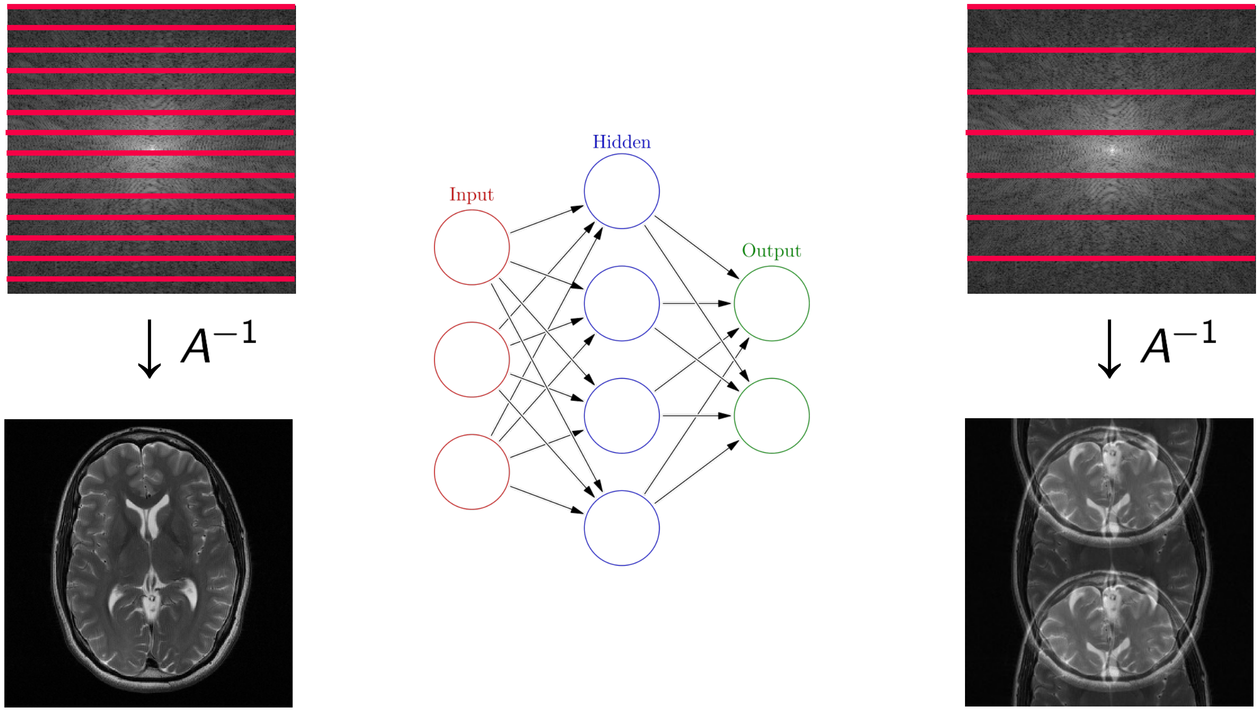
Computational MRI

Machine learning for image reconstruction

FRIEDRICH-ALEXANDER
UNIVERSITÄT
ERLANGEN-NÜRNBERG

NYU

ML image reconstruction

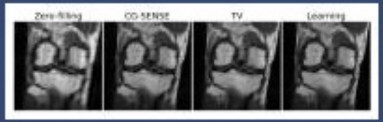


ISMRM 2016

08:00

magna cum laude

1088.

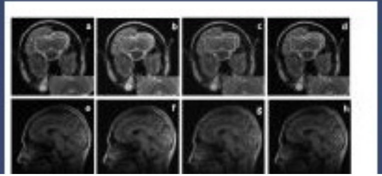


Learning a Variational Model for Compressed Sensing MRI Reconstruction

Kerstin Hammernik[1], Florian Knoll[2], Daniel K Sodickson[2], and Thomas Pock[1,3]

[1]Institute for Computer Graphics and Vision, Graz University of Technology, Graz, Austria and Research (CAI2R), Department of Radiology, NYU School of Medicine, New York, NY Technology GmbH, Vienna, Austria

1778.

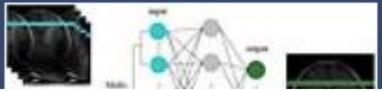


Exploiting deep convolutional neural network for fast magnetic resonance imaging

Shanshan Wang[1], Zhenghang Su[1,2], Leslie Ying[3], Xi Peng[1], and Dong Liang[1]

[1]Shenzhen Institutes of Advanced Technologies, Shenzhen, China, People's Republic of, [2]School of In Guangzhou, China, People's Republic of, [3]Department of Biomedical Engineering and Department o United States

1801.



Learning-based Reconstruction using Artificial Neural Network for Higher Acceleration

Kinam Kwon[1], Dongchan Kim[1], Hyunseok Seo[1], Jaejin Cho[1], Byungjai Kim[1], and HyunWook Park[1]

[1]KAIST, Daejeon, Korea, Republic of

ISMRM 2017

5663

Improving the PI+CS Reconstruction for Highly Undersampled Multi-contrast MRI using Local Deep Network

Enhao Gong[1], Greg Zaharchuk[2], and John Pauly[1]

3988

A Study of Simulated Training Data for Image Reconstruction from Subsampled MR Data using Artificial Neural Network

kinam kwon[1], Jaejin Cho[1], Seohee So[1], Byungjai Kim[1], Yoonmee Lee[1], kyungtak Min[1], and HyunWook Park[1]

0645

ccelerated knee imaging using a deep learning based econstruction

rian Knoll[1,2], Kerstin Hammernik[3], Elisabeth Garwood[1,2], Anna Hirschmann[4], Leon Rybak[1,2], Mary Bruno[1,2], Tobias Block[1,2], ies Babb[1,2], Thomas Pock[3,5], Daniel K Sodickson[1,2], and Michael P Recht[1,2]

0640

Neural Network MR Image Reconstruction with AUTOMAP: Automated Transform by Manifold Approximation

Bo Zhu[1,2,3], Jeremiah Z. Liu[1,4], Bruce R. Rosen[1,2], and Matthew S. Rosen[1,2,3]

Undersampling trajectory design for fast MRI with super-resolution convolutional neural network

Shanshan Wang[1], Taohui Xiao[1,2], Sha Tan[1,3], Yuanyuan Liu[1], Leslie Ying[4], and Dong Liang[1]

0688

Deep learning for fast MR Fingerprinting Reconstruction

Ouri Cohen[1,2], Bo Zhu[1,2], and Matthew S. Rosen[1,3]

0690

Accelerated Projection Reconstru Deep Residual Learning

Yo Seob Han[1], Dongwook Lee[1], JaeJun Yoo[1], and Jong Chu

0643

A Deep Cascade of Convolutional Neura Image Reconstruction

Jo Schlemper[1], Jose Caballero, Joseph V. Hajnal[2], Anthony Price[2], and Daniel Rueckert[3]

0644

ng Pattern Design on struction

and Thomas Pock[1,4]

3974

Cascaded Convolutional Neural Network (CNN) for Reconstruction of Undersampled Magnetic Resonance (MR) Images

Taejoon Eo[1], Yohan Jun[1], Taeseong Kim[1], Jinseong Jang[1], and Dosik Hwang[1]

0687

L2 or not L2: Impact of Loss Function Design for Deep Learning MRI Reconstruction

Kerstin Hammernik[1], Florian Knoll[2,3], Daniel K Sodickson[2,3], and Thomas Pock[1,4]

0641

Compressed sensing and Parall learning

1D Partial Fourier Parallel MR imaging with deep convolutional neural network

Shanshan Wang[1], Ningbo Huang[1,2], Tao Zhao[1,3], Yong Yang[2], Leslie Ying[4], and Dong Liang[1]

0686

Deep Convolutional Neural Network for Acceleration of Magnetic Resonance Angiography (MRA)

Yohan Jun[1], Taejoon Eo[1], Taeseong Kim[1], Jinseong Jang[1], and Dosik Hwang[1]

3985

Feasibility of Multi-contrast MR imaging via deep learning

Shanshan Wang[1], Tao Zhao[1,2], Ningbo Huang[1,3], Sha Tan[1,4], Yuanyuan Liu[1], Leslie Ying[5], and Dong Liang[1]

ISMRM Workshop on

Machine Learning

14-17 MARCH 2018

Chair:
Greg Zaharchuk, M.D., Ph.D., Stanford University, Stanford, CA, USA

ISMRM Workshop on

Machine Learning
Part II

25-28 October 2018

Chair: Greg Zaharchuk, M.D., Ph.D., Stanford University, Stanford, CA, USA
Vice-Chair: Florian Knoll, Ph.D., New York University School of Medicine, New York, NY, USA

Machine Learning for Medical Image Reconstruction (MLMIR)

MICCAI 2018 Granada SPAIN

Machine Learning for Medical Image Reconstruction (MLMIR)

International BASP Frontiers workshop 2019

February 3 - 8, 2019 - Villars-sur-Ollon, Switzerland

Machine Learning for Medical Image Reconstruction

ABSTRACT

Machine learning and artificial intelligence are expected to play an increasingly important role in our healthcare system, and in particular in imaging. While these technologies are usually associated with developments that aim to extract diagnostic information from medical images, research activities with the goal of using machine learning for image reconstruction have picked up significantly over the last two years. The presentations in this session will cover novel core machine learning developments like model architectures and learning algorithms, as well as application to MRI and CT reconstruction.

More on 'Detailed programme'

Organizer and Chair : Dr. ***Florian Knoll***

ISMRM Workshop on

Data Sampling & Image Reconstruction

26-29 January 2020 • Enchantment Resort, Sedona, AZ, USA

Session 3: Machine Learning

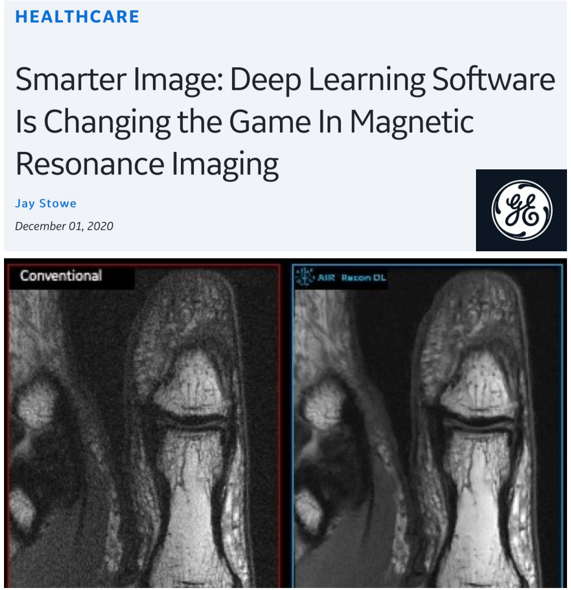
Moderators: Mariya Doneva, Ph.D., Florian Knoll, Ph.D. & Michael Lustig, Ph.D.

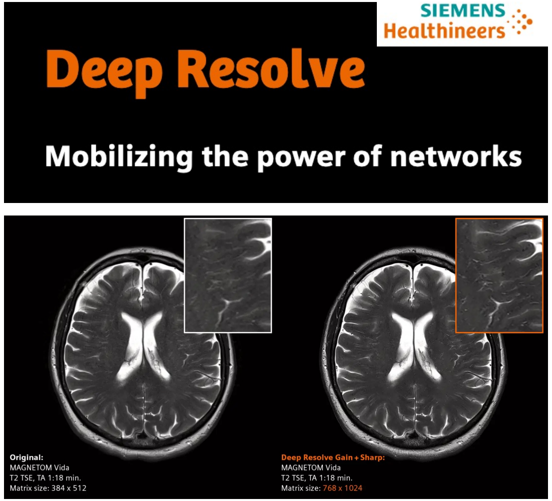
16:00	Basics of Machine Learning for Image Reconstruction	Kerstin Hammernik, Ph.D. Imperial College London London, England, UK
16:20	Learning Image Reconstruction with MR Physics Knowledge	Mehmet Akcakaya, Ph.D. University of Minnesota Minneapolis, MN, USA
16:30	Image Enhancement	Daniel Rueckert, Ph.D. Imperial College London London, England, UK
16:40	Panel Discussion	

Proffered Papers - Oral Session

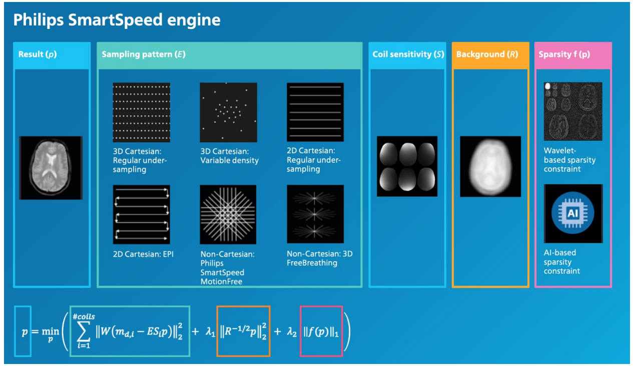
17:00	2-Minute Comprehensive Brain Exam Using Multi-Shot EPI with Synergistic Model-Based & Deep Learning Reconstruction	Wei-Ching Lo, M.Sc. Siemens Medical Solutions Malvern, PA, USA
17:10	Unsupervised Image Reconstruction Using Deep Generative Adversarial Networks	Elizabeth Cole, M.Sc. Stanford University Stanford, CA, USA

2022

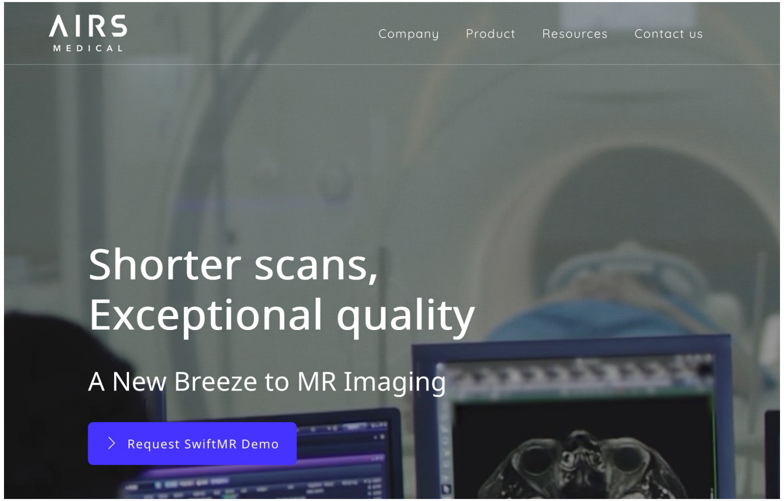

HEALTHCARE
Smarter Image: Deep Learning Software Is Changing the Game In Magnetic Resonance Imaging
Jay Stowe
December 01, 2020
Conventional
AIR Recon DL


SIEMENS Healthineers
Deep Resolve
Mobilizing the power of networks
Original:
MAGNETOM Vida
T2 TSE, TA 1:18 min.
Matrix size: 384 x 512
Deep Resolve Gain + Sharp:
MAGNETOM Vida
T2 TSE, TA 1:18 min.
Matrix size: 768 x 1024


PHILIPS
SmartSpeed
Science brief


Philips SmartSpeed engine
Result (p)
Sampling pattern (E)
Coil sensitivity (S)
Background (R)
Sparsity f (p)
3D Cartesian: Regular under-sampling
3D Cartesian: Variable density
2D Cartesian: Regular under-sampling
Wavelet-based sparsity constraint
2D Cartesian: EPI
Non-Cartesian: Philips SmartSpeed MotionFree
Non-Cartesian: 3D FreeBreathing
AI-based sparsity constraint
$p = \min_p \left(\sum_{i=1}^{\#coils} \|W(m_{d,i} - ES_i p)\|_2^2 + \lambda_1 \|R^{-1/2} p\|_2^2 + \lambda_2 \|f(p)\|_1 \right)$

2022



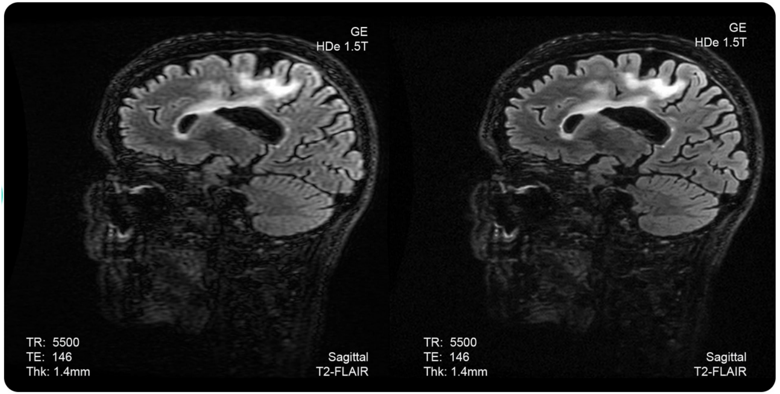
MRI scans, in just half the time

SUBTLE MEDICAL

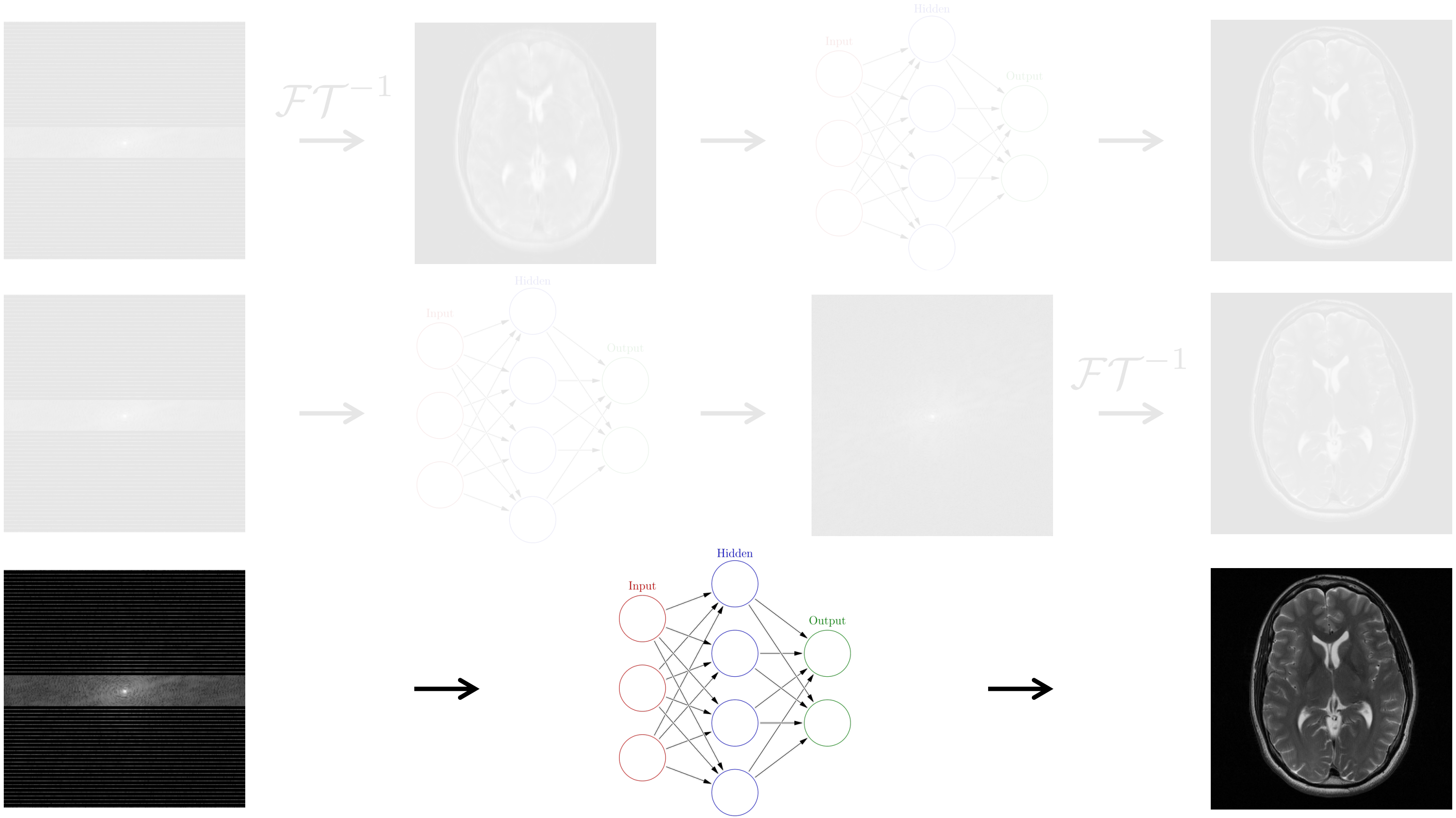
SubtleMR™ is a software solution that improves the quality of faster MRI images with increased resolution and denoising.

As Acquired

SubtleMR Enhanced

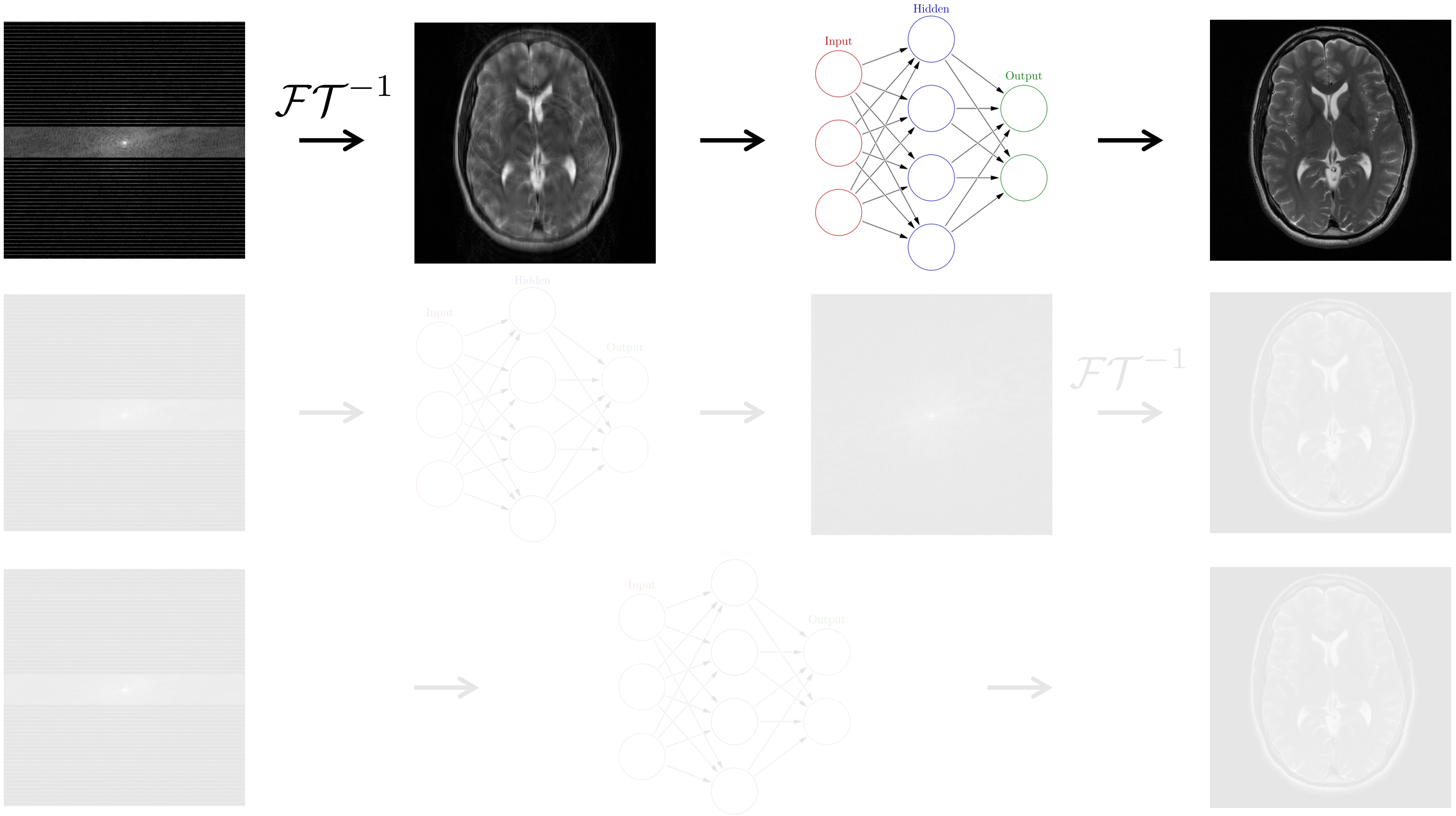


Approaches



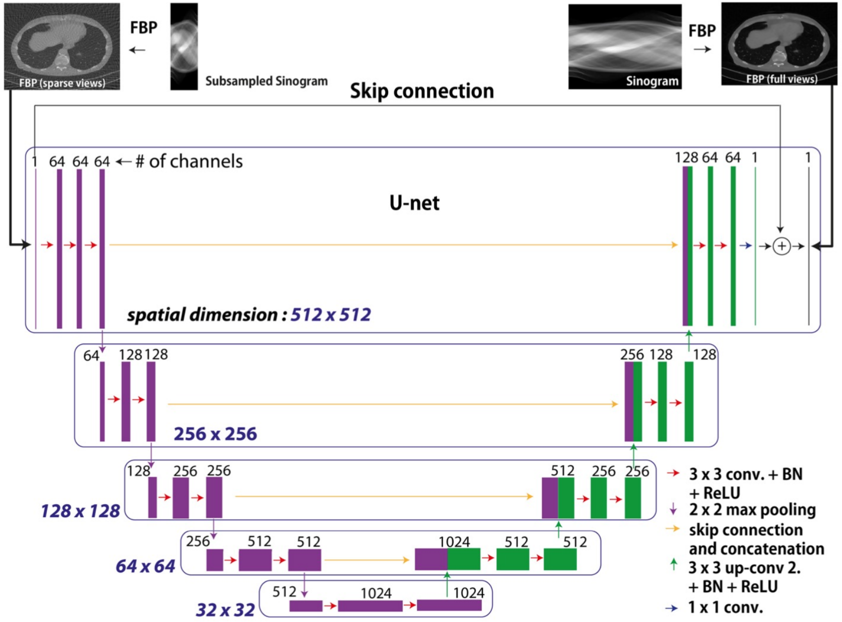
$\mathcal{FT}^{-1}$
Hidden
Input
Output
Hidden
Input
Output
$\mathcal{FT}^{-1}$
Hidden
Input
Output

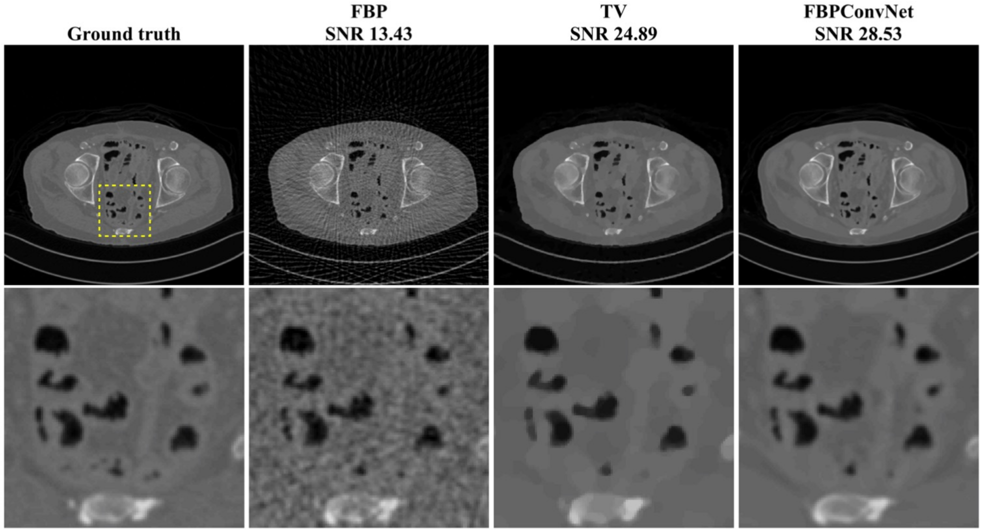
Approaches 1: Image processing based



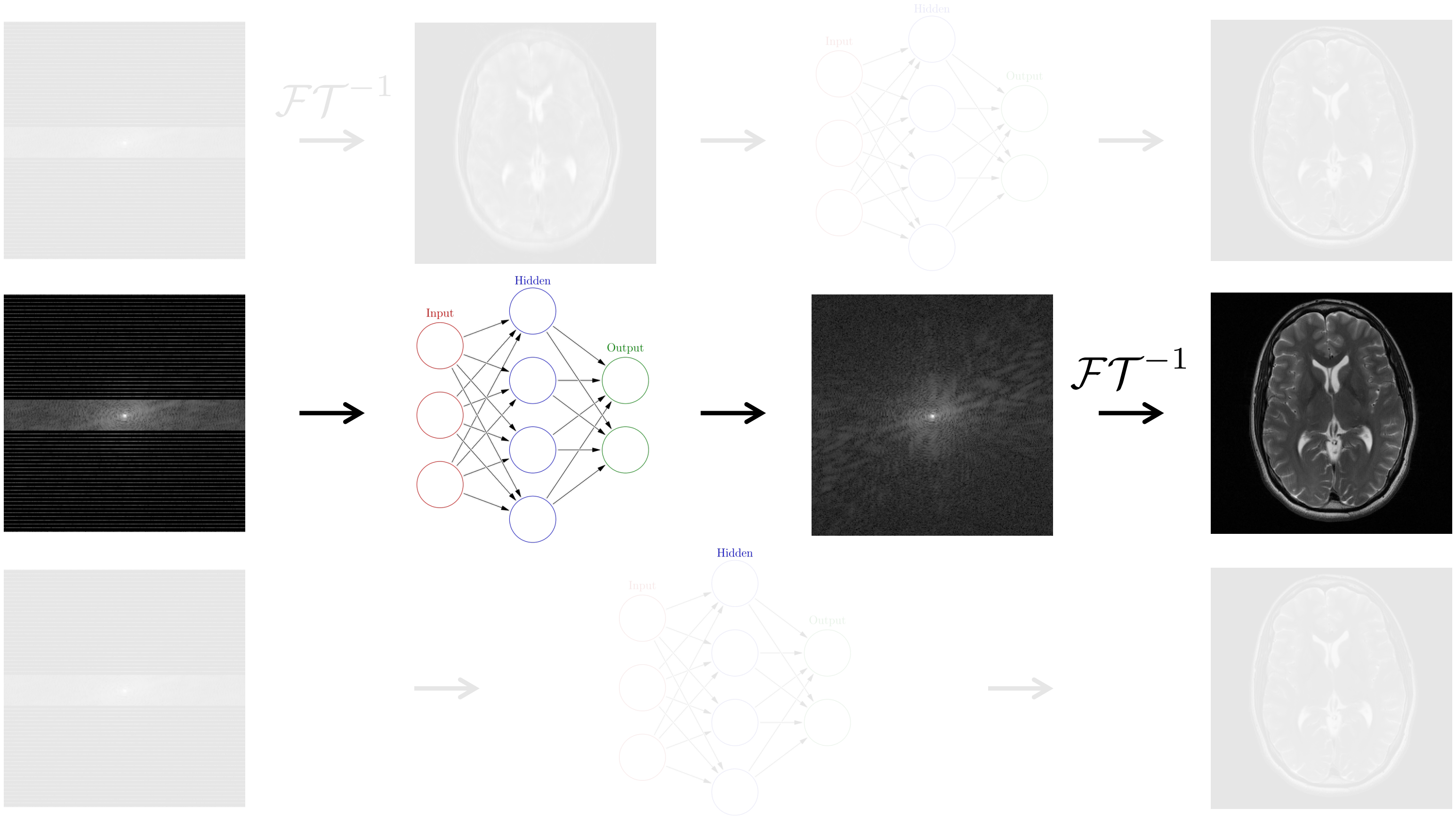
Deep Convolutional Neural Network for Inverse Problems in Imaging

Kyong Hwan Jin, Michael T. McCann, *Member, IEEE*, Emmanuel Froustey, and Michael Unser, *Fellow, IEEE*





Approaches 2: k-space recovery



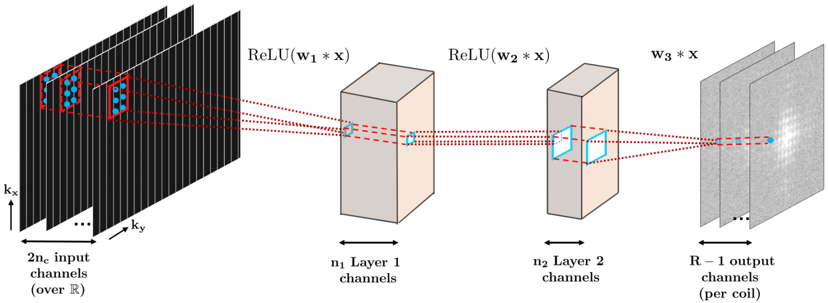
Received: 8 September 2017 | Revised: 27 April 2018 | Accepted: 2 June 2018
DOI: 10.1002/mrm.27420

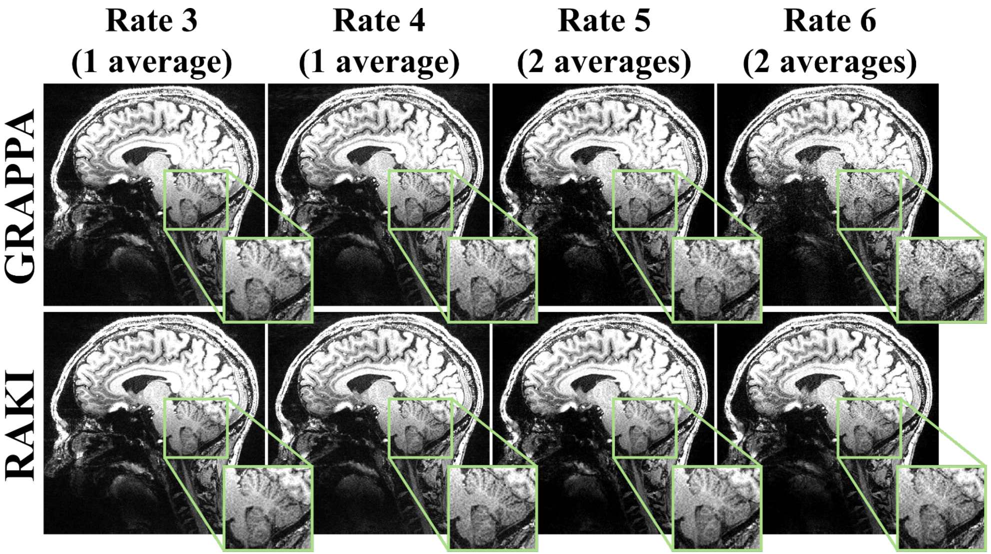
FULL PAPER
Magnetic Resonance in Medicine

Scan-specific robust artificial-neural-networks for k-space interpolation (RAKI) reconstruction: Database-free deep learning for fast imaging

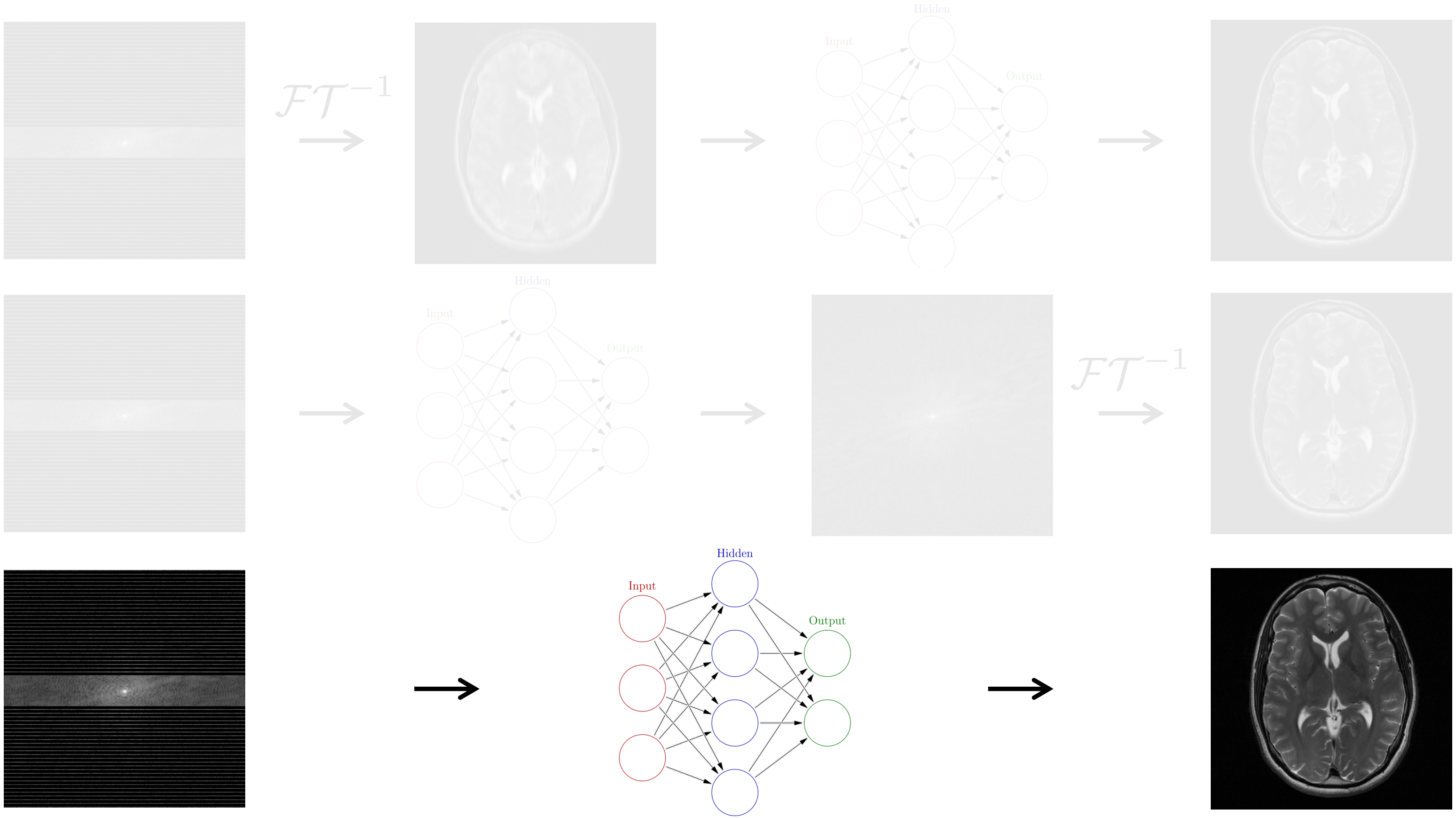
Mehmet Akçakaya[1,2] | Steen Moeller[2] | Sebastian Weingärtner[1,2,3] | Kâmil Uğurbil[2]

不需要大量dataset



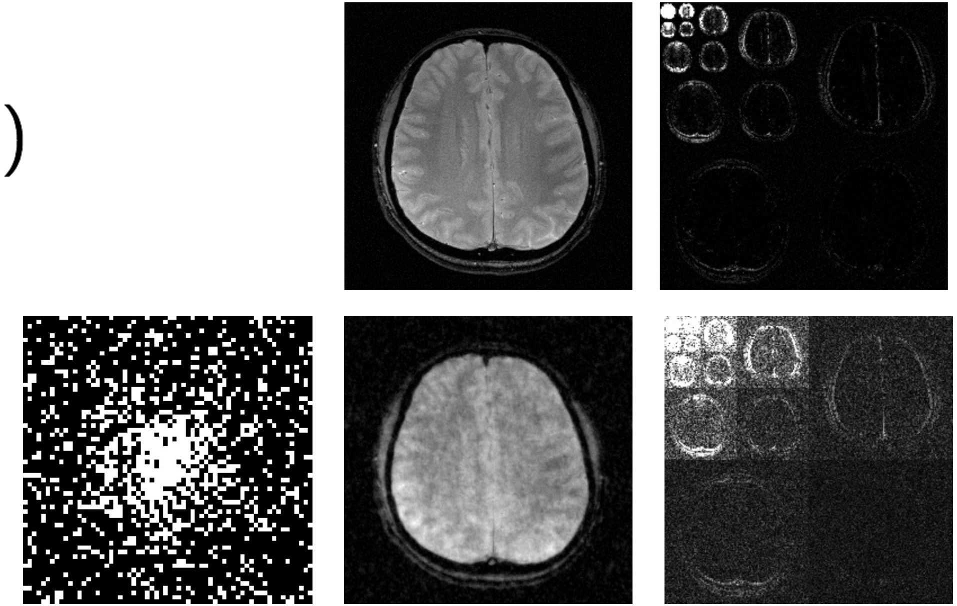


Approaches 3: DL iterative reconstruction



Compressed sensing: Sparse representation

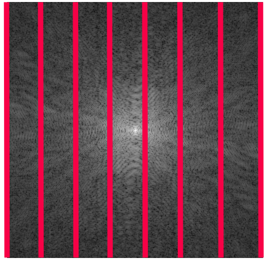
$$\min_u \frac{\lambda}{2}||Au - f||_2^2 + \mathcal{R}(u)$$



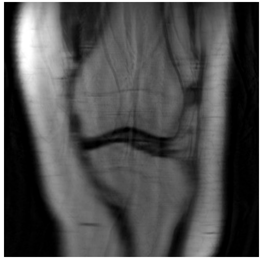
Lustig MRM (2007)

Numerical implementation

f

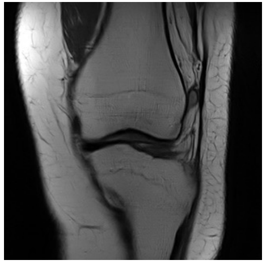


u_0



input

$\longrightarrow$ GD_1 $\longrightarrow$ GD_t $\longrightarrow$ GD_T $\xrightarrow{u_T}$



reconstruction

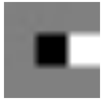
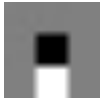
$$u_t = u_{t-1} - \frac{\partial}{\partial u}\left(\frac{\lambda}{2}||Au_{t-1} - f||_2^2 + \mathcal{R}(u_{t-1})\right)$$

Landweber Amer J Math 1951

CS → machine learning image reconstruction

Fully sampled | Zero-filling R=4

- Separate artifacts from image content
- Sparsifying transform → Spatial filter kernels

 ∇_x  ∇_y $K_i u \Leftrightarrow k_i * u$

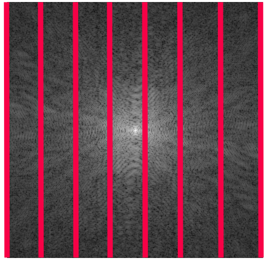
- L1 norm → Potential functions

$$\min_u \frac{\lambda}{2}||Au - f||_2^2 + \sum_i \rho_i(K_i u)$$

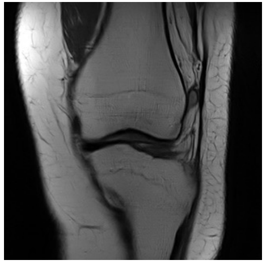
Hammernik ISMRM 2016, MRM 2018

Learning the numerical optimization

f

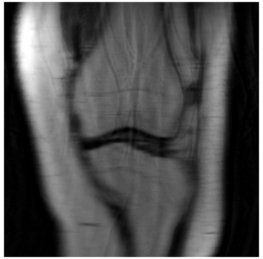


$\longrightarrow$ GD_1 $\longrightarrow$ GD_t $\longrightarrow$ GD_T $\xrightarrow{u_T}$



reconstruction

u_0

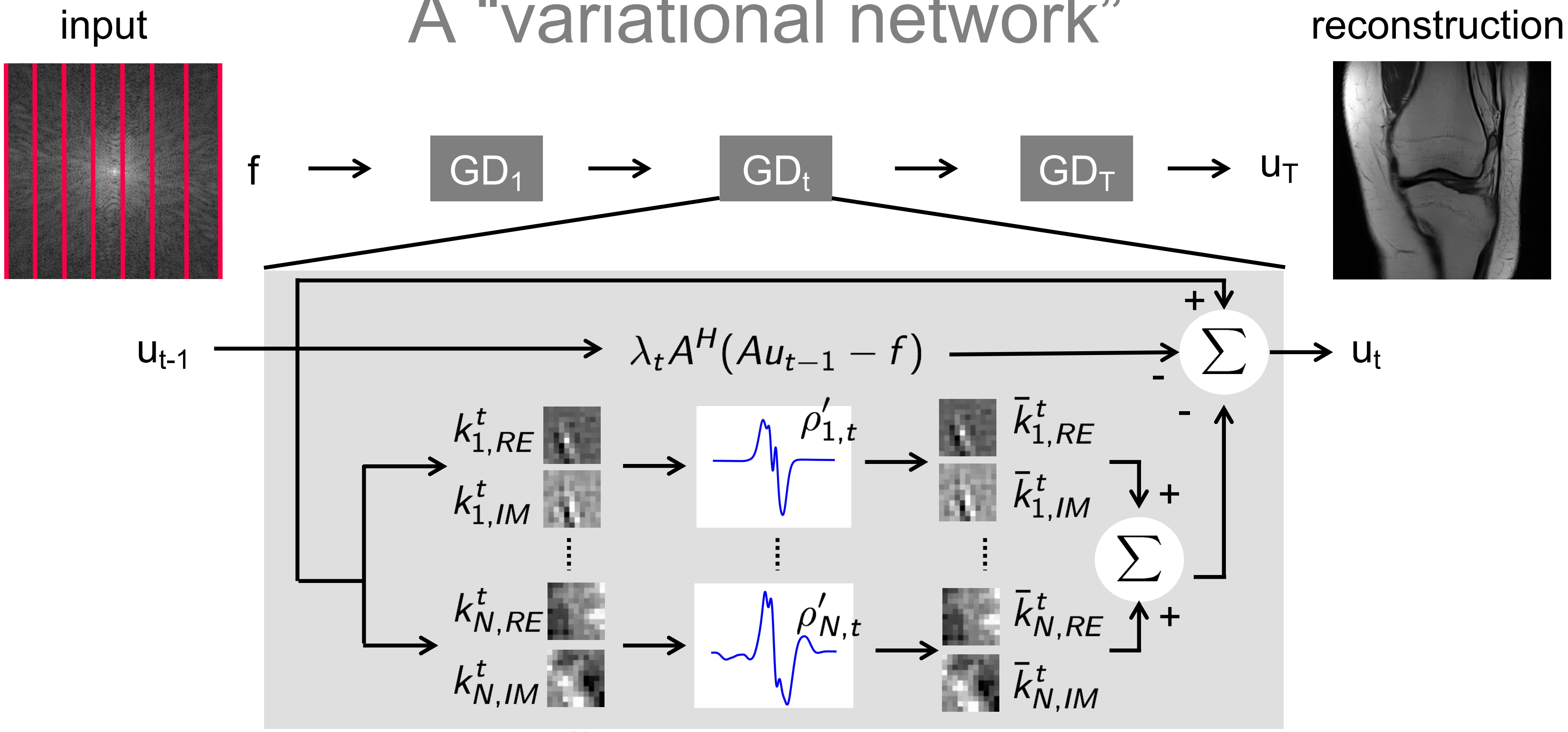


input

Learn T gradient descent (GD) steps

$$u_t = u_{t-1} - \sum_{i}^{N} K_{i,t}^{T} \rho'_{i,t}(K_{i,t} u_{t-1}) - \lambda_t A^H (A u_{t-1} - f)$$

A “variational network”

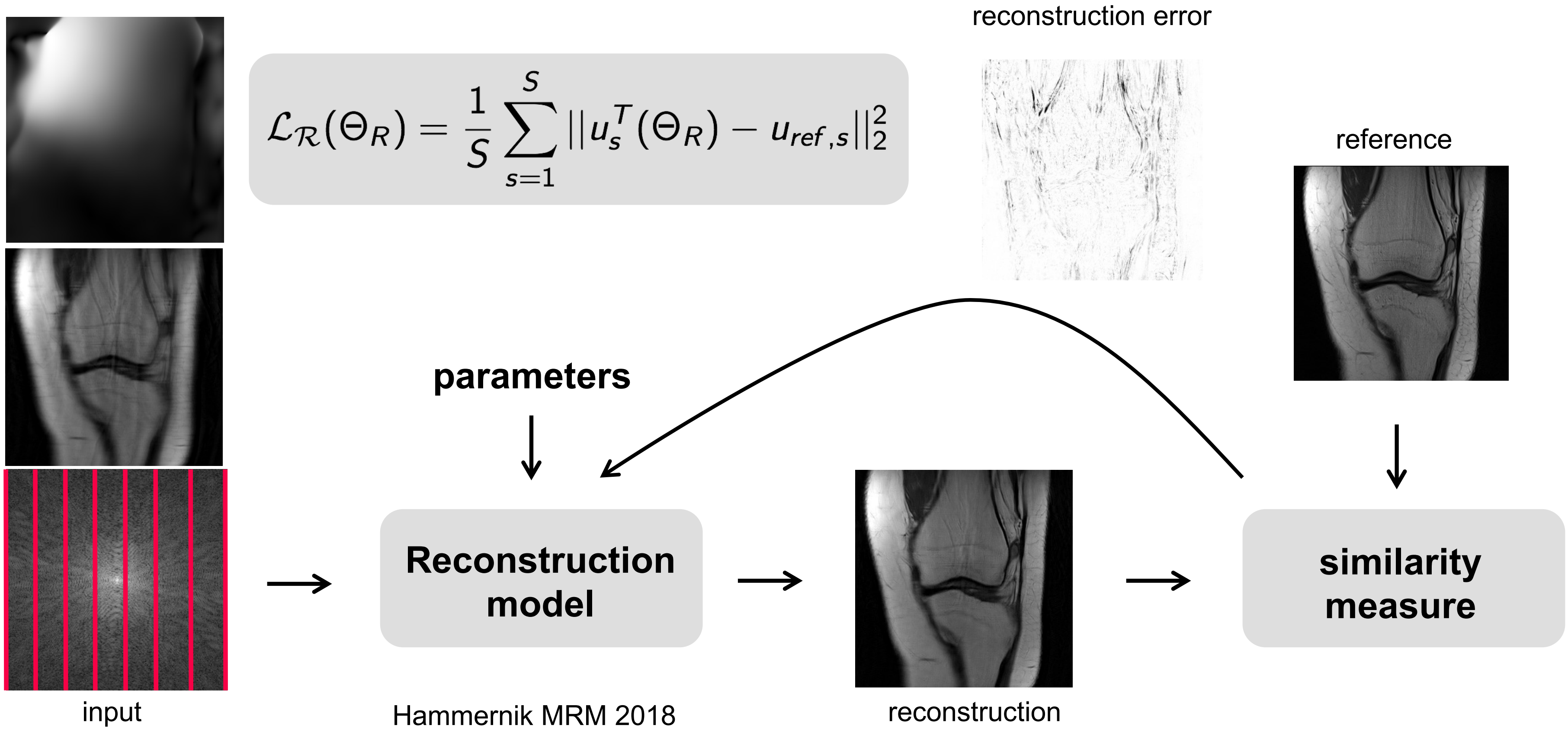


$$u_t = u_{t-1} - \sum_{i}^{N} K_{i,t}^T \rho'_{i,t}(K_{i,t} u_{t-1}) - \lambda_t A^H(Au_{t-1} - f)$$

Hammernik ISMRM 2016
Hammernik MRM 2018

Learning for image reconstruction

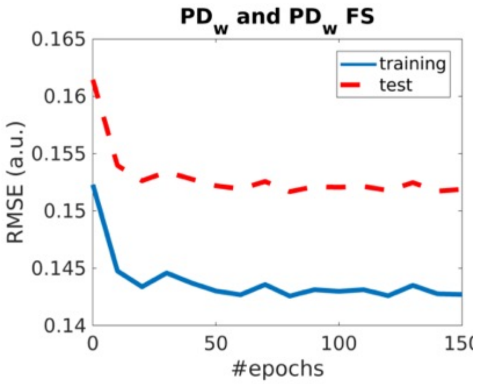
$$\mathcal{L}_{\mathcal{R}}(\Theta_R) = \frac{1}{S}\sum_{s=1}^{S} ||u_s^T(\Theta_R) - u_{ref,s}||_2^2$$

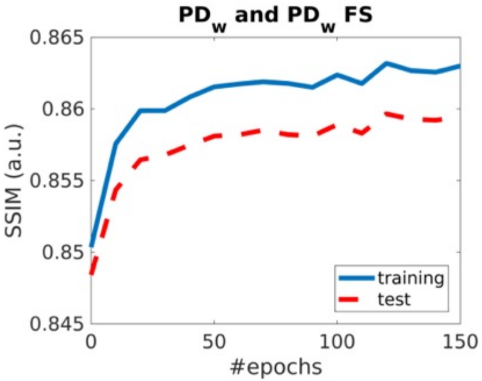


Hammernik MRM 2018

Training setup

- 3T knee exams, 15 channel knee coil, 5 sequences
- Cartesian subsampling: R=4, 24 reference lines
- ESPIRiT for coil sensitivity estimation
- 10 cases for training, 10 for testing
- 10 network stages
- 24 real and imaginary filter kernels, size 11x11
- Total number of parameters: 131050
- iPalm optimizer, 150 epochs, batch size 5

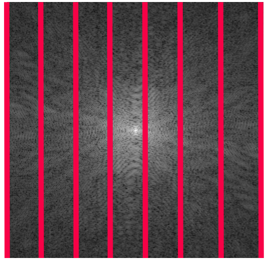




Hammernik MRM 2018
Uecker MRM 2014
Pock SIAM J Imag Sci 2016

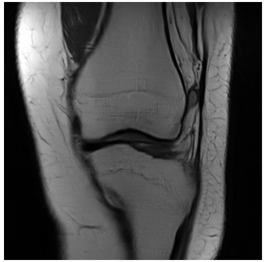
Reconstructing new test data

input



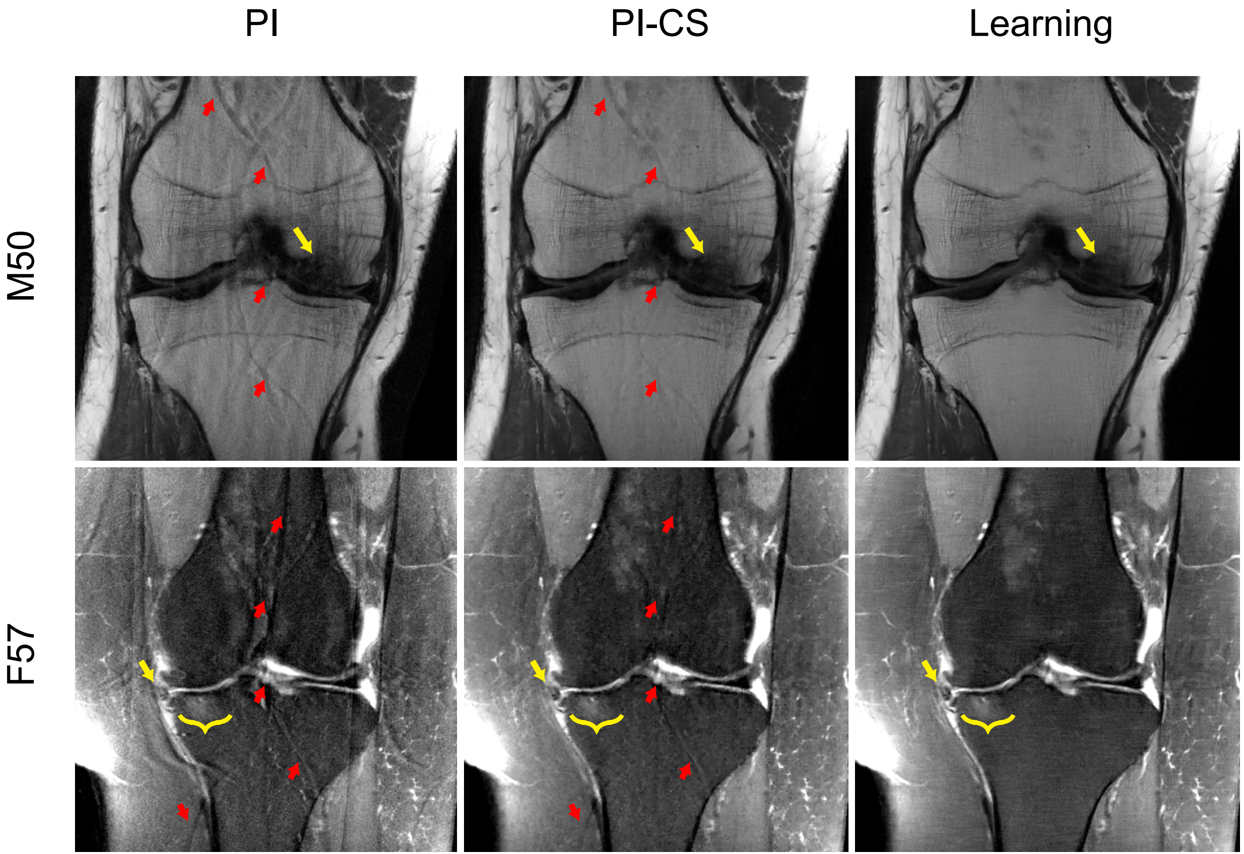
$f \longrightarrow \mathrm{GD}_1 \longrightarrow \mathrm{GD}_t \longrightarrow \mathrm{GD}_T \longrightarrow u_T$

reconstruction



Zero filling initialization

Some reconstruction examples, R=4



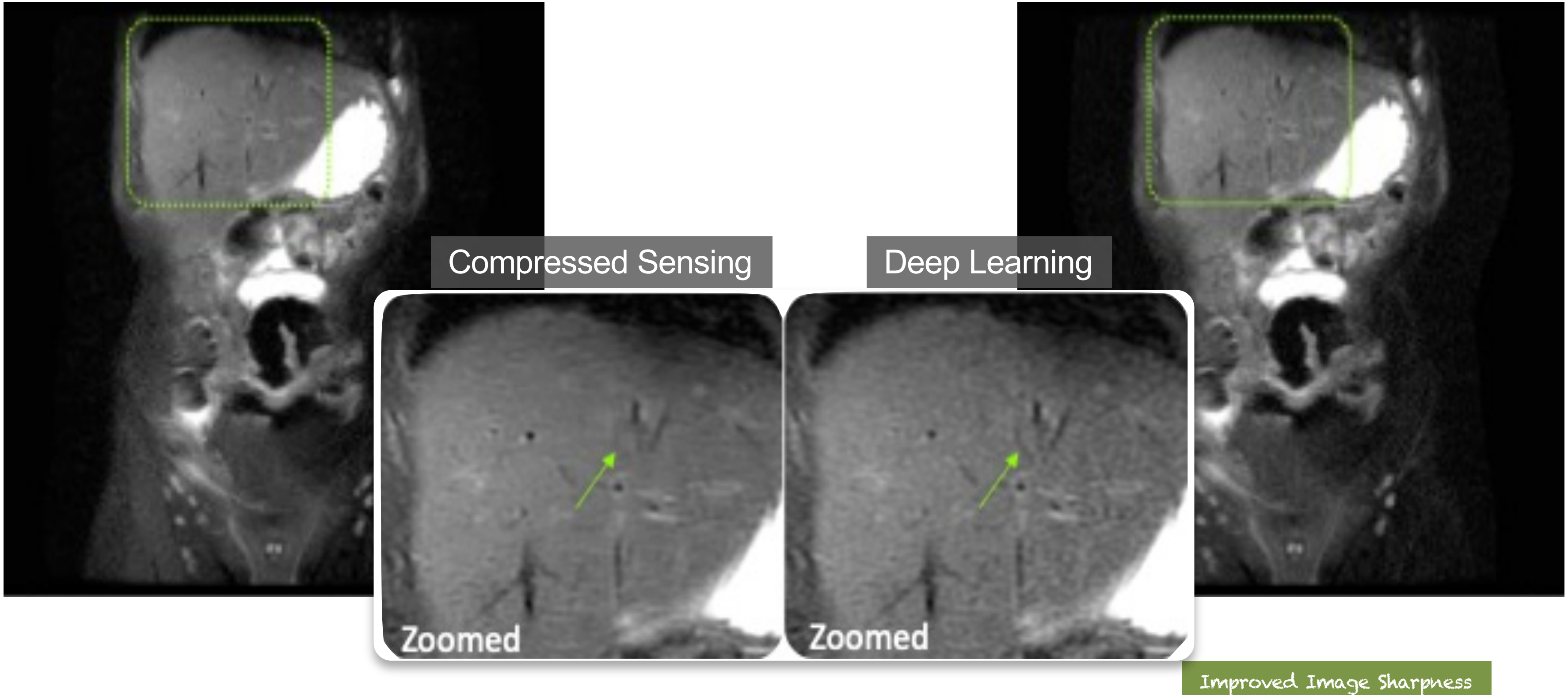
Hammernik, MRM 2018

Small fissure in tibial cartilage, R=4

PI PI-CS Learning

Hammernik, ISMRM 2016

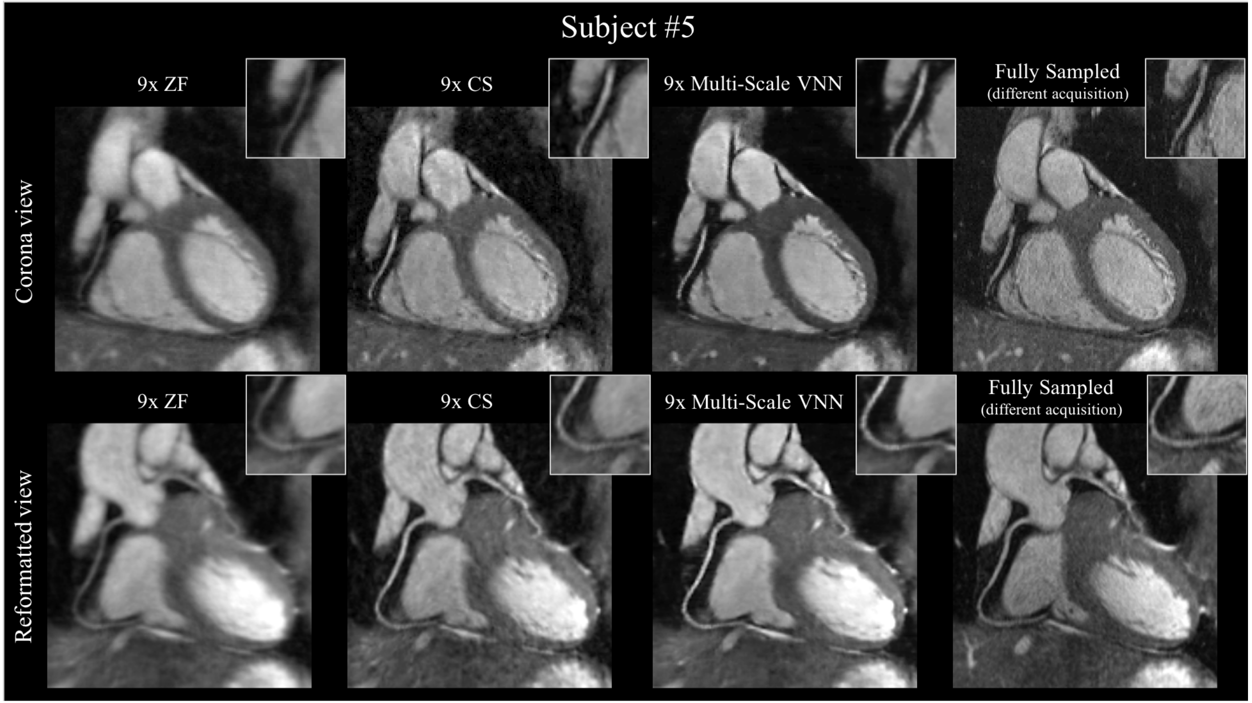
Abdominal Imaging: Clinical Study



Chen Radiology 2018

Slides courtesy of Joseph Cheng (Stanford)

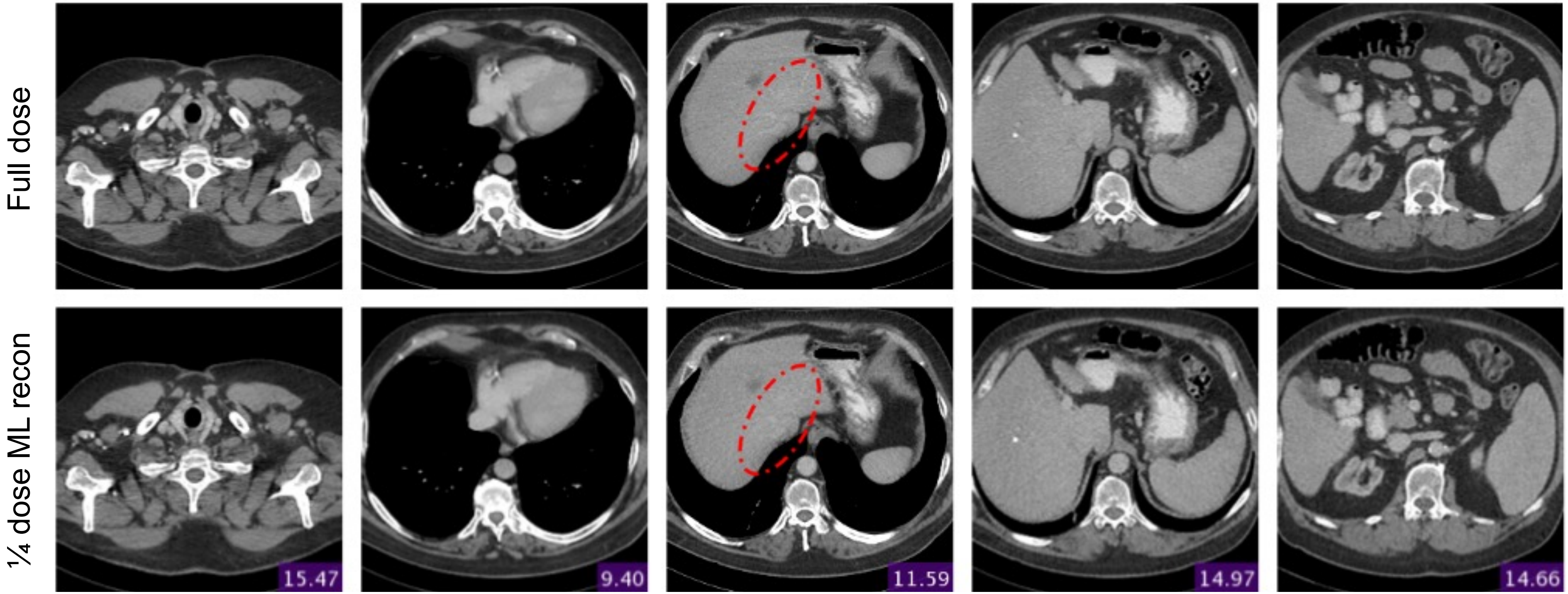
Free breathing 3D whole heart coronary angiography



- Average **acquisition time** (m:s) was **18:55 for the fully sampled** acquisition and **4:11 for an acceleration of 5x.**
- Average **reconstruction time** was **~5 minutes for CS** and **~20 seconds for the VNN framework**.

Slides courtesy of Claudia Prieto (Kings College)

Reconstruction of low dose CT data



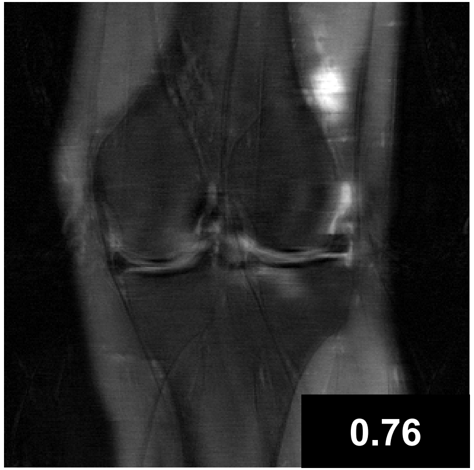
Kobler IEEE ICASSP (2018)

Properties of ML reconstruction

Reconstruction vs Image Processing

Reference

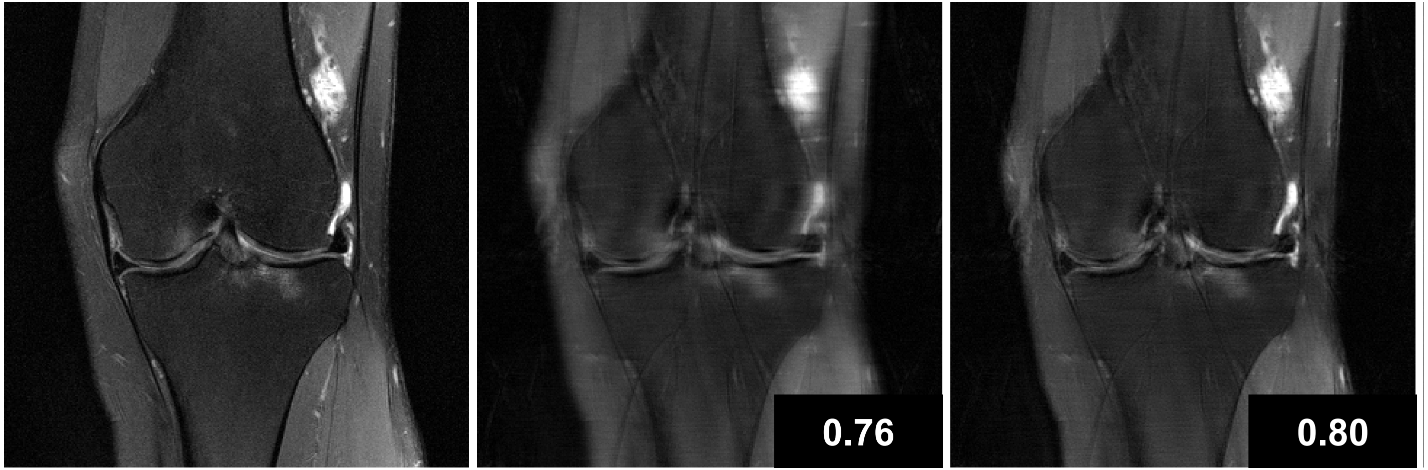
Zero-filling



Hammernik and Knoll, MICCAI Handbook 2019

Reconstruction vs Image Processing

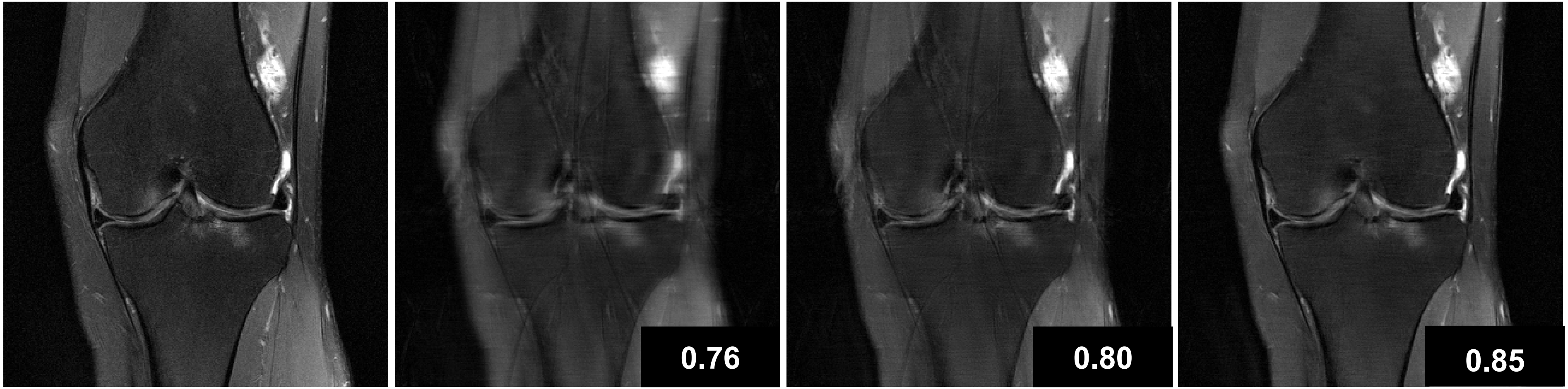
Reference Zero-filling VN postprocessing



Hammernik and Knoll, MICCAI Handbook 2019

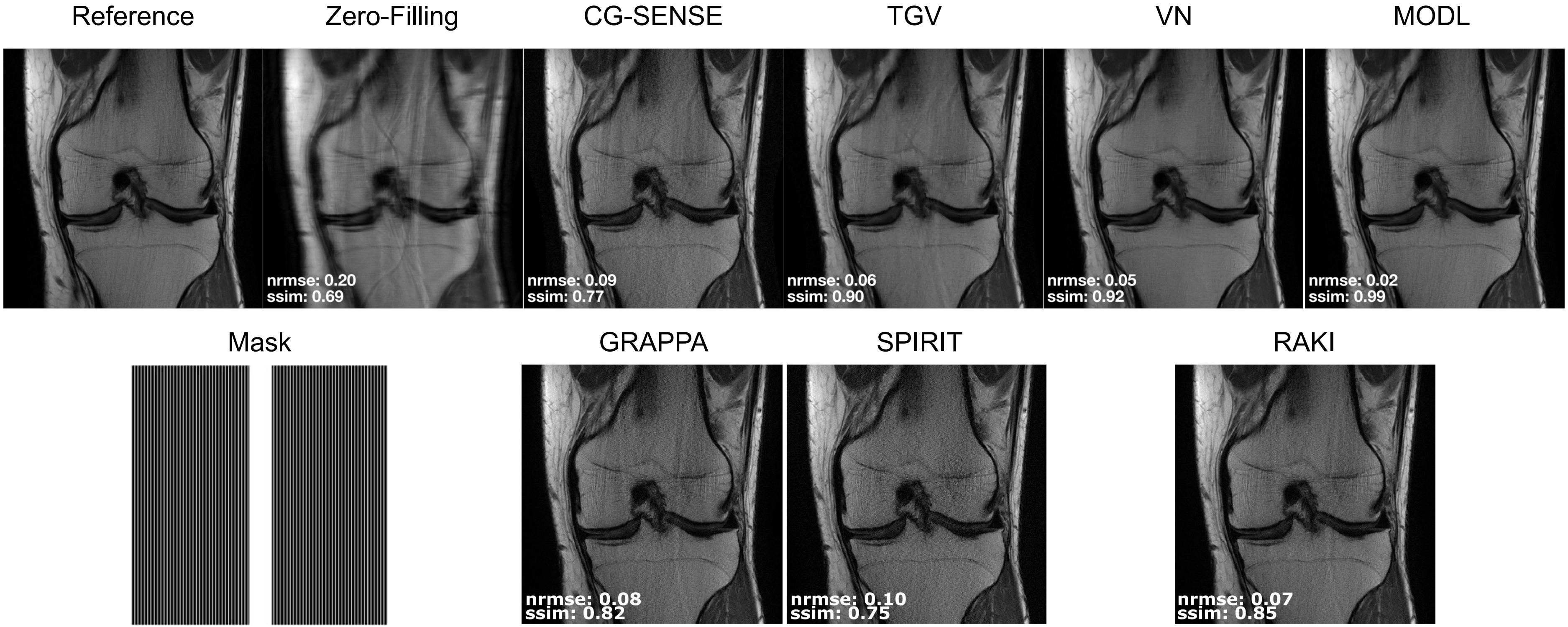
Reconstruction vs Image Processing

Reference | Zero-filling | VN postprocessing | VN reconstruction



Hammernik and Knoll, MICCAI Handbook 2019

An attempt at a comparison

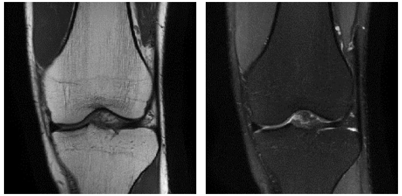


Knoll IEEE Sig Proc 2020

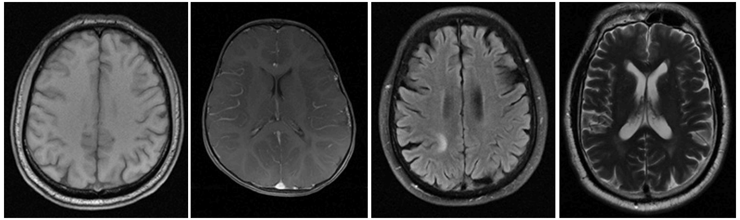
fastMRI dataset

数据集

- **MSK (knee)**
  - Rawdata (fully sampled): 1398 cases



- **Neuro (brain)**
  - Rawdata (fully sampled): 7002 cases
  - Challenge Transfer track:
    - GE (211 cases)
    - Philips (118 cases)



Knoll Radiology AI 2019
fastmri.med.nyu.edu

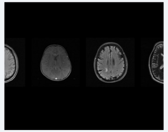
2019/2020 reconstruction challenges

Home | Public Leaderboard | Challenge Leaderboard | The Dataset | Submission Guidelines

fastMRI

Accelerating MR Imaging with AI

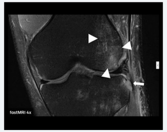
Latest News & Updates



09-17-2020

The 2020 fastMRI challenge opens for submissions on October 1

Read More



08-18-2

FastMRI

accelerat

Read Mor

What is fastMRI?

fastMRI is a collaborative research project between Facebook AI Research (FAIR) and NYU Langone Health. The aim is to investigate the use of AI to make MRI scans up to 10 times faster.

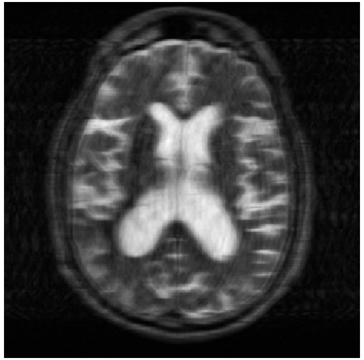
By producing accurate images from under-sampled data, AI image reconstruction has the potential to improve the patient's experience and to make MRIs accessible for more people.

To enable the broader research community to participate in this important project, NYU Langone Health has released fully anonymized raw data and image datasets. Visit our github repository, which contains baseline reconstruction models and PyTorch data loaders for the fastMRI dataset.

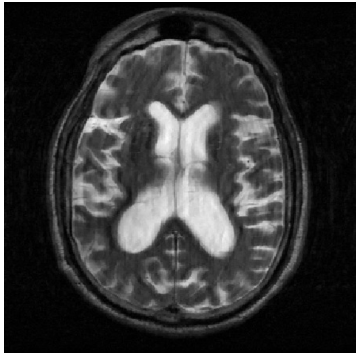
Knoll MRM 2020
Muckley TMI 2021

fastMRI reconstruction challenge

Undersampled

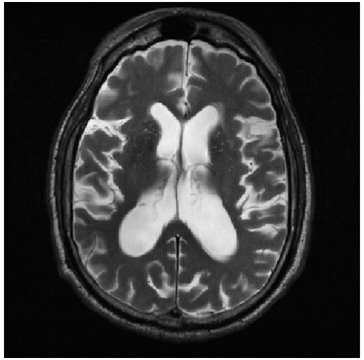


Reconstruction

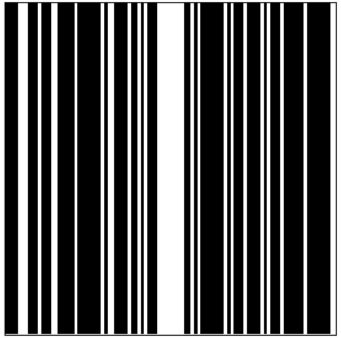


Error

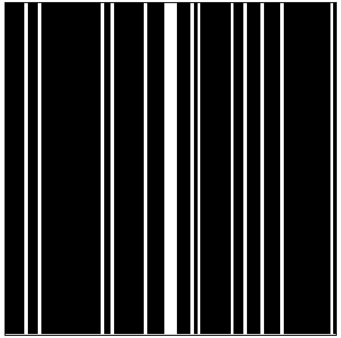
Reference

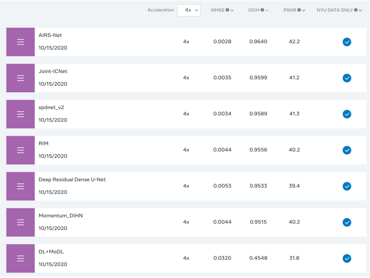


R=4



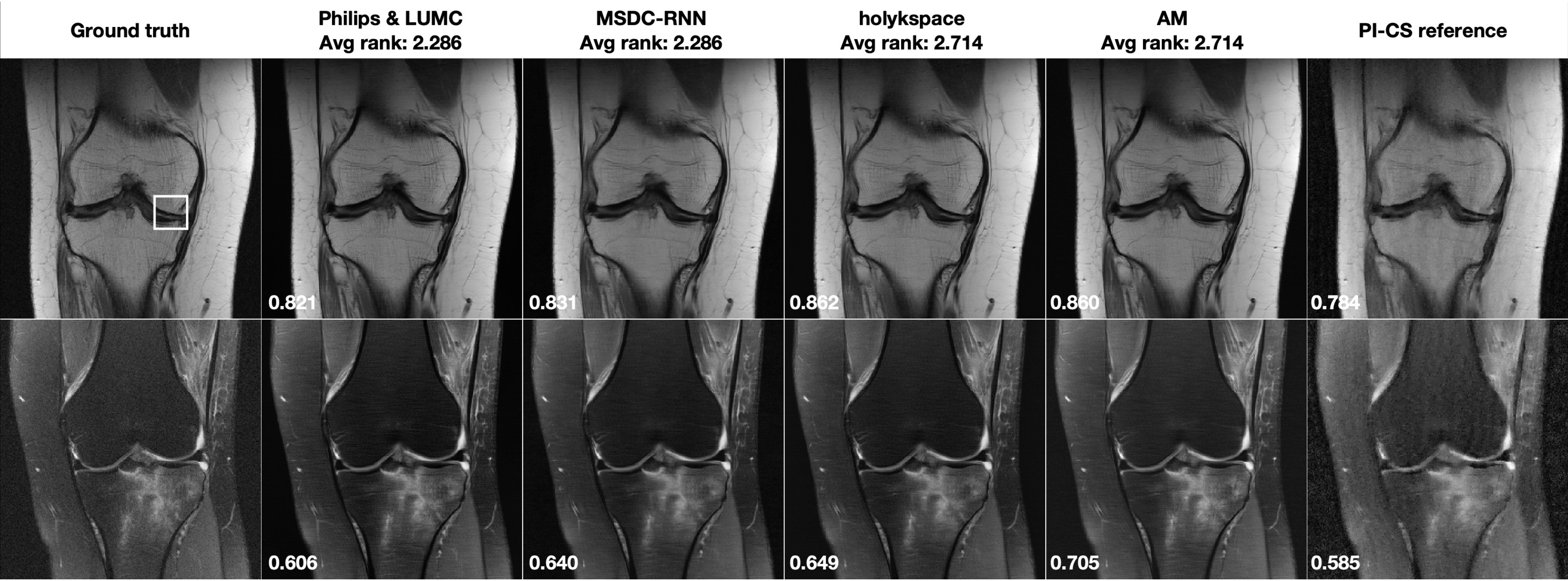
R=8





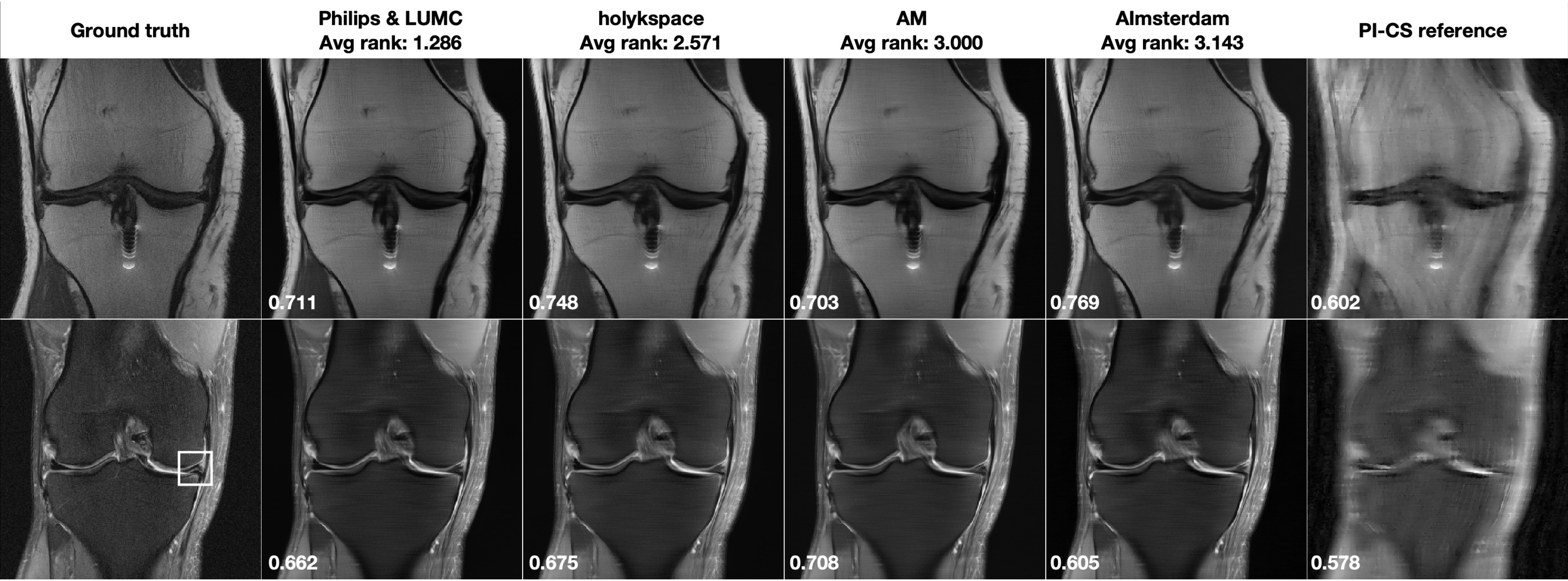
	Acceleration 4x	NMSE	SSIM	PSNR	NYU DATA ONLY
AIRS-Net 10/15/2020	4x	0.0028	0.9640	42.2	✓
Joint-ICNet 10/15/2020	4x	0.0035	0.9599	41.2	✓
xpdnet_v2 10/15/2020	4x	0.0034	0.9589	41.3	✓
RIM 10/15/2020	4x	0.0044	0.9556	40.2	✓
Deep Residual Dense U-Net 10/15/2020	4x	0.0053	0.9533	39.4	✓
Momentum_DIHN 10/15/2020	4x	0.0044	0.9515	40.2	✓
DL+MoDL 10/15/2020	4x	0.0320	0.4548	31.8	✓

Multi coil R=4 results



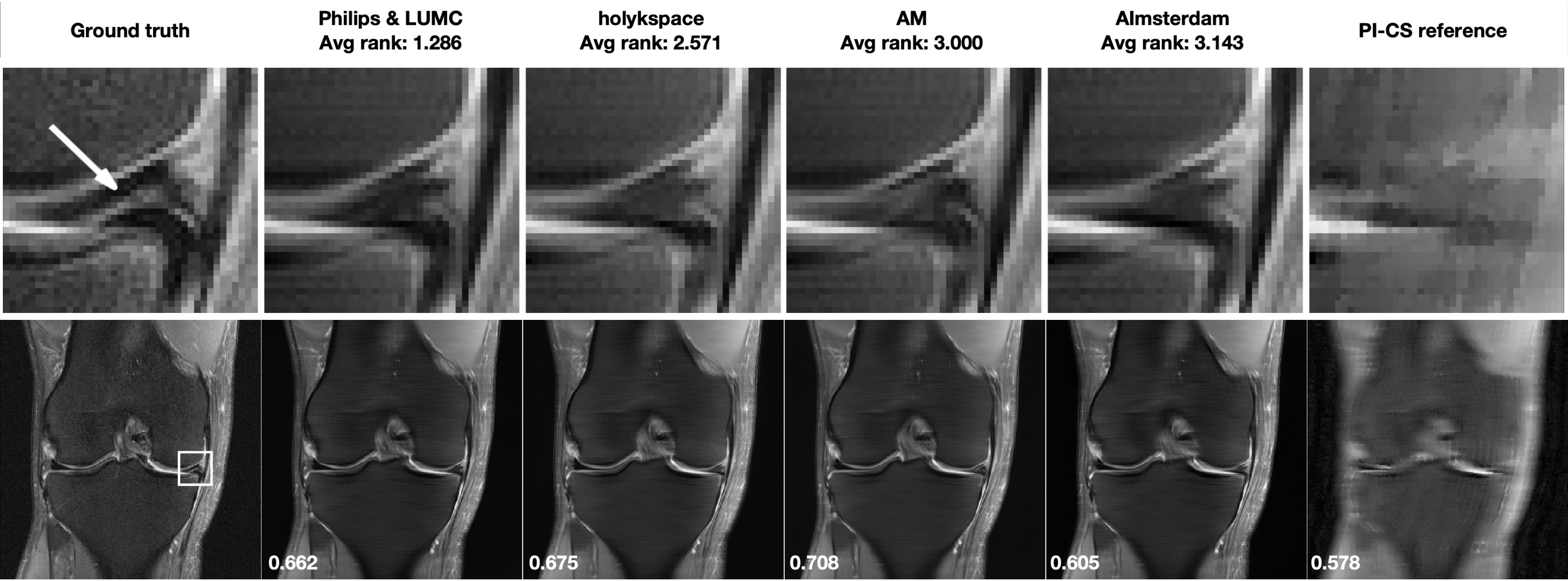
Knoll MRM 2020

Multi coil R=8 results



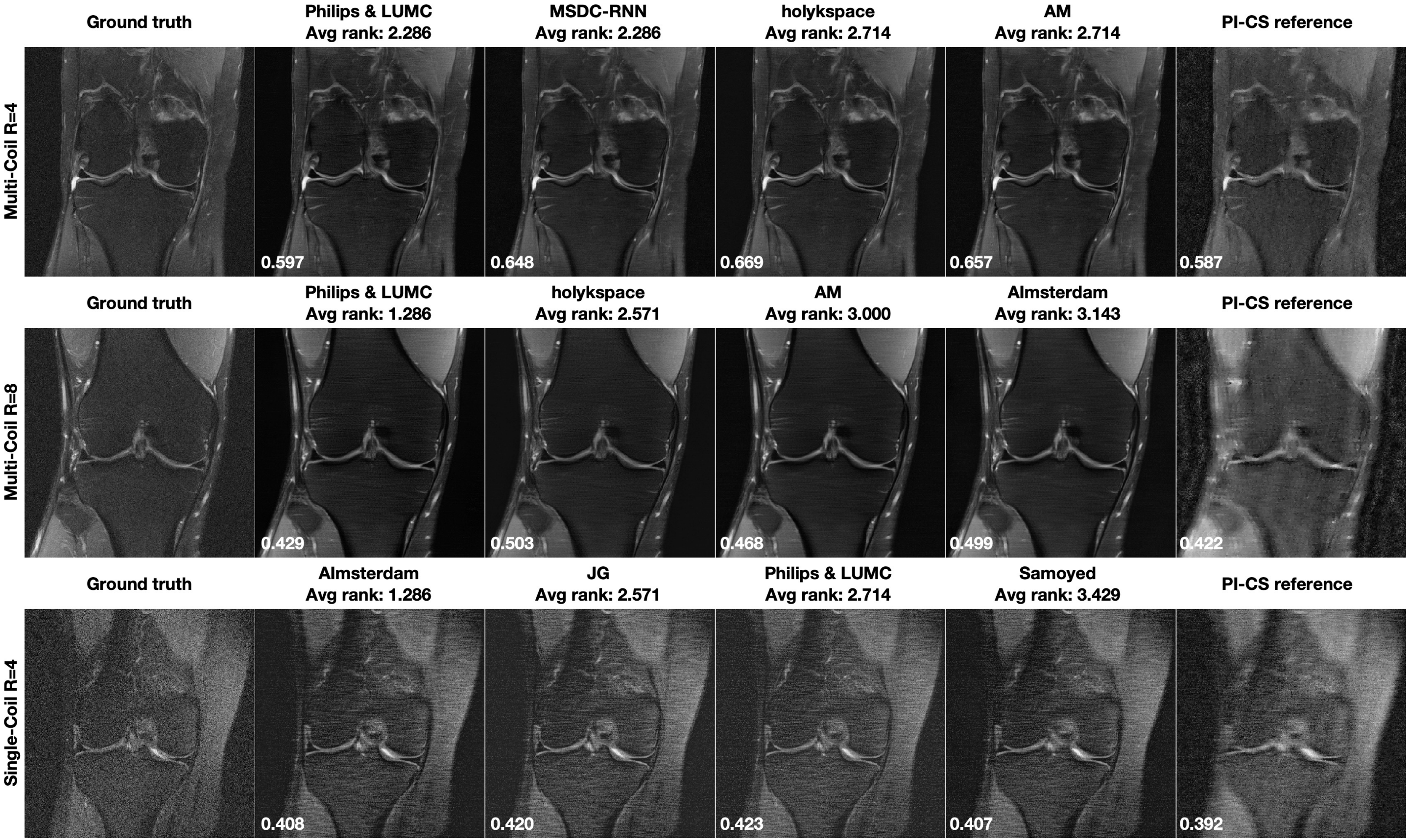
Knoll MRM 2020

Multi coil R=8 results: Pathology



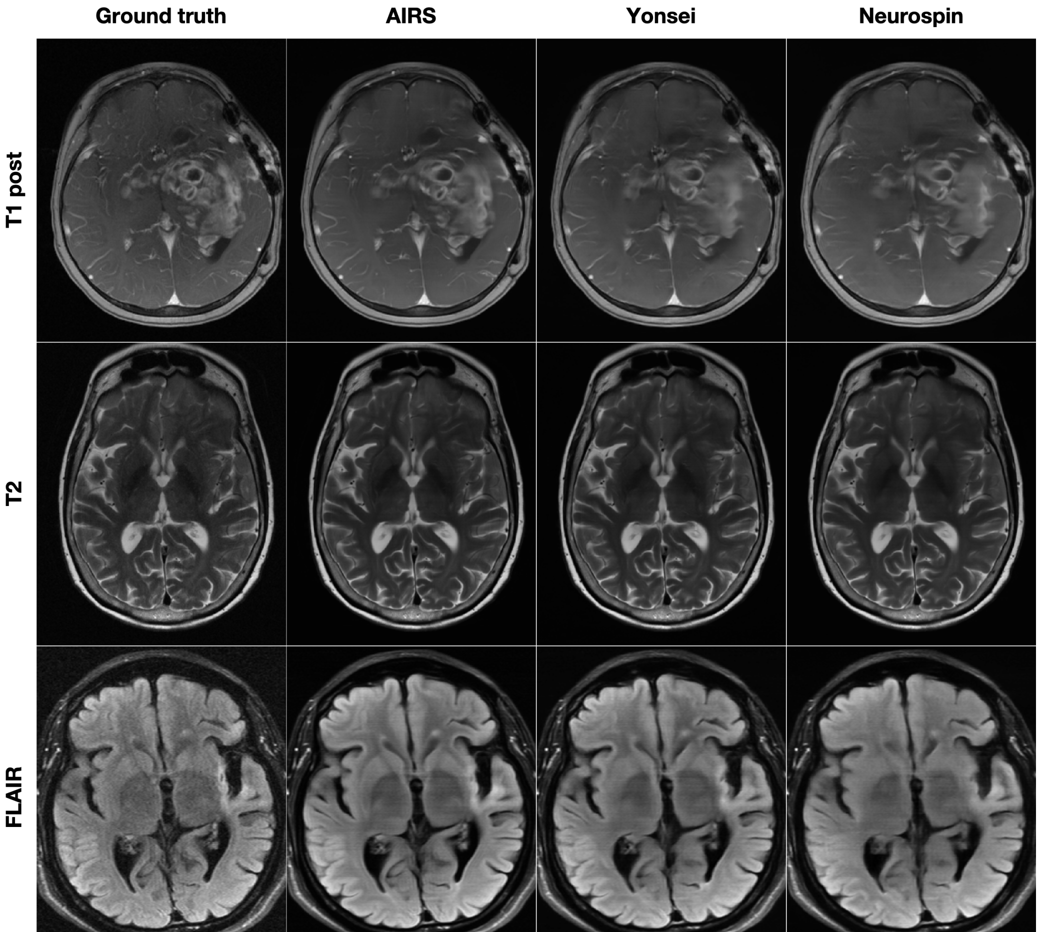
Knoll MRM 2020

Worst results from each track



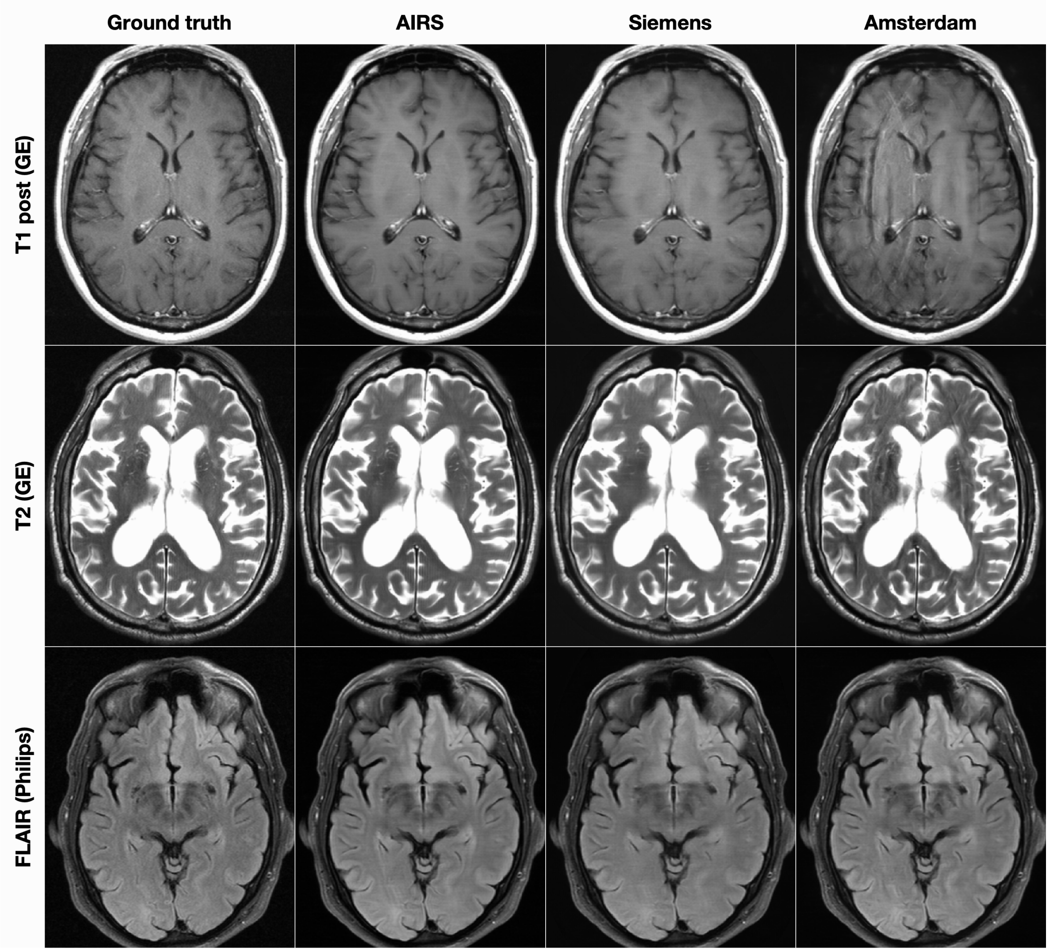
Knoll MRM (in press, 2020)

2020 multi coil R=8 results



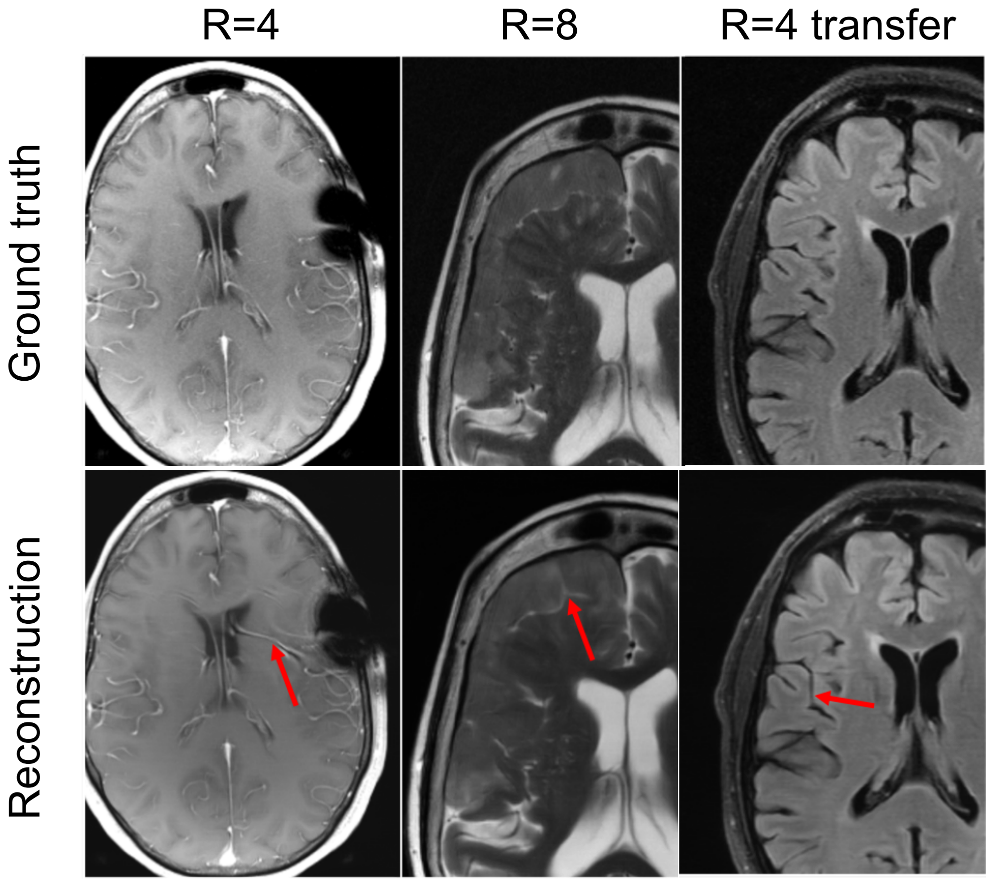
Muckley TMI 2021

2020 multi coil R=4 transfer results



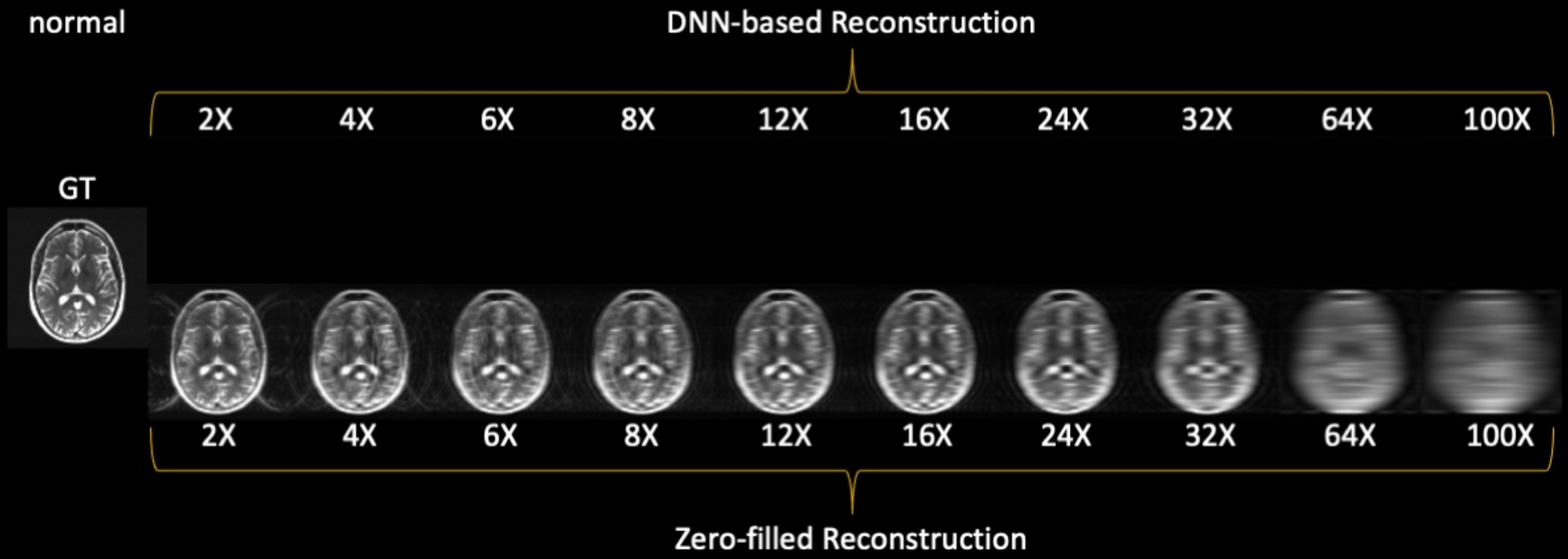
Muckley TMI 2021

2020 results Hallucinations



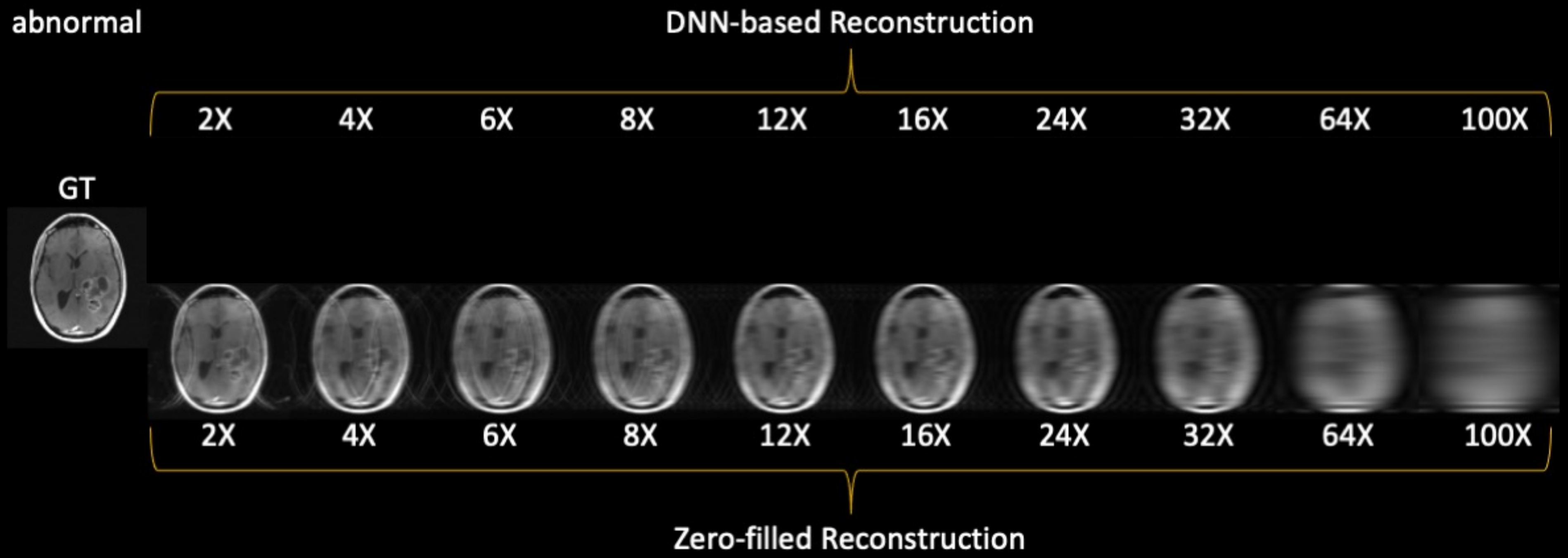
Muckley TMI 2021

Evaluation of model failure



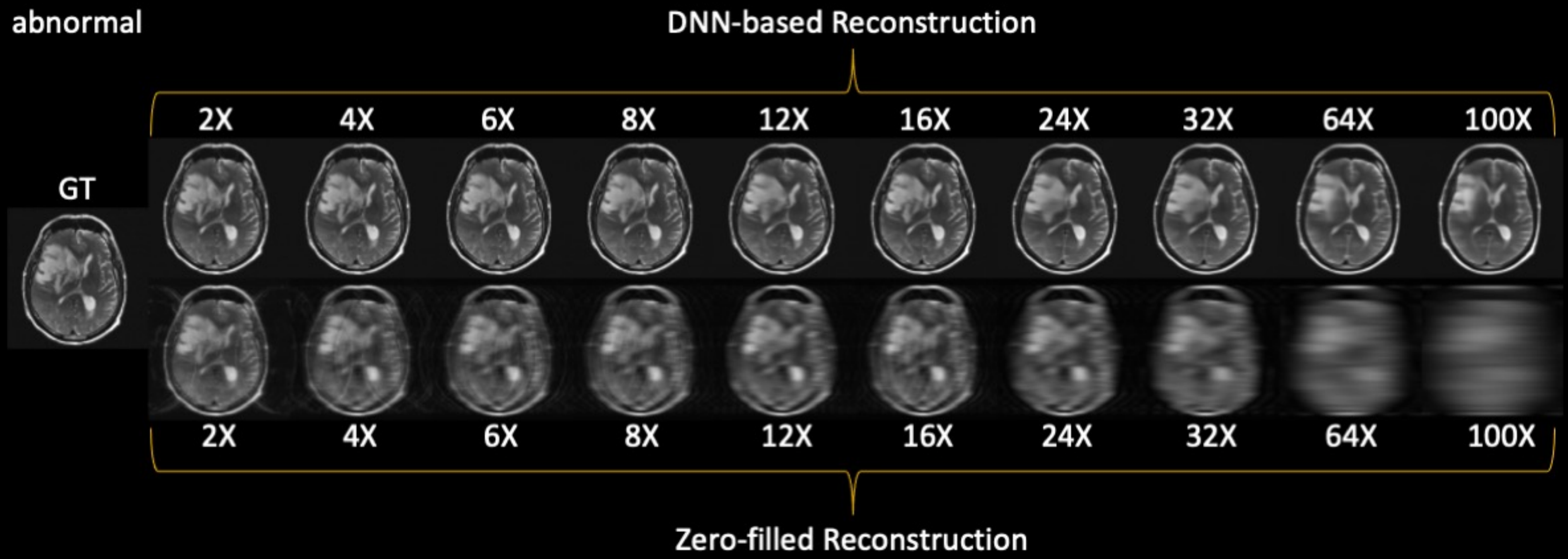
Murrel, submitted

Evaluation of model failure



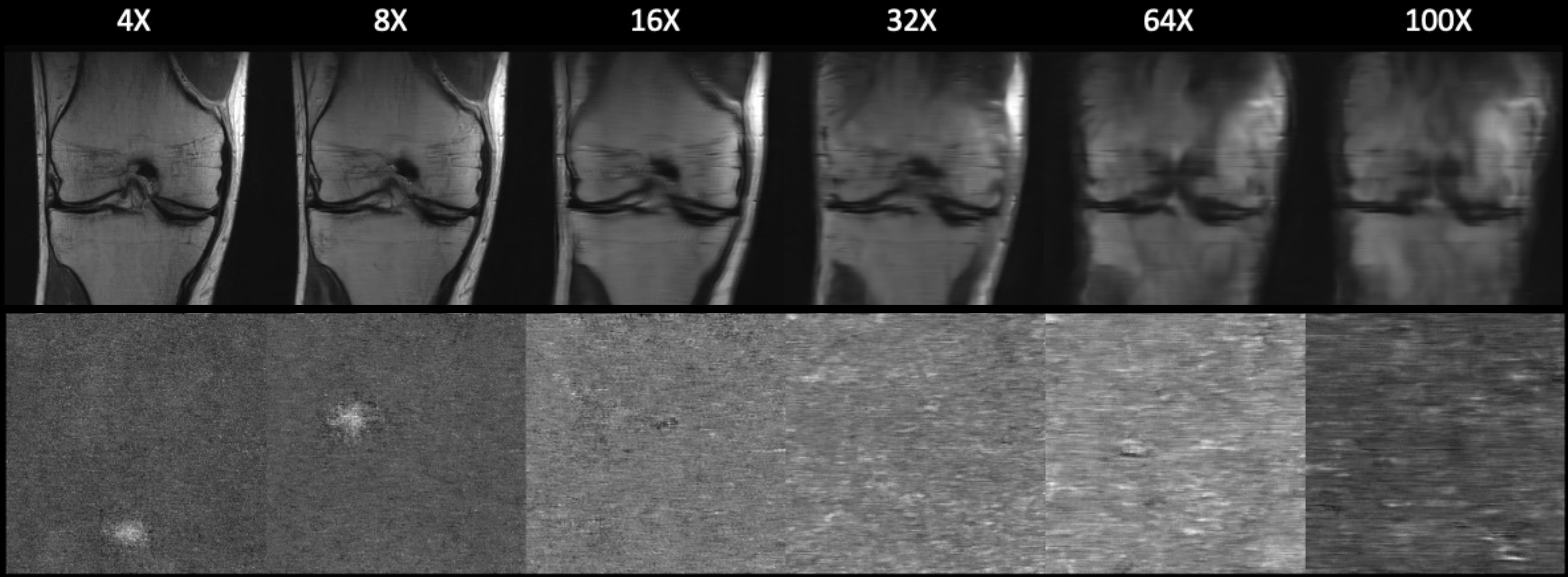
Murrel, submitted

Evaluation of model failure



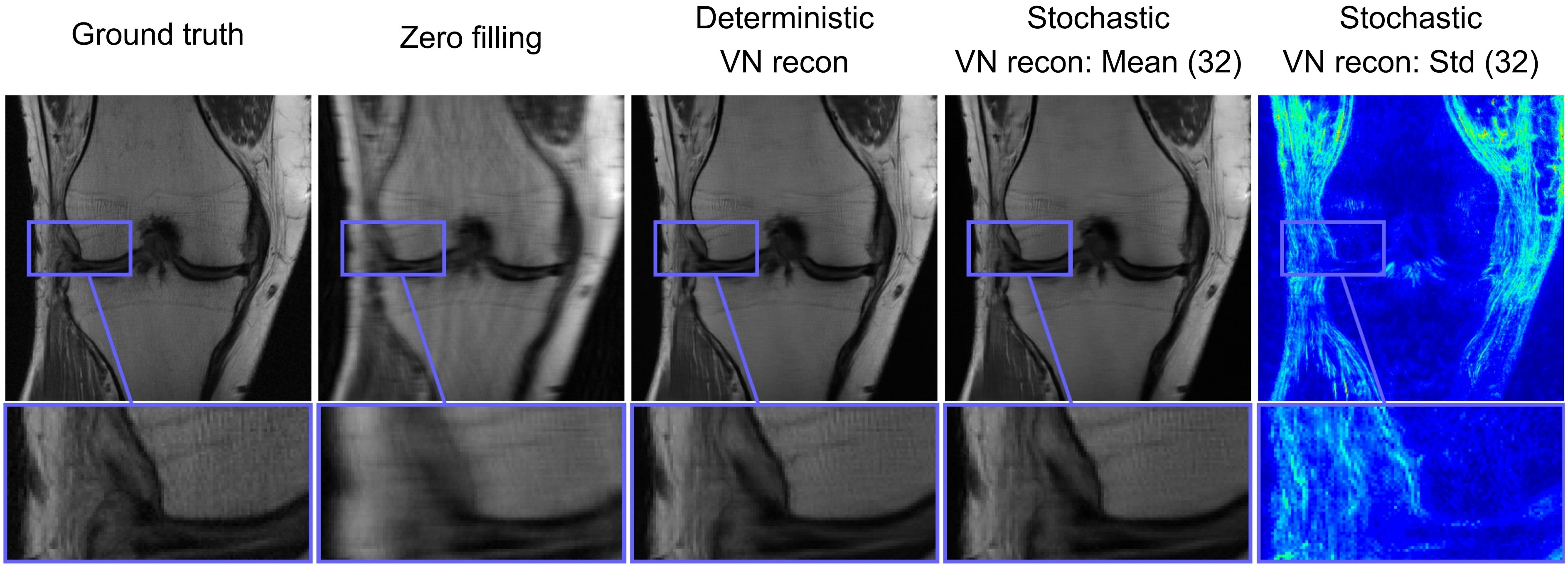
Murrel, submitted

Out of domain data



Murrel, submitted

Bayesian Uncertainty Estimation

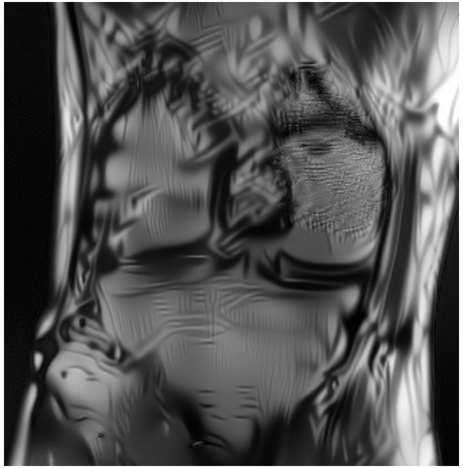


Narnhofer TMI 2021

Regularizer Eigenfunction Analysis

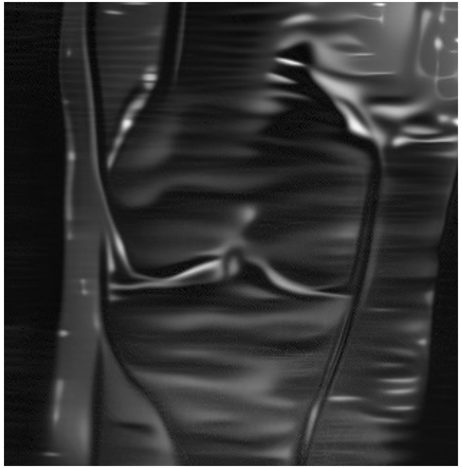
Ground truth

Eigenfunction



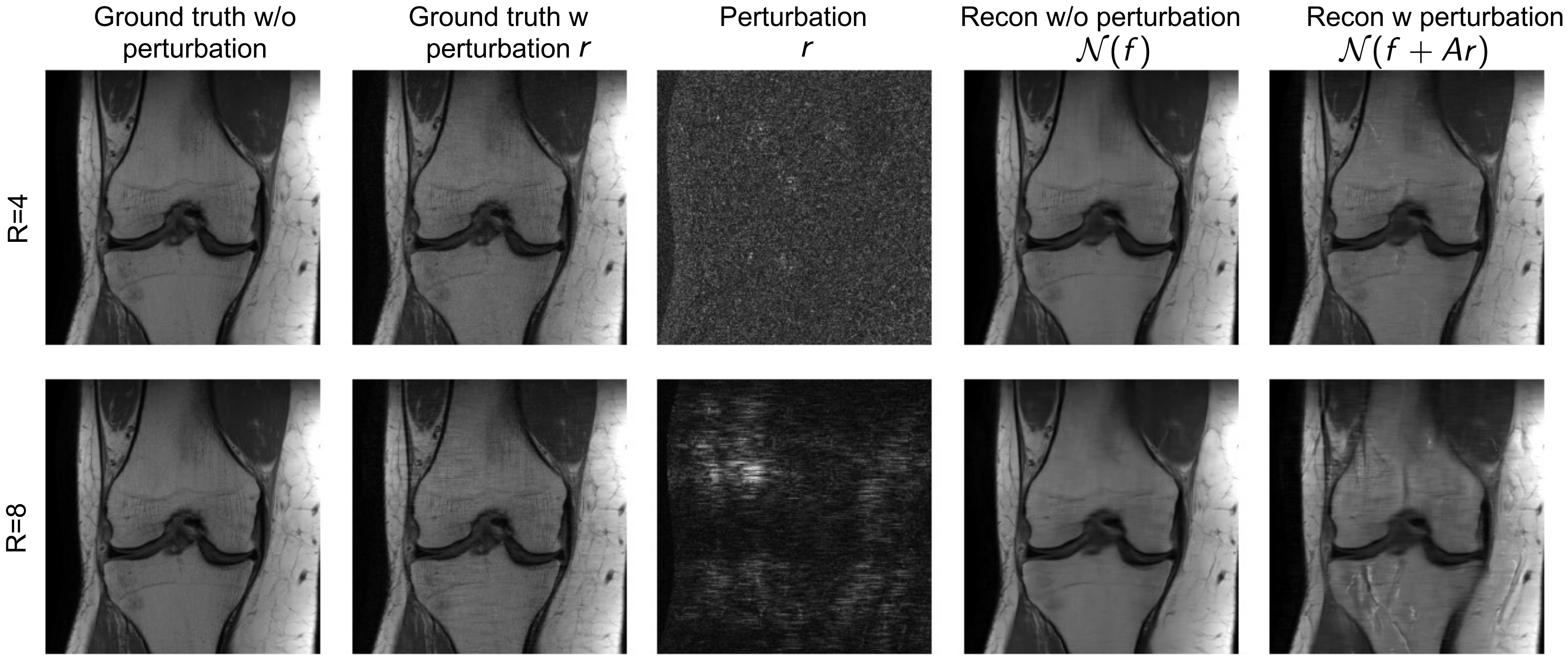
Ground truth

Eigenfunction



Narnhofer TMI 2021

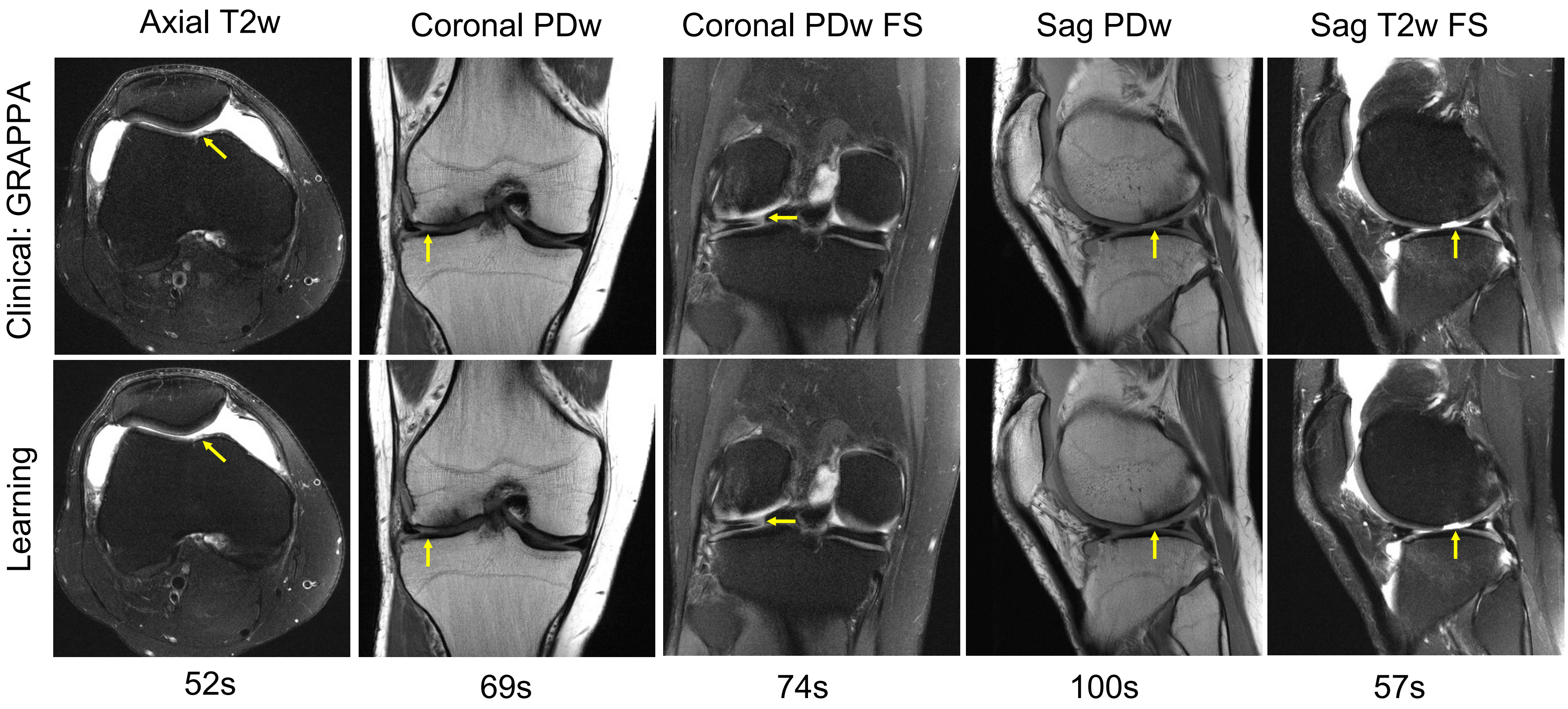
Adversarial attacks 对抗性攻击



$$\max_{r} \|\mathcal{N}(f + Ar) - \mathcal{N}(f)\|_2^2 - \|r\|_2^2$$

Antun PNAS 2020

Clinical evaluation

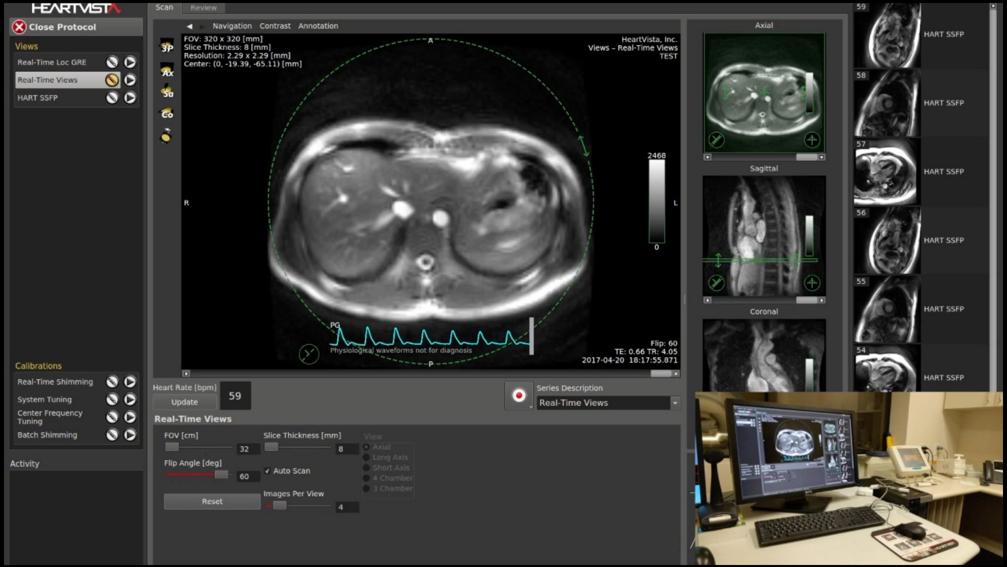


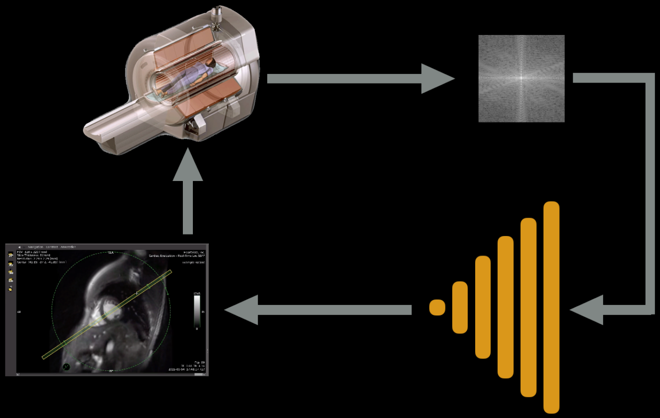
Scan times of accelerated sequences shown

Examples of interesting extensions

Real-Time Cardiac Localization

Rx to EF in less than 3 minutes

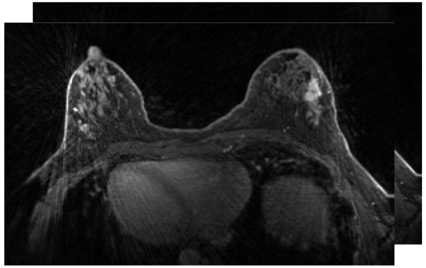




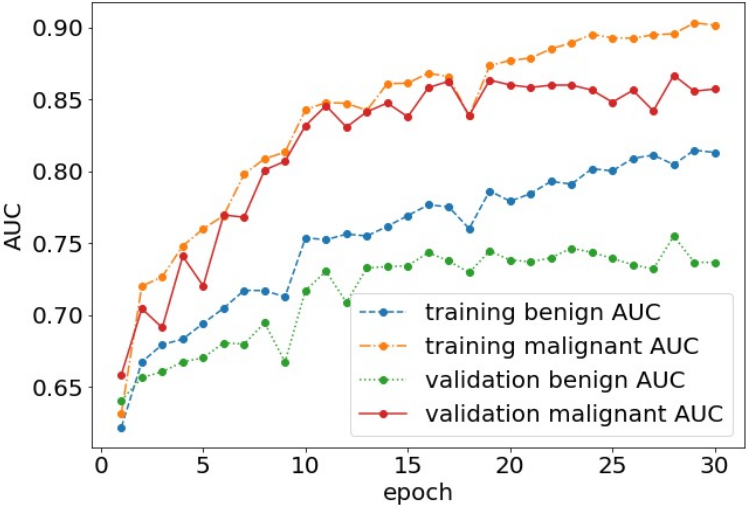
Addy, O. ISMRM ML Workshop 2018

Slides courtesy of Juan Santos (Heartvista)

Diagnostic classification



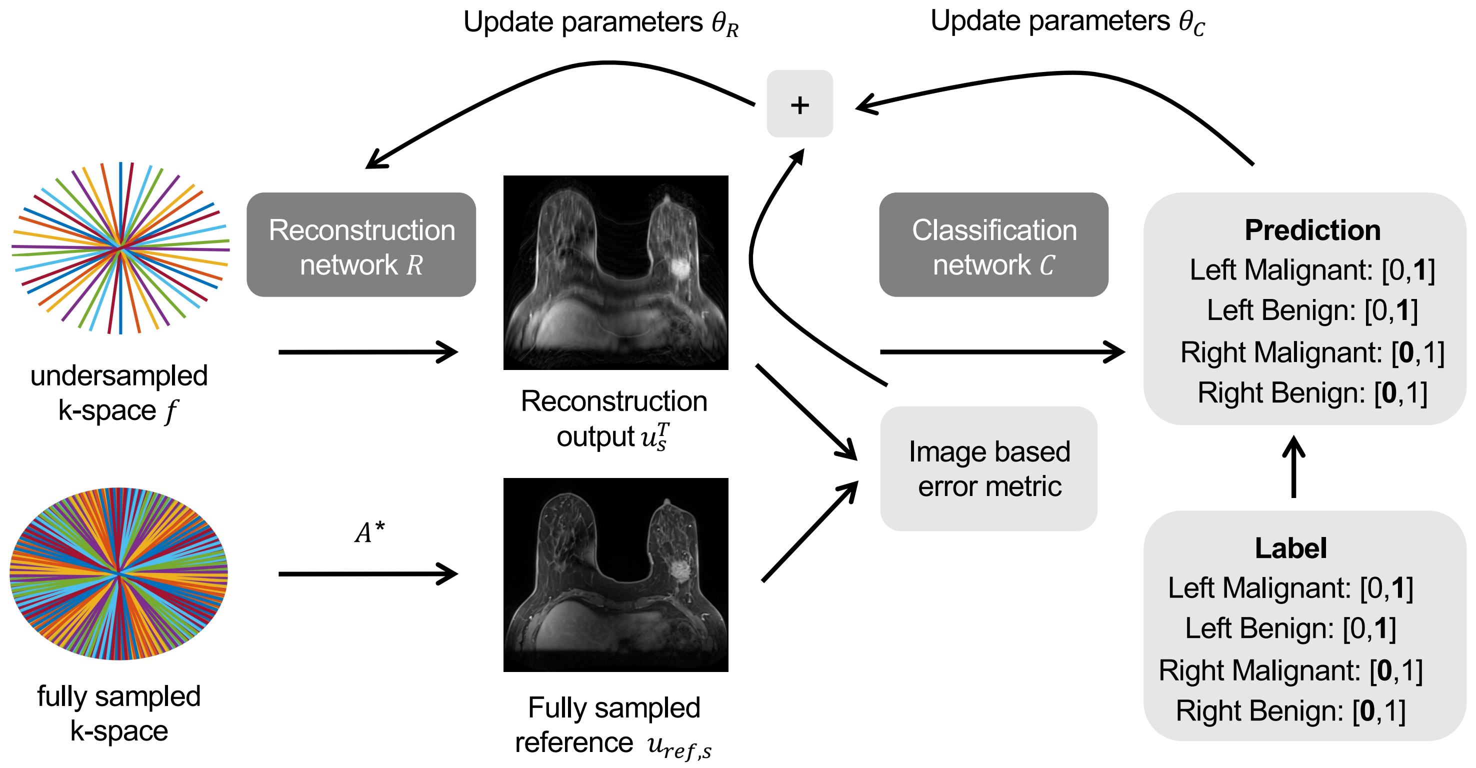
Predict presence of malignant and/or benign lesions in each breast



- 5000 training
- 1500 validation
- 1500 validation

Gong NeurIPS Medical Imaging (2019)

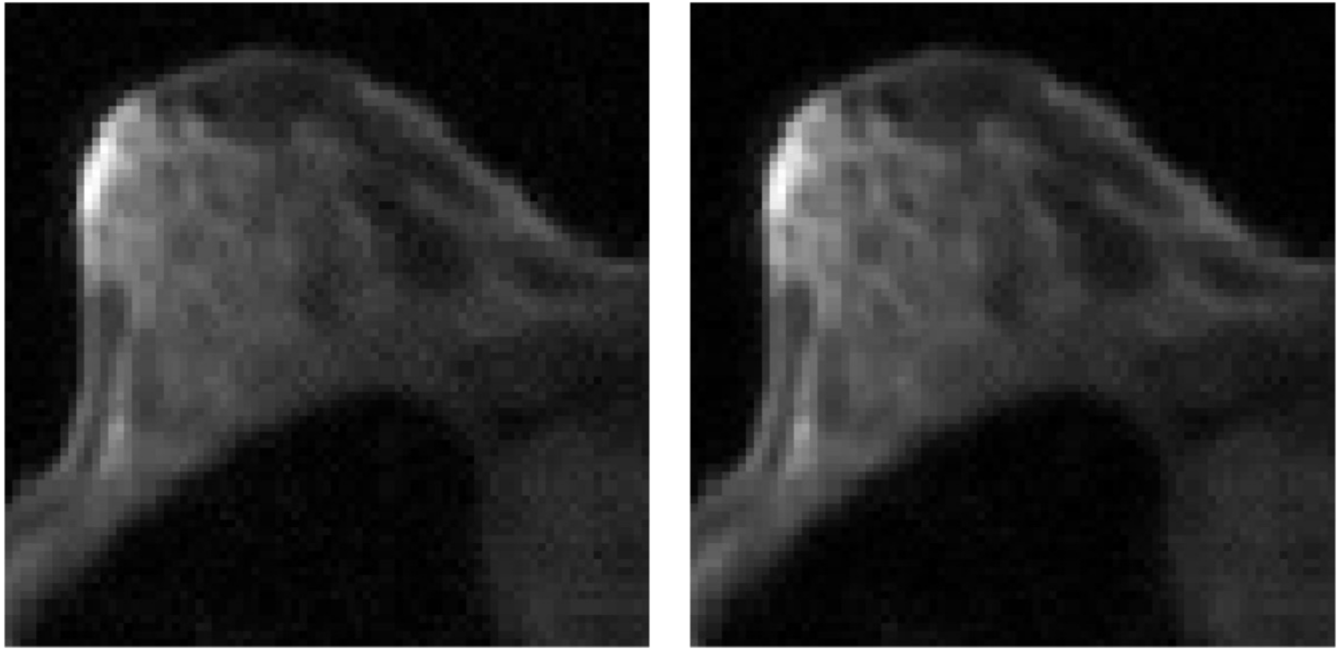
End to end reconstruction and classification



$$\mathcal{L}(\Theta_R, \Theta_C) = \mu \mathcal{L}_{\mathcal{R}}(\Theta_R) + (1-\mu)\mathcal{L}_{\mathcal{C}}(\Theta_C)$$

End to end reconstruction and classification

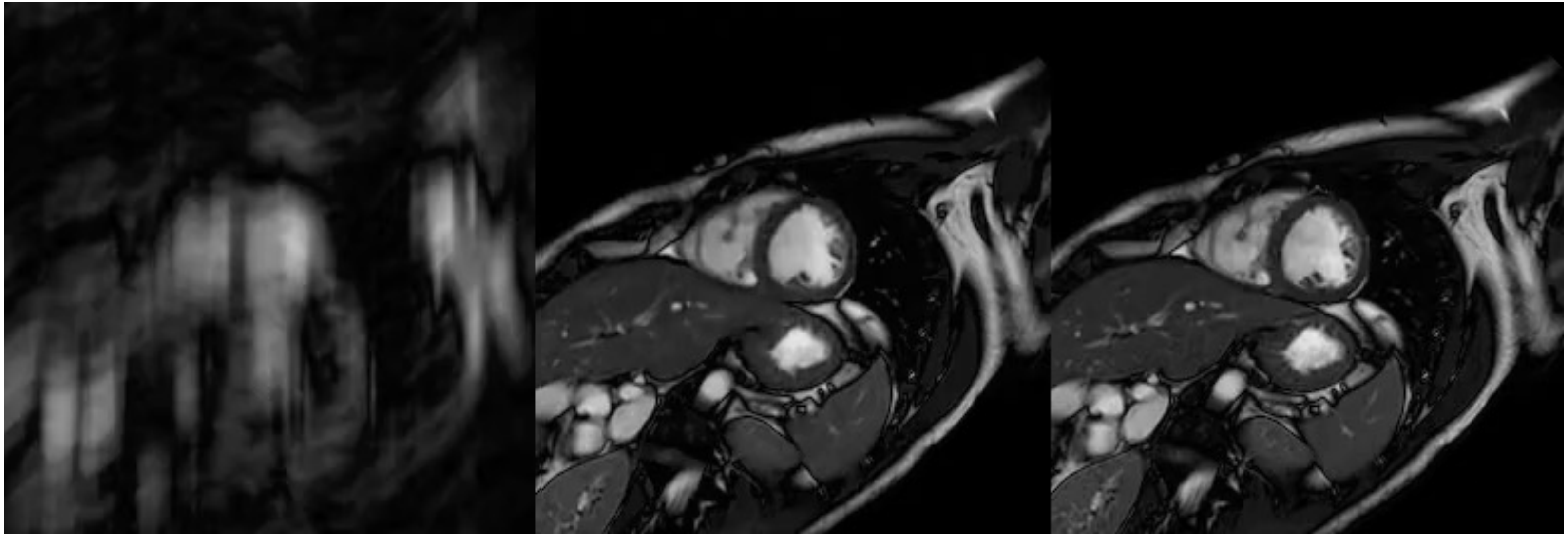
Separate | End-to-end



Work in progress :-)

Imperial College London

Dynamic cardiac recon (11-fold)



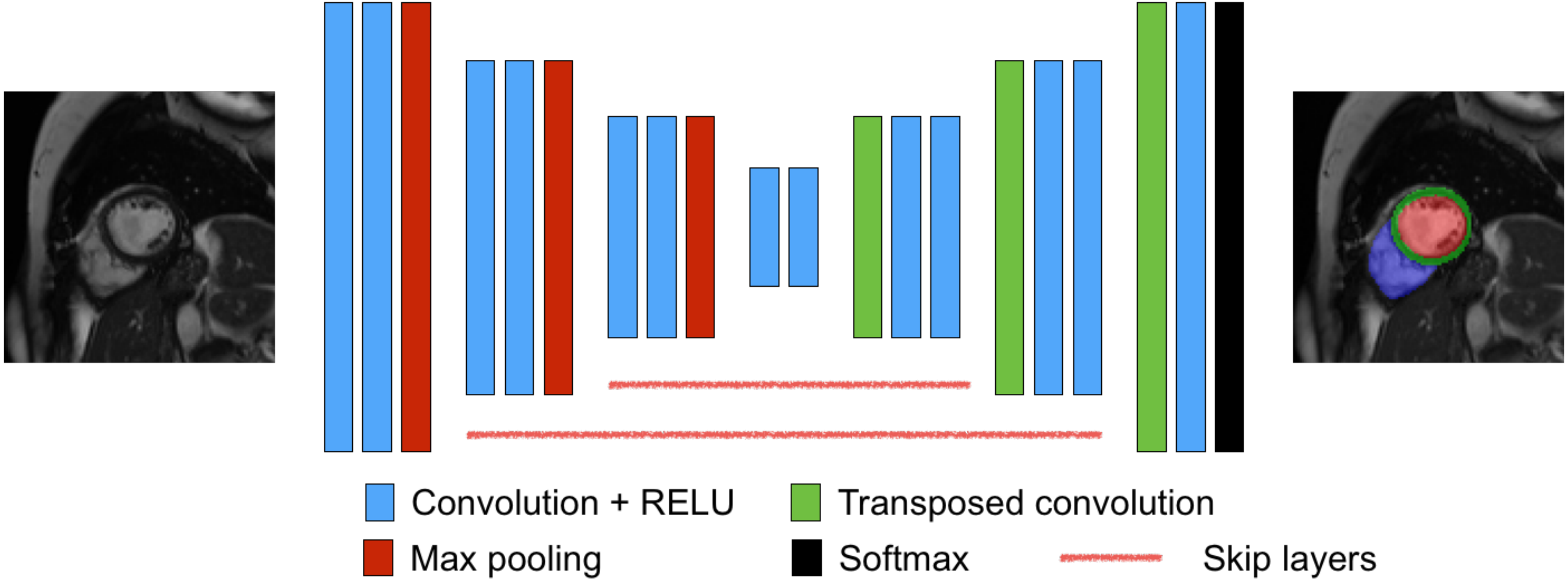
(a) 11x Undersampled (b) CNN reconstruction (c) Ground Truth

Schlemper IEEE TMI 2017

Slides courtesy of Daniel Rueckert (Imperial College London)

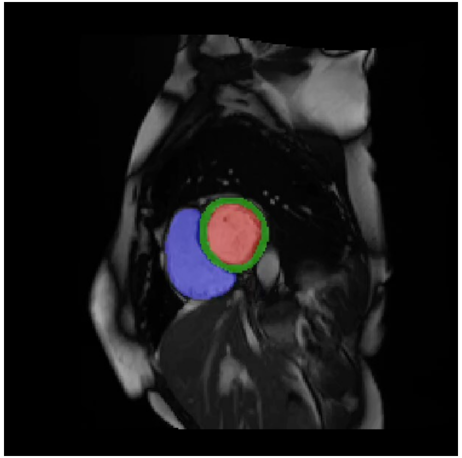
Imperial College London

Image segmentation

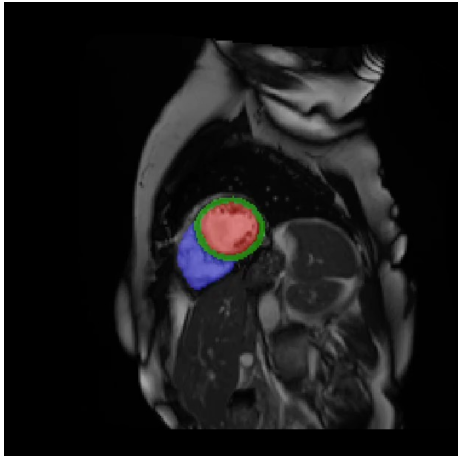


Bai JCMR 2018

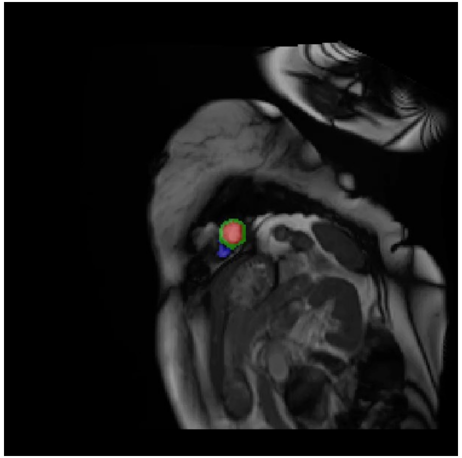
Slides courtesy of Daniel Rueckert (Imperial College London)



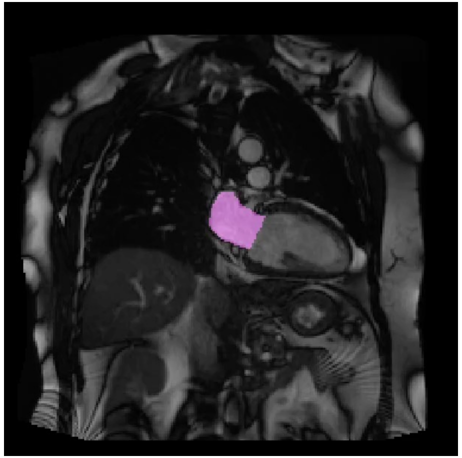
SA, basal



SA, mid-ventricular



SA, apical



LA, 2 chamber

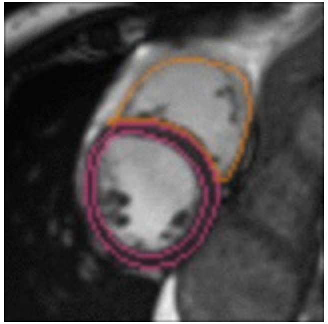
LA, 4 chamber

Bai JCMR 2018

Slides courtesy of Daniel Rueckert
(Imperial College London)

Assessment of LV and RV function from k-space

Ground truth

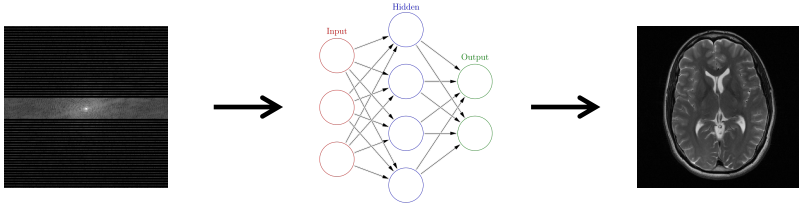


Schlemper MICCAI 2018

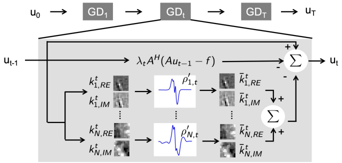
Slides courtesy of Daniel Rueckert (Imperial College London)

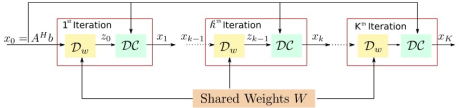
Summary

From CS to DL recon



Overview and model comparison





Challenges: Pitfalls/Validation