Artifacts in dramatically undersampled MRI techniques (CS and AI-based reconstruction)

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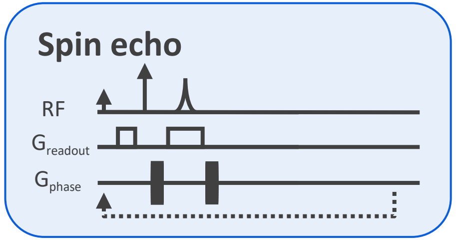
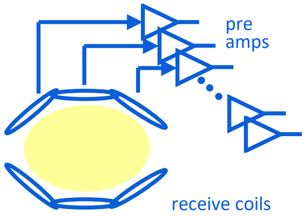
innovation + you

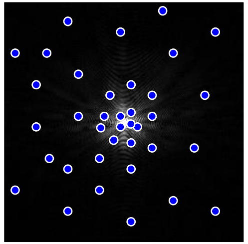
How to speed up MRI scans?

Scan Time = TR × (No. repetitions)

- **Collect data faster**
  - Reduce TR
  - Collect more data per TR (spiral, EPI)
- **Parallel Imaging**
  - Multiple receive coils
  - Less data per coil
- **Collect less data**
  - Undersampling
  - Constrained reconstruction





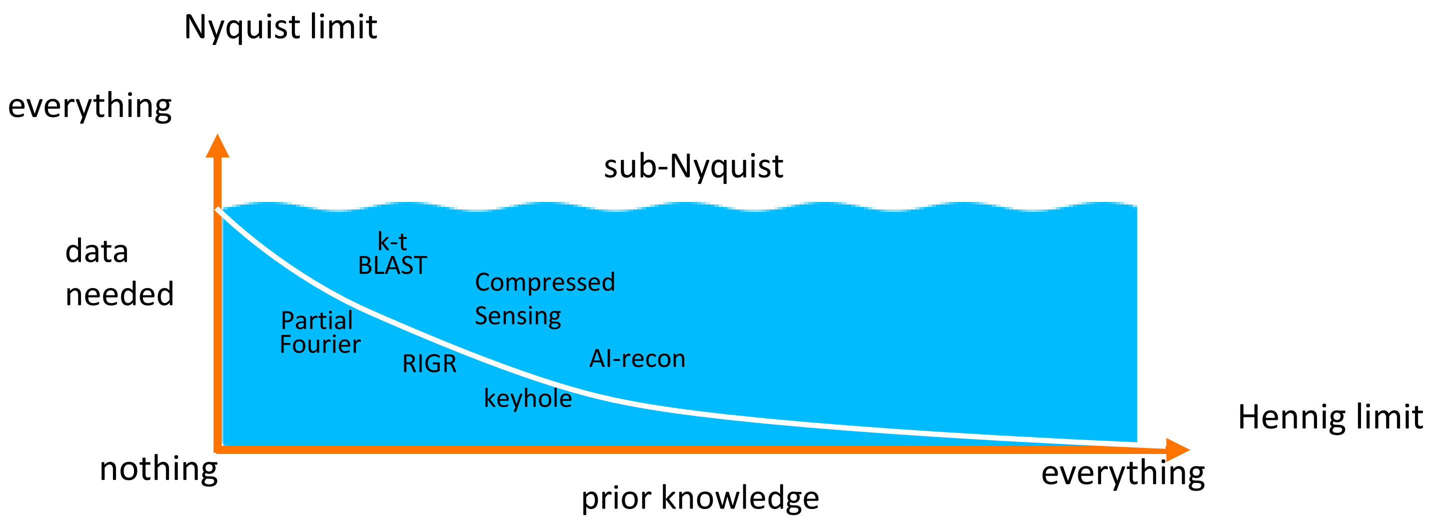


Scan acceleration using prior knowledge

The Hennig Limit: dynamic imaging with perfect spatio-temporal correlation (C. Mistretta ISMRM 2006)

$$I(x, y, z, t) = I(x, y, z) * g(t)$$

Given the spatial configuration, dynamic frames can be reconstructed from one k-space point per TR



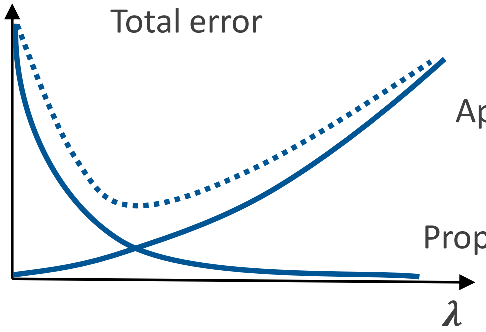
Courtesy of M. Lustig, EECS UC Berkeley

Including prior knowledge: Regularization

- Ill-conditioned/ill-posed problem: add regularization
  Regularized inverse problem

$$\hat{\boldsymbol{x}} = \underset{\boldsymbol{x}}{\operatorname{argmin}} \underbrace{\|\boldsymbol{F}\boldsymbol{x} - \boldsymbol{y}\|_2^2}_{\text{data consistency}} + \underbrace{\lambda R(\boldsymbol{x})}_{\text{regularization}}$$

- Regularization adds prior knowledge to stabilize the solution



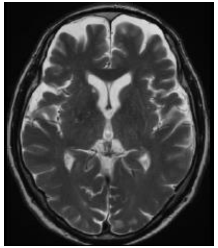
Examples:

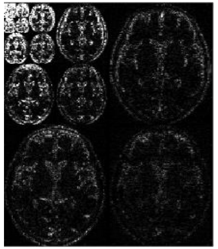
- L2 norm $R(\boldsymbol{x}) = \|\boldsymbol{x}\|_2^2$
- Total Variation $R(\boldsymbol{x}) = |\Delta\boldsymbol{x}|$
- L1 norm $R(\boldsymbol{x}) = |\boldsymbol{x}|$

Compressed Sensing

Prior: Images are sparse or compressible

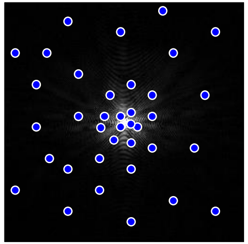
L1 norm: $R(\boldsymbol{\rho}) = |\Psi\boldsymbol{\rho}|$





Undersampling artifacts are not

Non uniform sampling



- L1 regularization requires iterative reconstruction

Neural Networks for image reconstruction

- Example: Variational NN

$$\hat{\rho} = \underset{\rho}{\operatorname{argmin}} \underbrace{\| F\rho - y \|_2^2}_{\text{data consistency}} + \lambda \underbrace{\sum_i \sigma_i(K_i\rho)}_{\text{regularization}}$$

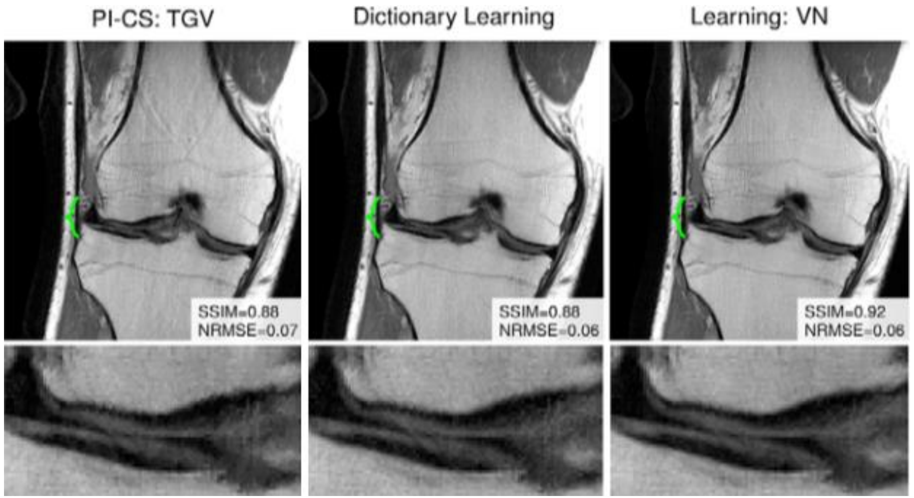
Parameters and transforms learned from data

K_i spatial convolution kernels

σ_i non-linear functions

λ regularization parameter

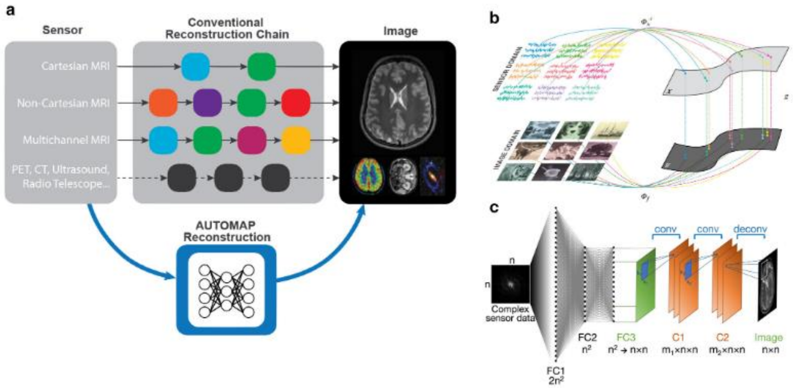
Regular sampling R=4

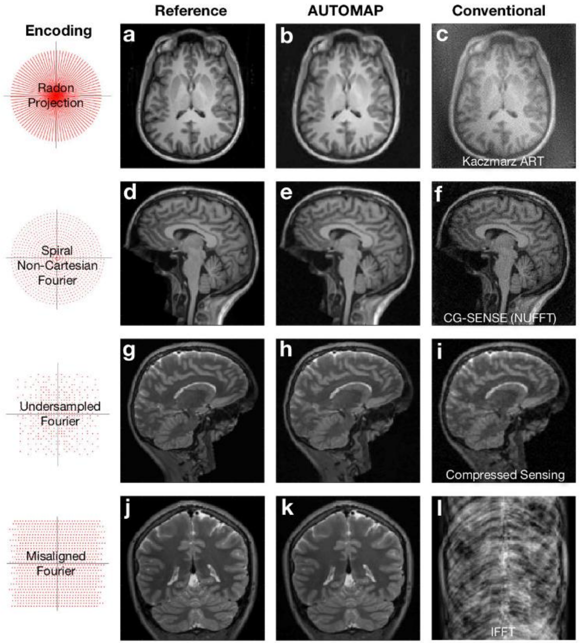


[1] Hammernik K et al Magn Reson Med 2018; 79:3055-3071
[2] Schlemper J et al IEEE TMI 2017; 37:491-503
[3] Zhu B et al Nature 1018; 555:487-492
[4] Mardani et al arXiv 2017

Neural Networks for image reconstruction

- Example: AUTOMAP[3)]
- Model is included in the training data generation
- NN learns to solve the inverse problem from examples

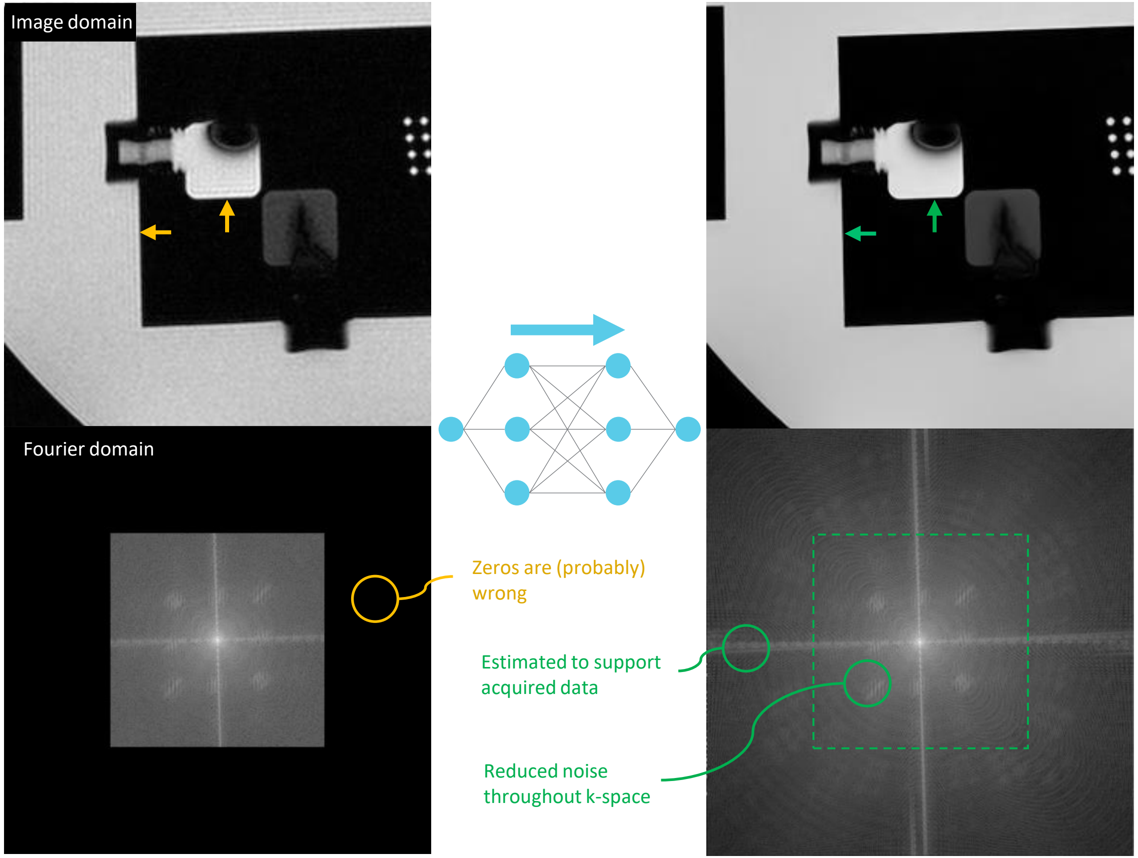




[1] Hammernik K et al Magn Reson Med 2018; 79:3055-3071
[2] Schlemper J et al IEEE TMI 2017; 37:491-503
[3] Zhu B et al Nature 1018; 555:487-492
[4] Mardani et al arXiv 2017

Neural Networks for image reconstruction

- Example: AIR™ Recon DL
  -AI removes ringing, noise, and interpolates images



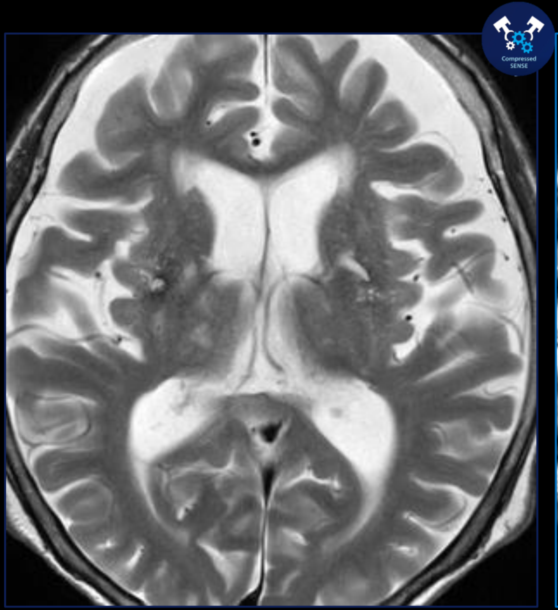
Courtesy of Marc Lebel

Examples for scan acceleration with CS and AI-based reconstruction

Accelerated 2D imaging

Brain 2D T2W TSE

Ax T2w TSE SENSE
0.5 x 0.51 x 5.0mm
1m43s



Ax T2w TSE Compressed SENSE
0.5 x 0.51 x 5.0mm
1min14s

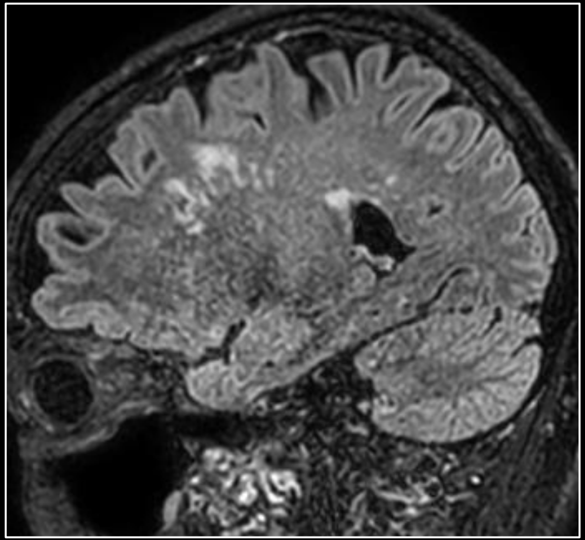
Ax T2w TSE SmartSpeed
0.5 x 0.51 x 5.0mm
59s

Courtesy: Tokyo Metropolitan Police Hospital, Japan

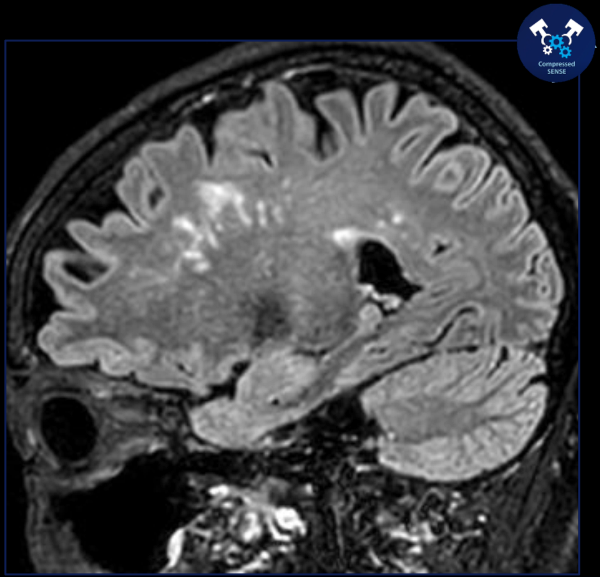
Ingenia Elition X 3.0T

Accelerated 3D imaging

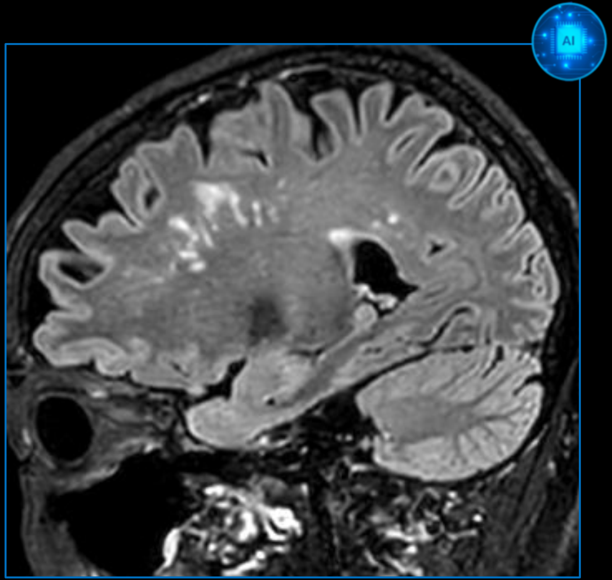
3D FLAIR



3D FLAIR SENSE
1.1 mm iso
2min24s



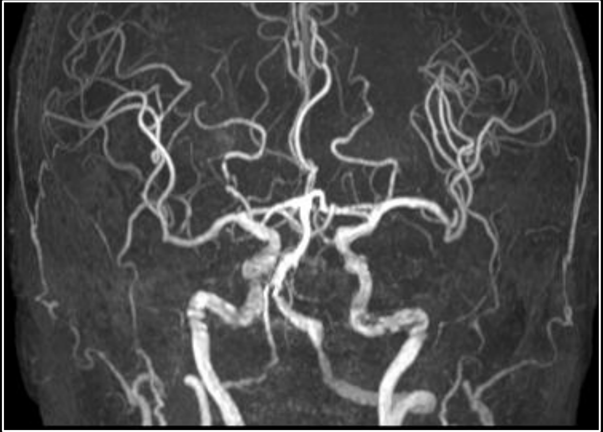
3D FLAIR Compressed SENSE
1.1 mm iso
2min24s



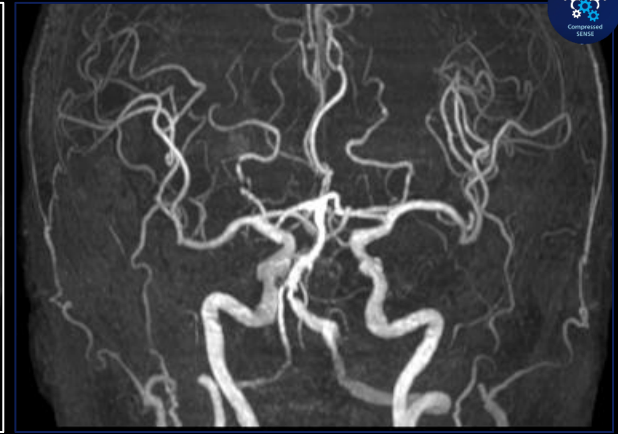
3D FLAIR SmartSpeed
1.1 mm iso
2min24s

Improved image quality at shorter scan times

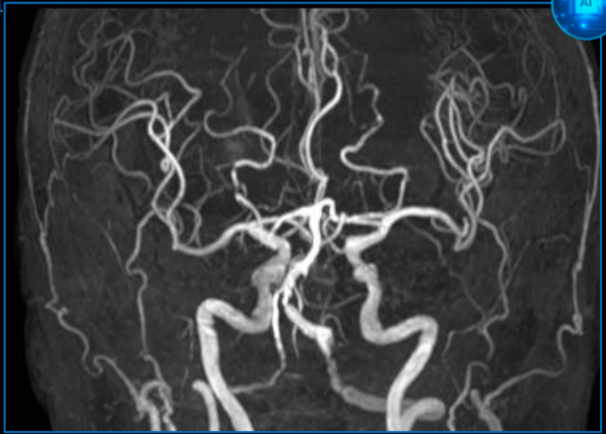
Inflow MRA



3D TOF SENSE
0.5 x 0.8 x 1.1mm
4min1s



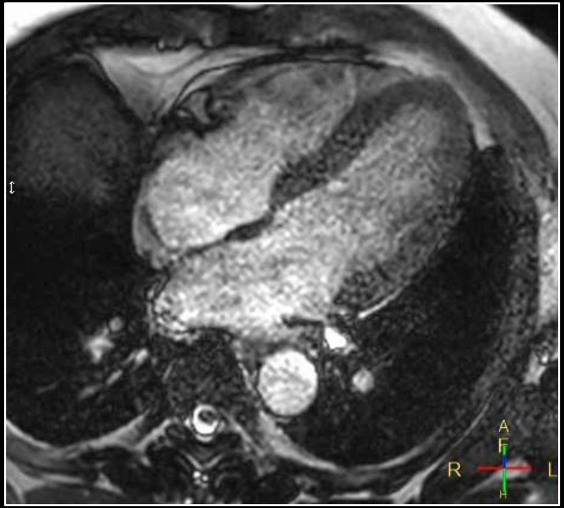
3D TOF Compressed SENSE
0.5 x 0.8 x 1.1mm
3min11s



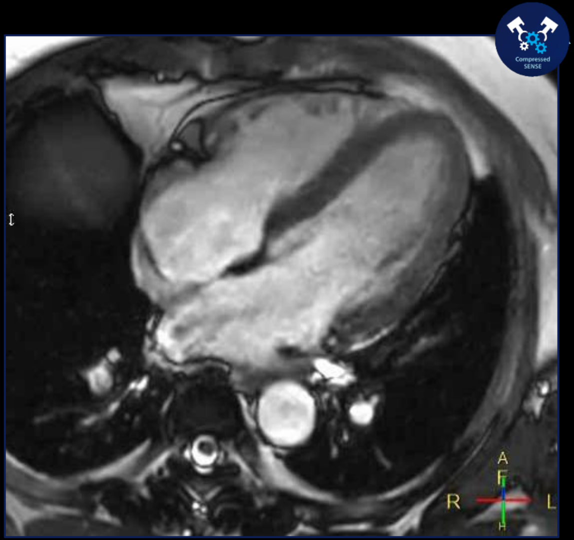
3D TOF SmartSpeed
0.5 x 0.8 x 1.1mm
2min35s

Improved Image Quality without increasing scan time

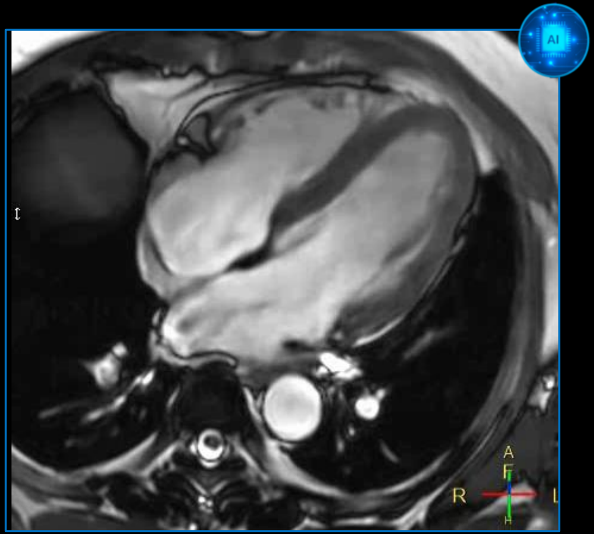
Cine 4CH



Cine bFFE SENSE
1.5x1.5x6.0mm
8.3s



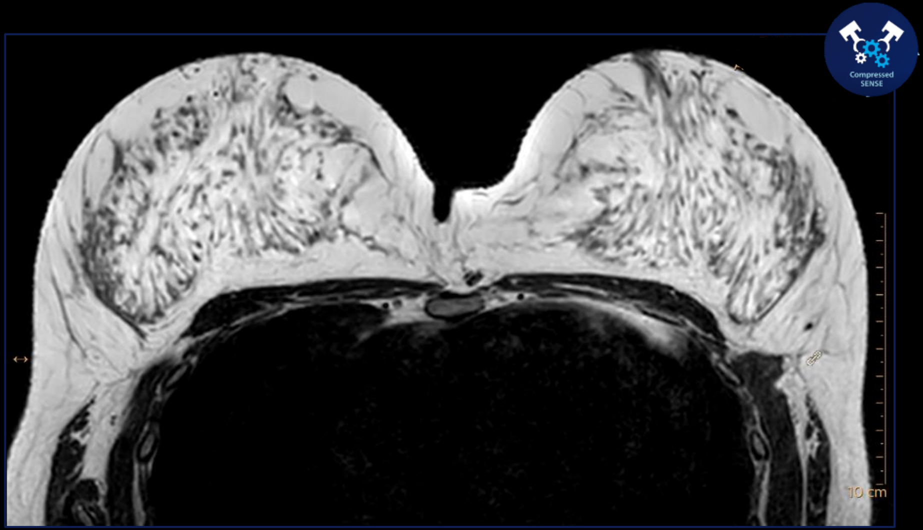
Cine bFFE Compressed SENSE
1.5x1.5x6.0mm
8.3s



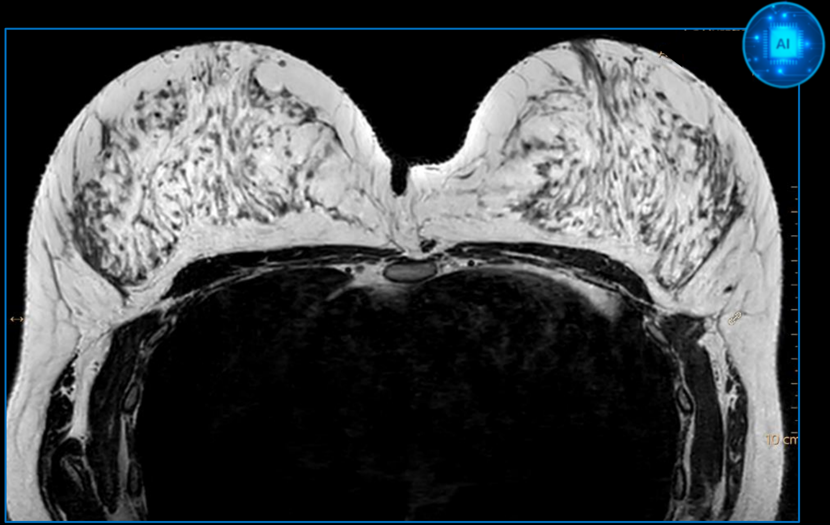
Cine bFFE SmartSpeed
1.5x1.5x6.0mm
8.3s

Improved resolution without increasing scan time

Breast 3D



3D T2w TSE Compressed SENSE
1.0x1.0x 2mm
2 min26s

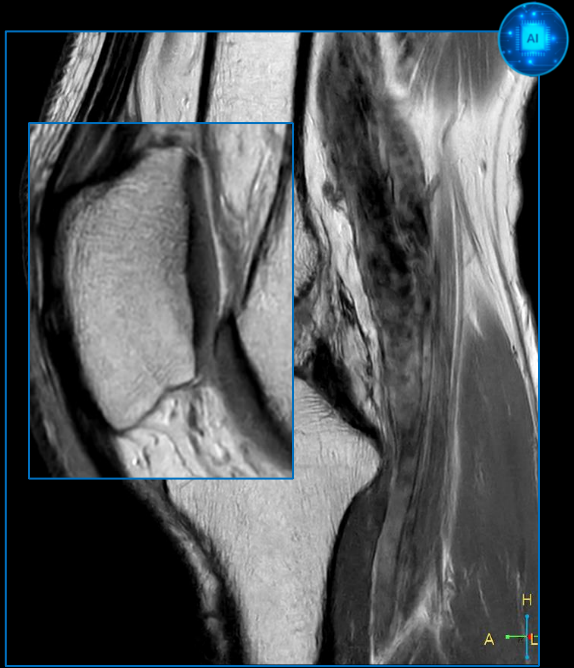


3D T2w TSE SmartSpeed
0.8x0.8x0.8 mm
2 min26s

Improved resolution without increasing scan time

Knee Proton Density

T2w TSE SENSE
0.5x0.5x3.0 mm
3min10s



T2w TSE SmartSpeed
0.33 x 0.34 x 3.0 mm
3min10s

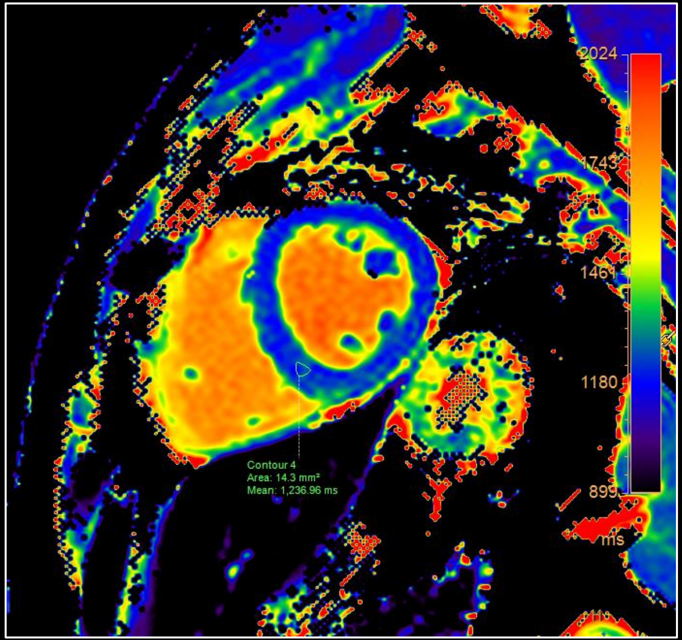
Courtesy: Tokyo Metropolitan Police Hospital, Japan

Pending 510(k), Not available for sale in the U.S.A. Not yet CE marked and not available for sale

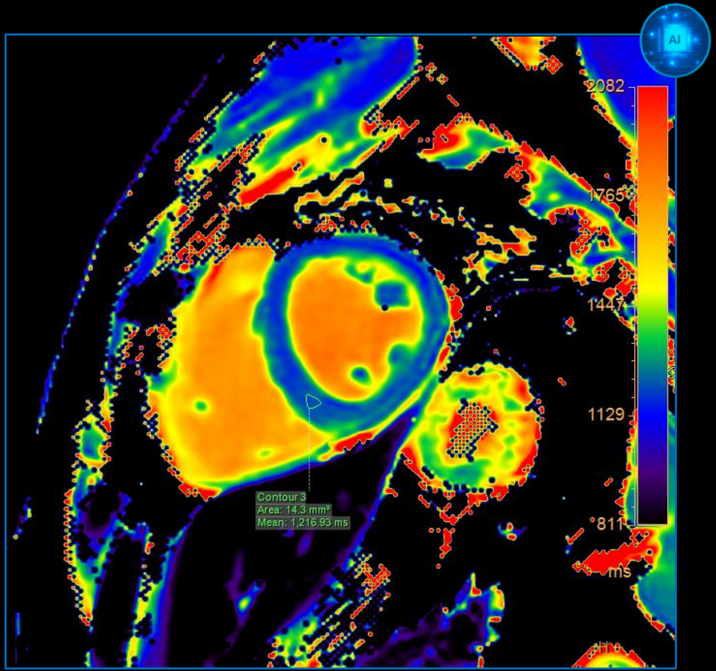
Ingenia Elition X 3.0T

Fast Quantitative Imaging

T1 Mapping protocol



T1 mapping SENSE
2x2x10mm
11s

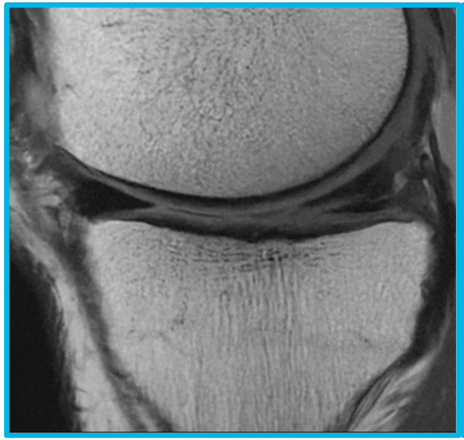


T1 mapping SmartSpeed
2x2x10mm
11s

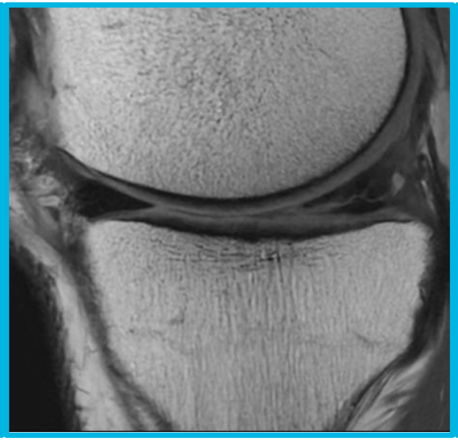
Courtesy: Tokyo Metropolitan Police Hospital, Japan

Ingenia Elition X 3.0T

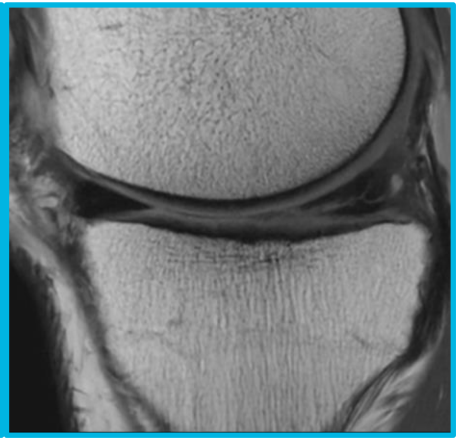
Acceleration by reducing the number of averages



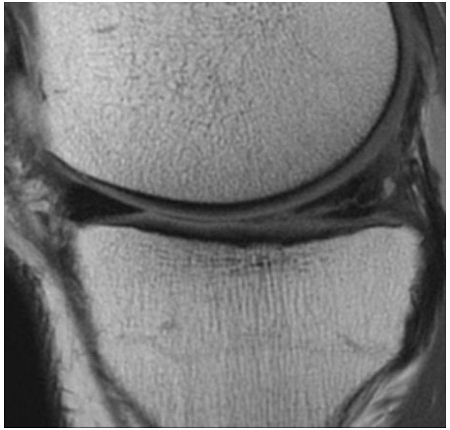
AIR™ Recon DL
0.3 x 0.3 x 3.0 mm
2 NEX
2:34 min.



AIR™ Recon DL
0.3 x 0.3 x 3.0 mm
4 NEX
5:02 min.



AIR™ Recon DL
0.3 x 0.3 x 3.0 mm
8 NEX
10:00 min.



Conventional
0.3 x 0.3 x 3.0 mm
16 NEX
19:54 min.

Courtesy of Marc Lebel

Artifacts in Undersampled MRI

Acquisition-related:

- We acquire less data: intrinsic SNR is reduced
- We acquire data differently, e.g. non-uniform sampling

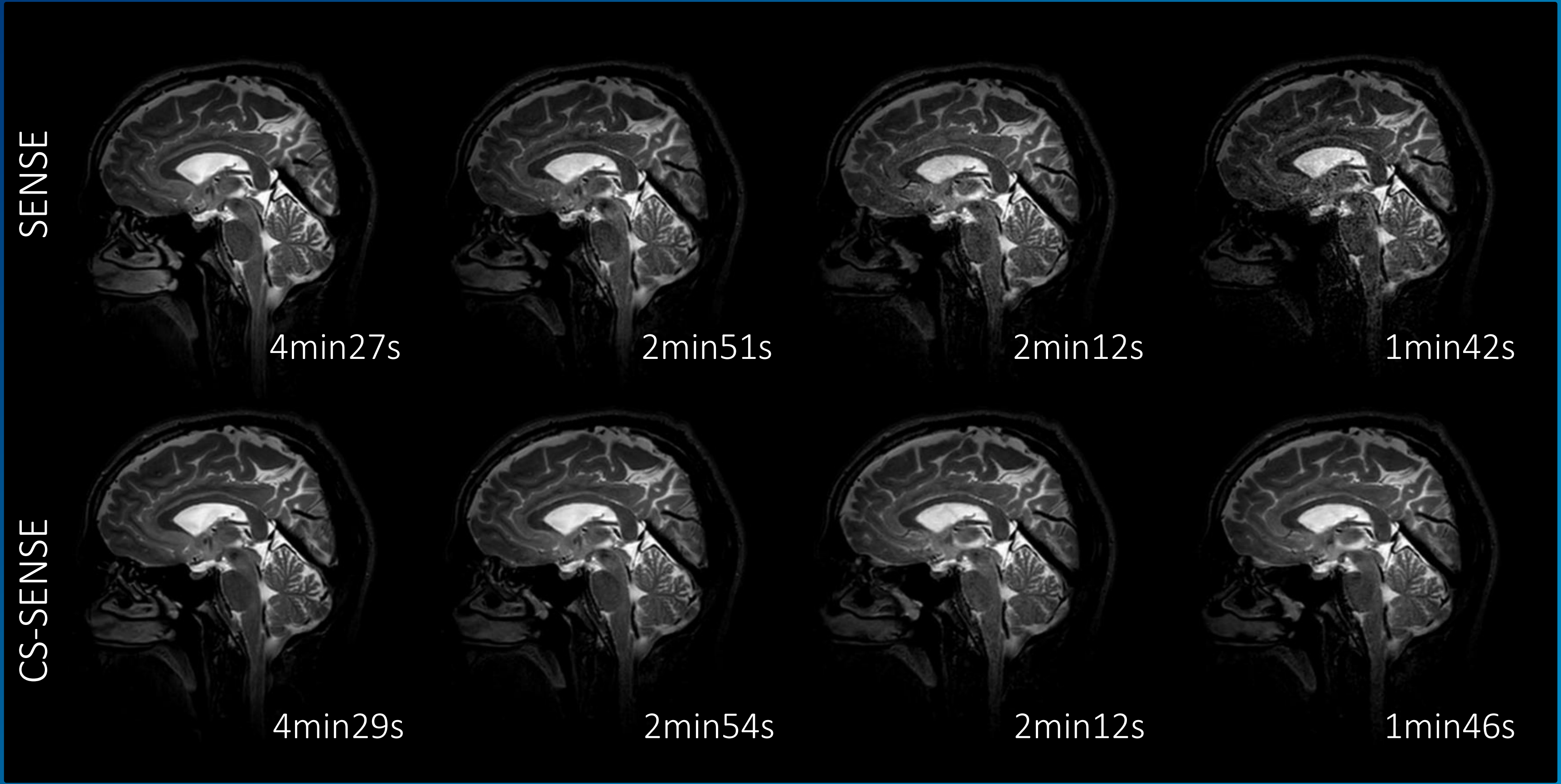
Reconstruction-related:

- Reconstruction applies prior knowledge: potential bias

Acquisition related artifacts

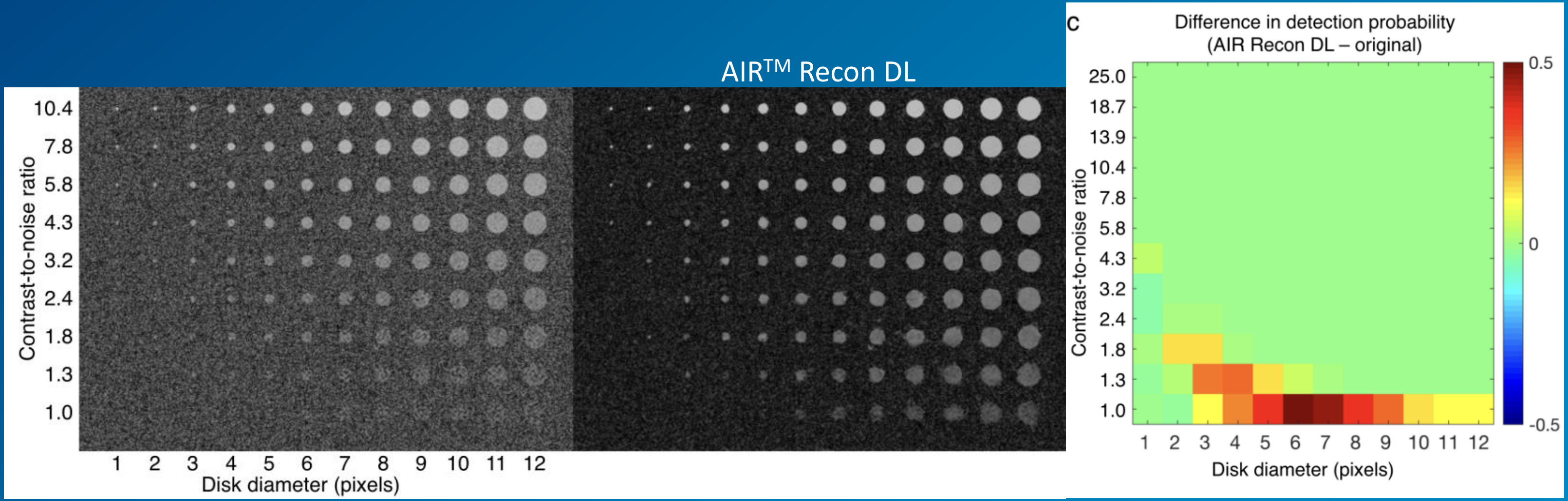
Increasing acceleration

3D T2W TSE – Higher acceleration leads to decreased SNR/reduced contrast



Low contrast detectability

– High contrast disks are clearly visible
– Low/moderate contrast disks have improved detectability with AIR Recon DL
– Very low contrast disks are abruptly and highly suppressed
  - It can be difficult to recognize critically low CNR



Courtesy M Lebel

Lebel, R.M. Performance characterization of a novel deep learning-based MR image reconstruction pipeline. August 2020. http://arxiv.org/abs/2008.06559

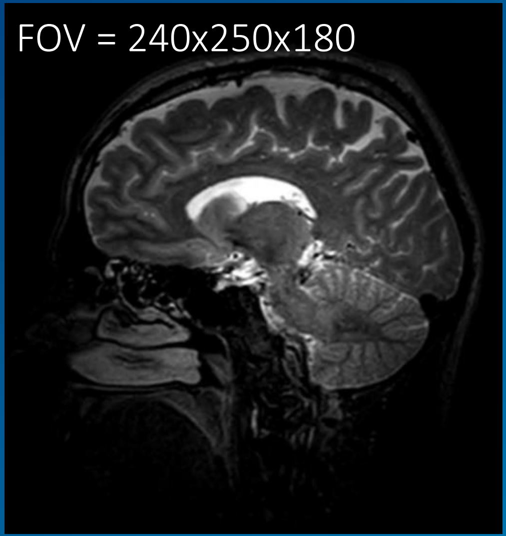
Reduced FOV

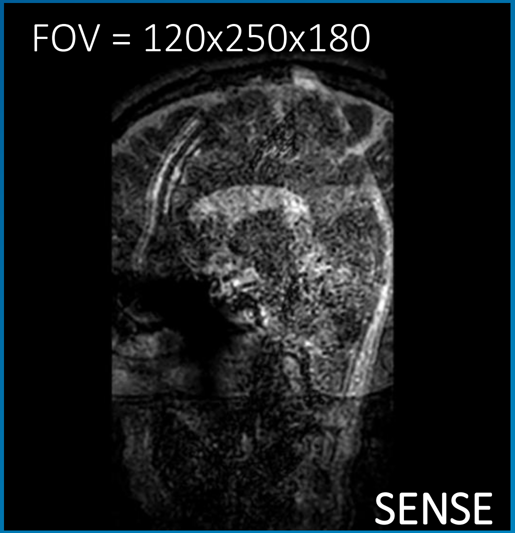
A too small FOV leads to foldover:

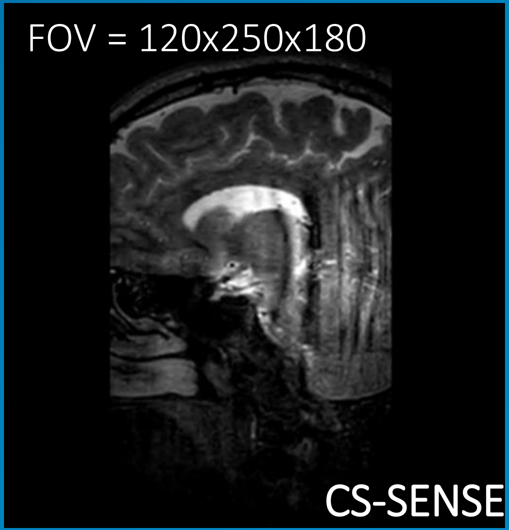
- Uniform undersampling: coherent artifacts
- Non-uniform sampling: incoherent artifacts

Mitigation approaches:

- accurate planning
- intrinsic fold-over suppression (CSM calibration scan)
- E-SPIRiT with multiple sets of CSM (auto-calibration)

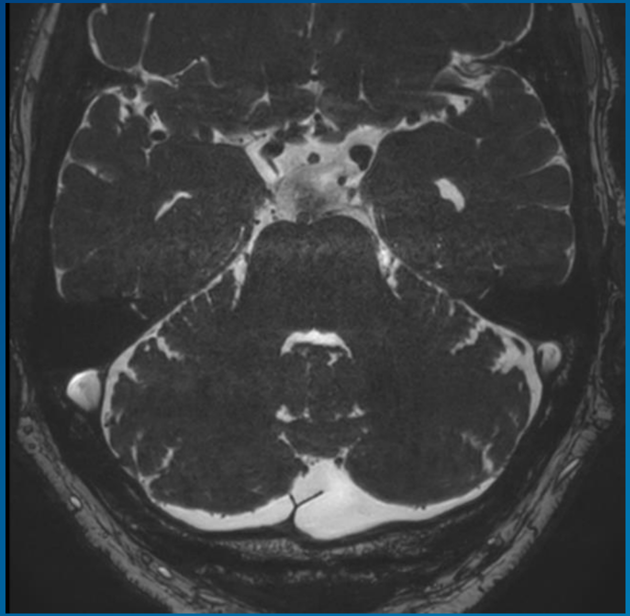




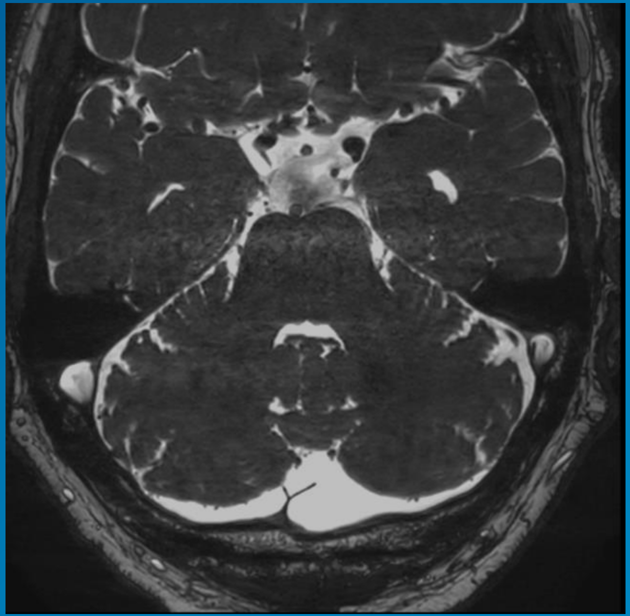


Pulsation artifacts

Pulsation artifacts are incoherent and spread over the PE direction



CS-SENSE

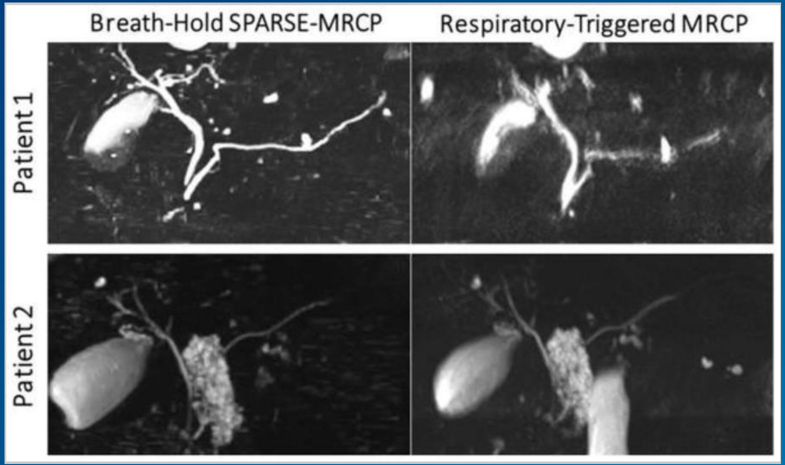


AI-based recon

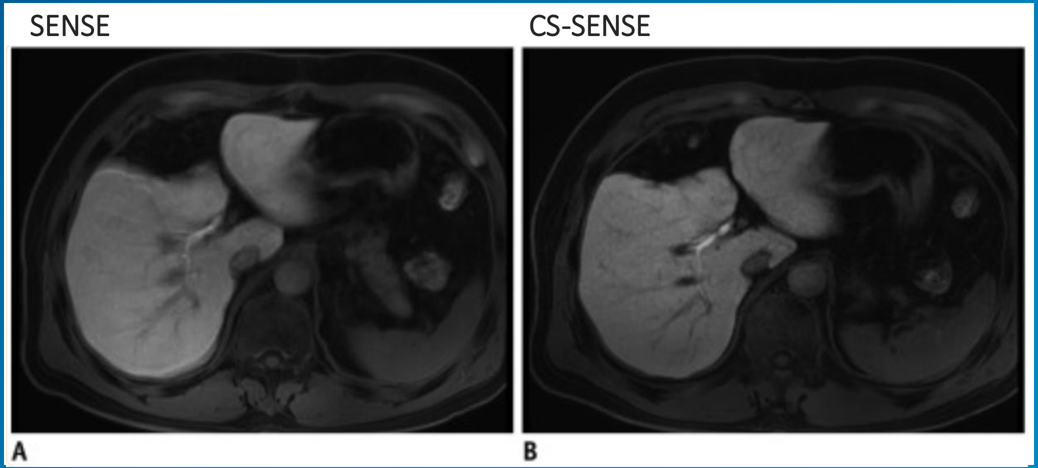
Motion artifacts

Reduced motion artifacts due to shorter scan

Breath-hold vs respiratory triggering [1)]



15s breath-hold   9s breath-hold [2)]



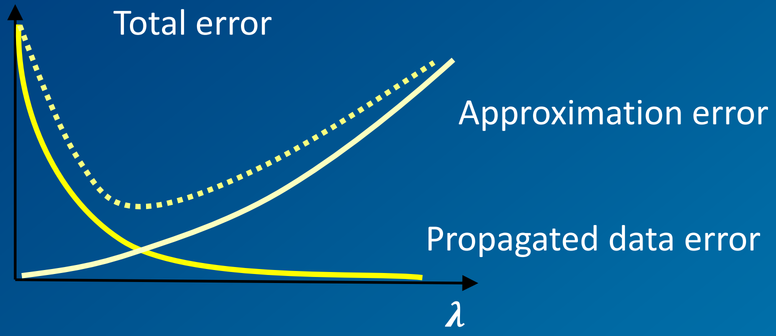
1) Feng L et al . JMRI 2017 45(4):966-987   2) Nam JG et al. KJR 2019 20(3):438-448

Reconstruction related artifacts

Compressed Sensing

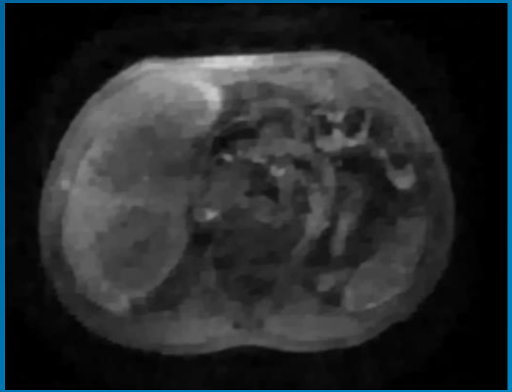
Regularization parameter selection

$$\hat{\boldsymbol{x}} = \operatorname{argmin} \|\boldsymbol{F}\boldsymbol{x} - \boldsymbol{y}\|_2^2 + \lambda \boldsymbol{R}(x)$$



- Too large λ leads to bias
- Too small λ leads to noise amplification/residual aliasing
- Good selection of λ range can be done automatically

TV artifacts



Wavelet artifacts

AI-based reconstruction

Learned prior quality related artifacts

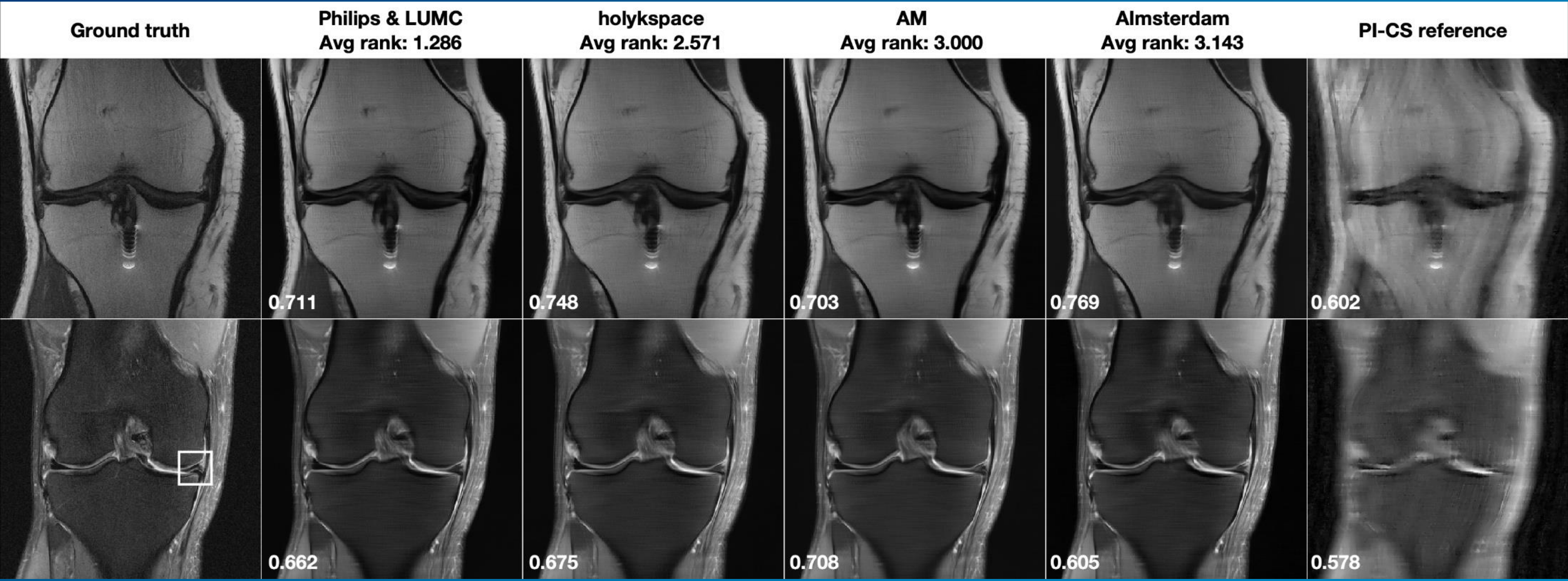
Not one but a thousand or even a million parameters ….

Factors influencing the image quality in AI-based reconstruction:

- Choice of network architecture
- How much data is used for training? Overfitting
- Is the data representative? Generalization to different contrasts and anatomies

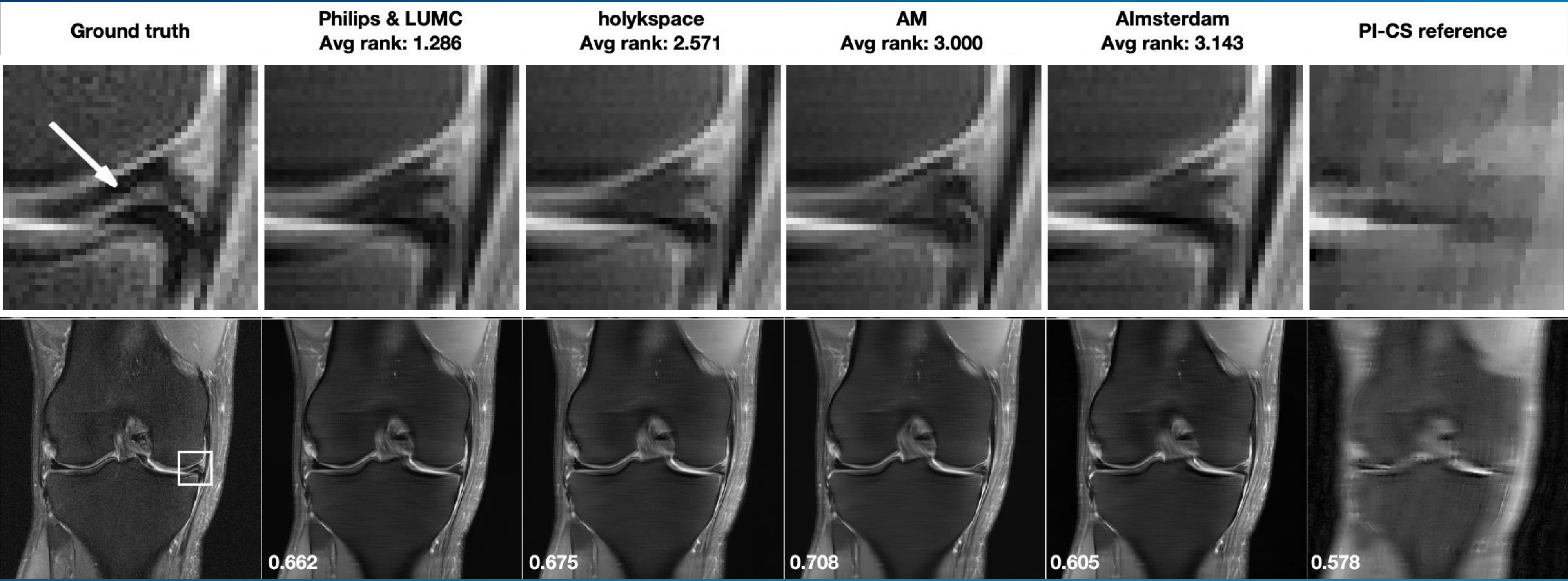
AI-recon: Results from the Fast MRI challenge

2019 multi coil R=8 results



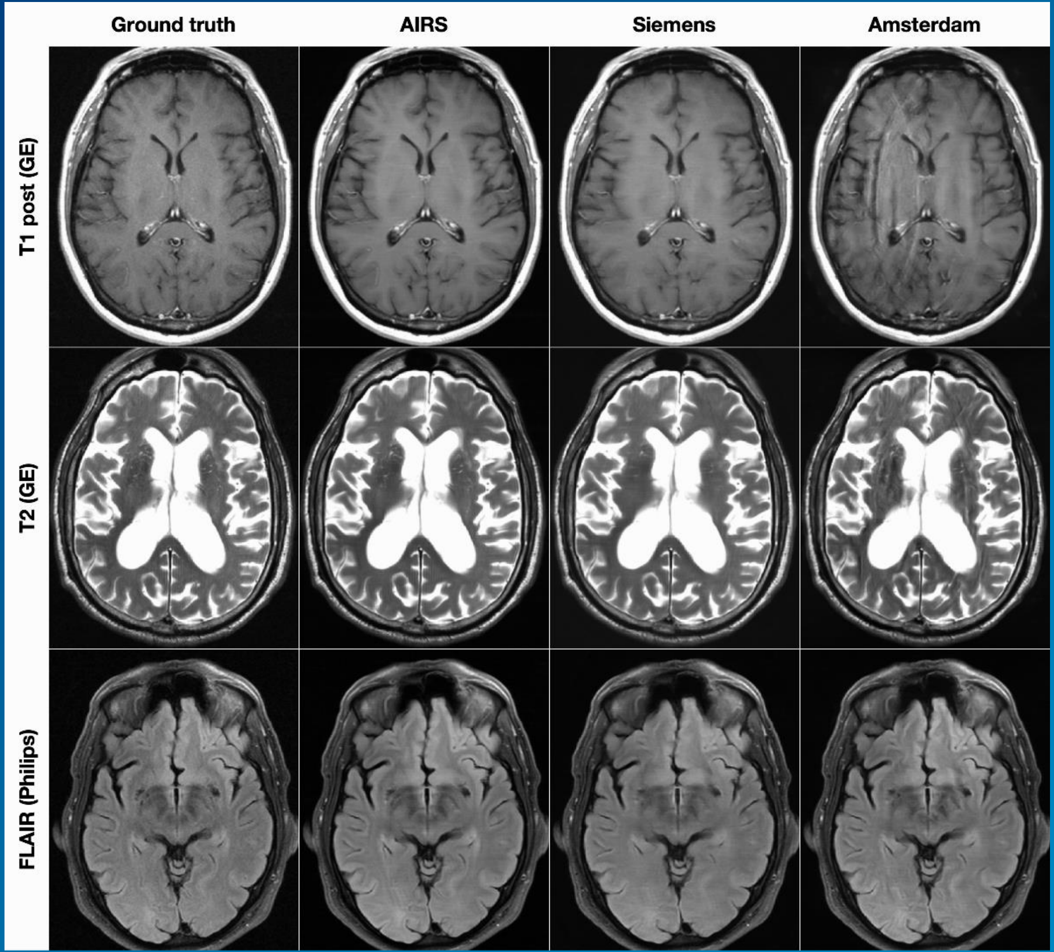
AI-recon: Results from the Fast MRI challenge

2019 multi coil R=8 results: Pathology



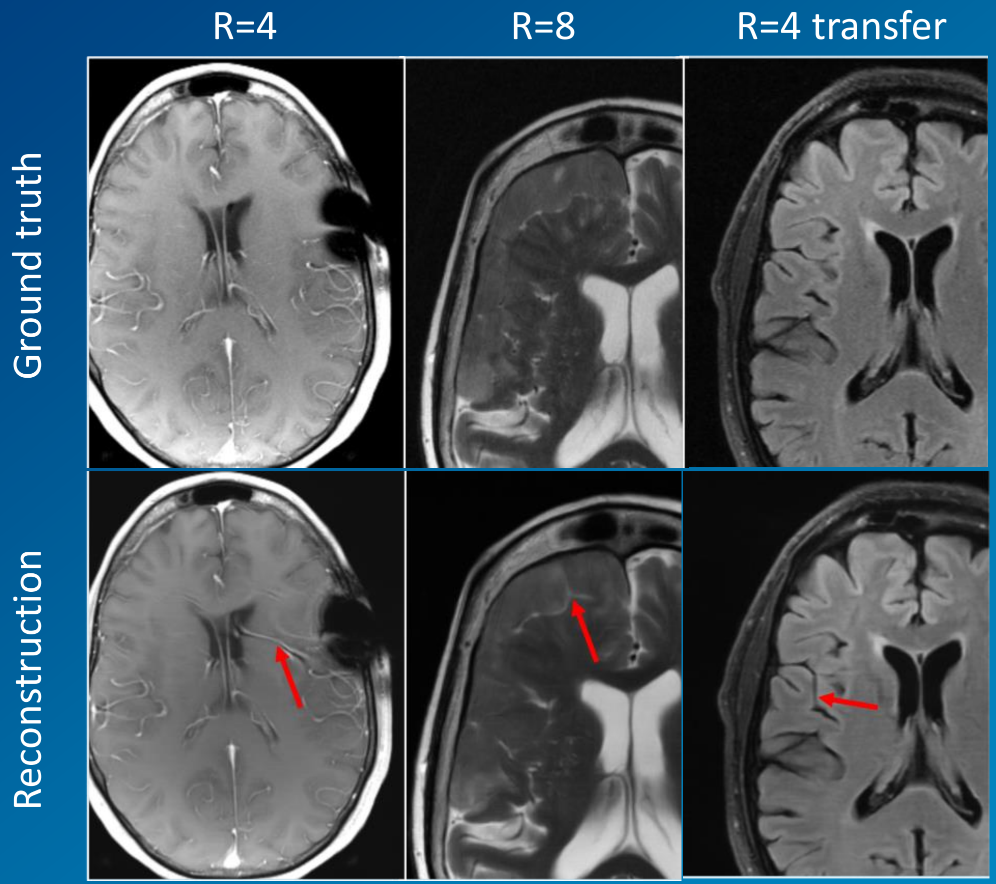
Knoll MRM 2020

AI-recon: 2020 multi coil R=4 transfer results



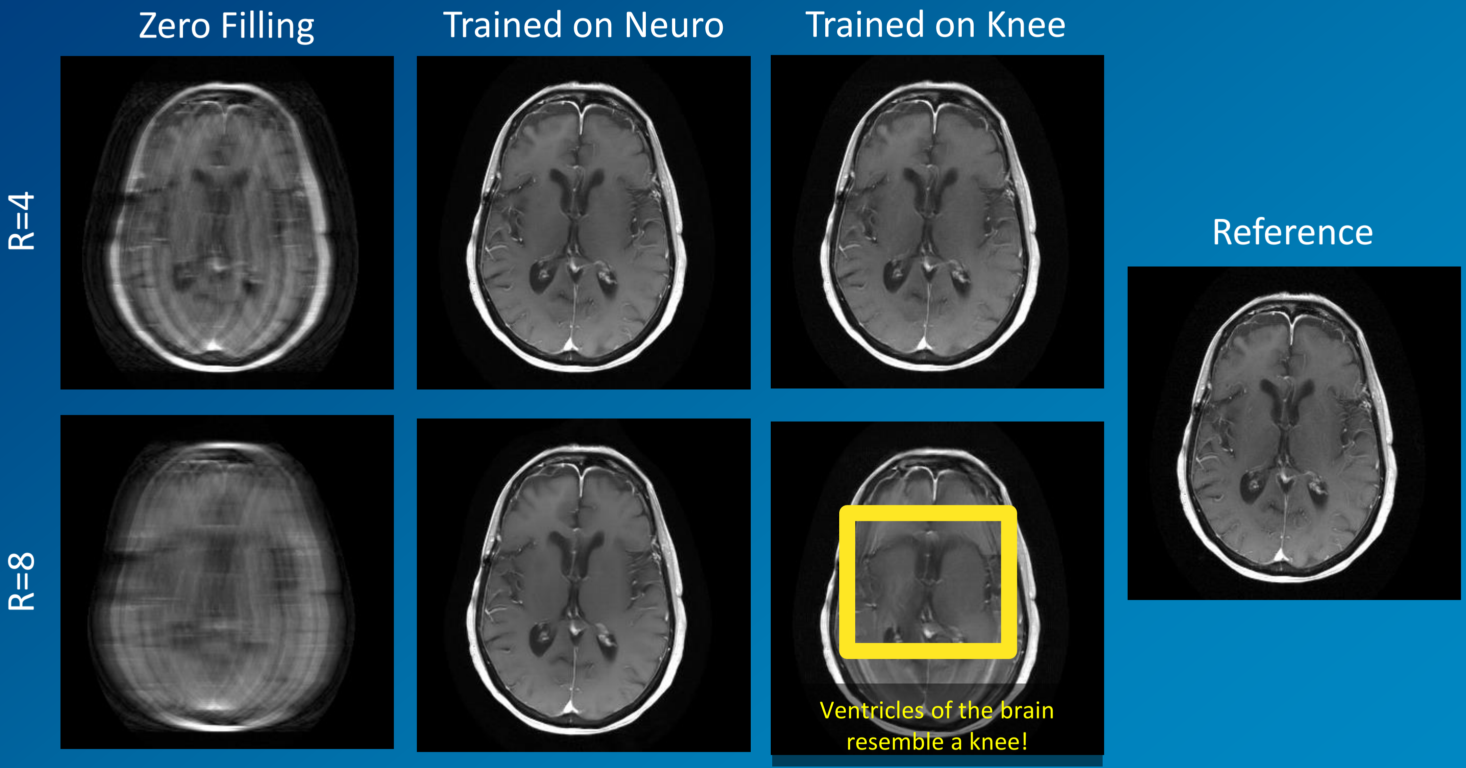
Muckley TMI 2021

AI recon: 2020 results Hallucinations



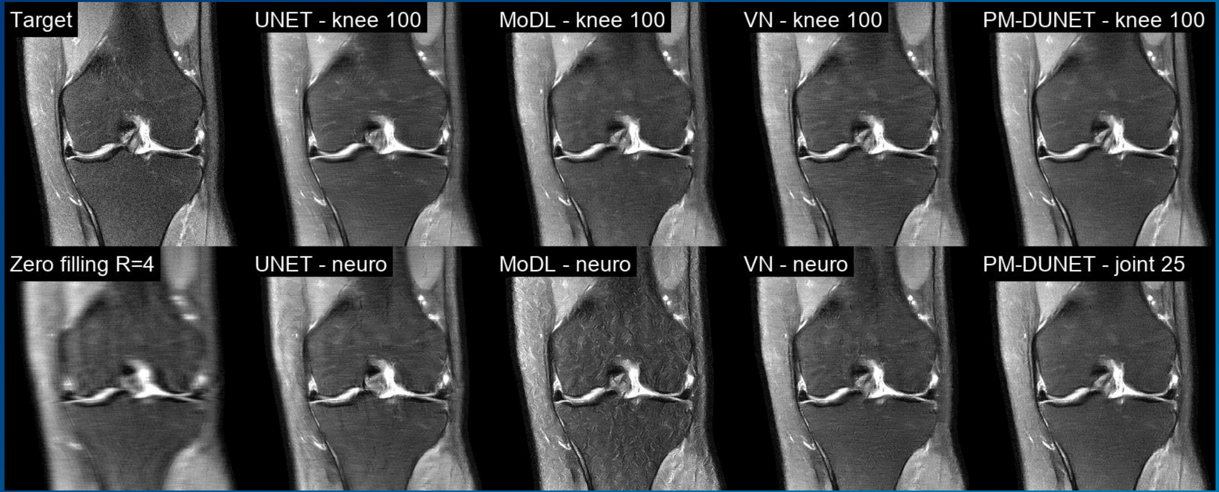
Muckley TMI 2021

Impact of domain shift in learned MRI reconstruction



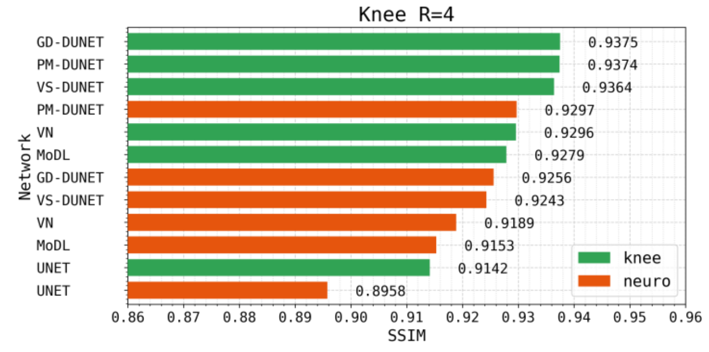
Courtesy K. Hammernik

Systematic Evaluation Knee R=4



Best training database

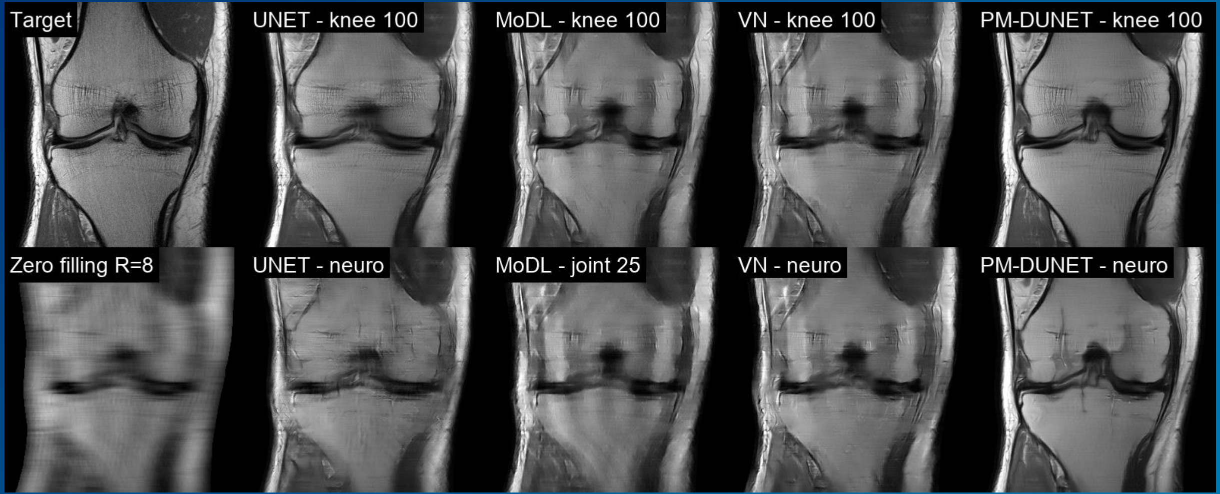
Worst training database



- Type of training data is less important

Courtesy K. Hammernik

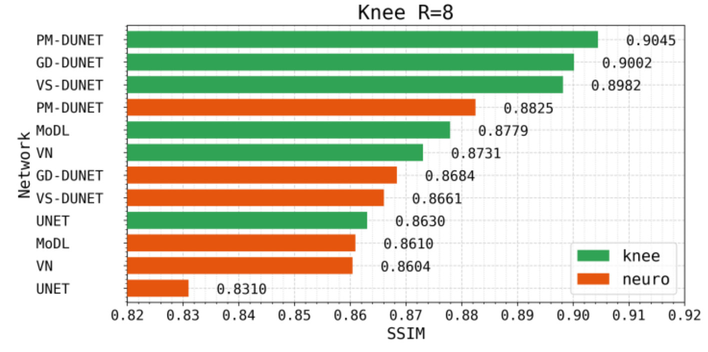
Systematic Evaluation Knee R=8



Best training database

Worst training database

- MoDL / VN fail for high acceleration
- Expressive regularization network is important
- Type of training data is more important for higher acceleration

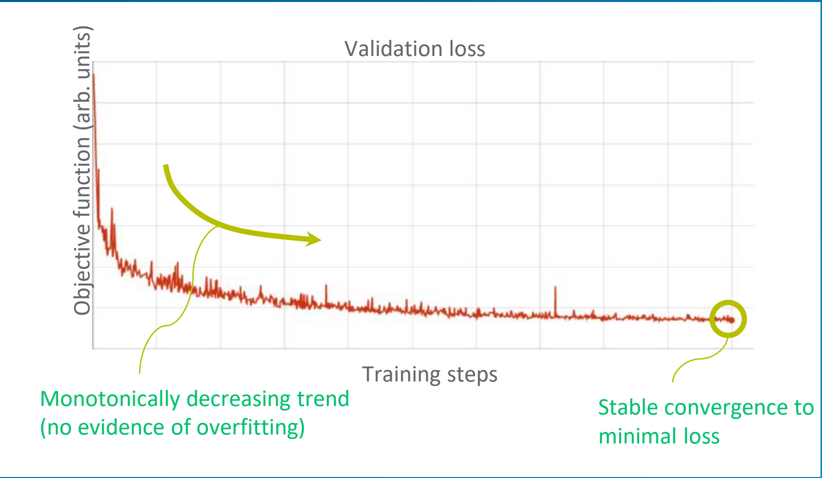


Courtesy K. Hammernik

Considerations for AI-based recon product development

Reliable behaviour is critical

- Must work regardless of the object or contrast weighting
- Maintain expected appearance of rare/uncommon artifacts
- Achieved with diverse training data, effective augmentations, boundaries on model behaviour, proper validation, and good data science practices



Summary and take home points

- CS and AI-based recon are very impactful scan acceleration techniques. Use them!
- Use acceleration responsibly! High acceleration leads to reduced SNR, blurring, loss of low contrast structures
- If you can, experiment with the parameters and try to push the acceleration limits (in a volunteer scan)
- Plan carefully. Too small FOV causes aliasing also with non-uniform sampling. Some safety mechanisms are most likely in place.
- If the image looks too blurry, try reducing the regularization strength/denoising level. If this does not help, try less acceleration.

Acknowledgements

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Marc Lebel
Mehmet Akcakaya