Machine Learning for MR Image Reconstruction: From First Results to Ongoing Challenges

Florian Knoll

Computational Imaging Lab
Department of Artificial Intelligence in Biomedical Engineering
FAU Erlangen-Nuremberg

florian.knoll@fau.de
https://www.cil.tf.fau.de/

Friedrich-Alexander-Universität
Computational Imaging Lab

Jinho Kim

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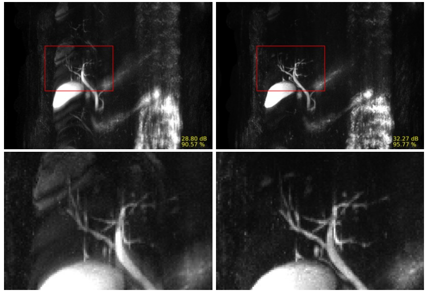

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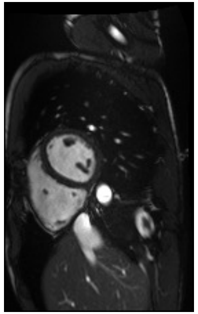
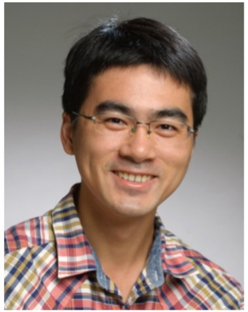
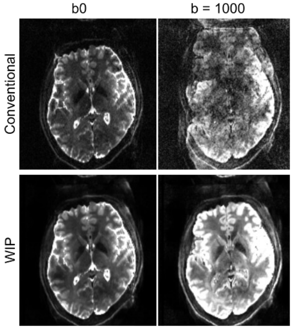


Nan Lan

Zhengguo Tan





Vanya Saksena

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Soundarya Soundarresan

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Erlangen-Nürnberg

NYU

Jakob Asslaender
Tobias Block
Mary Bruno
Hersh Chandarana
Zhengnan Huang
Patricia Johnson
Gene Kim (now at Cornell)
Yvonne Lui
Ali Radmanesh
Michael Recht
Dan Sodickson
Rouxun Xi

TU Graz
Graz University of Technology

Kerstin Hammernik
(now at TUM)
Dominik Narnhofer
Thomas Pock

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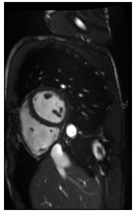

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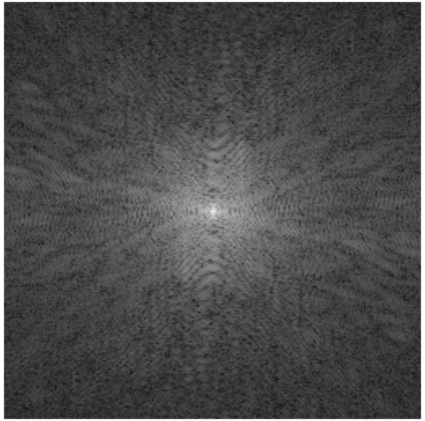
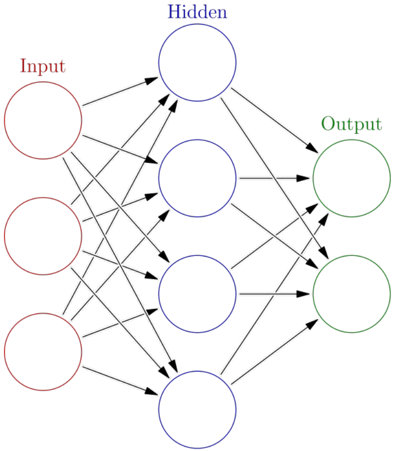
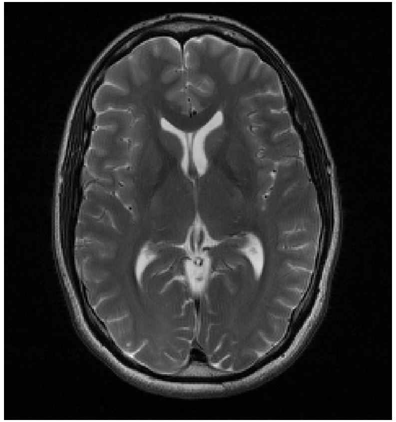
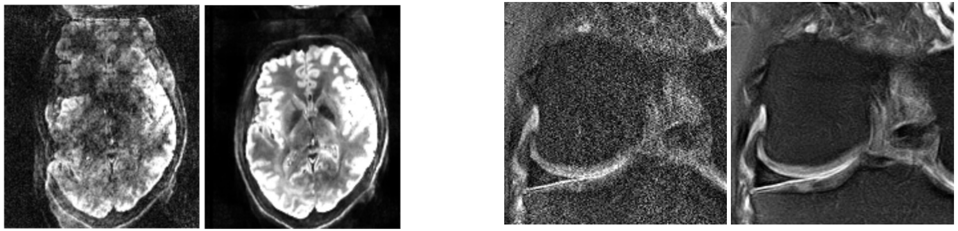
Biograph mMR




Input
Hidden
Output



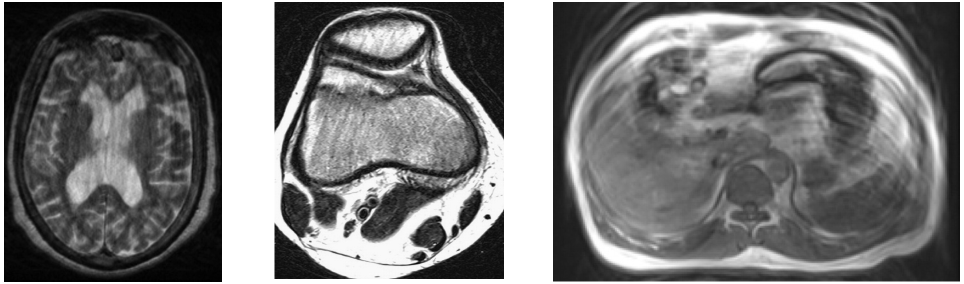
Improved image quality



Tan (WIP), Hammernik 2016

Shorter scans

Motion



Nyberg AJNR 2013, Lavdas MRI 2012, Zhuo RG 2006

Time resolved scans

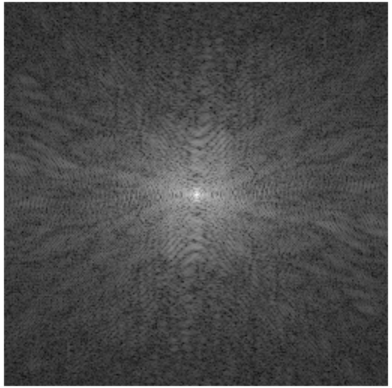
Feng MRM 2016, Stern ISMRM Sedona 2020

MRI data acquisition

Forward problem

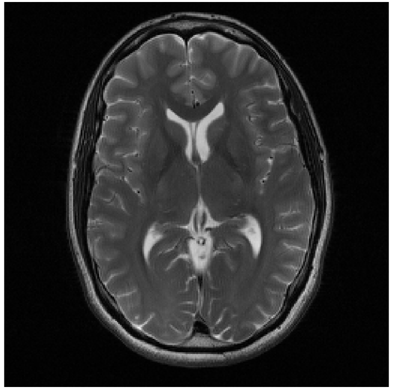
$$Au = f$$

f



$\xleftarrow{A}$

u



MRI data acquisition

Forward problem

$$Au = f$$

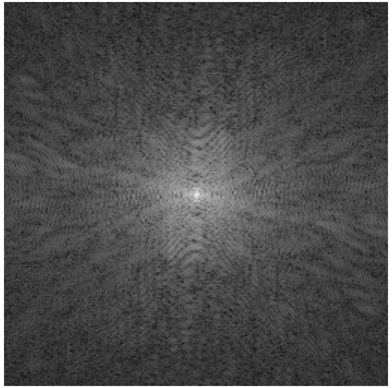
Inverse problem

$$u = A^{-1}f$$

Numerical optimization

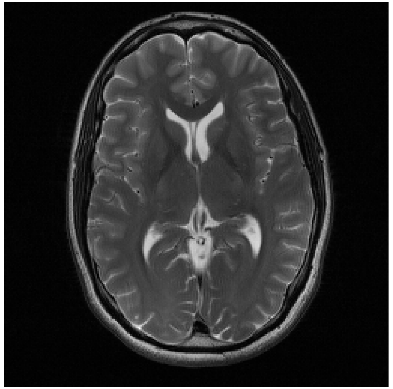
$$min||Au - f||_2^2$$

f



$\xrightarrow{A^{-1}}$

u



MRI data acqusition: Fourier space

$$f_k(k_x, k_y) = \int\int c_k(x,y)e^{-i(k_x x + k_y y)}u(x,y)dxdy$$

$$f_k(k_x, k_y) = \sum\sum c_k(x,y)e^{-i(k_x x + k_y y)}u(x,y)dxdy$$

$$f = Au$$

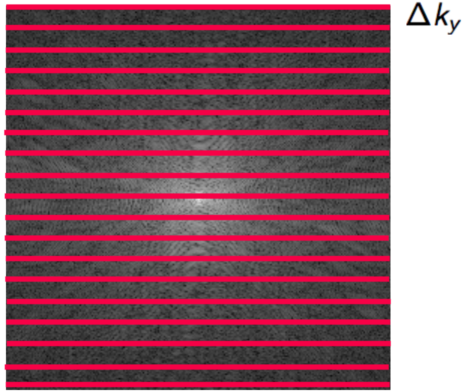


Image reconstruction

$$f_k(k_x, k_y) = \int\int c_k(x,y) e^{-i(k_x x + k_y y)} u(x,y) dxdy$$

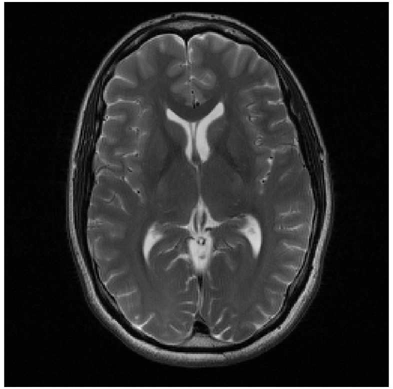
$$f_k(k_x, k_y) = \sum\sum c_k(x,y) e^{-i(k_x x + k_y y)} u(x,y) dxdy$$

$$f = Au$$

Δk_y

$$u = A^{-1} f$$

$\longrightarrow$



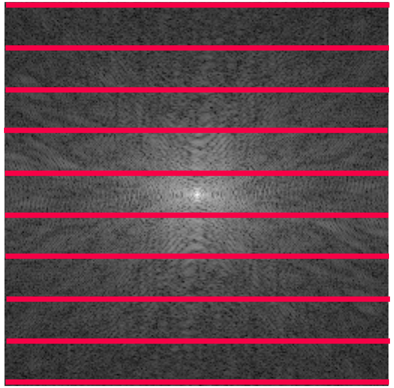
FOV

Image reconstruction: Inverse problem

$$f_k(k_x, k_y) = \int\int c_k(x,y)e^{-i(k_x x + k_y y)}u(x,y)dxdy$$

$$f_k(k_x, k_y) = \sum\sum c_k(x,y)e^{-i(k_x x + k_y y)}u(x,y)dxdy$$

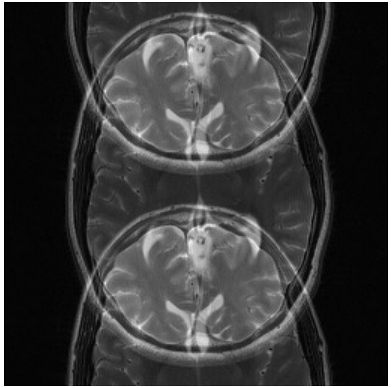
$$f = Au$$



$2\Delta k_y$

$$u = A^{-1}f$$

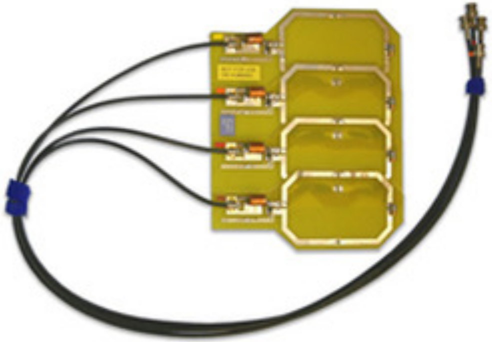
$$\longrightarrow$$



$\frac{FOV}{2}$

Parallel Imaging: 1990s to 2000s

$$f_k(k_x, k_y) = \int\int c_k(x,y) e^{-i(k_x x + k_y y)} u(x,y)\,dxdy$$

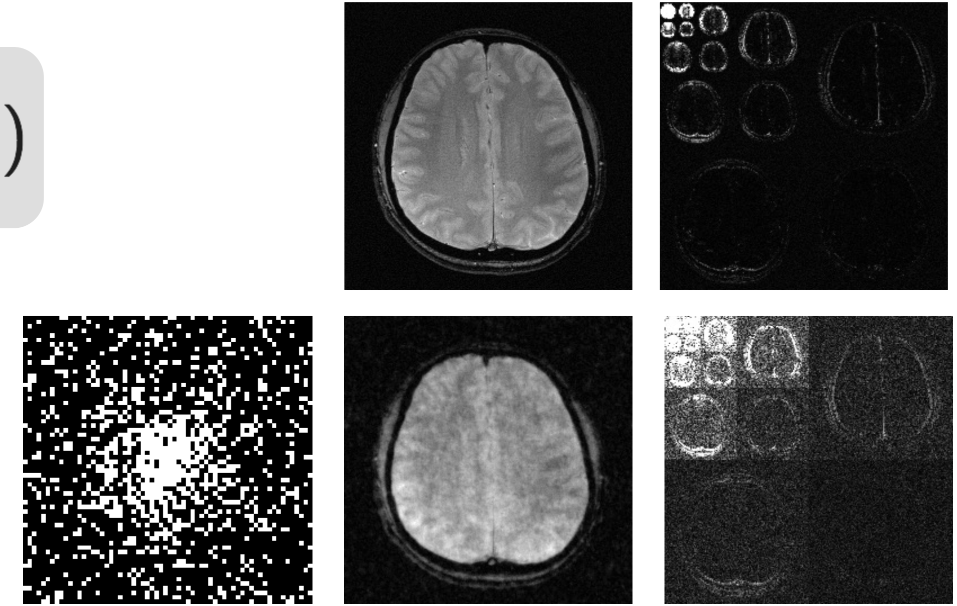


$$min||Au - f||_2^2$$

Sodickson MRM 1997
Pruessmann MRM 1999
Pruessmann MRM 2001
Griswold MRM 202

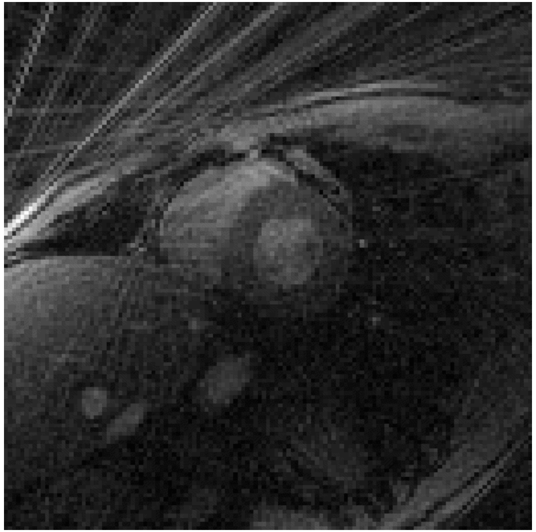
Compressed sensing: Late 2000s

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

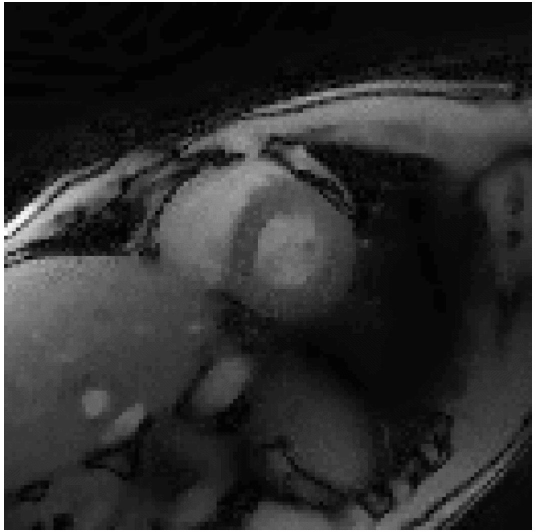


Lustig MRM 2007

Compressed sensing (38ms per frame)



$$min||Au - f||_2^2$$

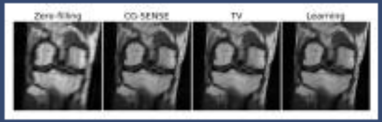


$$min||Au - f||_2^2$$
$$+ \lambda_s||\Psi_s(u)||_1$$
$$+ \lambda_t||\Psi_t(u)||_1$$

Knoll MRM 2011

ISMRM 2016

08:00 1088.

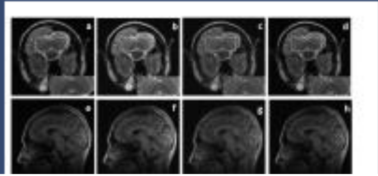


Learning a Variational Model for Compressed Sensing MRI Reconstruction

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.

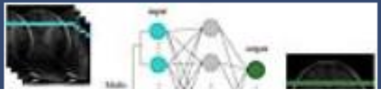


Exploiting deep convolutional neural network for fast magnetic resonance imaging

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 Ir 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],
ıes 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
ıg 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]

Asilomar Conference Grounds, Pacific Grove, CA, USA

ISMRM Workshop on

Machine Learning

14-17 MARCH 2018

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

Capital Hilton, Washington, D.C., 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)

MICCAI2018 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

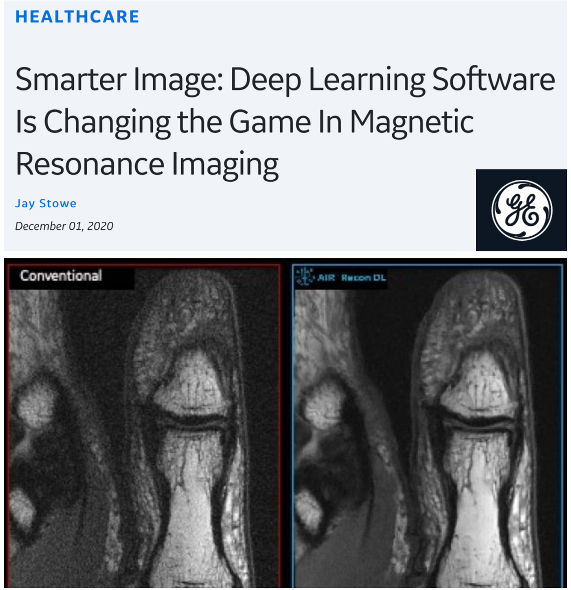
Moderators: Mariya Doneva, Ph.D., Florian Knoll, Ph.D. & Michael Lustig, Ph.D.

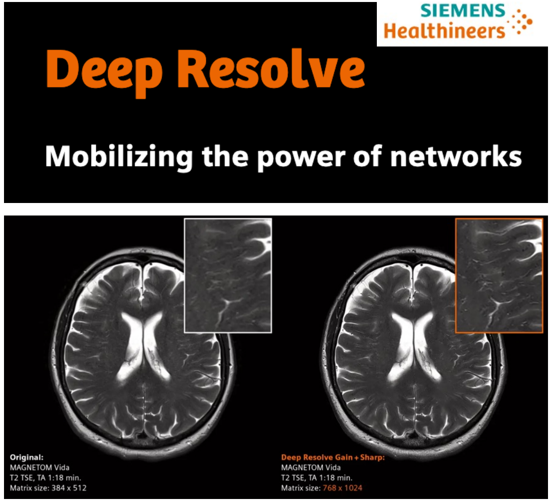
16:00	Basics of Machine Learning for Image Reconstruction	Kerstin Hammernik, Ph.D. Imperial College London London, England, UK
16:20	Learning Image Reconstruction with MR Physics Knowledge	Mehmet Akcakaya, Ph.D. University of Minnesota Minneapolis, MN, USA
16:30	Image Enhancement	Daniel Rueckert, Ph.D.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

Proffered Papers - Oral Session

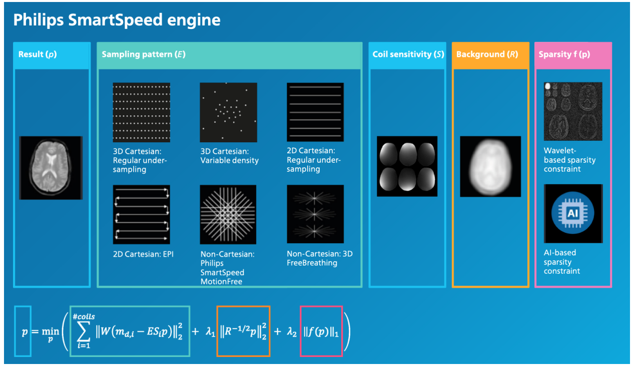
17:00	2-Minute Comprehensive Brain Exam Using Multi-Shot EPI with Synergistic Model-Based & Deep Learning Reconstruction	Wei-Ching Lo, M.Sc. Siemens Medical Solutions Malvern, PA, USA
17:10	Unsupervised Image Reconstruction Using Deep Generative Adversarial Networks	Elizabeth Cole, M.Sc. Stanford University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

2022

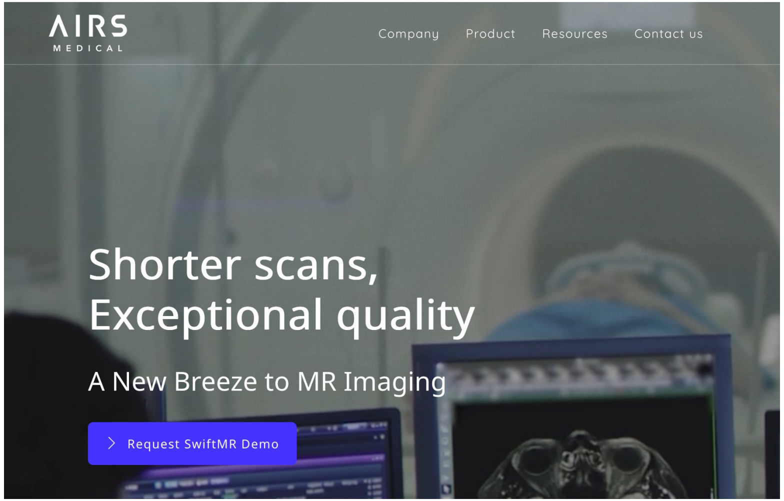

HEALTHCARE
Smarter Image: Deep Learning Software Is Changing the Game In Magnetic Resonance Imaging
Jay Stowe
December 01, 2020
Conventional
AIR Recon DL


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
2D Cartesian: EPI
Non-Cartesian: Philips SmartSpeed MotionFree
Non-Cartesian: 3D FreeBreathing
Wavelet-based sparsity constraint
AI-based sparsity constraint
$p = \min_p \left(\sum_{l=1}^{\#coils} \|W(m_{d,l} - ES_l p)\|_2^2 + \lambda_1 \|R^{-1/2} p\|_2^2 + \lambda_2 \|f(p)\|_1 \right)$

2022



MRI scans, in just half the time

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

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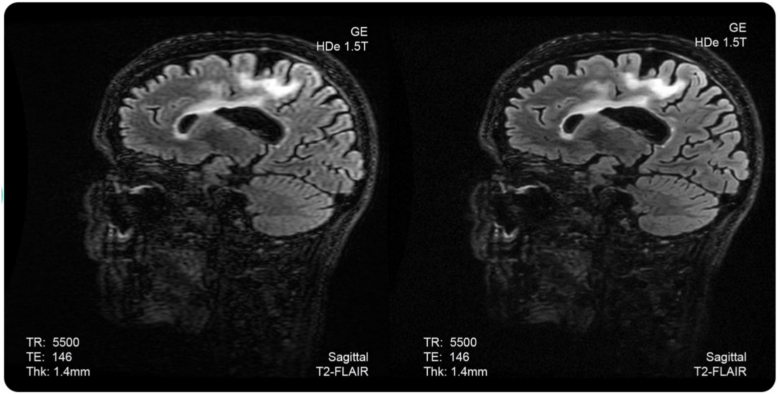
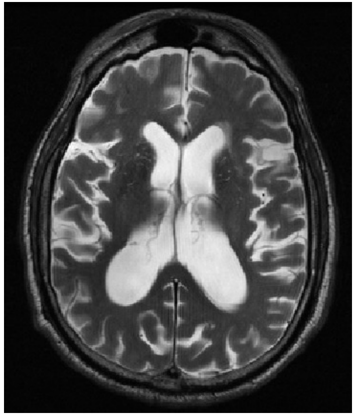
As Acquired | SubtleMR Enhanced

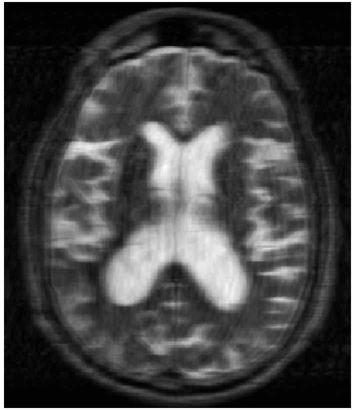


Back to compressed sensing

Fully sampled



Zero-filling R=4



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

Exploit inherent redunancy in images

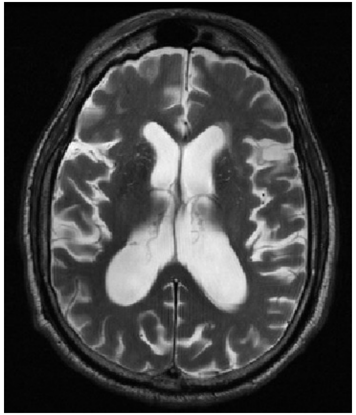
Sparsifying transform

Nonlinear reconstruction

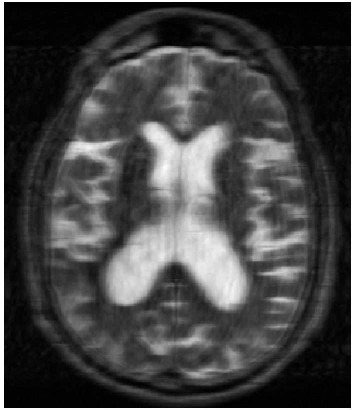
Lustig MRM 2007

Machine learning for image reconstruction

Fully sampled



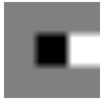
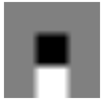
Zero-filling R=4



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

Separate artifacts from image content

Sparsifying transform → Spatial filter kernels

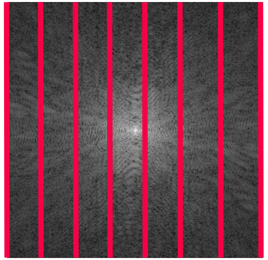
 ∇_x  ∇_y $K_i u \Leftrightarrow k_i * u$

L1 norm → Potential functions

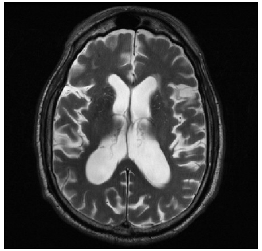
Hammernik ISMRM 2016
Hammernik MRM 2018
Knoll IEEE SPM 2020

Numerical implementation

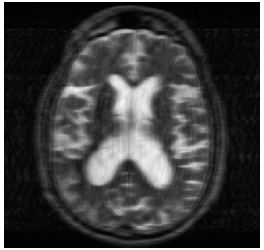
f



$\longrightarrow$ GD$_1$ $\longrightarrow$ GD$_t$ $\longrightarrow$ GD$_T$ $\xrightarrow{u_T}$



u_0



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

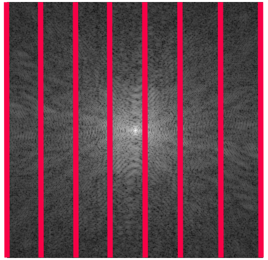
reconstruction

input

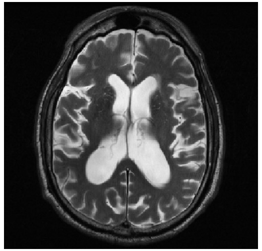
Landweber Amer J Math 1951

Learning the numerical optimization

f

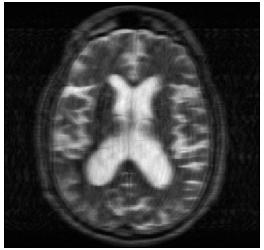


$\longrightarrow$ GD_1 $\longrightarrow$ GD_t $\longrightarrow$ GD_T $\xrightarrow{u_T}$



reconstruction

u_0

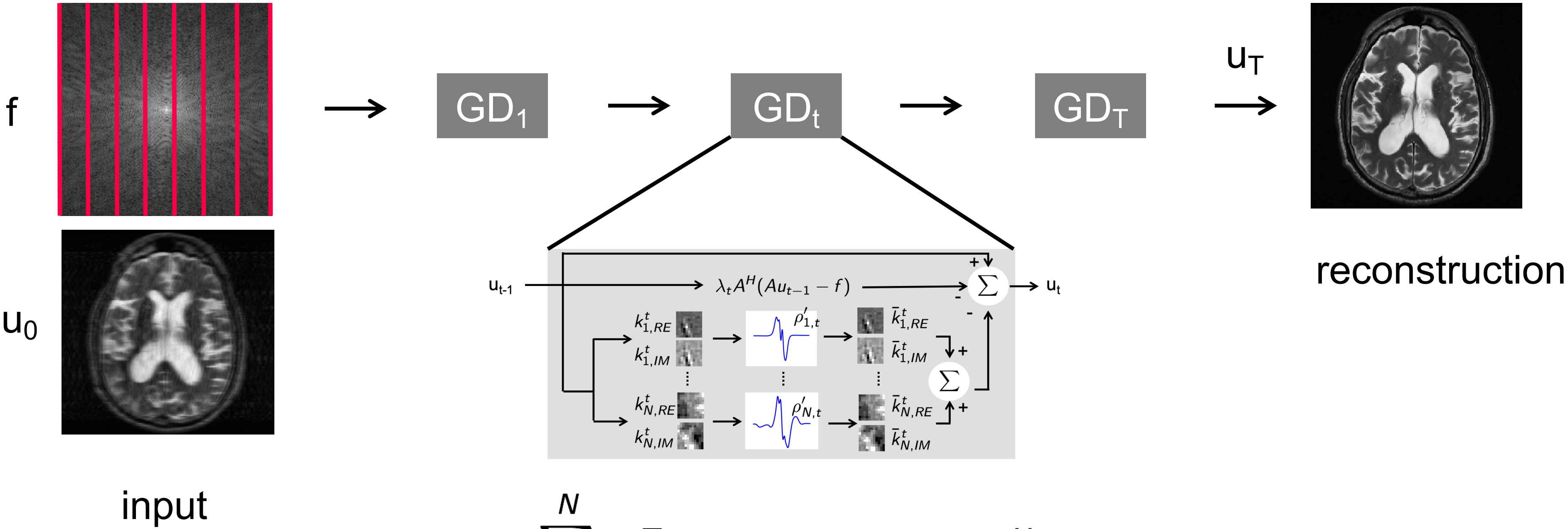


input

Learn T gradient descent (GD) steps

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

Neural network model for reconstruction

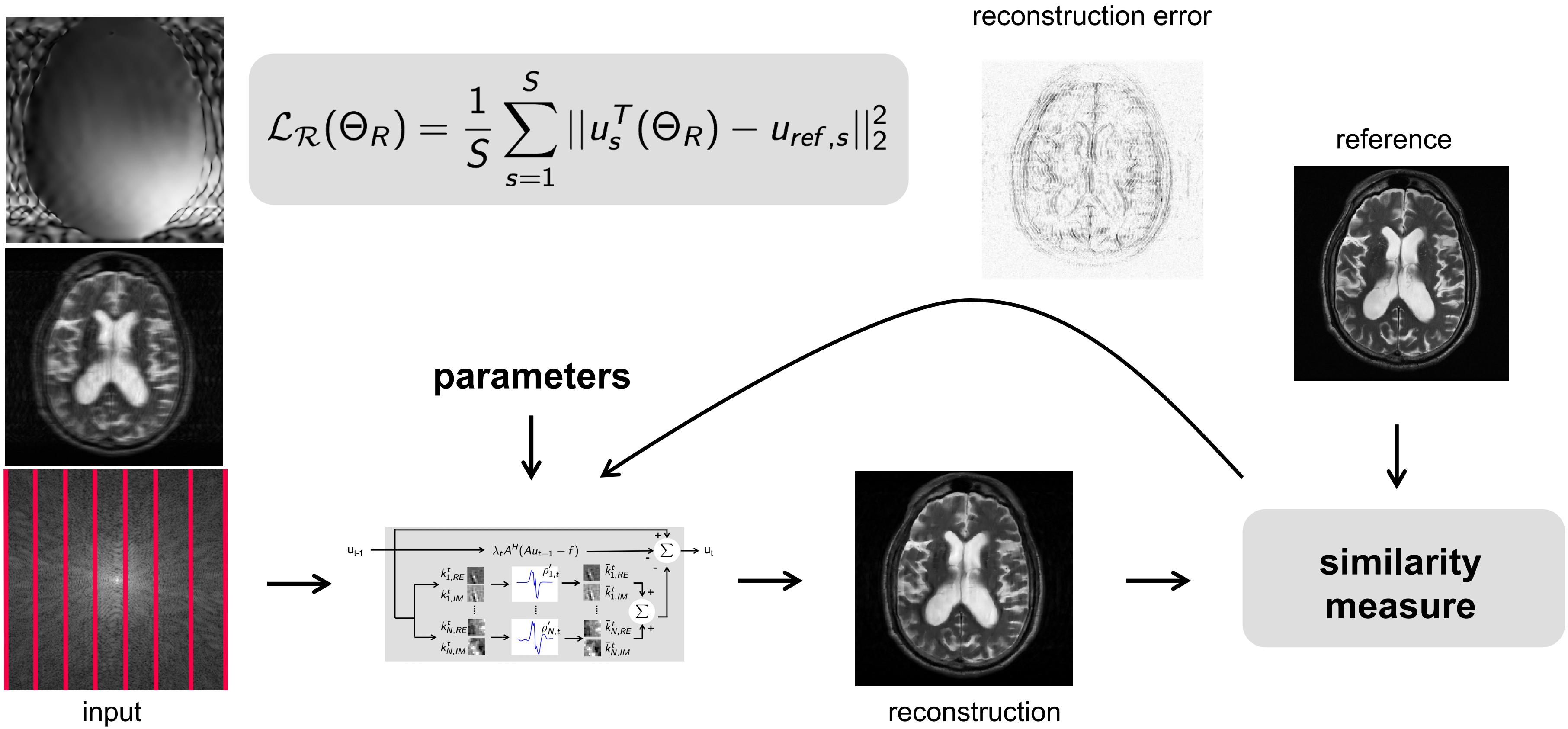


$$u_t = u_{t-1} - \sum_{i}^{N} K_{i,t}^{T} \rho'_{i,t}(K_{i,t} u_{t-1}) - \lambda_t A^H (A u_{t-1} - f)$$

Hammernik MRM 2018

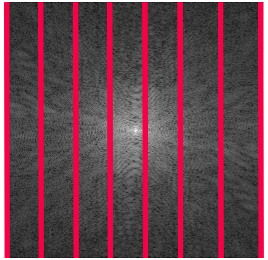
Neural network training

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



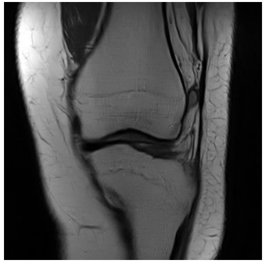
Reconstructing new test data

input



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

reconstruction



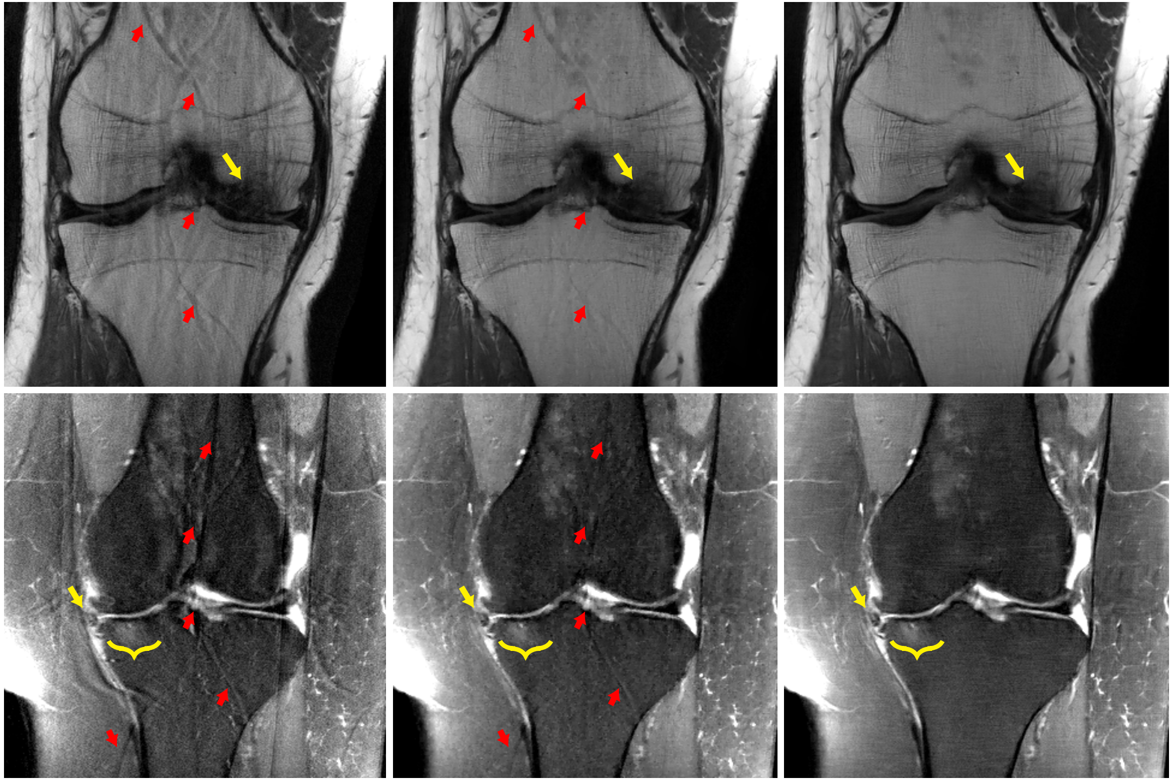
Zero filling initialization

Some reconstruction examples, R=4

PI | PI-CS | Learning

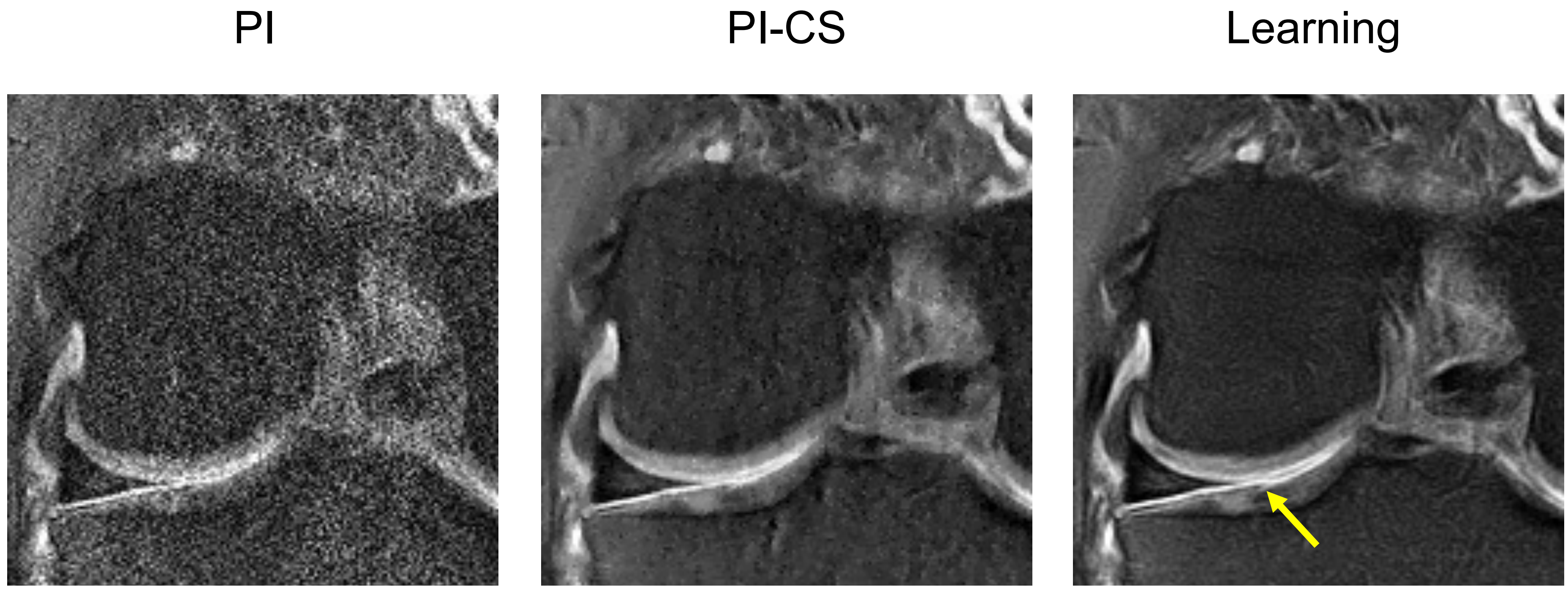
M50

F57



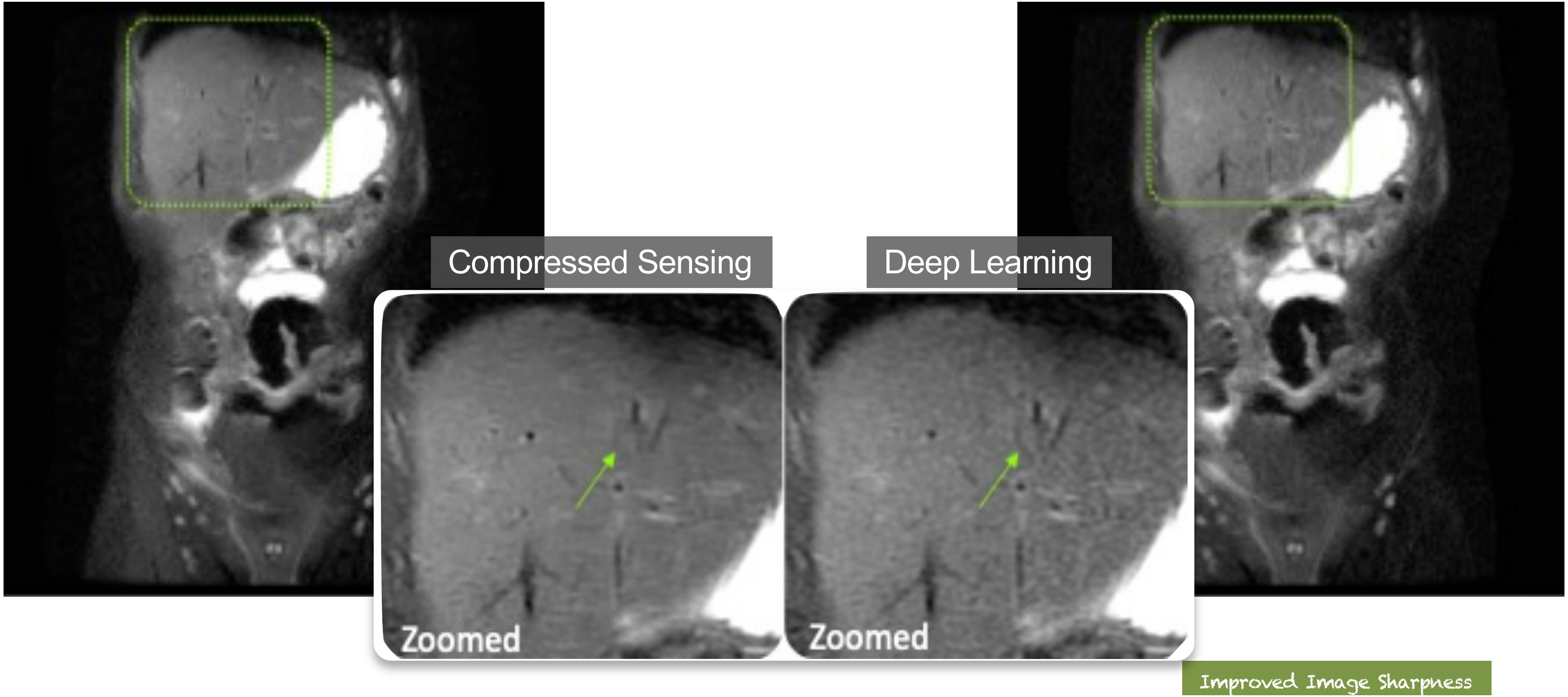
Hammernik, MRM 2018

Some reconstruction examples, R=4



Hammernik, ISMRM 2016

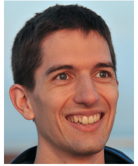
Examples from other research sites

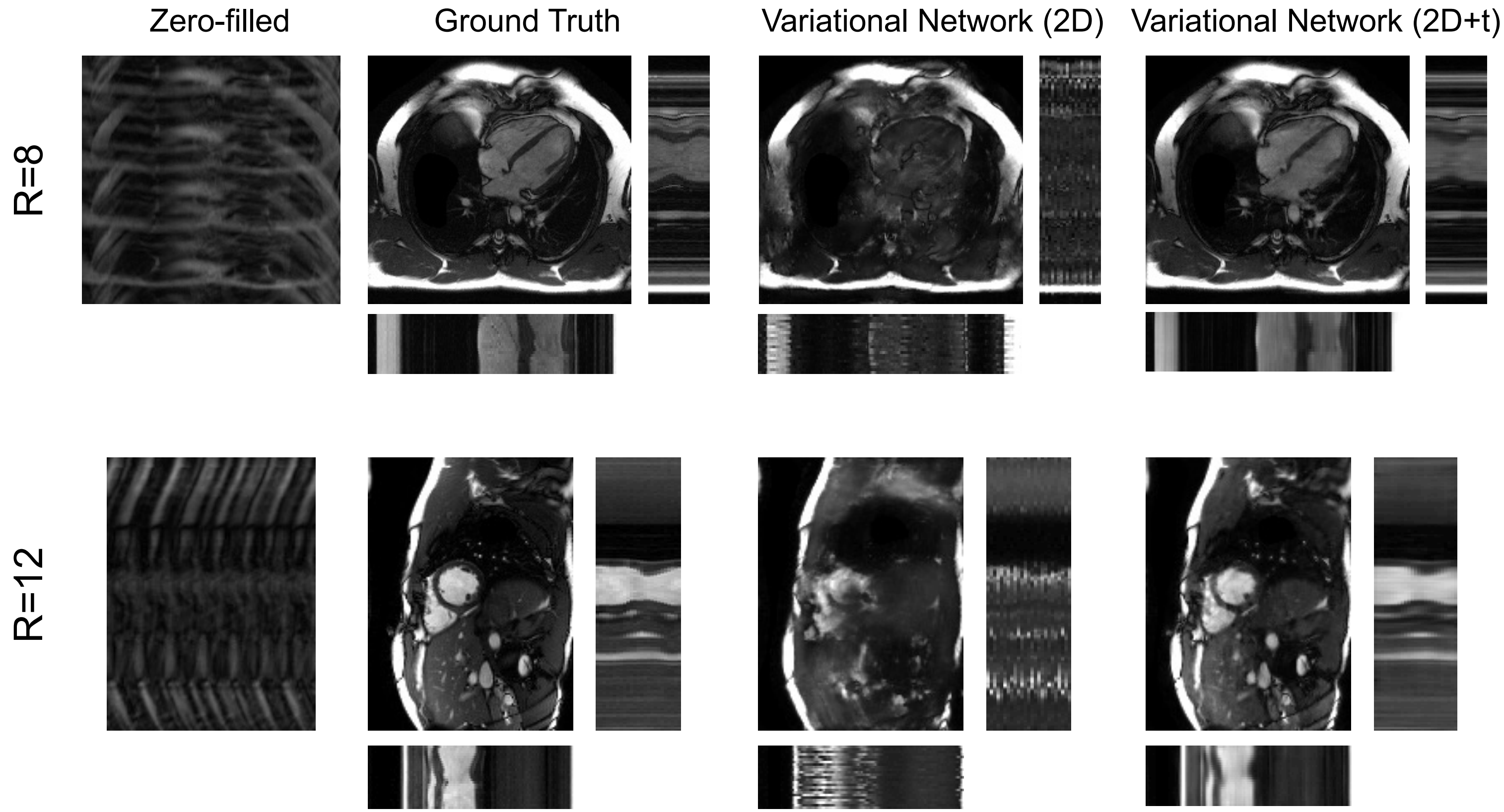


Chen Radiology 2018

Slides courtesy of Joseph Cheng (Stanford)

Dynamic Cardiac MR

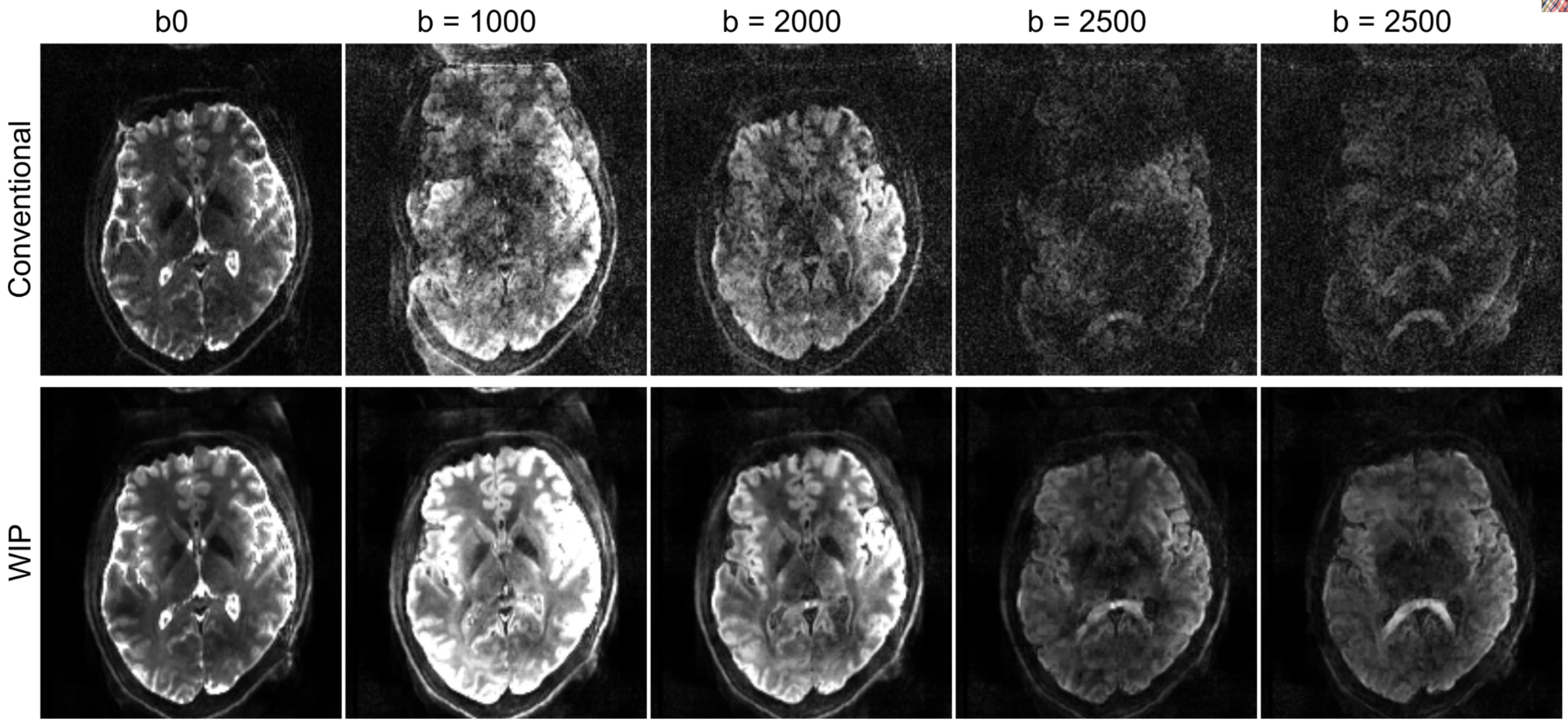




R	2D	2D+t
8x	0.84	0.97
12x	0.71	0.95

SSIM scores

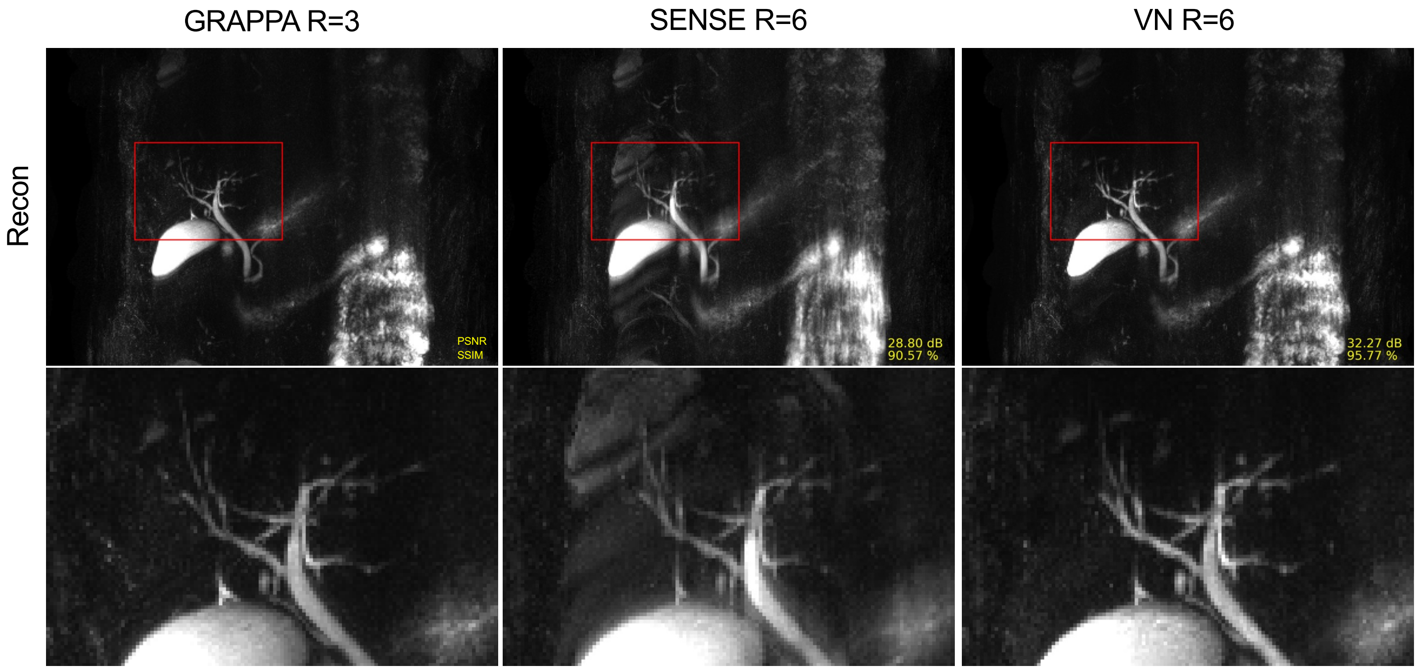
2-Shot EPI Diffusion MRI at 7T



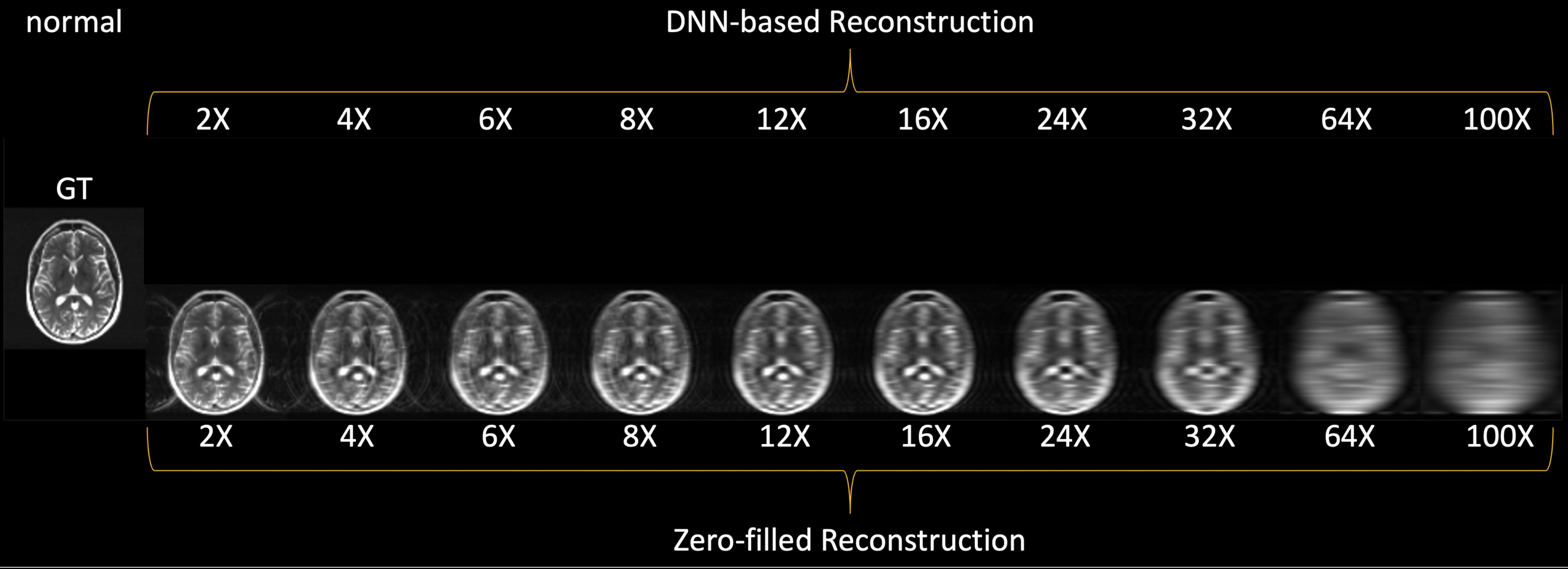
In-plane resolution 1.4 mm^3, in-plane acc=3, pf=6/8, 126 diffusion encodings, t_{acq}=15min

SIEMENS Healthineers

Accelerated MRCP



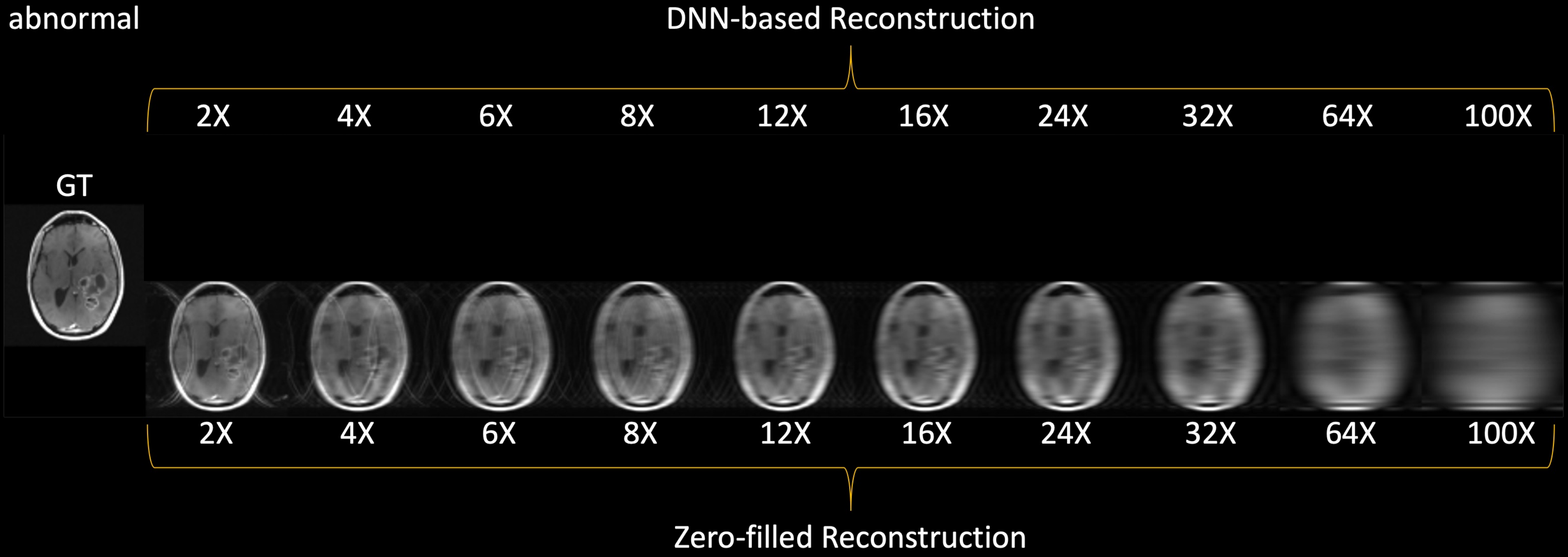
Performance at progressive acceleration



Murrel Radiology AI 2022

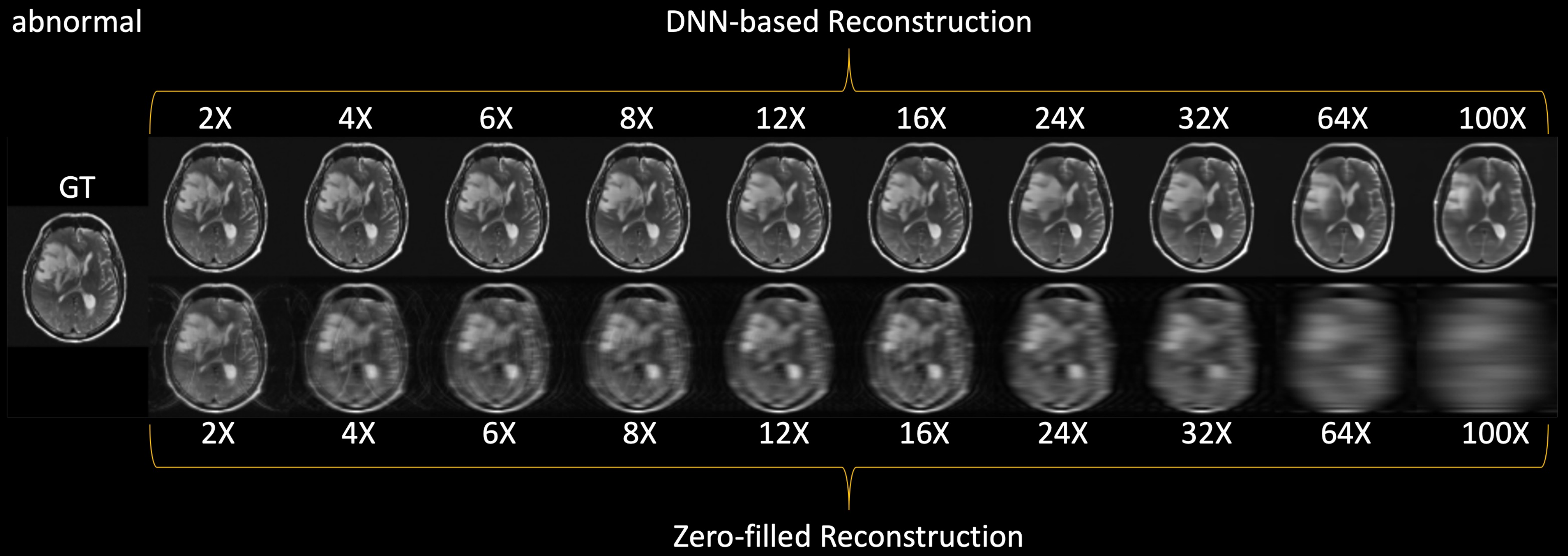
Performance at progressive acceleration

abnormal



Murrel Radiology AI 2022

Performance at progressive acceleration



Murrel Radiology AI 2022

When does it break?

PNAS Proceedings of the National Academy of Sciences of the United States of America

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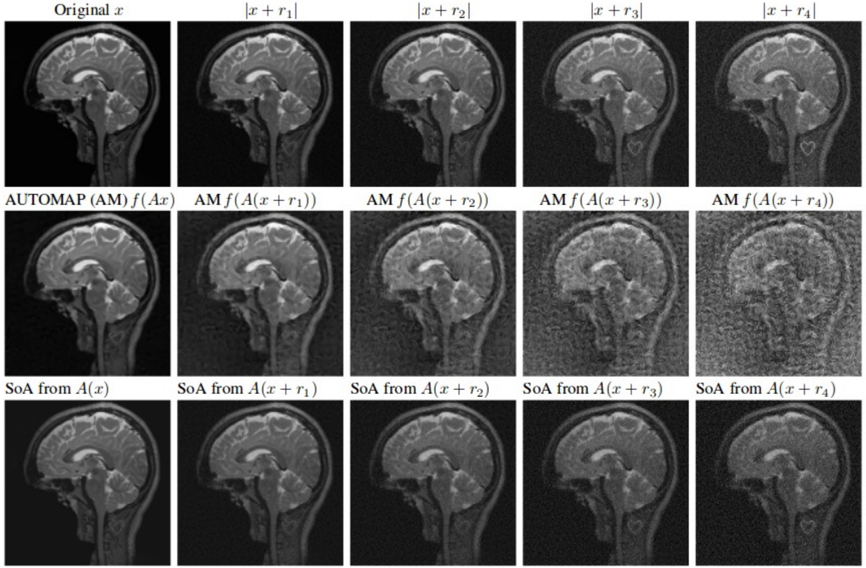
PHYSICAL SCIENCES

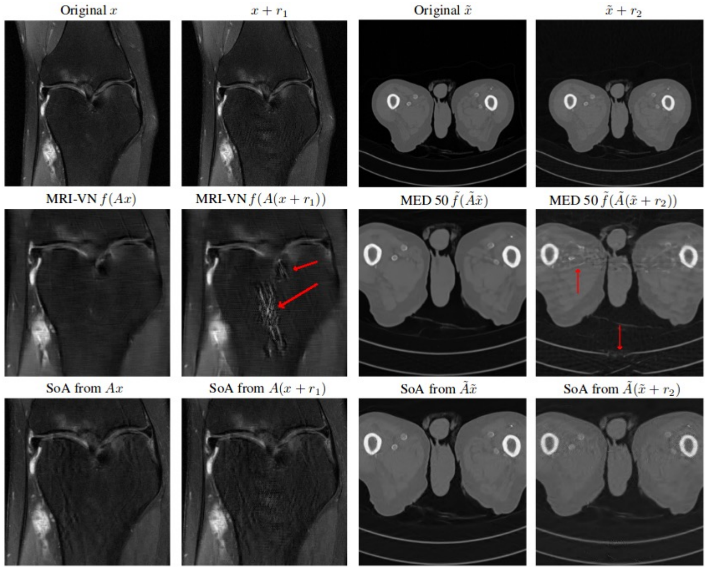
On instabilities of deep learning in image reconstruction and the potential costs of AI

Vegard Antun, Francesco Renna, Clarice Poon, Ben Adcock, and Anders C. Hansen

PNAS first published May 11, 2020 https://doi.org/10.1073/pnas.1907377117

Edited by David L. Donoho, Stanford University, Stanford, CA, and approved March 12, 2020 (received for review June 4, 2019)





Reproducibility?

Evaluation

We tested our algorithm on data from 10 clinical patients per sequence and reconstructed the whole imaged vol-

Hammernik MRM 2018

Evaluation on raw MRI scanner data. Cartesian *k*-space test data (of Fig. 4) were acquired from a healthy volunteer on a 3T Siemens Trio MRI scanner with a spin-

Zhu Nature 2018

Evaluation of the trained VN model was performed in the remaining 27 patients (nine males, 18 females) in comparison with the PICS reconstruction.

Chen Radiology 2018

The evaluation was done via a 3-fold cross validation, where for two folds we train on 7 subjects then test on 3 subjects, and for the remaining fold we train on 6 subjects and test on 4 subjects. While the original sequence has size $256 \times 256 \times T$,

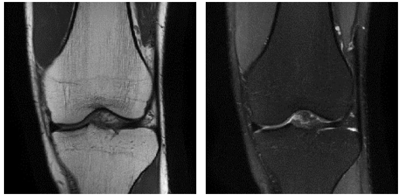
Qin IEEE TMI 2018

The aggregated test error across 10 subjects

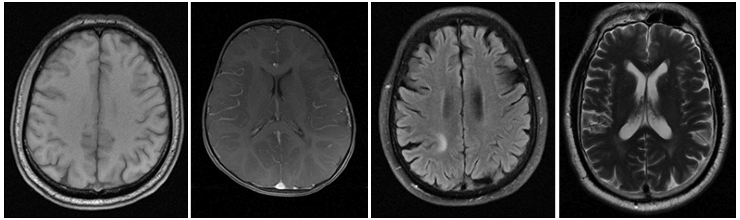
Schlemper IEEE TMI 2018

fastMRI dataset

- **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

facebook
Artificial Intelligence Research

Dataset stats

Registry of Open Data on AWS

NYU Langone & FAIR FastMRI Dataset

biology | health | image processing | imaging | life sciences | magnetic resonance imaging | neurobiology | neuroimaging

Description

This dataset contains deidentified raw k-space data and DICOM image files of over 1,500 knees and 6,970 brains.

Update Frequency

The dataset is estimated to grow annually to include MRI raw data and imaging for additional body structures.

License

MIT License

Documentation

https://fastmri.med.nyu.edu/

Managed By

FastMRI

See all datasets managed by FastMRI.

Contact

Florian Knoll

9000 unique visitors per year

961 TB of data downloaded per year

Amazon AWS public dataset grant

Top 10 of all AWS life sciences datasets (use and downloads)

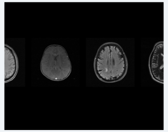
2019/2020 reconstruction challenges

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

fastMRI

Accelerating MR Imaging with AI

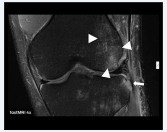
Latest News & Updates



09-17-2020

The 2020 fastMRI challenge opens for submissions on October 1

Read More



08-18-2(

FastMRI b
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.

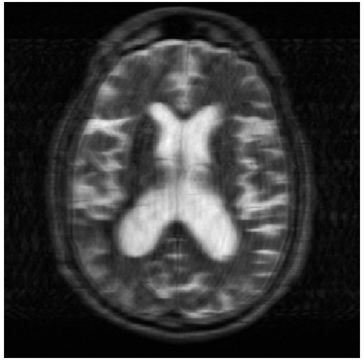
To enable the broader research community to participate in this important project, NYU Langone Health has released fully anonymized raw data and image datasets. Visit our github repository, which contains baseline reconstruction models and PyTorch data loaders for the fastMRI dataset.

Knoll MRM 2020
Muckley TMI 2021

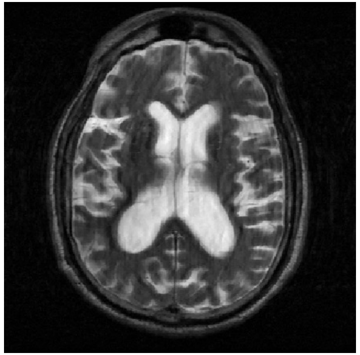
facebook
Artificial Intelligence Research

fastMRI reconstruction challenge

Undersampled

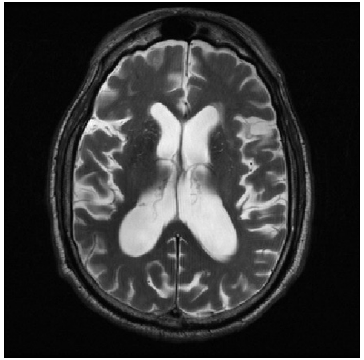


Reconstruction

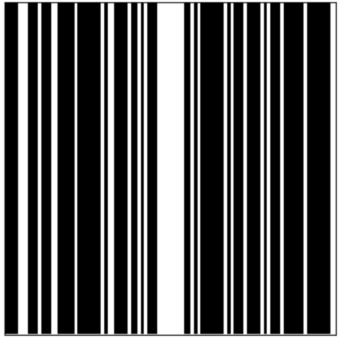


Error

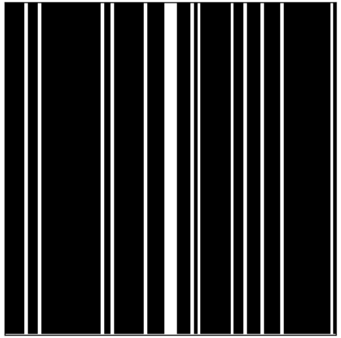
Reference



R=4

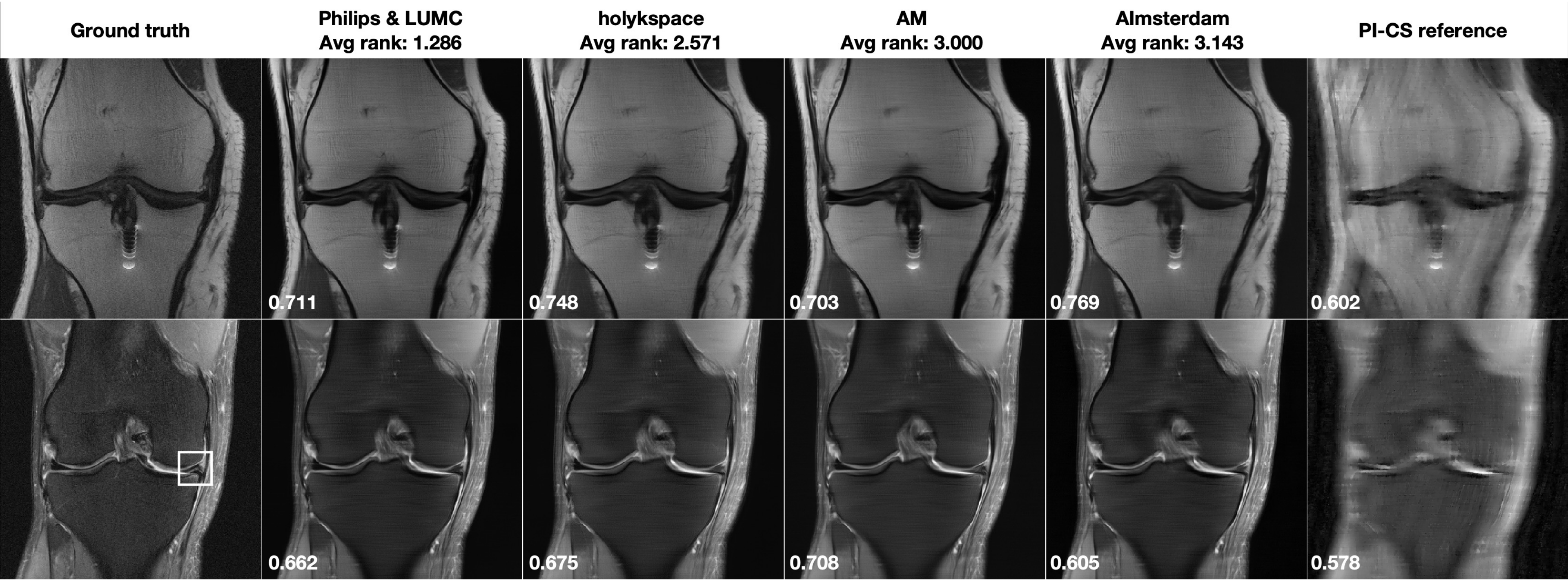


R=8



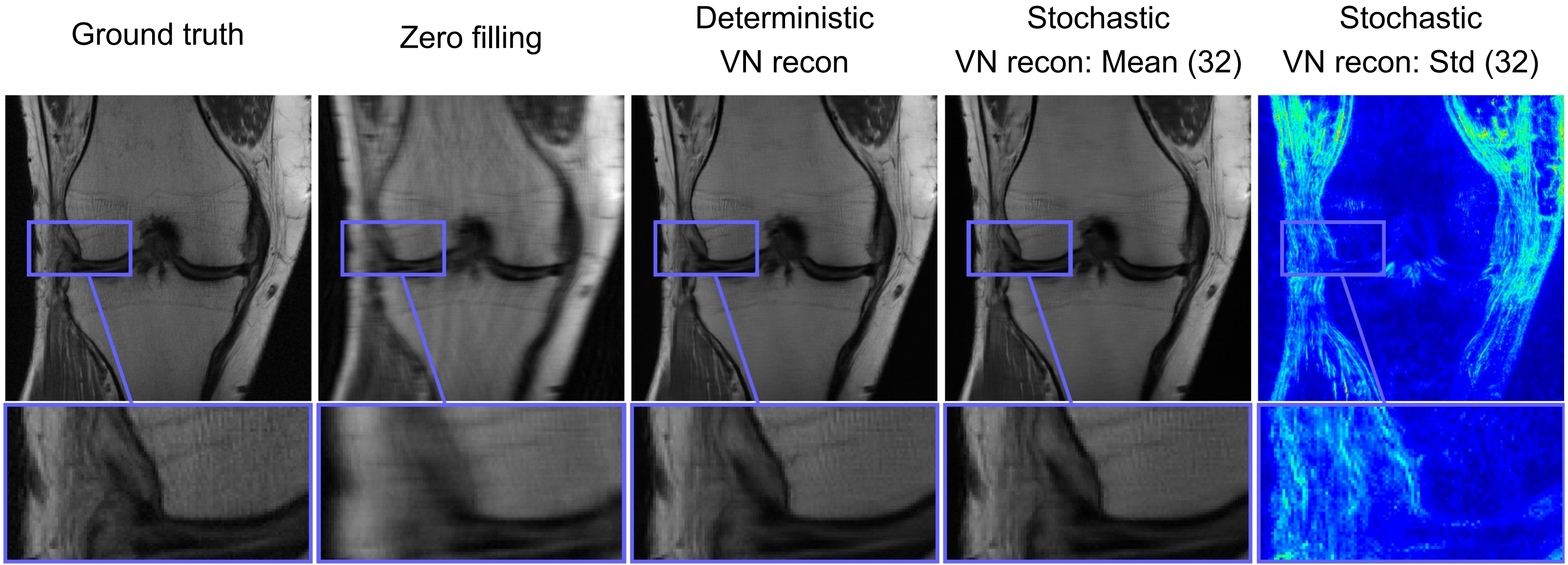
	Acceleration 4x	NMSE	SSIM	PSNR	NYU DATA ONLY
AIRS-Net 10/15/2020	4x	0.0028	0.9640	42.2	✓
Joint-ICNet 10/15/2020	4x	0.0035	0.9599	41.2	✓
xpdnet_v2 10/15/2020	4x	0.0034	0.9589	41.3	✓
RIM 10/15/2020	4x	0.0044	0.9556	40.2	✓
Deep Residual Dense U-Net 10/15/2020	4x	0.0053	0.9533	39.4	✓
Momentum_DIHN 10/15/2020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

2019 multi coil R=8 results



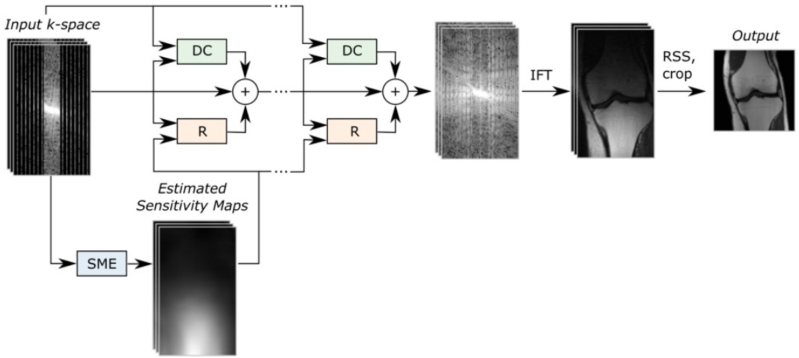
Knoll MRM 2020

Bayesian Uncertainty Estimation



Narnhofer IEEE TMI 2021

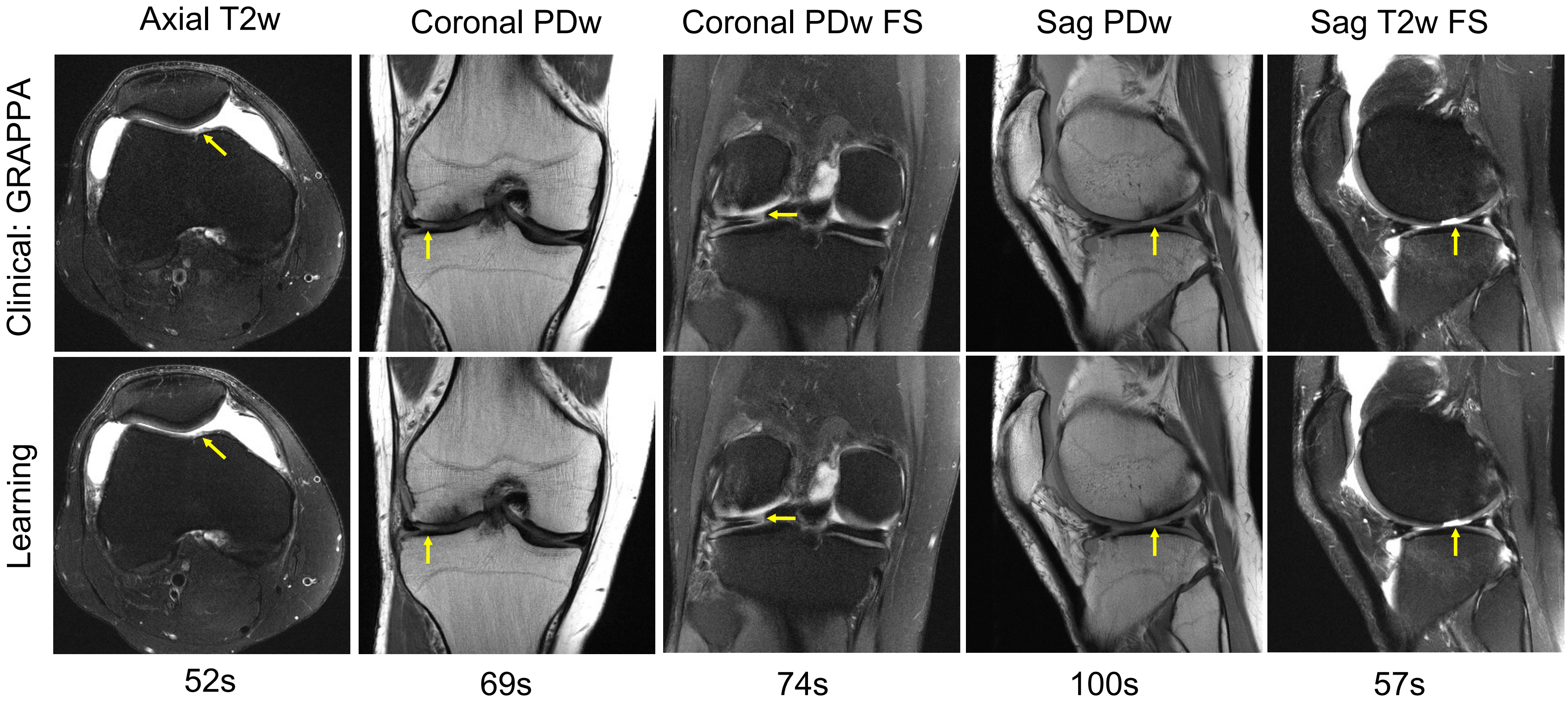
Clinical integration and dissemination



Block ISMRM Sedona 2016
Sriram MICCAI 2020, fastMRI.org

PACS

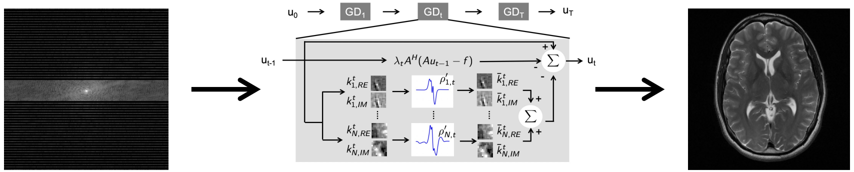
M26: chondral defects, meniscal tear



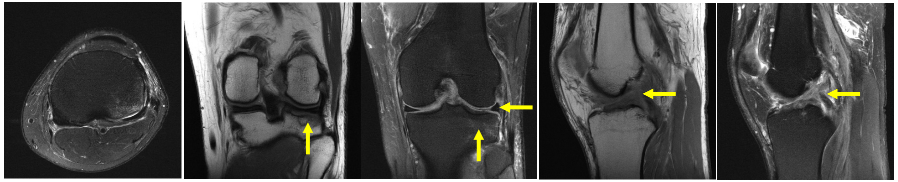
Prospective study, 300 patients enrolled, scan times of accelerated sequences shown

Summary

Introduction to MRI recon



From CS to DL recon



Challenges/Validation