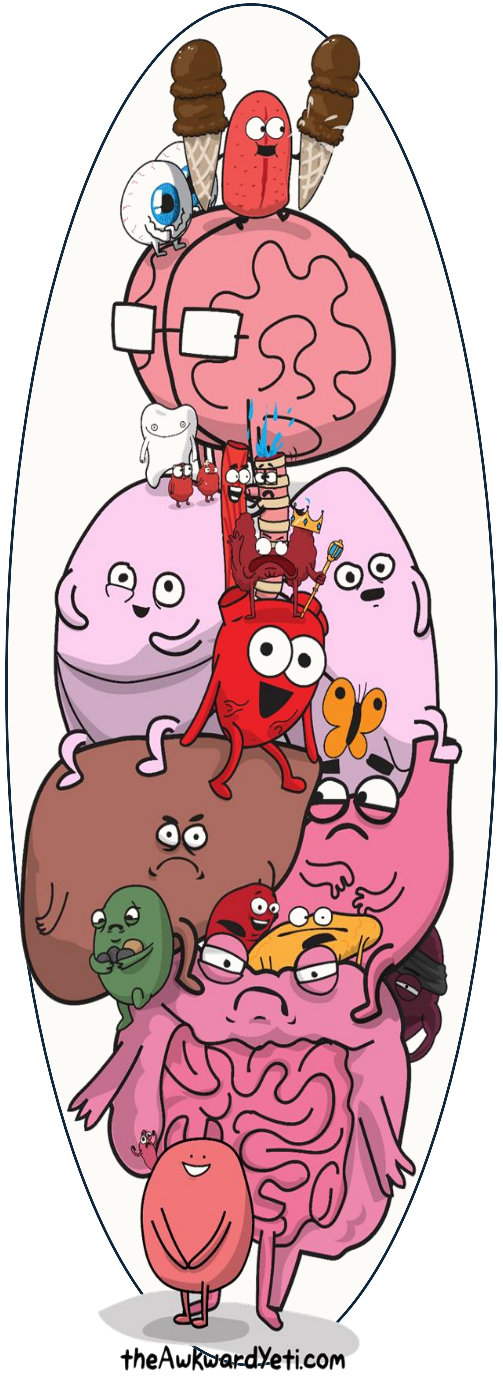
Fetal MRI

Low spatial resolution 3D acquisition

Reconstruction (1mm isotropic)

Motion compensated





Slide Courtesy by Laura Bortolotti (with adaptions)
Roy et al. et al. ISMRM (2021), Uus et al. Brit. J. Radiol (2023)

Motion in different body parts – “It varies”

Categories of motion

TYPE:

- **Rigid** (spatial relationships between points are maintained) - *Head*
- **Deformable** – *Abdomen, Heart*

PATTERN:

- **Random** (Head)
- **Periodic** (Respiration, Heartbeat)
- **Quasi-periodic** (Head)
- **Continuous** (Abdomen, Head)

OCCURRENCE:

- **Inter-image** (motion occurs between acquisitions of volumes)
- **Inter-Scan** (between excitation pulses within a volume)
- **Intra- Scan** (during a signal acquisition and signal excitation)

DIRECTION:

- **In-plane** (within the excited slice plane)
- **Through-plane** (perpendicular to the slice)

Slide Courtesy by Laura Bortolotti (with adaptions)
Godenschweger et al. PMB (2016)

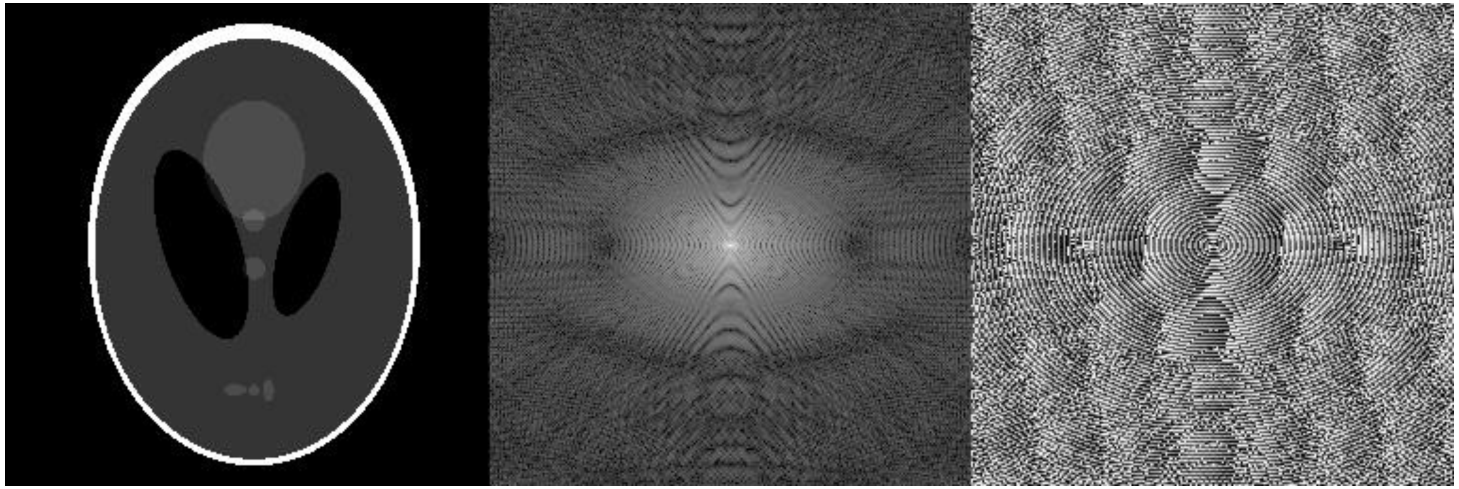
Motion in the k-space

- Translations

$$s(\bar{k}) = F\{\rho(\bar{x})\}(\bar{k}) = \int_{-\infty}^{\infty} \rho(\bar{x}) e^{-i2\pi\bar{k}\cdot\bar{x}}\, d\bar{x} \xrightarrow{\bar{a} = (\Delta_x, \Delta_y, \Delta_z)} F\{\rho(\bar{x}-\bar{a})\}(\bar{k}) = \int_{-\infty}^{\infty} \rho(\bar{x}-\bar{a})\, e^{-i2\pi\bar{k}\cdot\bar{x}} d\bar{x}$$

Fourier Shift Theorem

$$F\{\rho(\bar{x}-\bar{a})\}(\bar{k}) = e^{-i2\pi\bar{k}\cdot\bar{a}}\, F\{\rho(\bar{x})\}(\bar{k})$$



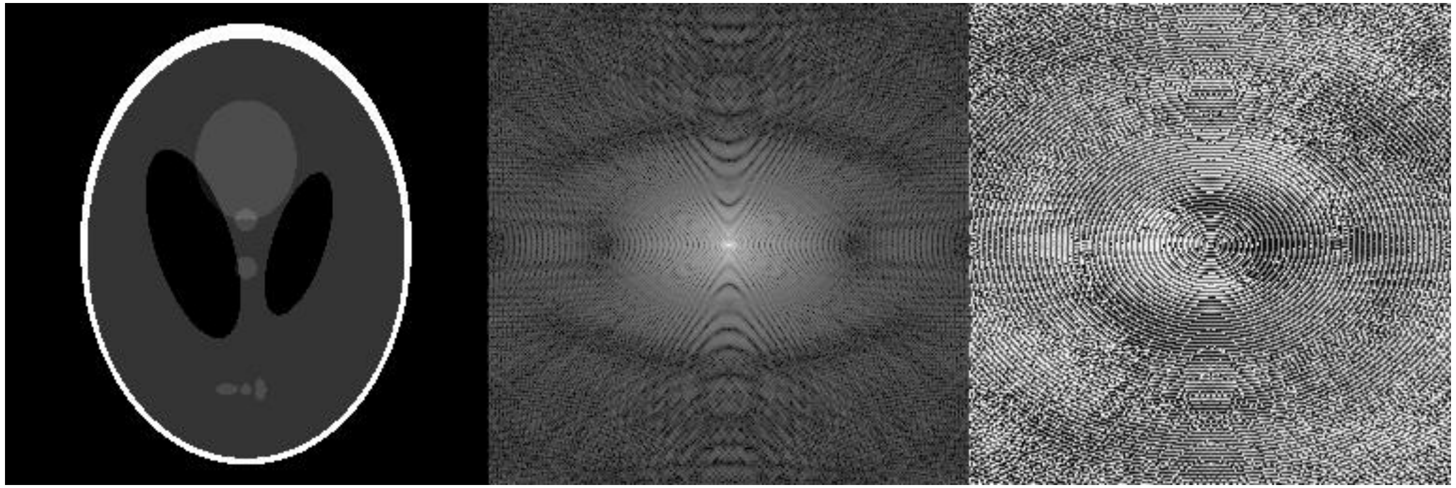
Motion in the k-space

- Rotations

$$F\{\rho(R\bar{x})\}(\bar{k}) = \int_{-\infty}^{\infty} \rho(R\bar{x}) e^{-i2\pi\bar{k}\cdot\bar{x}}\, d\bar{x}$$

$$= \int_{-\infty}^{\infty} \rho(\bar{y}) e^{-i2\pi(R\bar{k})\cdot\bar{y}} d\bar{y}$$

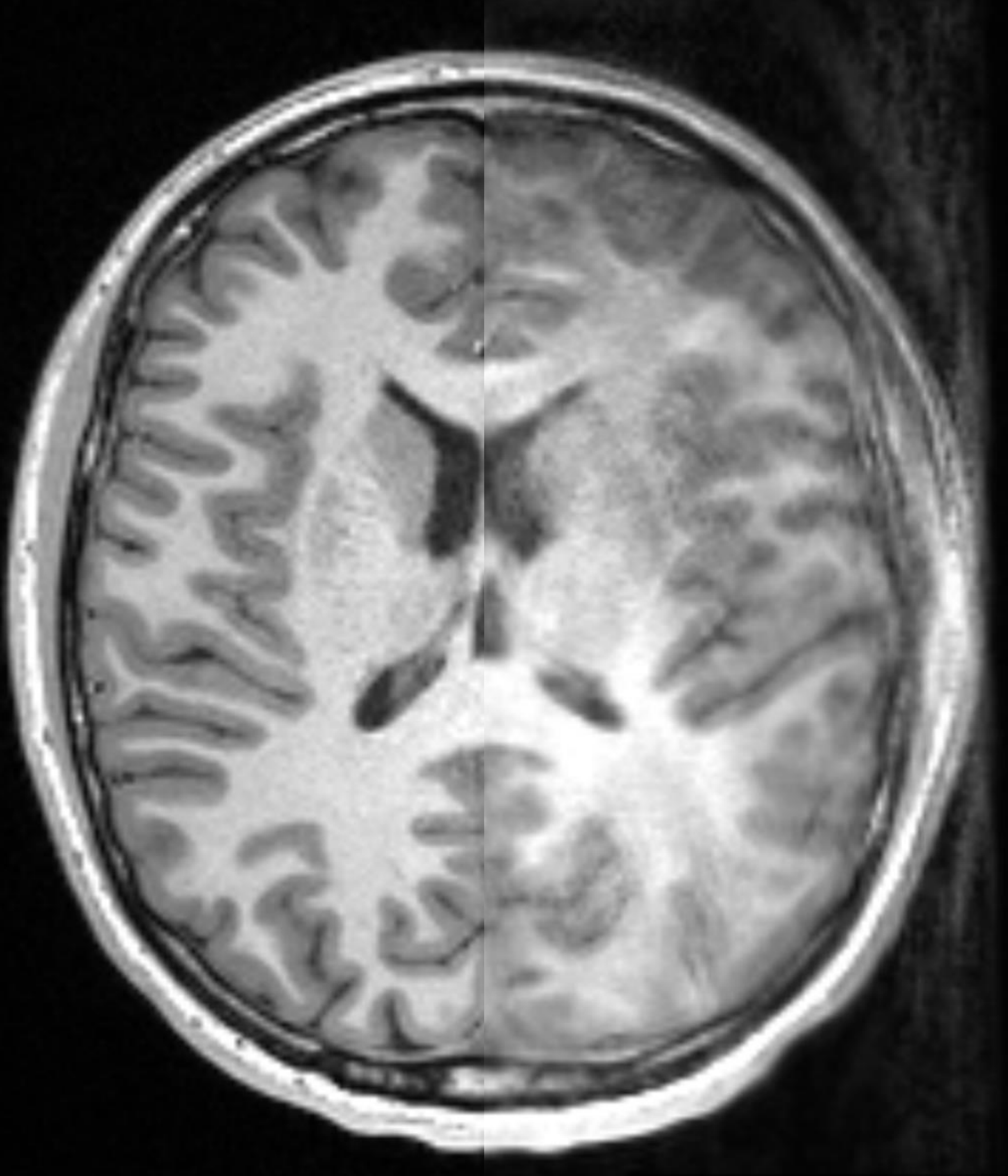
$$F\{\rho(R\bar{x})\}(\bar{k}) = F\{\rho(\bar{x})\}(R\bar{k})$$



Linear phase in a rotated k-space: $F\{\rho(R\bar{x} - \bar{a})\}(\bar{k}) = e^{-i2\pi(R\bar{k})\cdot\bar{a}}\, F\{\rho(\bar{x})\}(R\bar{k})$

Motion in MRI

Strategies



Motion Mitigation

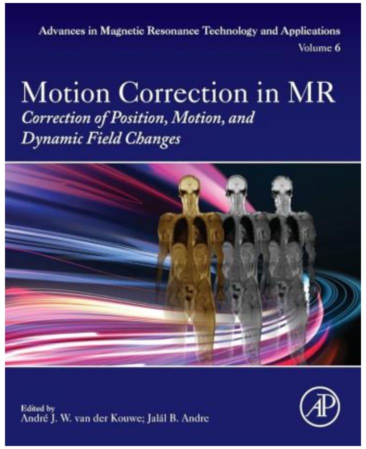
Patient Positioning

Guidance / Training

Sedation / GA

Motion Estimation

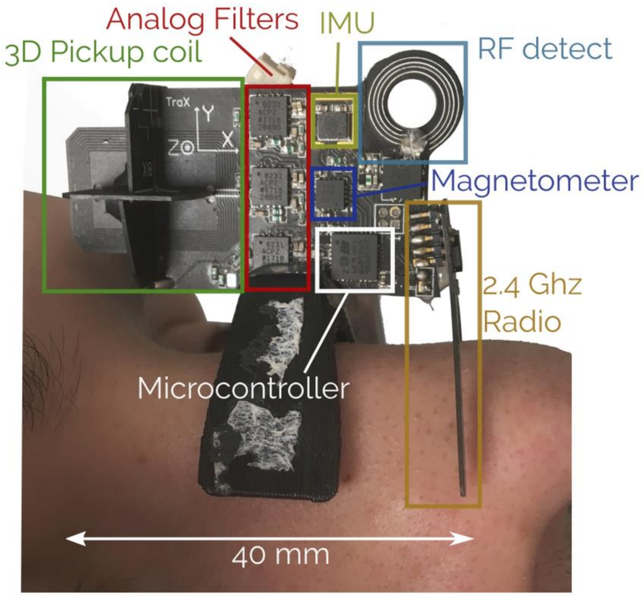
- External Tracking Systems
- Navigators
- Navigators without Gradients



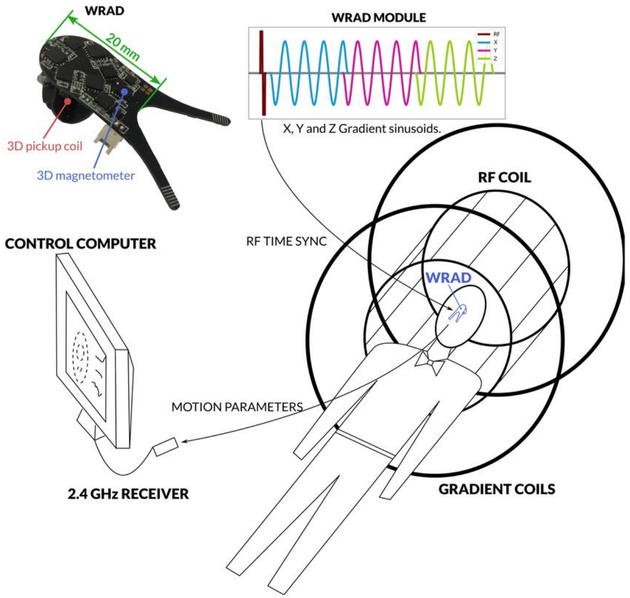
MoCo Virtual Seminars:
Educational/Scientific Talks

Attached Sensors

- Physically attached
- Field detection methods
- RF markers or magnetometers to detect the scanner gradient fields changing



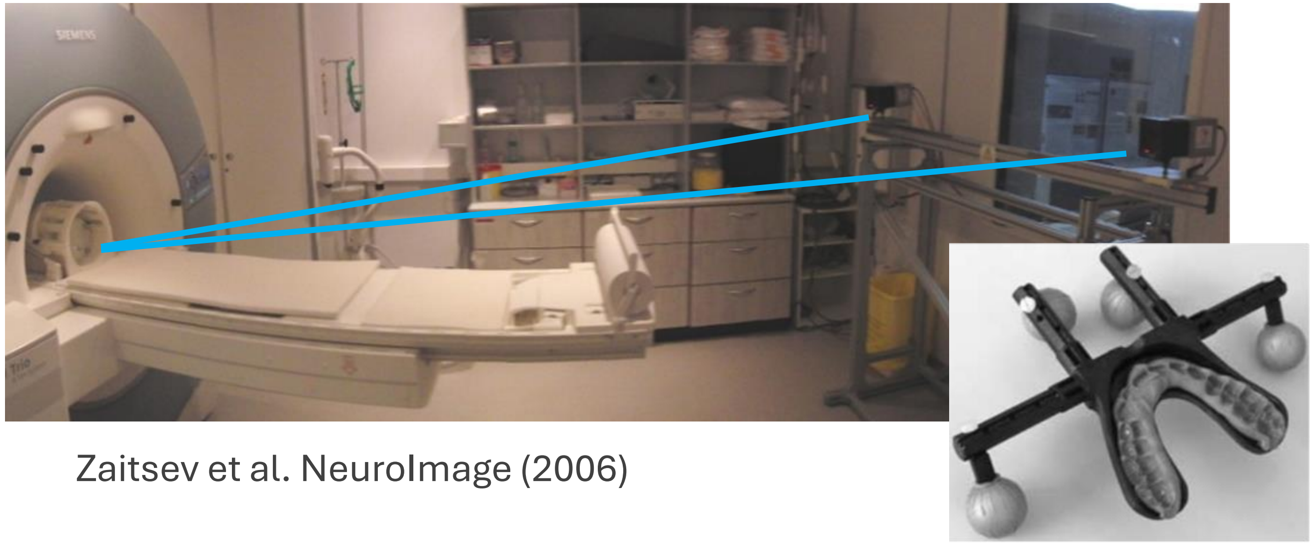
Niekerk et al. IEEE Trans Med Imaging (2019)



Norbeck et al. MRM (2020)

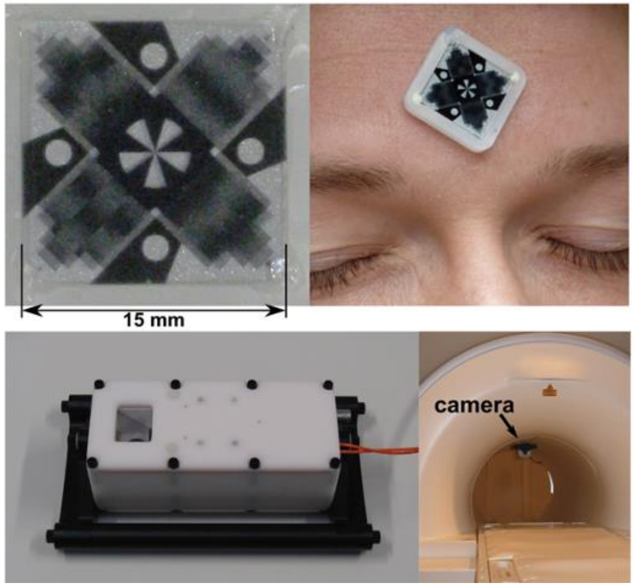
Camera systems using markers

Multi-camera systems



Zaitsev et al. NeuroImage (2006)

Single camera systems



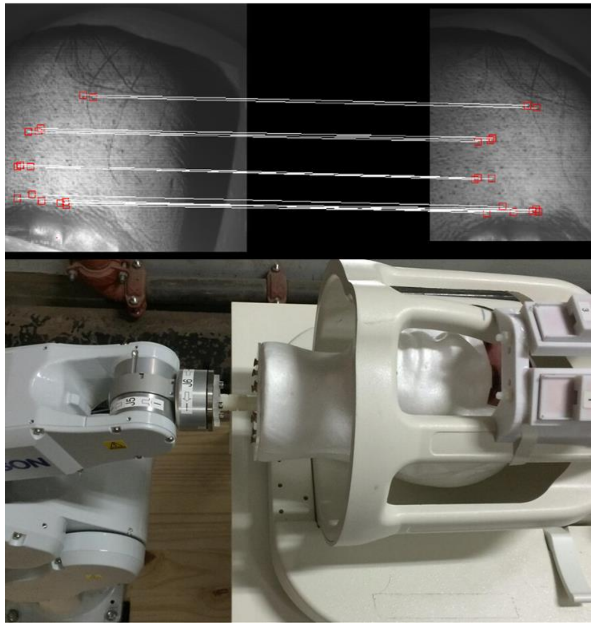
Maclaren et al. PLOS One (2012)

- Physically attached markers
  - Reflective markers
  - Pattern markers
    - e.g., Moiré Phase Tracking

Camera systems without markers

- Tracking based on natural face or body features
  - Structured-light
  - Stereo-camera

Tracoline TCL3.1
Image courtesy of Stefan Glimberg

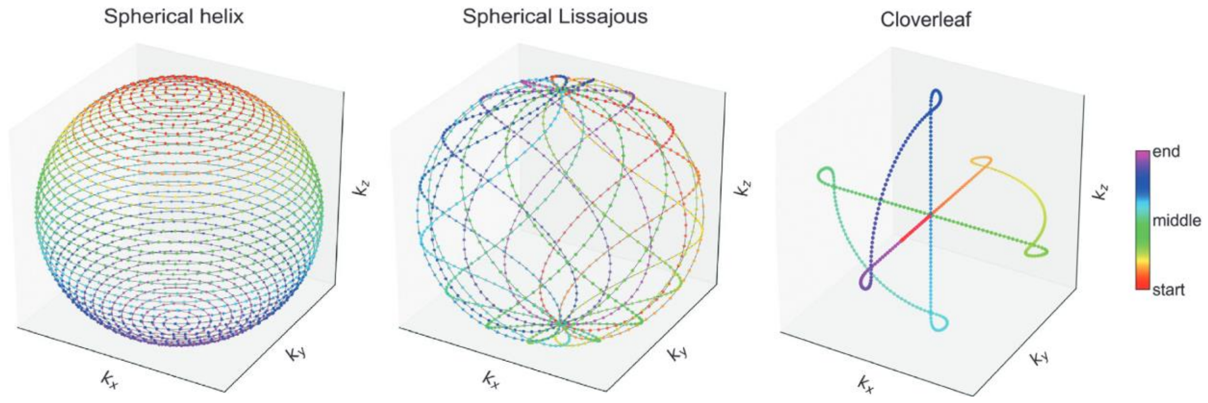


Kyme et al. Med. Phys. (2020)

Review: Madore et al., External hardware and sensors, for improved MRI, JMRI (2023)

K-space-based navigators

- Based on Fourier properties
  - Rotations affect the magnitude
  - Translations affect the phase
- Different k-space trajectories



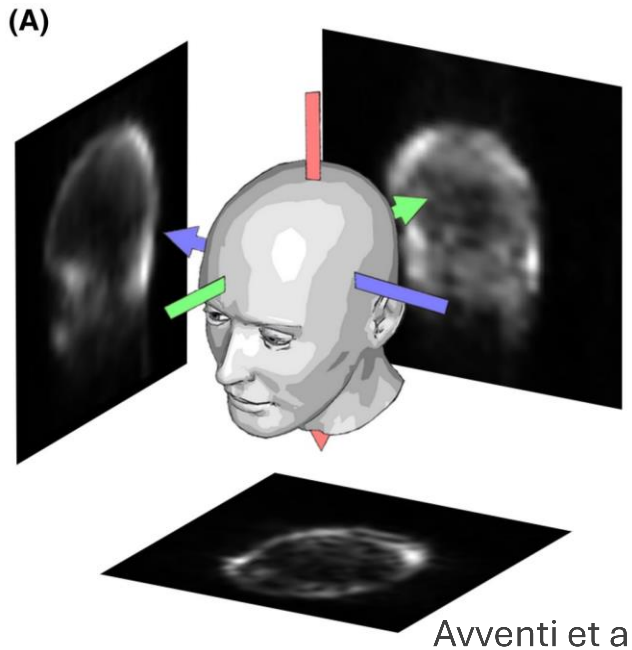
Welch et al. MRM (2002)

Bushbeck et al. MRM (2019)

van der Kouwe et al. MRM (2006)

Image-based navigators

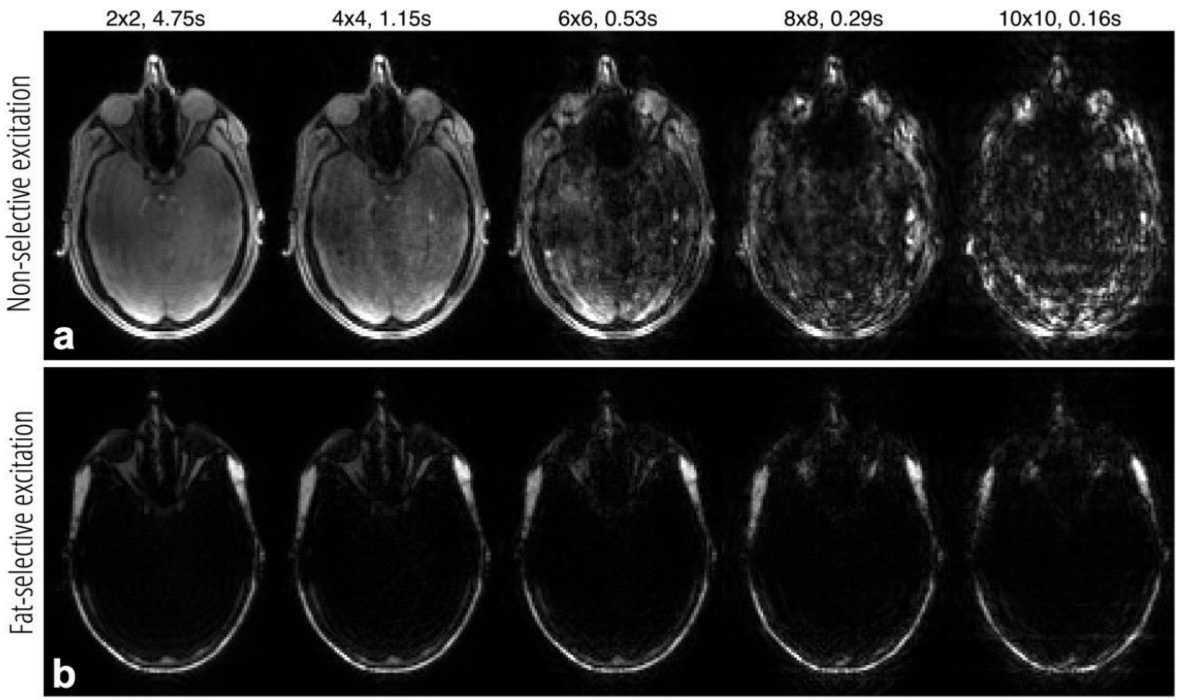
- Motion estimates derived reconstructed low-resolution images
- Fast 2D/3D acquisition



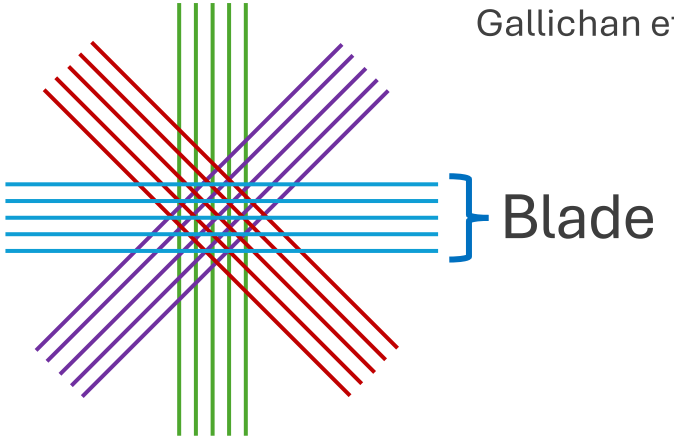
Avventi et al., MRM (2020)

Image-based navigators

- Motion estimates derived reconstructed low-resolution images
- Fast 2D/3D acquisition
- Highly accelerated 3D volumes
- Enables self-navigated motion correction
    - *PROPELLER (Pipe, MRM 1999)*

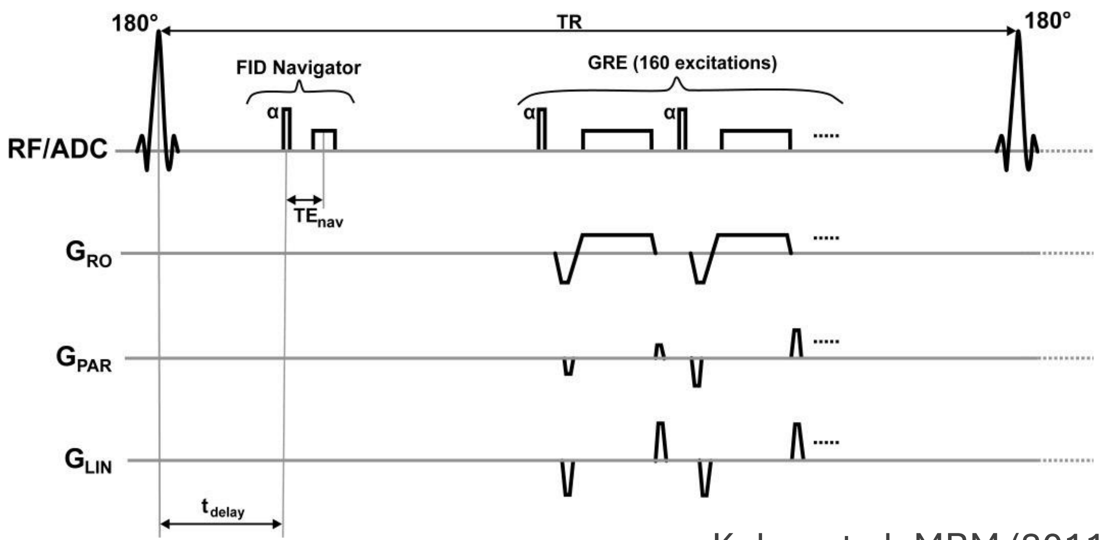


Gallichan et al. MRM (2016)

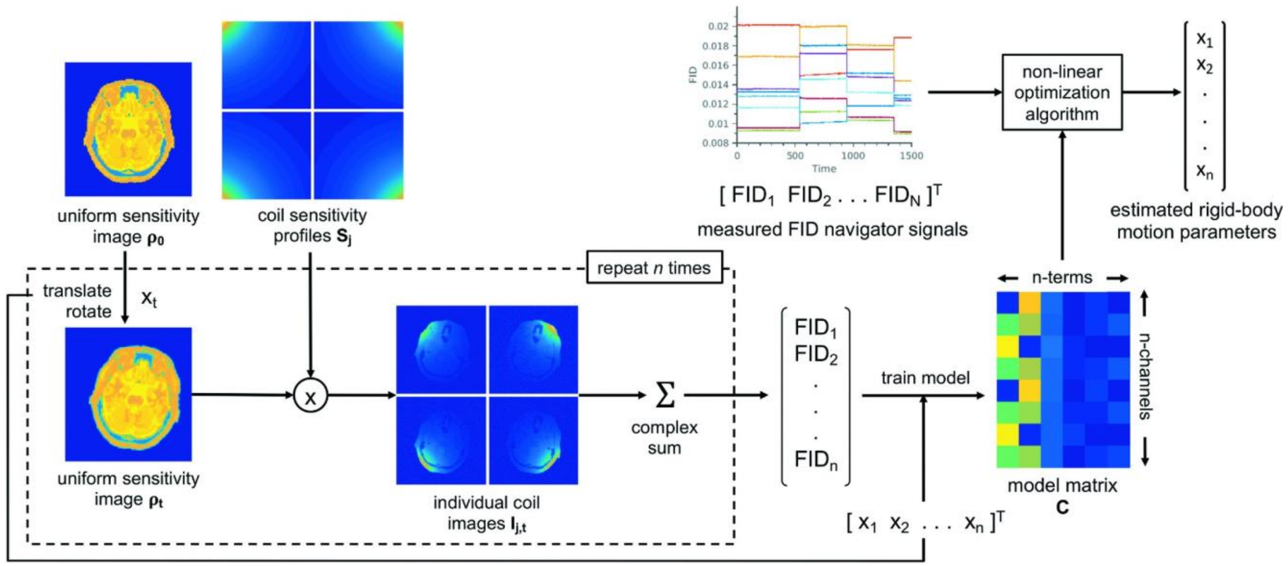


FID-Navigators

- Measuring the Free Induction Decay signal after an excitation pulse
- Monitor the signal information coming from a multi-channel coils over time
- Model of the FID signal in presence of motion

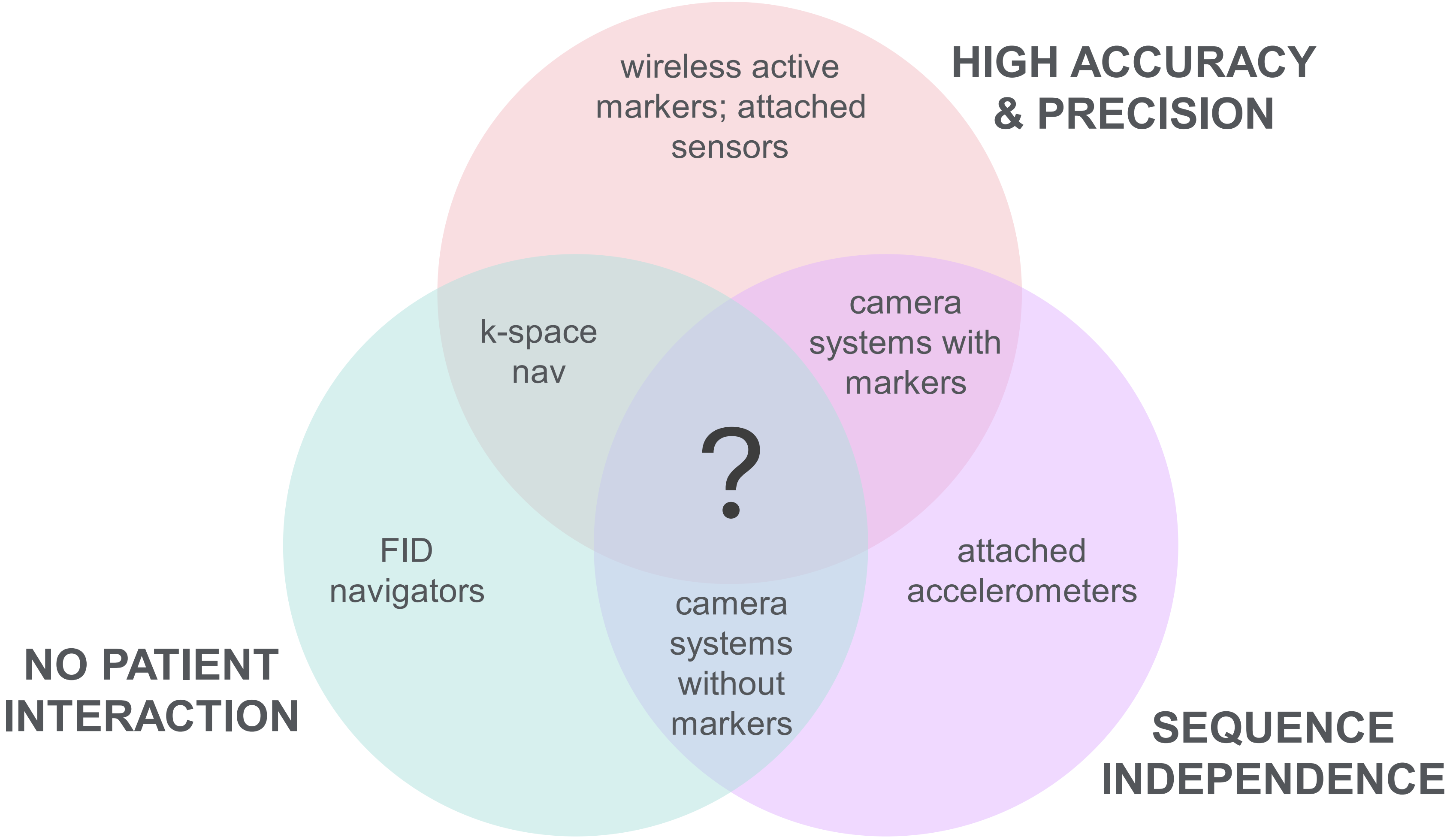


Kober et al. MRM (2011)



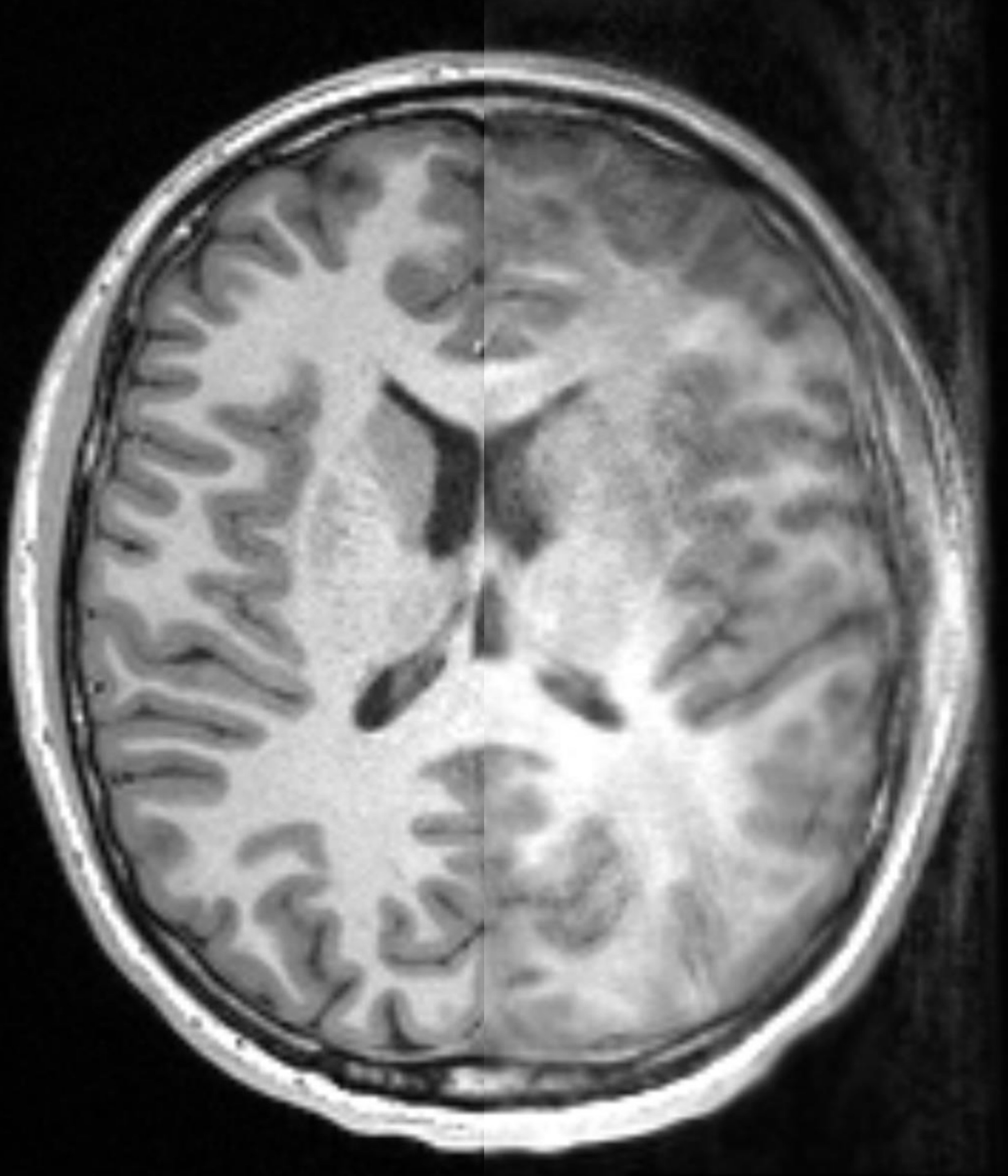
Wallace et al. MRM (2019)

Motion Estimation

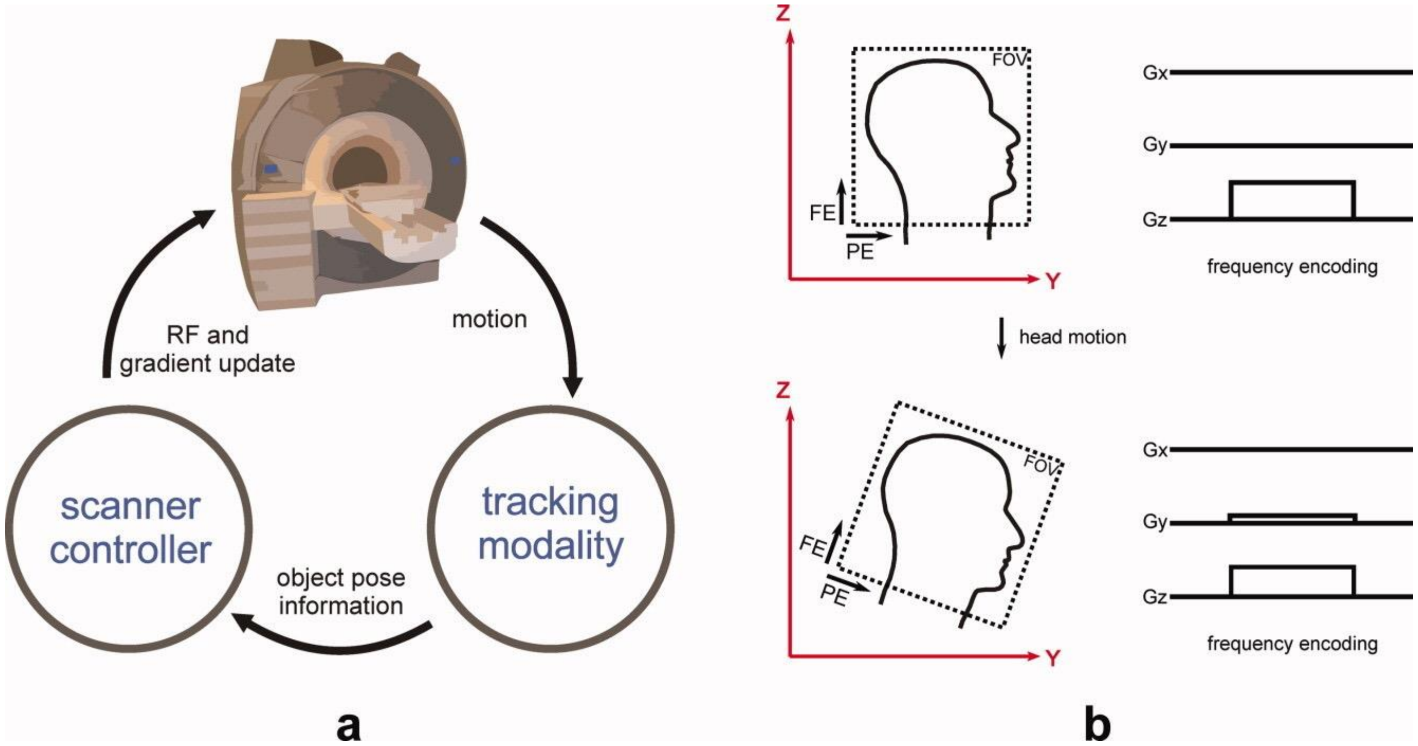


Motion in MRI

Correction



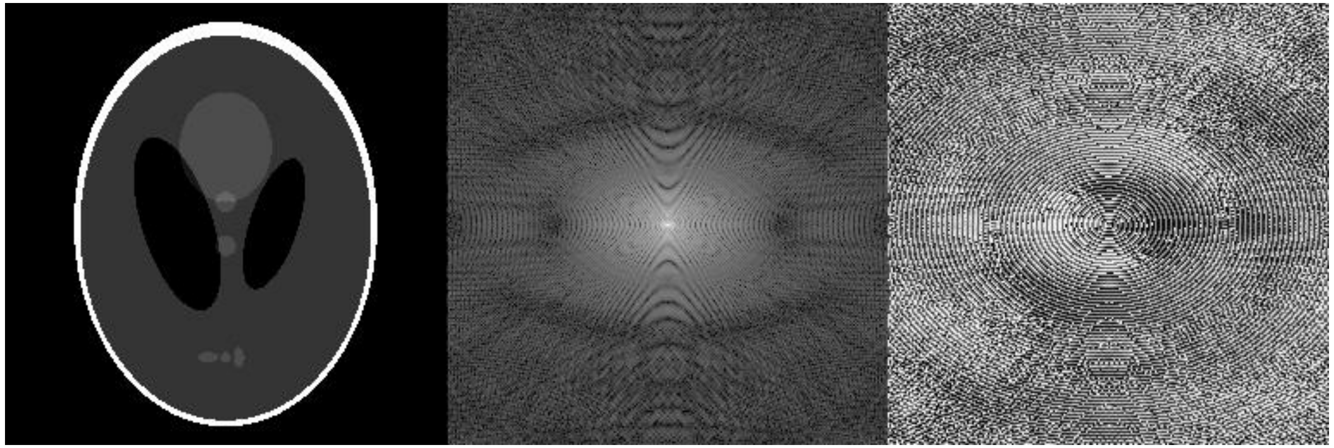
Prospective Motion Correction



- Real-time motion correction
- Update of the scanner gradients
- Minimize latency
- Un-corrected image is not available

Maclaren et al. MRM (2012)

Retrospective Motion Correction

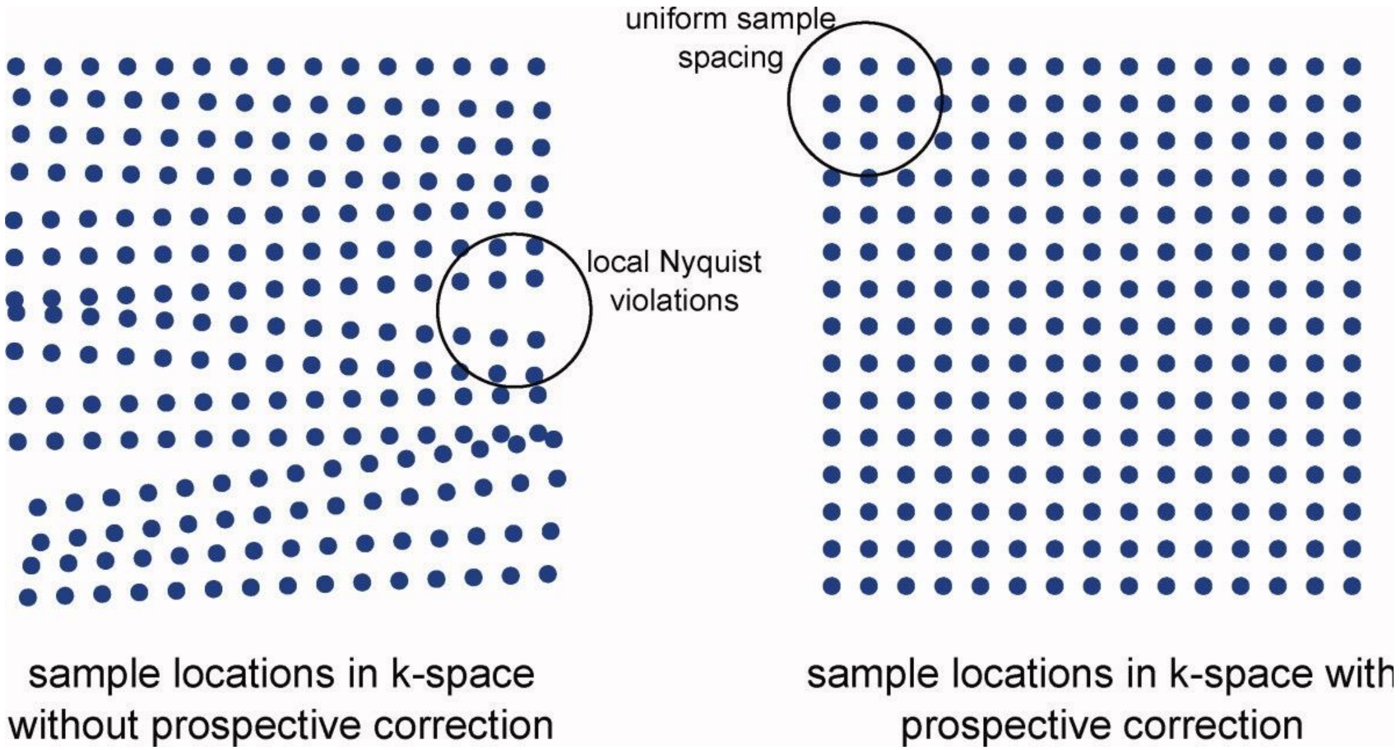


$$F\{\rho(R\bar{x}-\bar{a})\}\left(\bar{k}\right)=e^{-i2\pi\left(R\bar{k}\right)\cdot\bar{a}}\,F\{\rho(\bar{x})\}\left(R\bar{k}\right)$$

- Applies Fourier properties
  - Fourier Shift Theorem
  - Rotation Theorem
- Uncorrected image is available
- Does not require any sequence adjustments

Zaitsev et al. JMRI (2015), Maclaren et al. MRM (2012), Fessler et al. IEEE Transactions on Signal Processing (2003)

Retrospective Motion Correction



- Applies Fourier properties
    - Fourier Shift Theorem
    - Rotation Theorem
- Uncorrected image is available
- Does not require any sequence adjustments
- Rotations can cause the *pie-slice* effect, which can cause striking and ghosting artifacts
- Requires NFFT to resample the k-space into a Cartesian grid.

Zaitsev et al. JMRI (2015), Maclaren et al. MRM (2012), Fessler et al. IEEE Transactions on Signal Processing (2003)

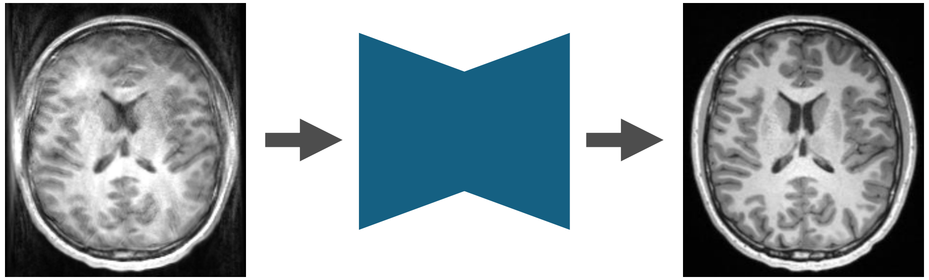
Autofocusing

- Iterative correction based on Fourier shift and rotation theorems
- Correct motion estimates minimize a cost-function (e.g., image entropy in Atkinson et al. MRM 1999)
- **Cons**
  - Incorrect motion estimates can introduce artifacts if errors propagate through k-space
  - Computationally expensive
- **Potential use**
  - Improve efficiency using prior information (e.g., navigators)
  - Address residual artifacts remaining after initial motion correction

Review:

Motion correction with Deep Learning

Deep Learning has shown capability to cope with complex problems



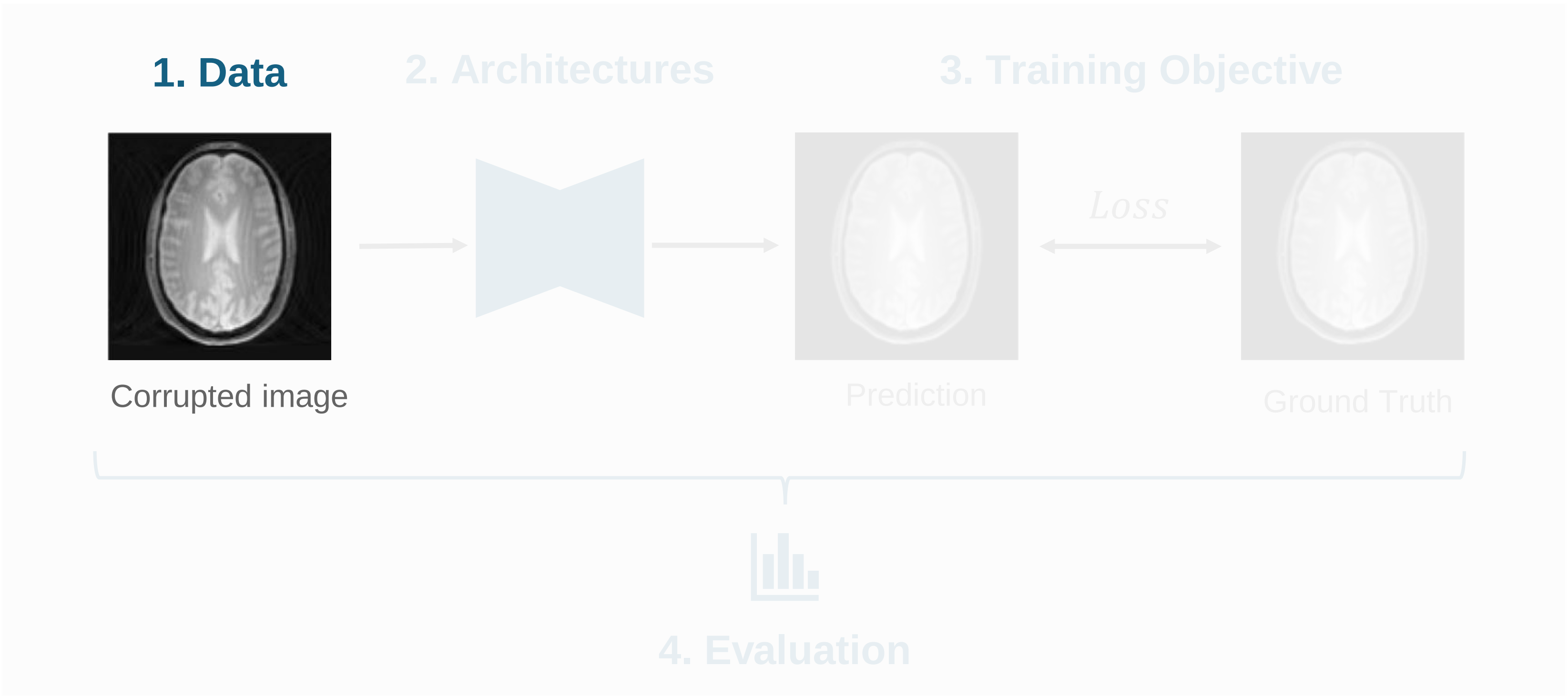
Various approaches for retrospective motion correction

Spieker and Eichhorn et al., IEEE TMI (2024)

Motion correction with Deep Learning

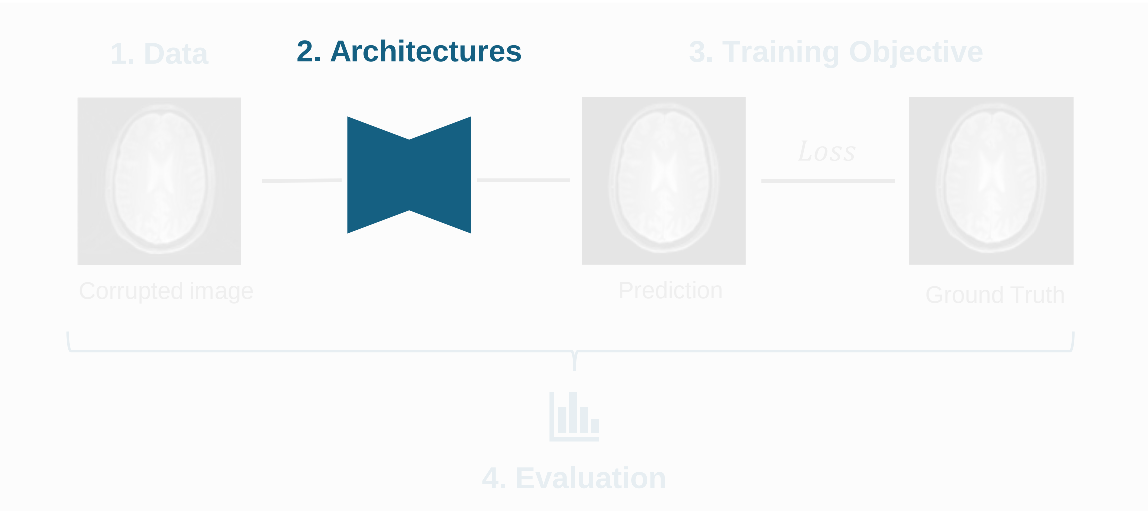
Aspects of learning-based motion correction

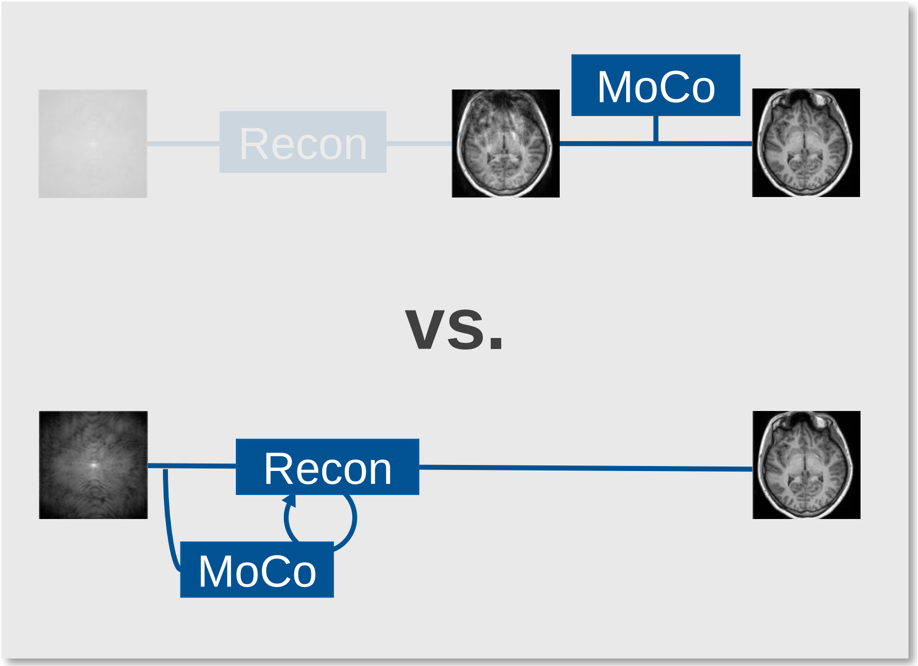
Review:



Motion correction with Deep Learning

Architectures: image-based vs. k-space-based

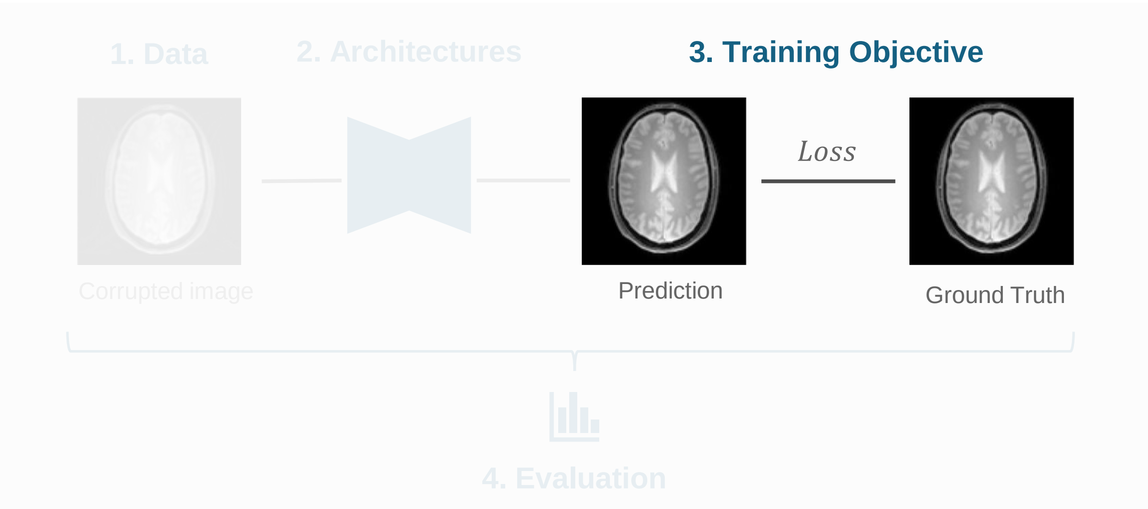


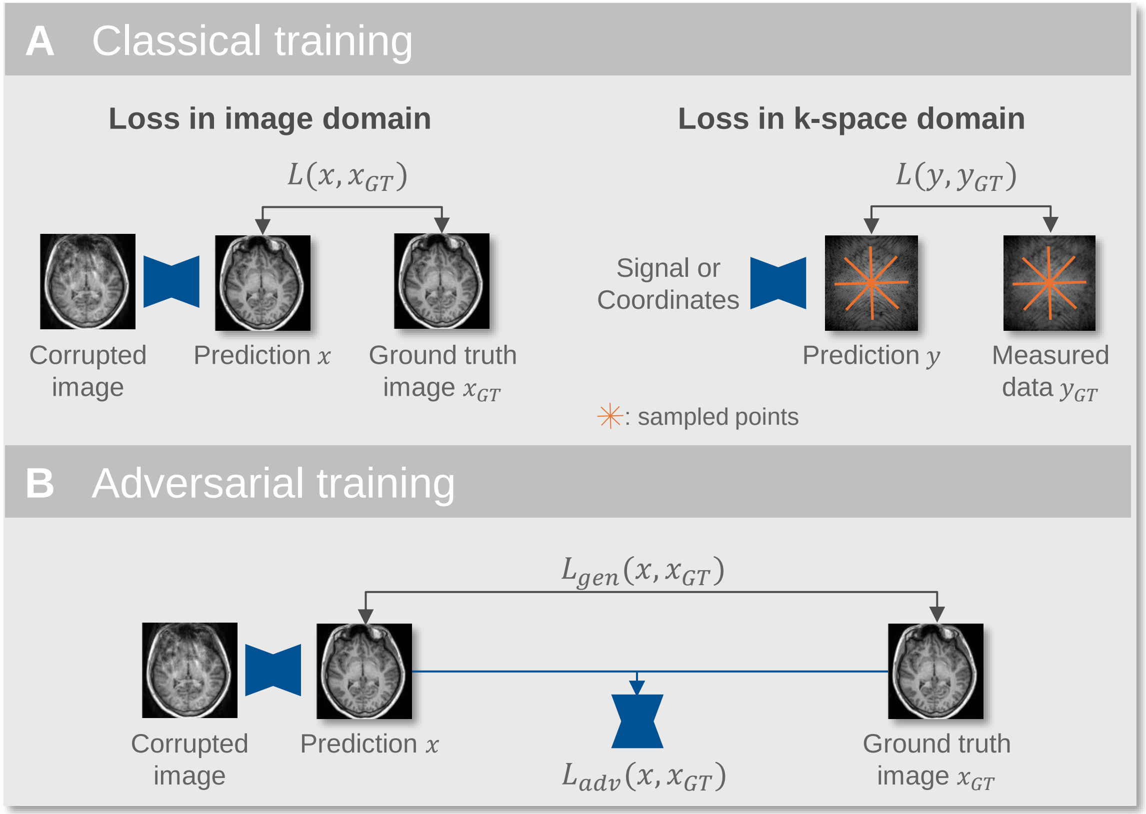


Spieker and Eichhorn et al., IEEE TMI (2024)

Motion correction with Deep Learning

Training objectives: how much supervision?

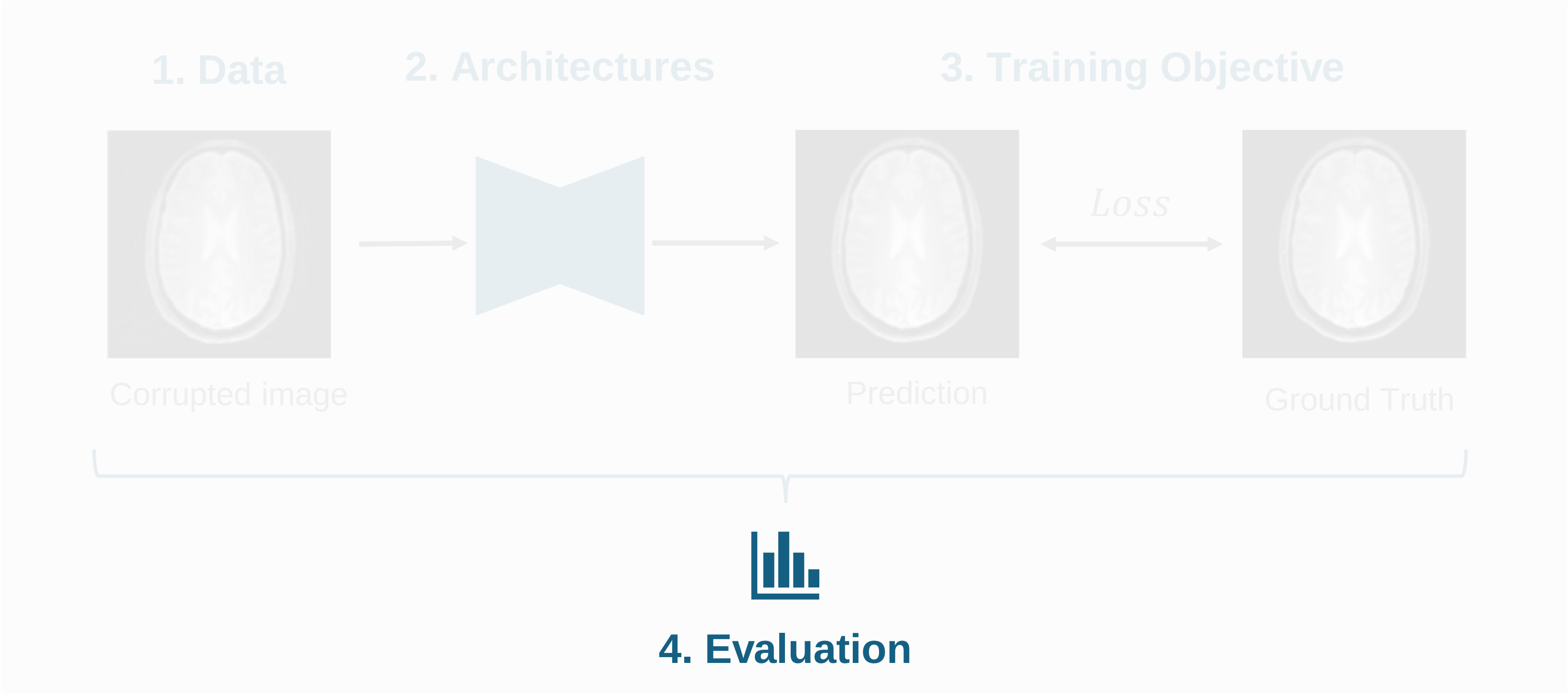




Spieker and Eichhorn et al., IEEE TMI (2024)

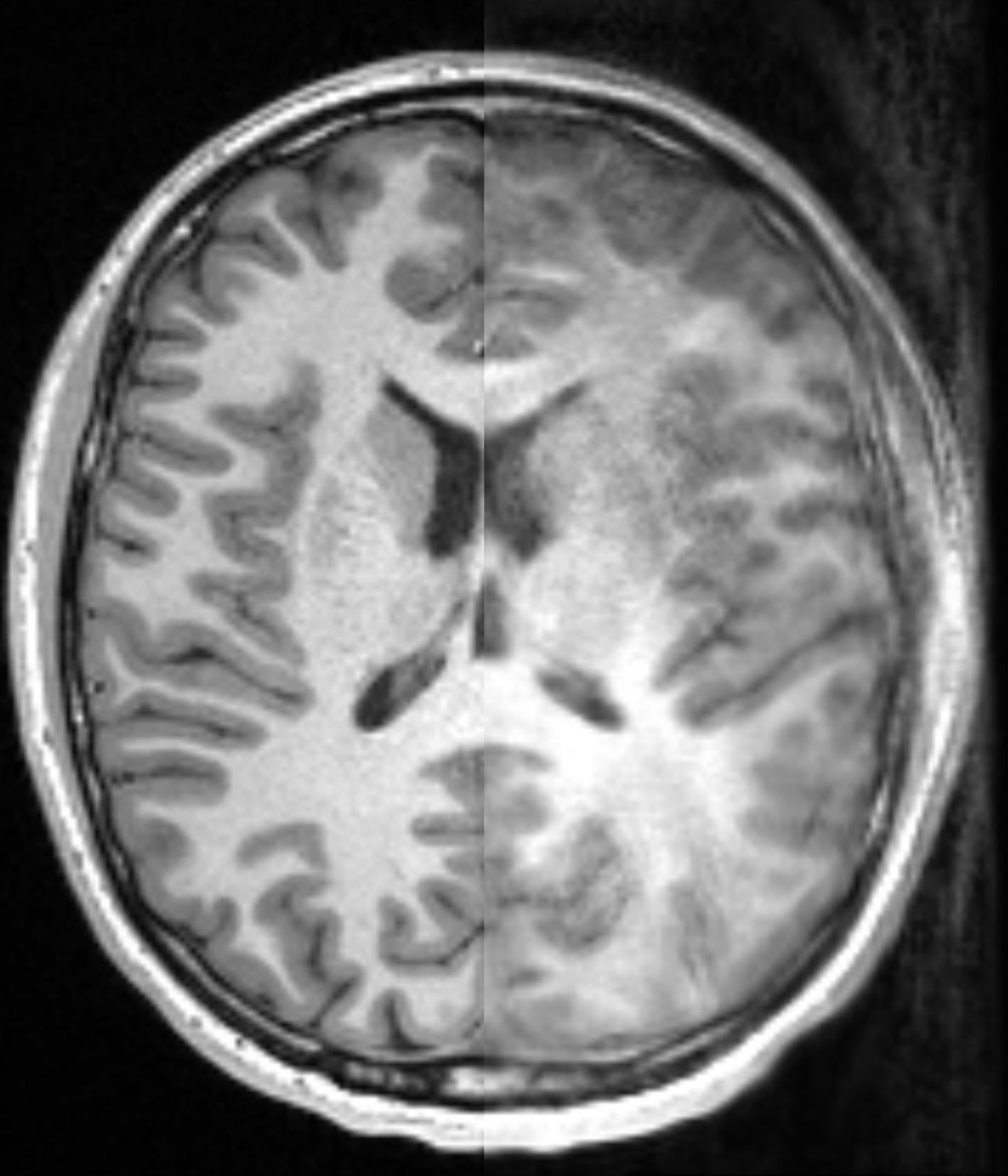
Motion correction with Deep Learning

Aspects of learning-based motion correction



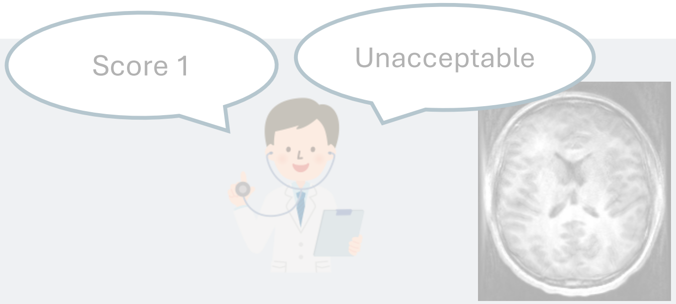
Motion in MRI

Image Quality Evaluation

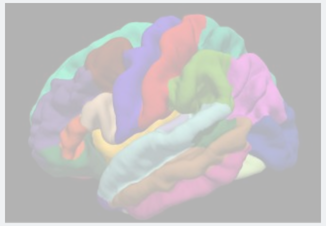


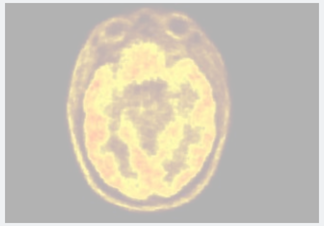
Types of image quality evaluation

Qualitative assessment



Task-based





Reference-based vs. reference free image quality metrics (IQMs)

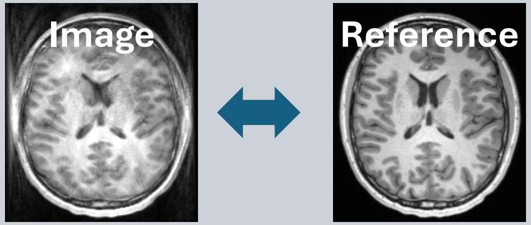
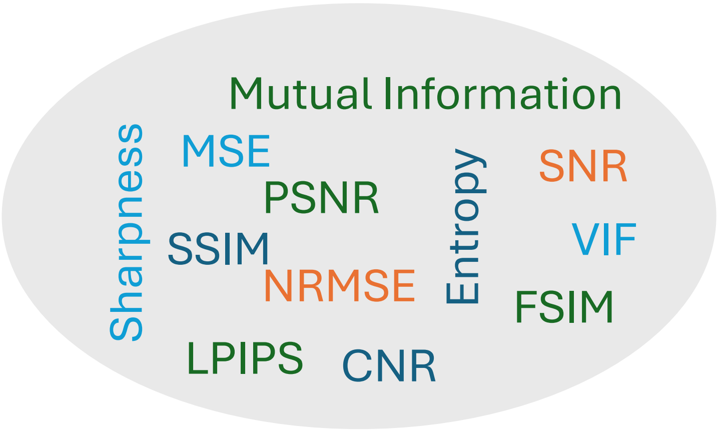


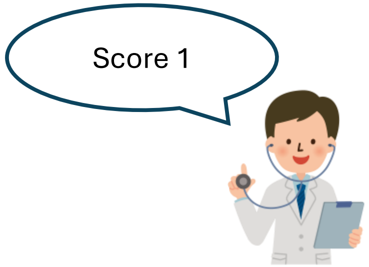
Image quality metrics



- Large number of IQMs used in literature
  → lack of standardization

- Most IQMs originally designed for natural images

- Medical image quality:
  How well can the desired clinical information be extracted?
  → radiological evaluation gold standard



Heckel et al. MAGMA (2024), Breger et al. arXiv (2024)

“To SSIM or not to SSIM?”

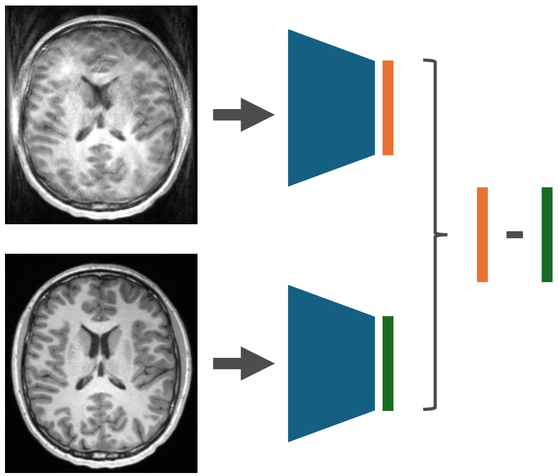
- SSIM and PSNR most used IQMs

- fastMRI challenges:
    1. SSIM consistent with radiological evaluation
    2. SSIM failed to detect hallucinations

- Recent studies:
    - SSIM and PSNR perform worse than more advance IQMS (e.g. FSIM, VIF)
    - SSIM less sensitive to simulated motion than e.g. VIF

Terpstra et al. ISMRM (2024), Knoll et al. MRM (2020), Muckley et al. IEEE TMI (2021), Mason et al. IEEE TMI (2020), Kastryulin et al. IEEE Access (2023)

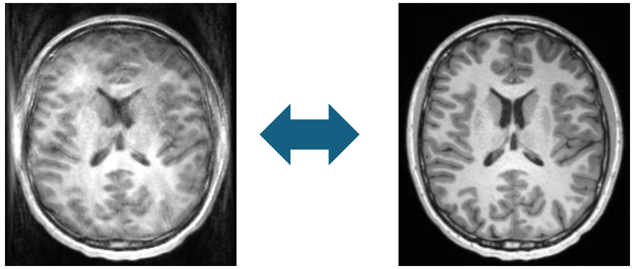
Perceptual metrics based on deep features



- Increasingly used in computer vision community
- First studies analyzing their potential in MRI (accelerated reconstruction)
- Comprehensive evaluation for motion in MRI missing

Zhang et al. CVPR (2018), Adamson et al. MRM (2025), Breger et al. arXiv (2024)

Reference-based vs. reference-free IQMs



- Reference-based IQMs rely on **high-quality reference**
  - “Hidden noise” problem
  - Reference not available for all applications

Reference-free image quality evaluation challenging

Agreement of Image Quality Metrics with Radiological Evaluation in the Presence of Motion Artifacts

Performance of ten commonly used IQMs

Selection of IQMs focused on **relevance & usage** in the MoCo field

Based on **real motion** data

Effect of common **pre-processing** steps

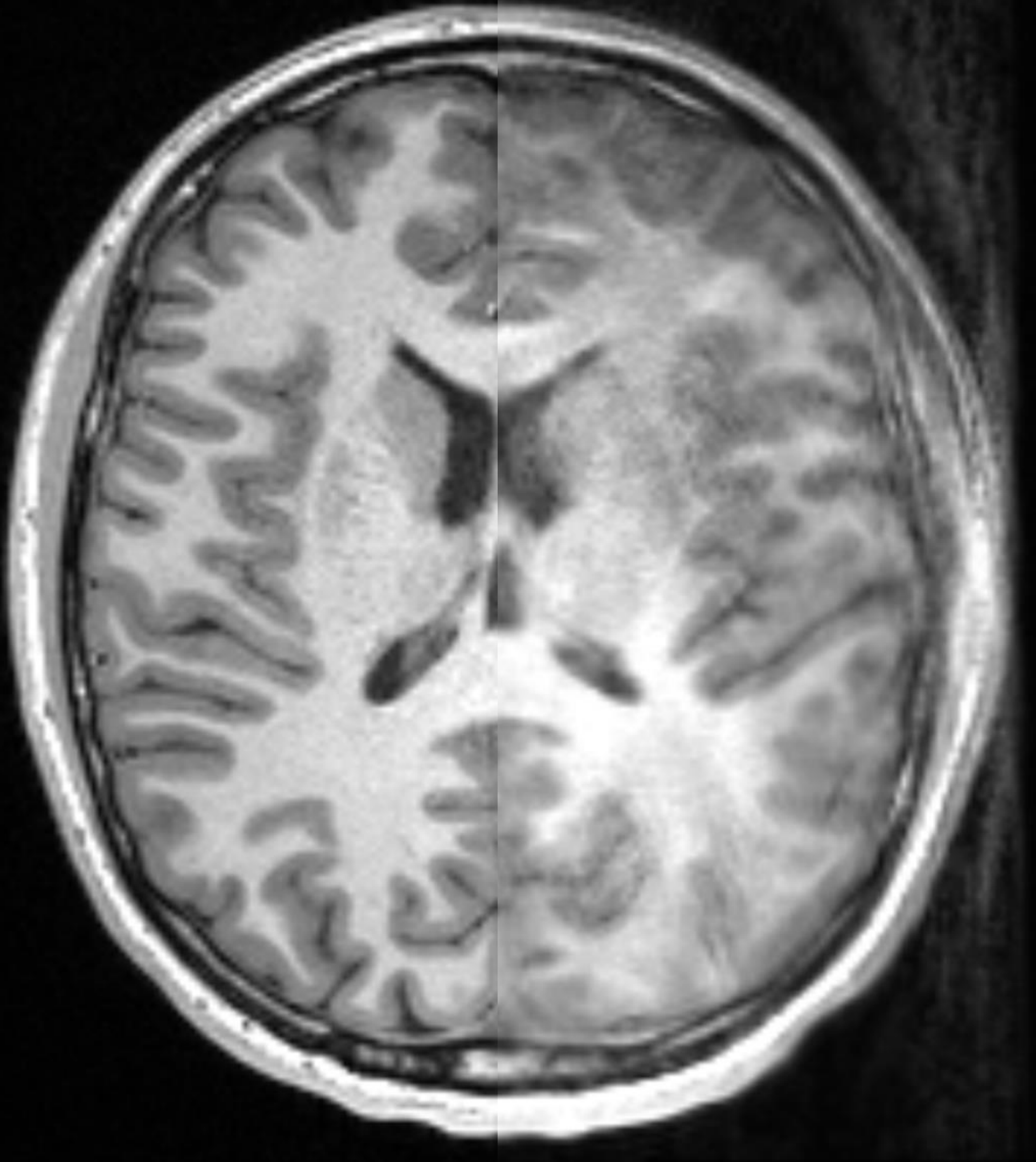
Preprint:

Code:

Marchetto and Eichhorn et al. arXiv (2024)

Methods

Image Quality Evaluation



Code:

Image Quality Metrics

- Comparison of 10 different image quality metrics
  - **5 Reference-Based**: require a reference (ground-truth) image
    - Reference image *without motion* and *without motion correction*
    - Good quality is not *always* guaranteed
    - Not always available in clinical practice

Structural Similarity Index Measure (SSIM)	Wang et al., IEEE (2004)
Peak Signal-to-Noise Ratio (PSNR)	Hore et al., 20th ICPR (2010)
Feature Similarity Index Measure (FSIM)	Zhang et al., IEEE (2011)
Visual Information Fidelity (VIF)	Sheikh et al., IEEE (2006)
Perceptual Image Patch Similarity (LPIPS)	Zhang et al., Proc. IEEE (2018)

Marchetto and Eichhorn et al. arXiv (2024)

Code:

Image Quality Metrics

- Comparison of 10 different image quality metrics
  - **5 Reference-Free**: no reference (ground-truth) image required

Tenengrad (TG)	Kecskemeti et al., Radiology (2018)
Average Edge Strength (AES)	Pannetier et al., MRM (2016)
Normalized Gradient Square (NGS)	McGee et al., JMRI (2000)
Image Entropy (IE)	Atkinson ET AL., IEEE (1997)
Gradient Entropy (GE)	McGee et al., JMRI (2000)

Image Acquisition

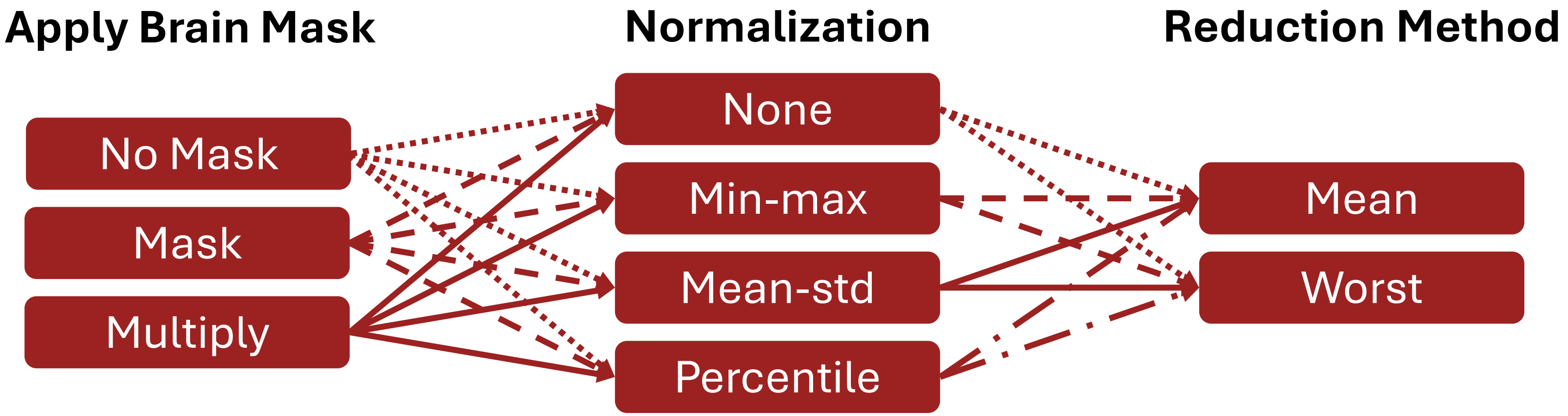
Datasets from 2 research institutes:

1. Neurobiology Research Unit - NRU (Copenhagen, Denmark)
2. Cardiff University Brain Research Imaging Centre - CUBRIC (Cardiff, UK)

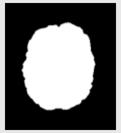
	Dataset 1 (NRU)	Dataset 2 (CUBRIC)
Scanner	Prisma 3T	Prisma 3T
Participants	22 healthy subjects	9 healthy subjects
Sequences	3D MP-RAGE, 3D T_2 FLAIR, 2D T_2 TSE, 2D T_1 TIRM	3D MP-RAGE
Motion	Nodding and shaking	Nodding, circular-motion and stepwise motion
Motion correction	Prospective motion correction with marker-based method	Retrospective motion correction with marker-based and navigator-based methods.
Total images	584	217
Image quality assessment	2 Radiologists and 2 Radiographers	1 Radiologist

Ganz et al. Dataset – OpenNeuro (Accessed 2023), Marchetto et al. MRM (2023)

Pre-Processing Evaluation



Mask:

$\sum$  if  = 1

Multiply:

 ✖ $\sum$

Min-max:

$$\frac{x - min(x)}{max(x) - min(x)}$$

Mean-std:

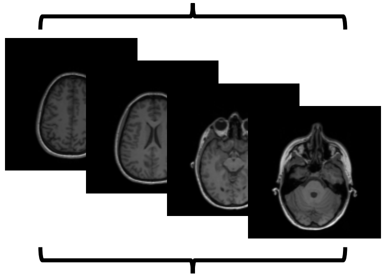
$$\frac{x - mean(x)}{std(x)}$$

Percentile:

$$\frac{x - p(x)}{P(x) - p(x)}$$

Mean

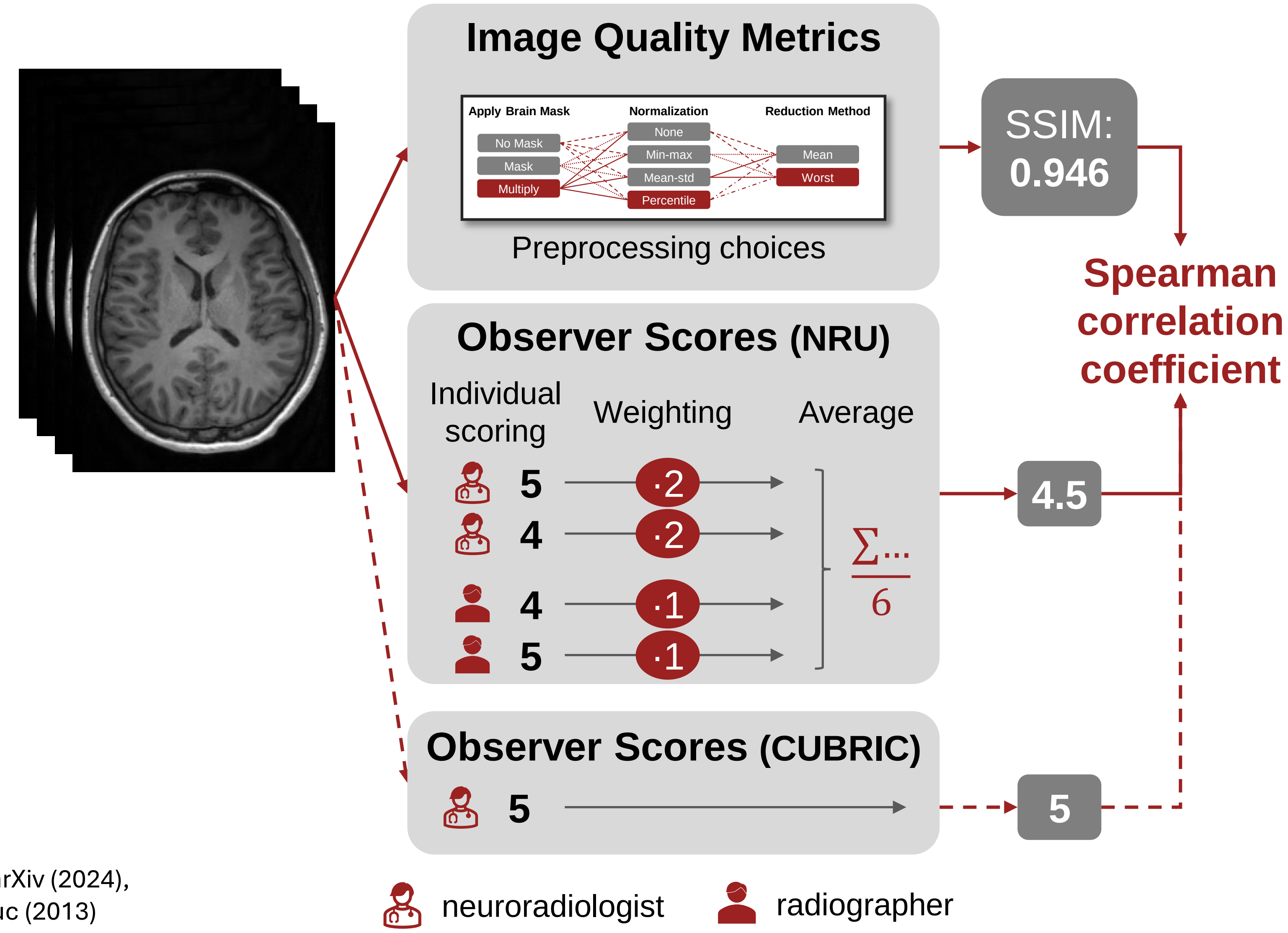
of all slices



Worst slice

min / max value

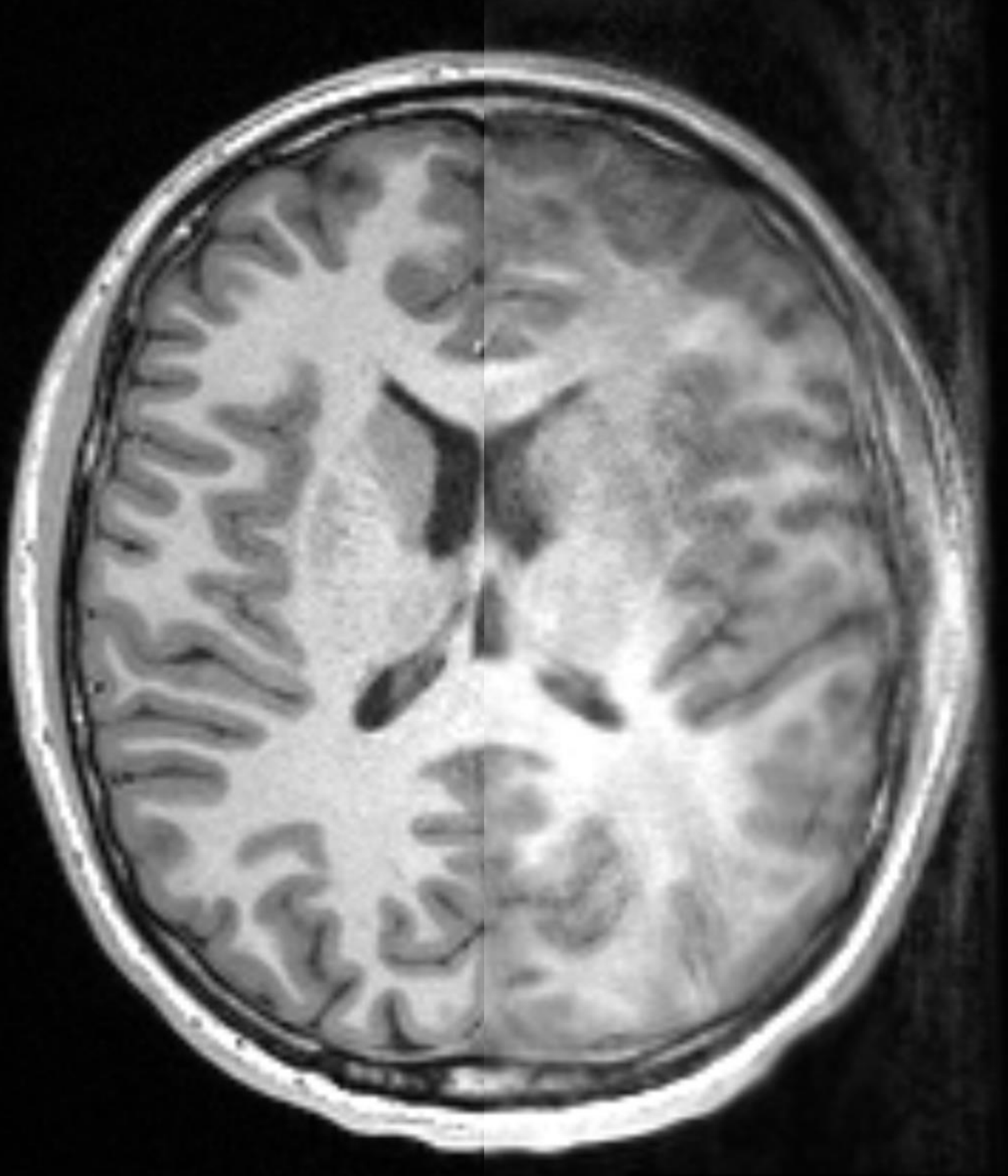
Correlation Analysis



Marchetto and Eichhorn et al., arXiv (2024),
Sullivan et al. J Grad Med Educ (2013)

Results

Image Quality Evaluation

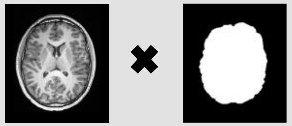


Correlation Analysis

"Default" settings:

- Apply Mask:

Multiply:



- Normalization:

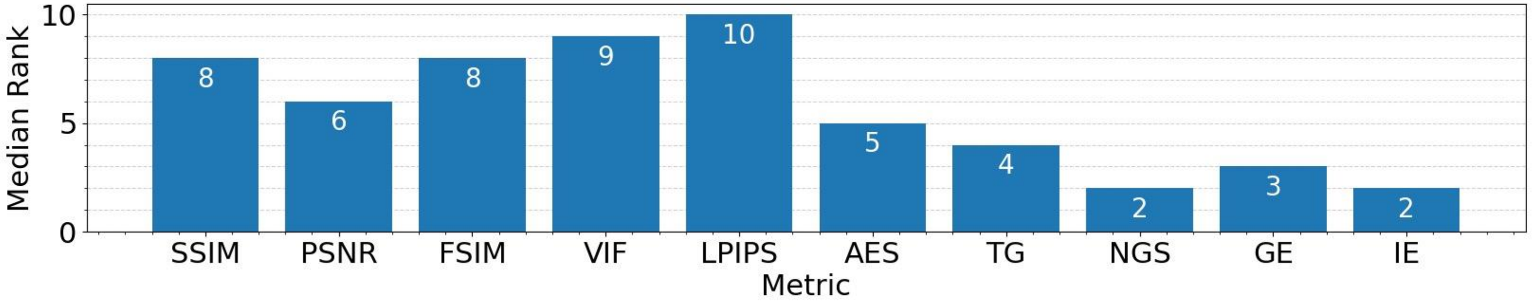
Percentile:

$$\frac{x - p(x)}{P(x) - p(x)}$$

- Reduction:

Worst slice

min / max value



Marchetto and Eichhorn et al., arXiv (2024)

MP-RAGE

*could not be calculated because metric requires a certain range

No significant correlation

Dataset 1

	Apply Brain Mask			Normalization				Reduction	
	Mask	Multiply	No Mask	Percentile	Min-Max	Mean-Std	None	Worst	Mean
SSIM	0.92	0.92	0.82	0.92	0.89	0.91	0.90	0.92	0.93
PSNR	0.92	0.91	0.70	0.91	0.44	0.78	0.75	0.91	0.93
FSIM	*	0.89	0.20	0.89	0.88	*	*	0.89	0.91
VIF	*	0.92	0.15	0.92	0.88	*	*	0.92	0.94
LPIPS	*	-0.90	-0.76	-0.90	-0.90	*	*	-0.90	-0.91
AES	0.79	0.79	0.52	0.79	0.18	0.38	0.34	0.79	0.80
TG	0.75	0.76	0.22	0.76	0.22	0.56	0.53	0.76	0.79
NGS			0.21						
GE			-0.30						
IE			-0.15						

−1.0 −0.5 0.0 0.5 1.0

ρ

Dataset 2

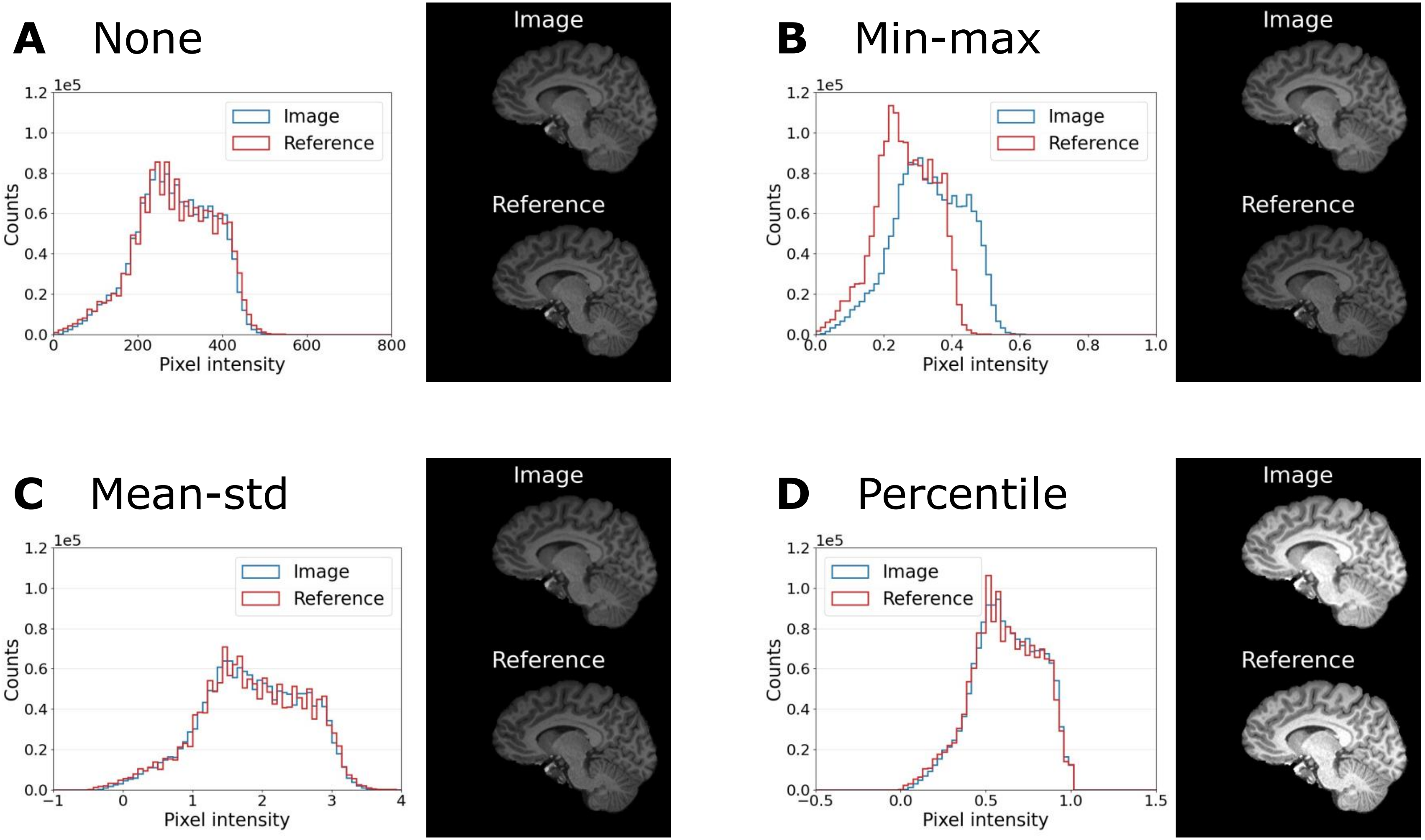
	Apply Brain Mask			Normalization				Reduction	
	Mask	Multiply	No Mask	Percentile	Min-Max	Mean-Std	None	Worst	Mean
SSIM	0.88	0.88	0.84	0.88	0.86	0.83	0.85	0.88	0.88
PSNR	0.85	0.83	0.66	0.83	0.73	0.64	0.62	0.83	0.84
FSIM	*	0.86	0.19	0.86	0.81	*	*	0.86	0.87
VIF	*	0.86		0.86	0.79	*	*	0.86	0.86
LPIPS	*	-0.89	-0.76	-0.89	-0.88	*	*	-0.89	-0.89
AES	0.41	0.31	0.61	0.31	0.18	0.52		0.31	0.38
TG	0.44	0.31	-0.28	0.31	0.25	0.55		0.31	0.45
NGS			-0.26						
GE			0.40						-0.14
IE			0.30				-0.30		

−1.0 −0.5 0.0 0.5 1.0

ρ

Marchetto and Eichhorn et al., arXiv (2024)

Effect of Normalization

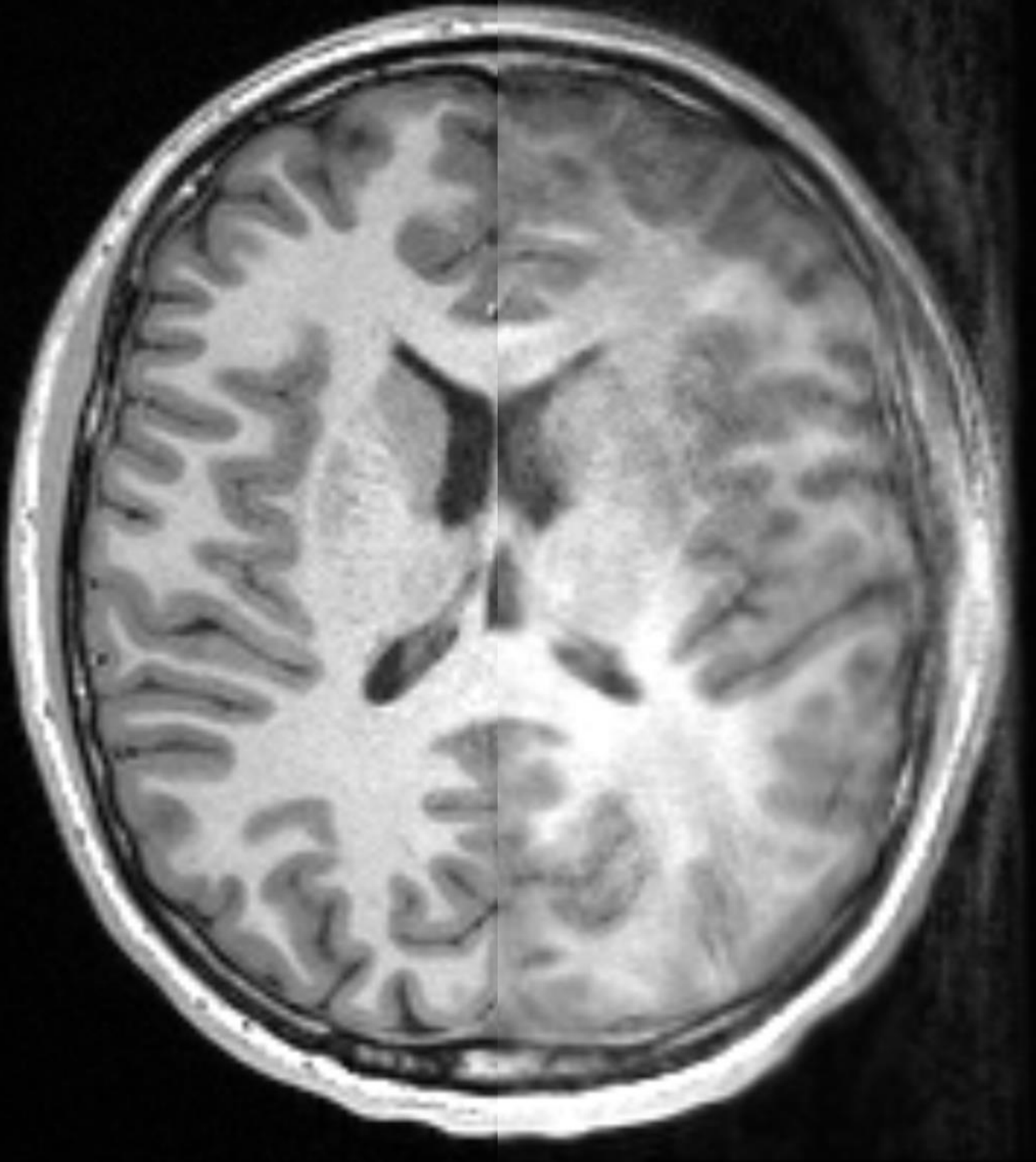


*Calculated within the brain mask

Marchetto and Eichhorn et al., arXiv (2024)

Discussion

Image Quality Evaluation



Discussion

Reference-based IQMs more consistent than reference-free IQMS

Best reference-free IQMS: Average Edge Strength & Tenengrad

Normalization and masking proved essential

We recommend: percentile normalization and using a brain mask

! Masking might be application-specific

Outlook & future work

Further pre-processing steps

Influence of mis-registration

→ *quality inspection, clear documentation & code sharing*

Distribution-based metrics & learning-based approaches promising

Mortamet et al. MRM (2009), Pizarro et al. Front. neuroinform. (2016),
Küstner et al. Magn Reson Mater Phy (2018), Ecker et al. ISMRM (2024)

Thank you!

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Work together with **Melanie Ganz**,
Daniel Gallichan, Julia A. Schnabel

Preprint: **Code:**

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NYU Langone Health

Let’s start the discussion…

… What are key barriers for real-time quality evaluation in the clinical workflow and how to overcome them?

… What would be requirements for AI-based automated quality evaluation methods?

… How can we ensure AI-based methods remain interpretable and generalizable?

… How can the MR community establish standardized datasets and benchmarks to ensure consistent IQM comparisons across studies?

Preprint: **Code:**

Work together with **Melanie Ganz**, Daniel Gallichan, Julia A. Schnabel