RISE OF THE MACHINES

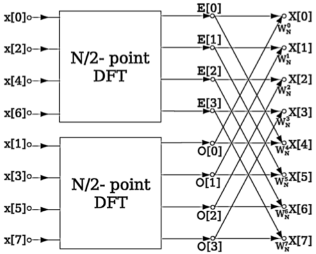
(IN MR IMAGE ACQUISITION AND RECONSTRUCTION)

FLORIAN KNOLL

NYU

UCLA 2020 A.D.

Medical imaging in the 1970/1980s



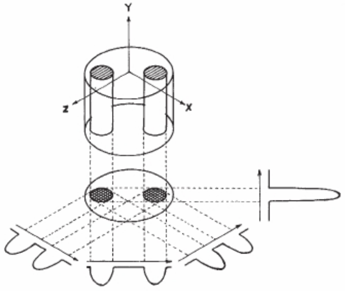
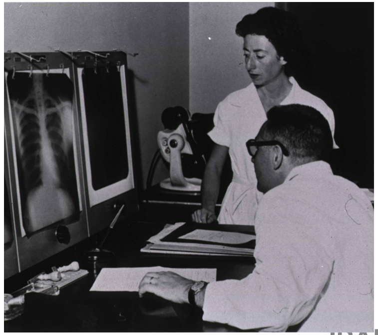


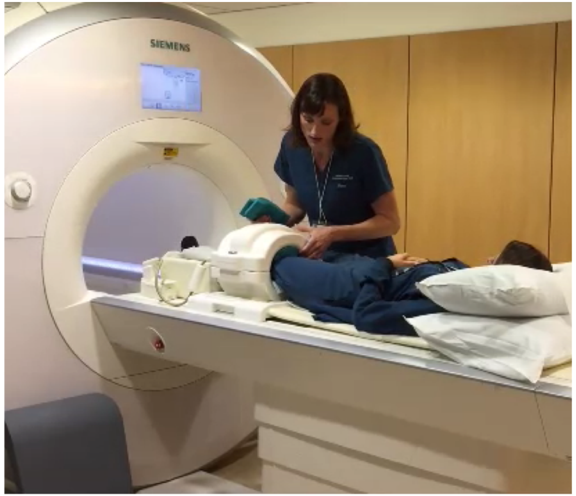
Fig. 1 Relationship between a three-dimensional object, its two-dimensional projection along the Y-axis, and four one-dimensional projections at 45° intervals in the XZ-plane. The arrows indicate the gradient directions.

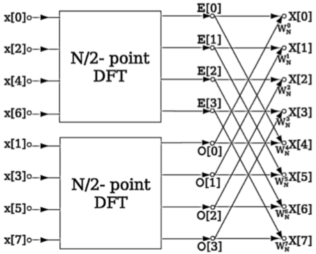


Cooley, Tukey 1965

Lauterbur 1973

Medical imaging today





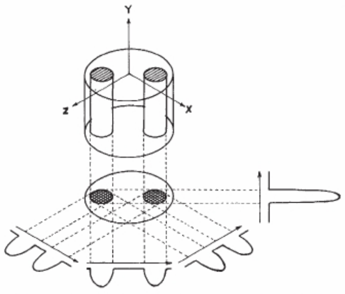


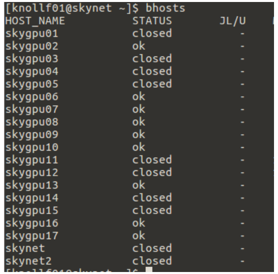
Fig. 1 Relationship between a three-dimensional object, its two-dimensional projection along the Y-axis, and four one-dimensional projections at 45° intervals in the XZ-plane. The arrows indicate the gradient directions.

Cooley, Tukey 1965

Lauterbur 1973

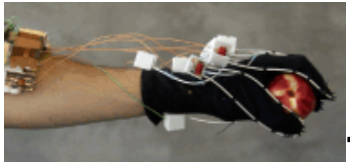
Computing/DL

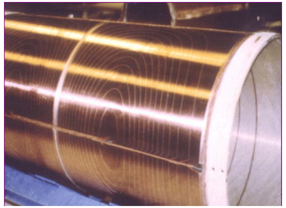
SKYNET
NEURAL NET-BASED ARTIFICIAL INTELLIGENCE


```
[knollf01@skynet ~]$ bhosts
HOST_NAME          STATUS       JL/U
skygpu01           closed        -
skygpu02           ok            -
skygpu03           closed        -
skygpu04           closed        -
skygpu05           closed        -
skygpu06           ok            -
skygpu07           ok            -
skygpu08           ok            -
skygpu09           ok            -
skygpu10           ok            -
skygpu11           closed        -
skygpu12           closed        -
skygpu13           ok            -
skygpu14           closed        -
skygpu15           closed        -
skygpu16           ok            -
skygpu17           ok            -
skynet             closed        -
skynet2            closed        -
```

Elements of the diagnostic pipeline

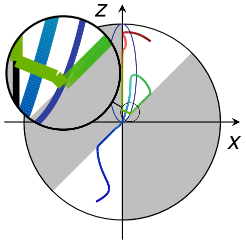
Hardware

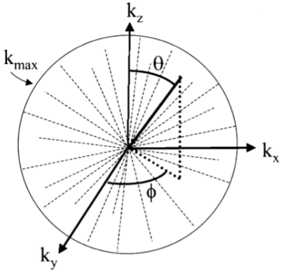




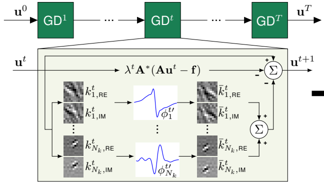
Data acquisition

Pulse sequence design

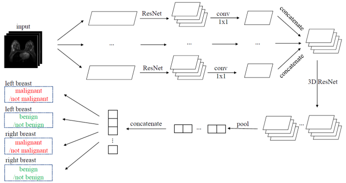




Reconstruction

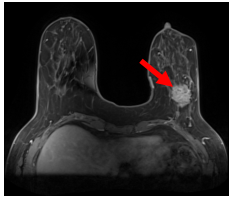


Classification



Diagnosis

Benign/Malignant



Cooperations

TU Graz
Graz University of Technology

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Artificial Intelligence Research

Tom Pock & Co

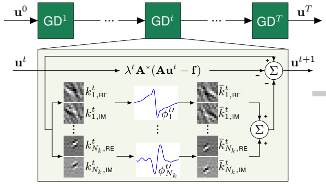
Image reconstruction

Hardware

Data acquisition

Pulse sequence design

Reconstruction



Classification

Diagnosis

Benign/Malignant

MR data acquisition: Fourier (k-) space

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

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

$$f = Au$$

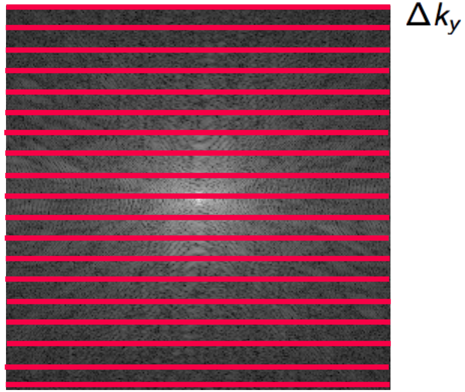


Image reconstruction: Inverse problem

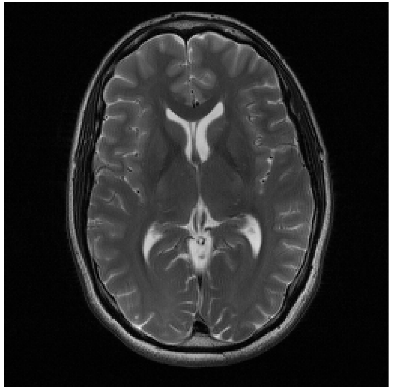
$$f_k(k_x, ky) = \int\int c_k(x,y) e^{-i(k_x x + k_y y)} u(x,y)\, dx dy$$

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

$$f = Au$$

Δk_y

$$u = A^{-1} f \quad \longrightarrow$$



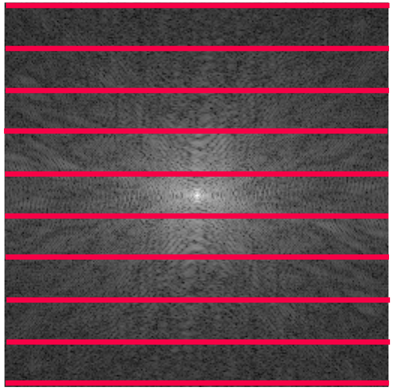
FOV

Image reconstruction: R=2

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

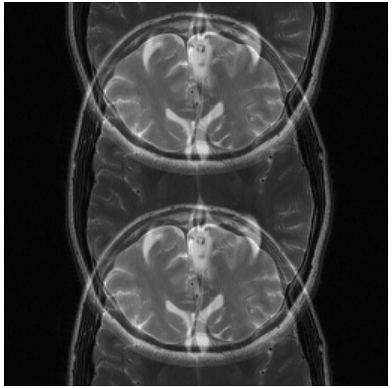
$$f_k(k_x, ky) = \sum\sum c_k(x,y)e^{-i(k_x x + k_y y)}u(x,y)$$

$$f = Au$$



$2\Delta k_y$

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



$\frac{FOV}{2}$

Compressed sensing: Sparse representation

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

Lustig MRM (2007)

Compressed sensing: Sparse representation

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

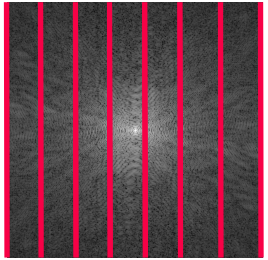
Total Variation (TV)

$$\min_u \frac{\lambda}{2} ||Au - f||_2^2 + ||\nabla(u)||_1$$

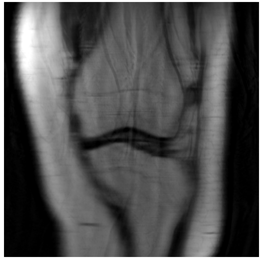
Lustig MRM (2007)
Rudin (1992)
Block MRM (2007)

Numerical implementation

f

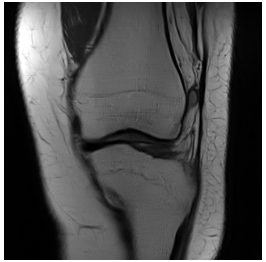


u_0



input

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



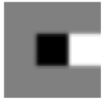
reconstruction

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

Landweber Amer J Math 1951

CS → machine learning image reconstruction

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

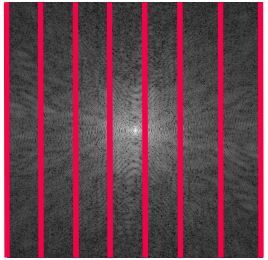
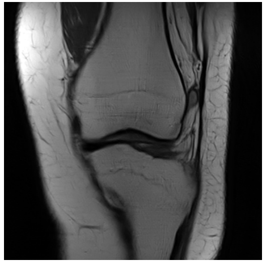
 ∇_x  ∇_y $K_i u \Leftrightarrow k_i * u$

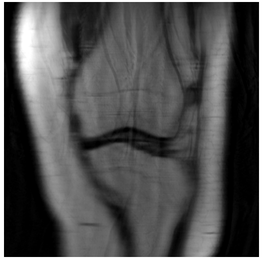
- L1 norm → Potential functions

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

Hammernik ISMRM 2016, MRM 2018

Learning the numerical optimization

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

u_0 

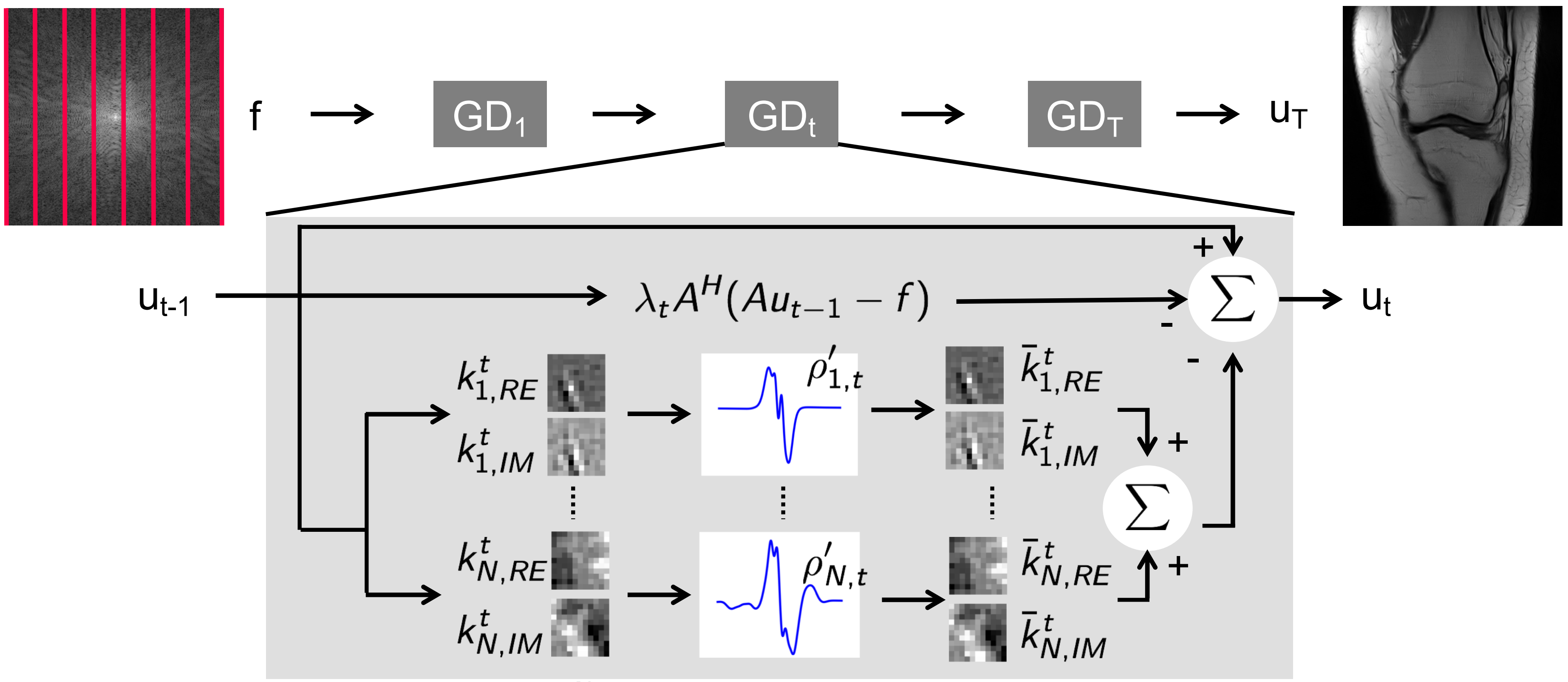
input

reconstruction

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”



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

Hammernik ISMRM 2016
Hammernik MRM 2018

Learning for image reconstruction

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

reconstruction error

reference

input

parameters

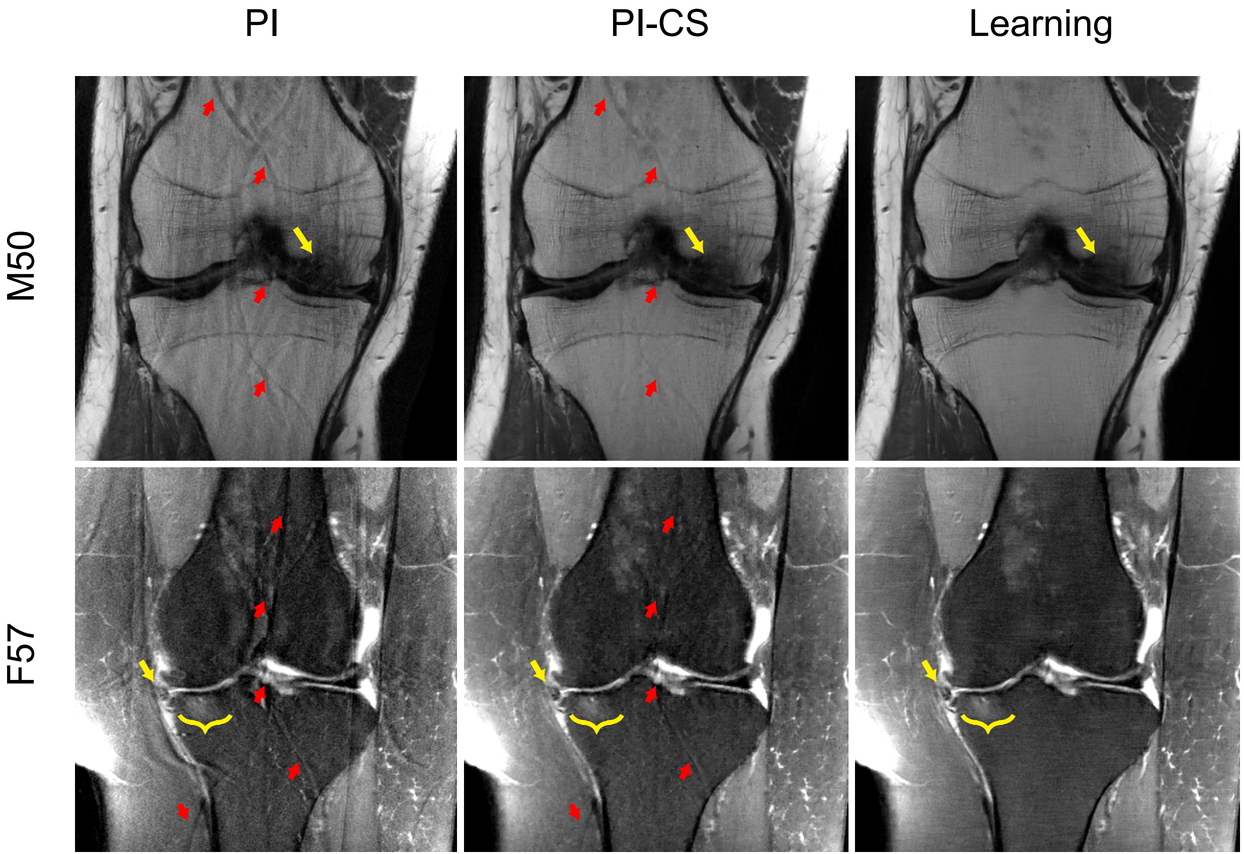
Reconstruction model

reconstruction

similarity measure

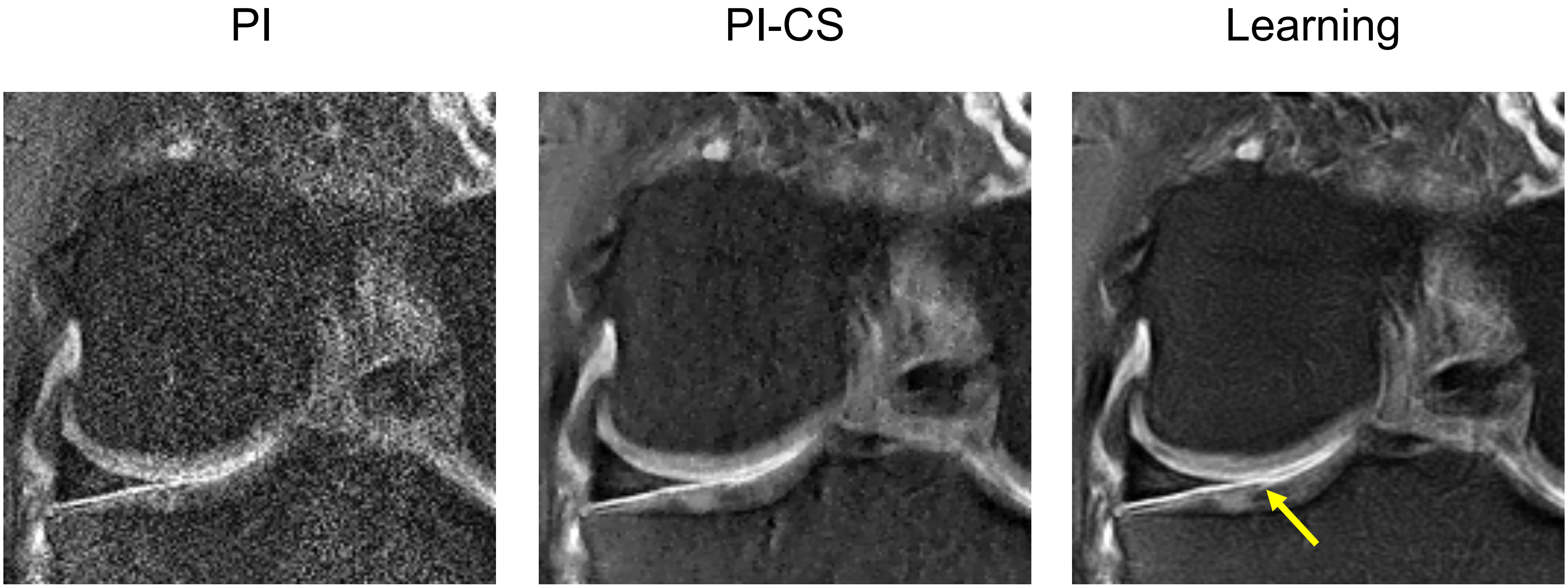
Hammernik MRM 2018

Some reconstruction examples, R=4



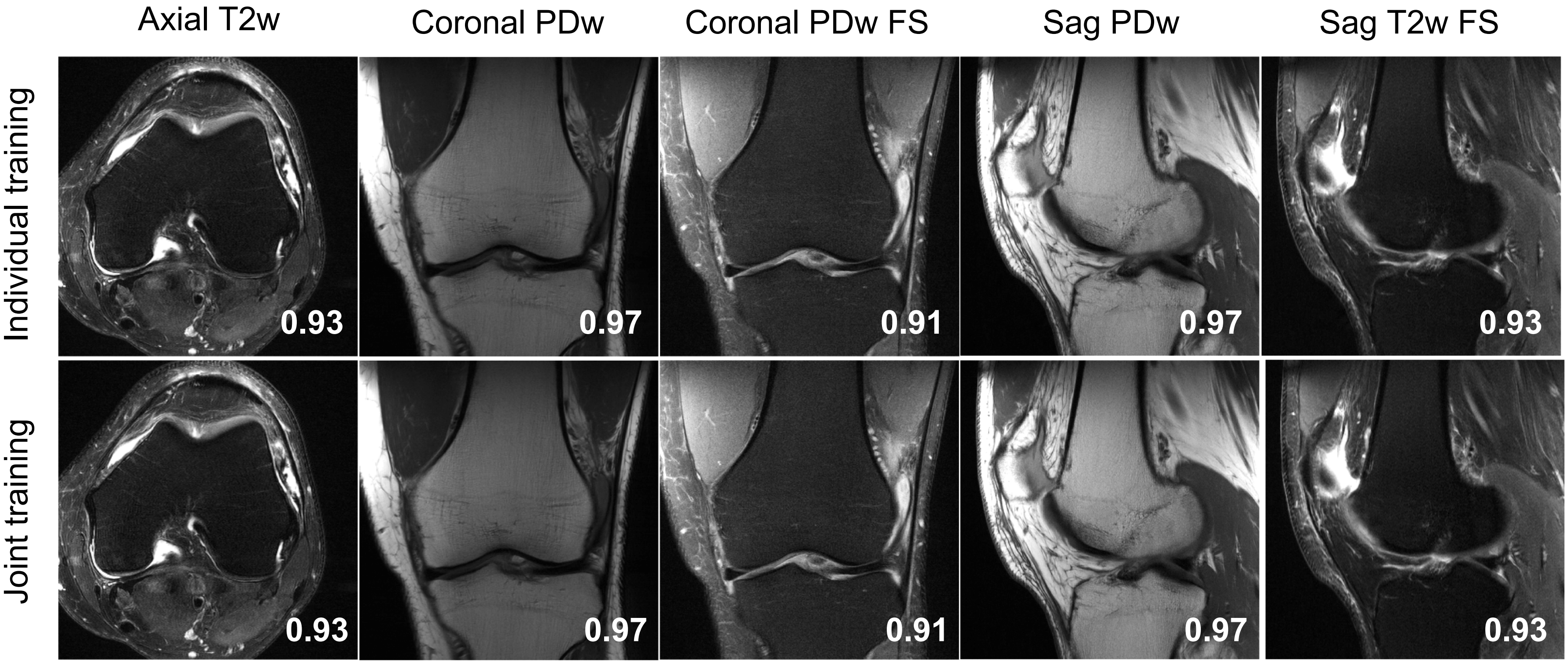
Hammernik, MRM 2018

Small fissure in tibial cartilage, R=4

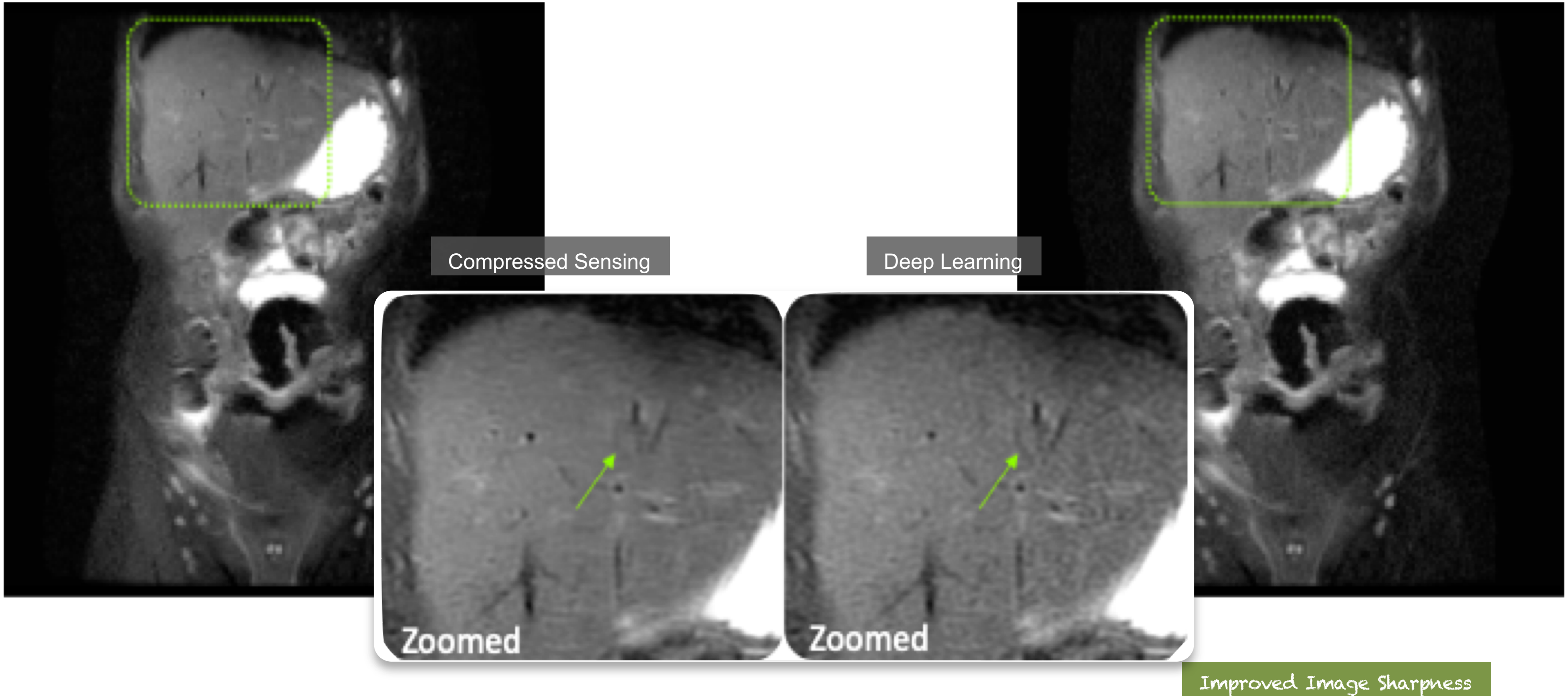


Hammernik, ISMRM 2016

Robustness and generalization: Sequences



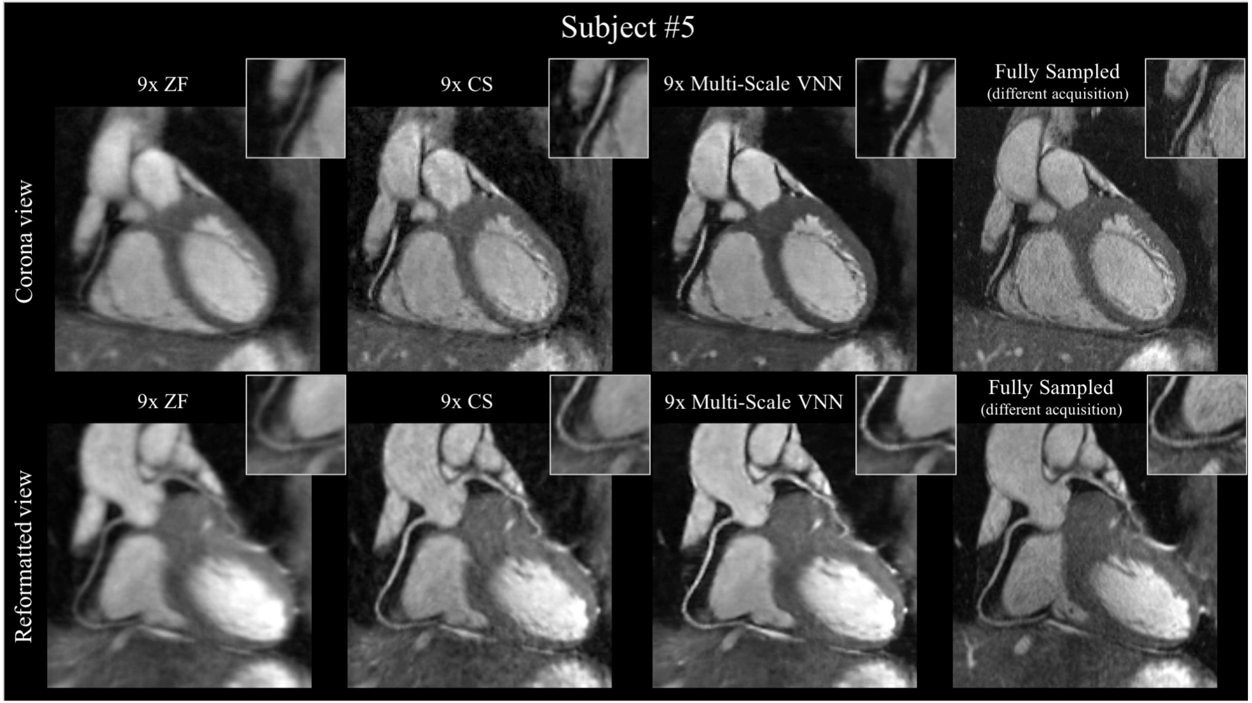
Abdominal Imaging: Clinical Study



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)

Where are we as a field?

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

Comparison to computer vision

IMAGENET

14,197,122 images, 21841 synsets indexed

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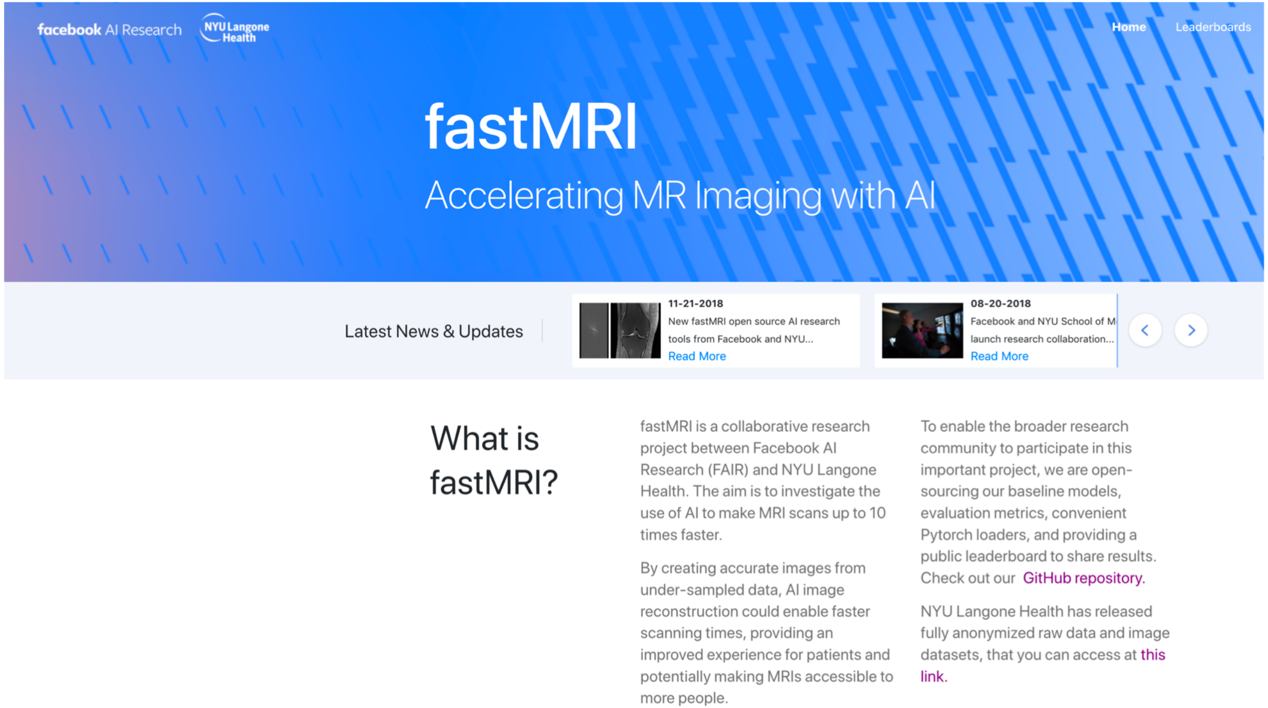
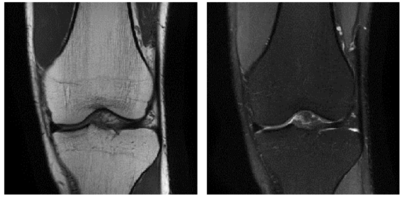
2019 fastMRI reconstruction challenge and dataset



https://arxiv.org/abs/2001.02518

Public data set for image reconstruction

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

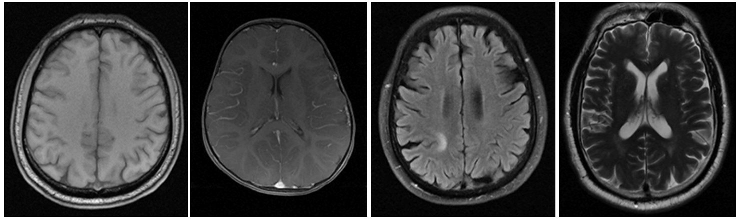


Knoll Radiology AI (in press, 2019)
fastmri.med.nyu.edu

Public data set for image reconstruction

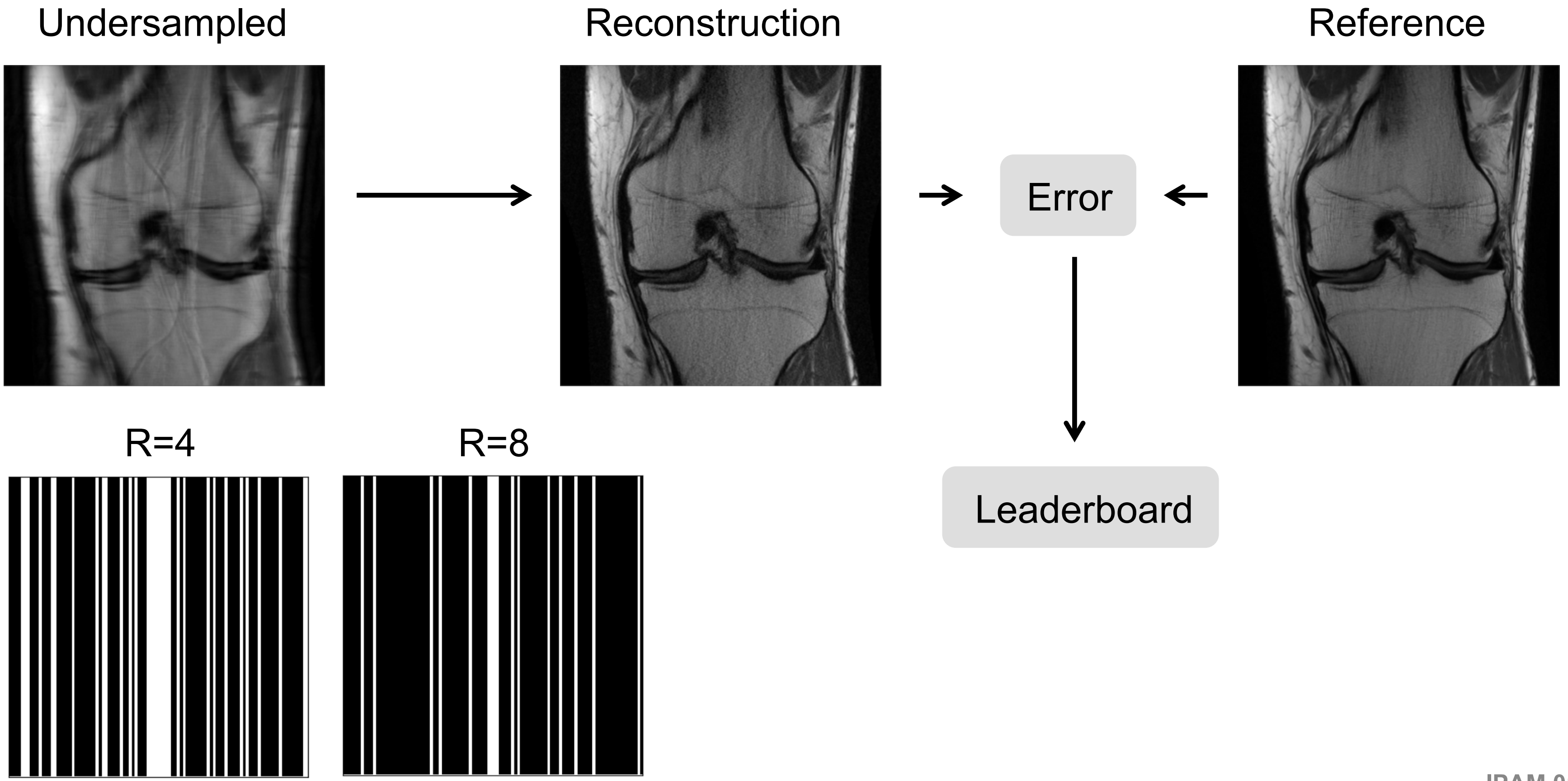
- **MSK (knee)**
  - Rawdata (fully sampled): 1398 cases

- **Neuro (brain)**
  - Rawdata (fully sampled): 7002 cases



Knoll Radiology AI (in press, 2019)
fastmri.med.nyu.edu

Reconstruction challenge



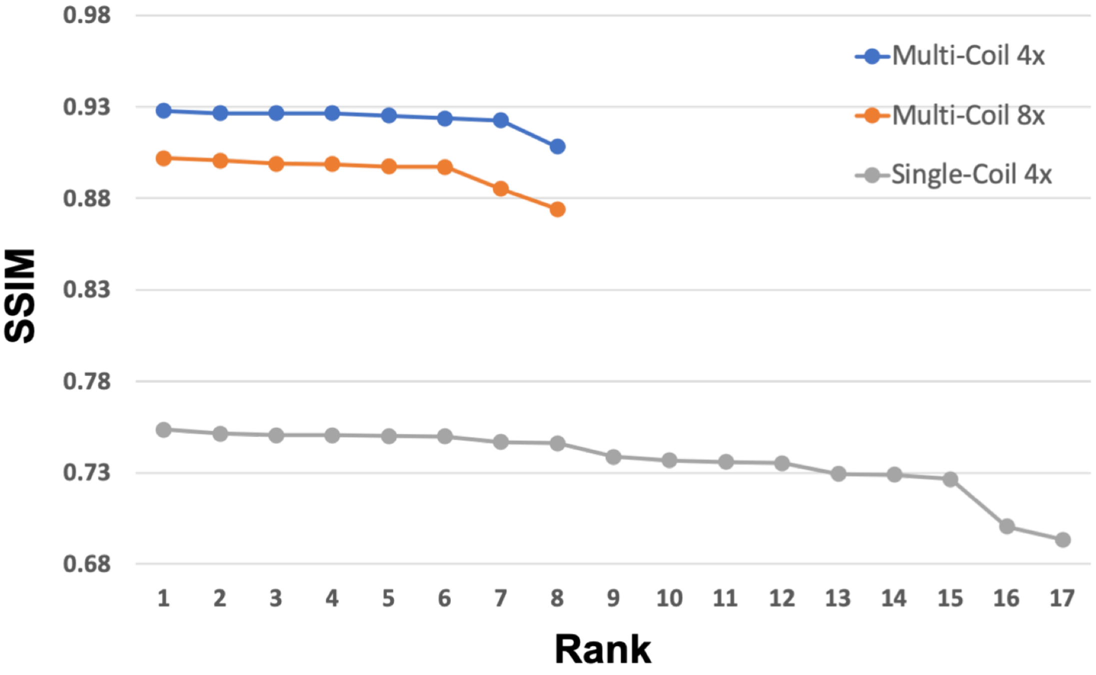
Challenge tracks

- **Multi coil 4x:**
  - Clinically relevant, 2x faster than clinical standard
  - 8 submissions (>25 on test leaderboard)

- **Multi coil 8x:**
  - Push models to limits. 4x faster than clinical standard
  - 8 submissions (>25 on test leaderboard)

- **Single coil 4x:**
  - Easier to experiment, single coil measurement, not used clinically
  - 17 submissions (>70 on test leaderboard)

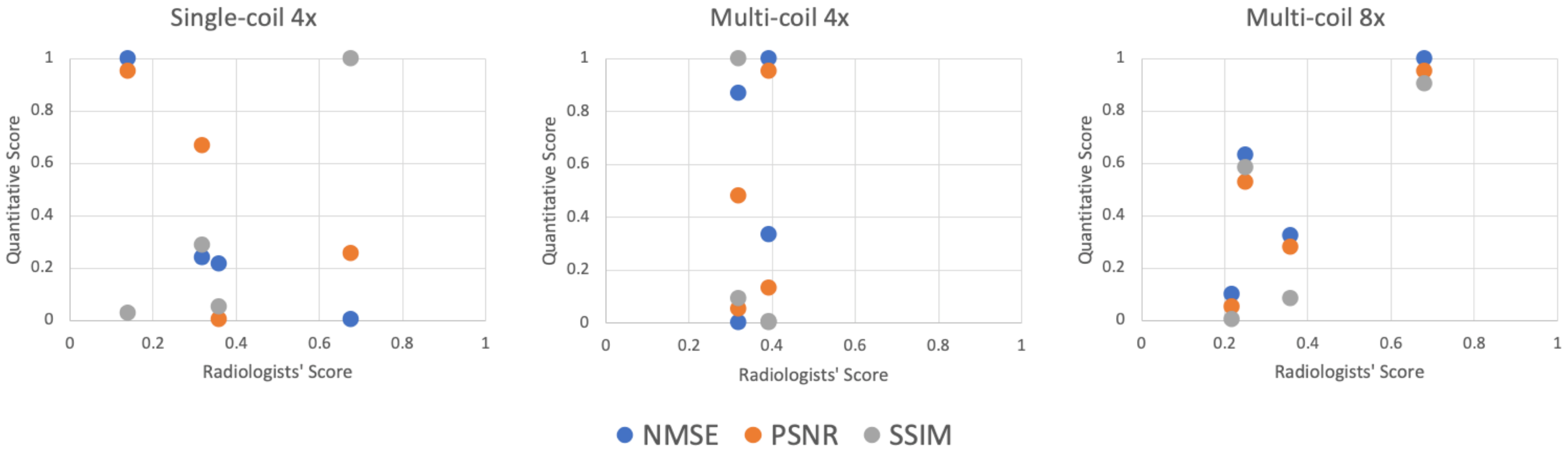
Two stage evaluation: 1: SSIM



		NMSE	SSIM	PSNR	NYU DATA ONLY
Adaptive-CS-Net by Philips & LUMC 9/17/2019	4x 8x	0.005 0.009	0.927 0.902	39.907 37.437	
Auto-calibrating deep learning by AM 9/19/2019	4x 8x	0.005 0.009	0.928 0.901	39.807 37.173	
SigmaNet by holykspace 9/19/2019	4x 8x	0.005 0.009	0.927 0.899	39.715 37.009	
i-RIM by AImsterdam 9/18/2019	4x 8x	0.006 0.010	0.925 0.899	39.223 36.816	
MSDC-RNN by MSDC-RNN 9/19/2019	4x 8x	0.005 0.009	0.927 0.897	39.740 37.081	
Dense Head UNet by BiSPL Lab 9/19/2019	4x 8x	0.006 0.010	0.924 0.897	39.065 36.605	
PI-DCN by Samoyed 9/18/2019	4x 8x	0.006 0.012	0.922 0.885	39.111 35.817	
0919 by fo 9/19/2019	4x 8x	0.007 0.014	0.908 0.874	37.484 34.851	

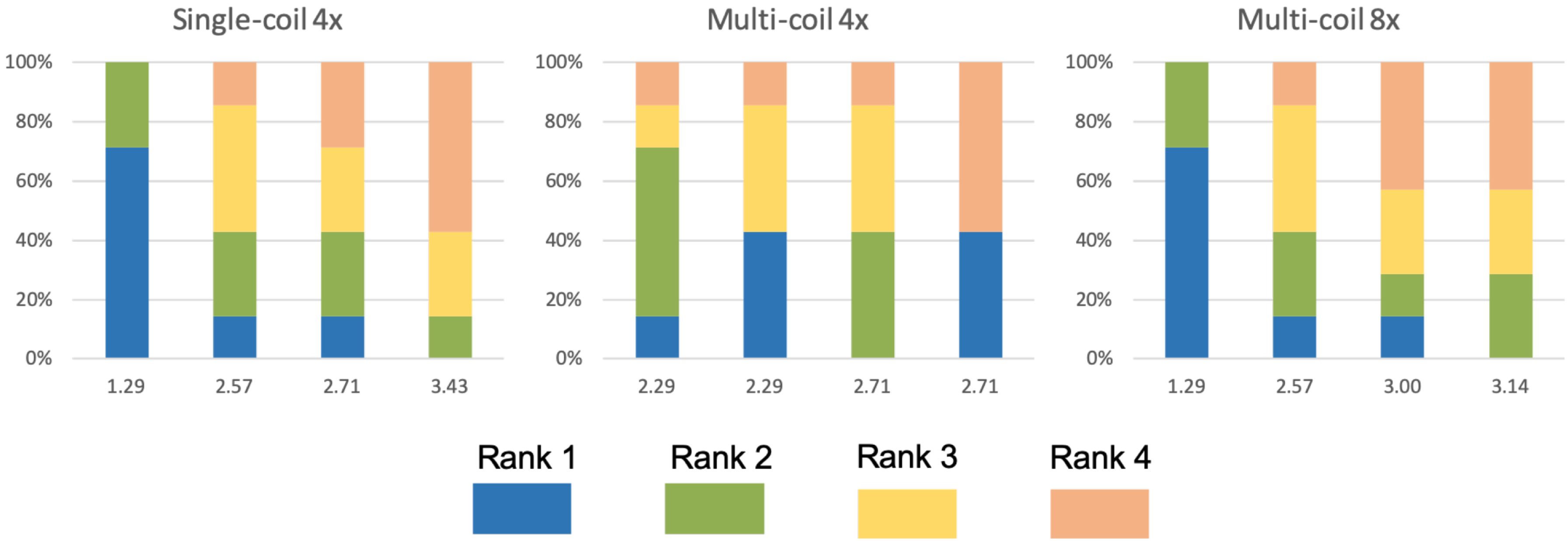
https://arxiv.org/abs/2001.02518

Quantitative scores vs radiologists



https://arxiv.org/abs/2001.02518

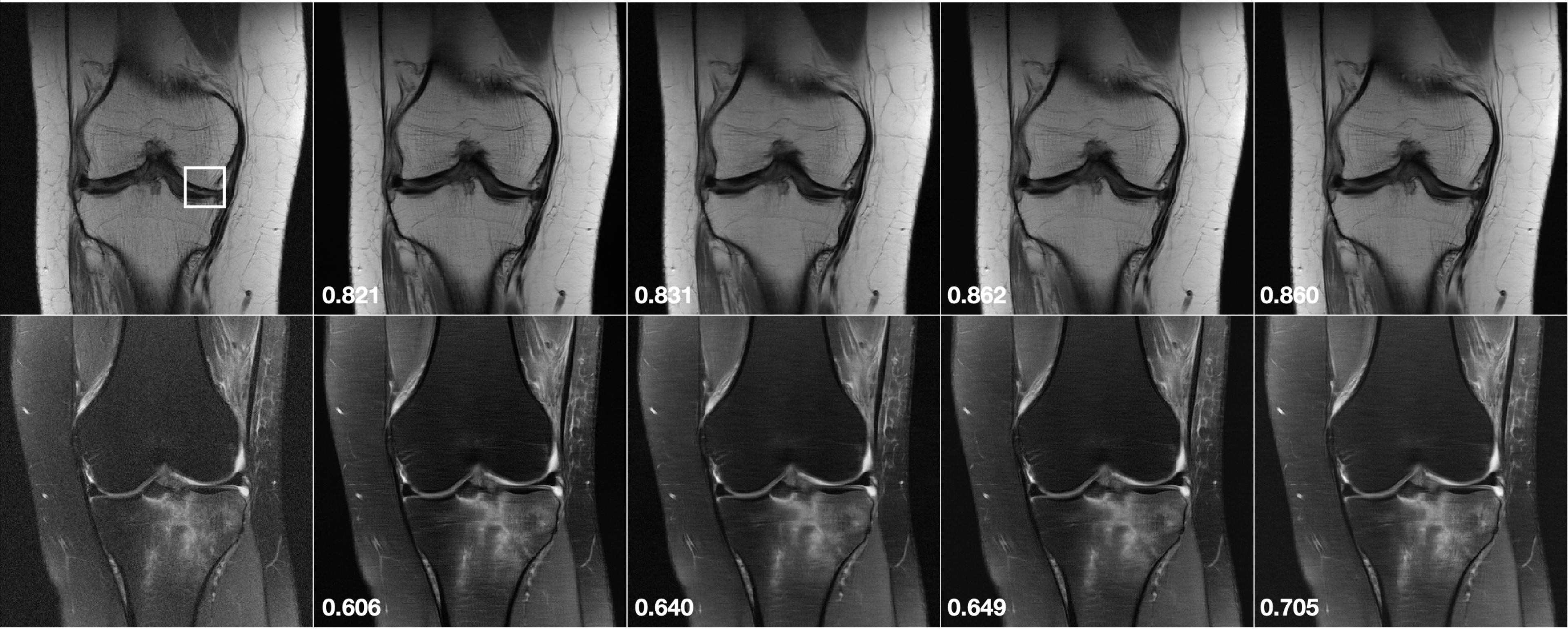
Quantitative scores vs radiologists



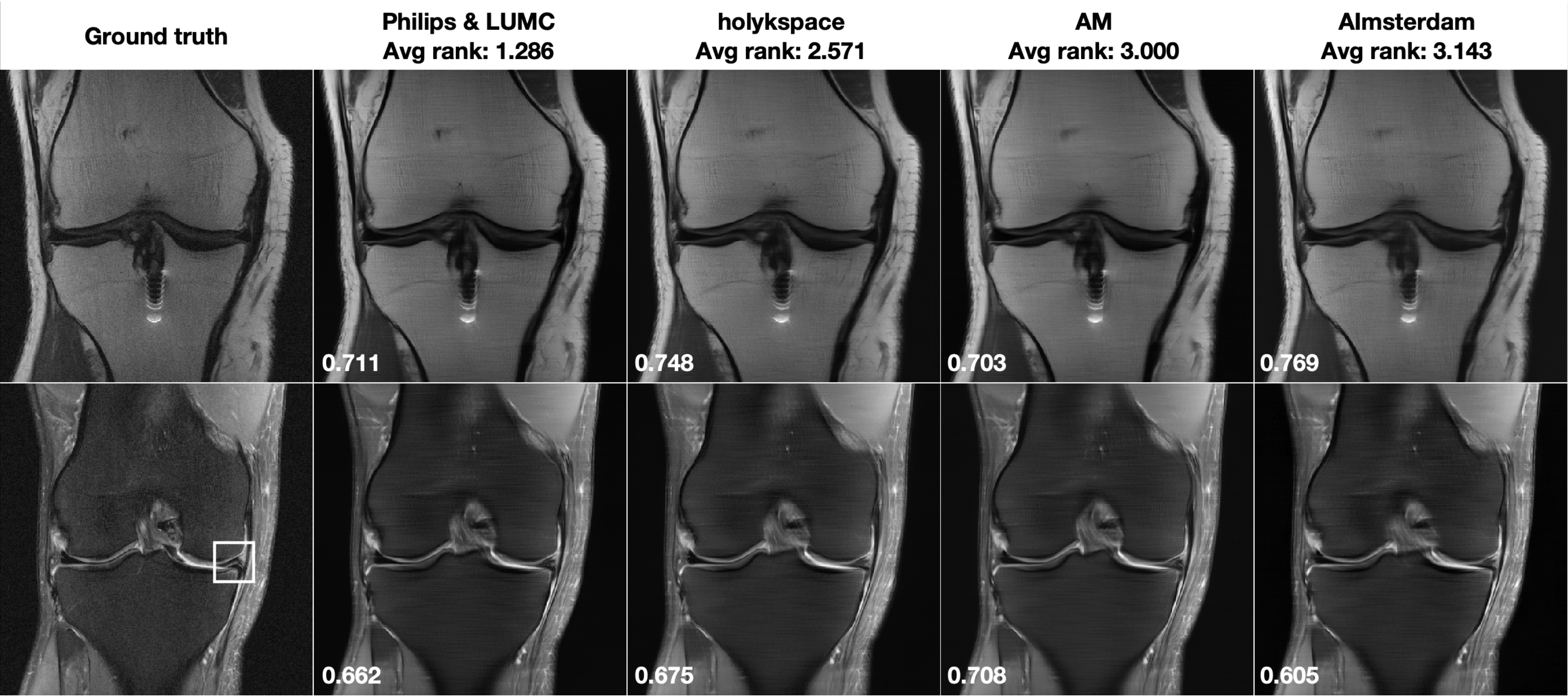
https://arxiv.org/abs/2001.02518

Multi coil R=4 results

Ground truth	Philips & LUMC Avg rank: 2.286	MSDC-RNN Avg rank: 2.286	holykspace Avg rank: 2.714	AM Avg rank: 2.714

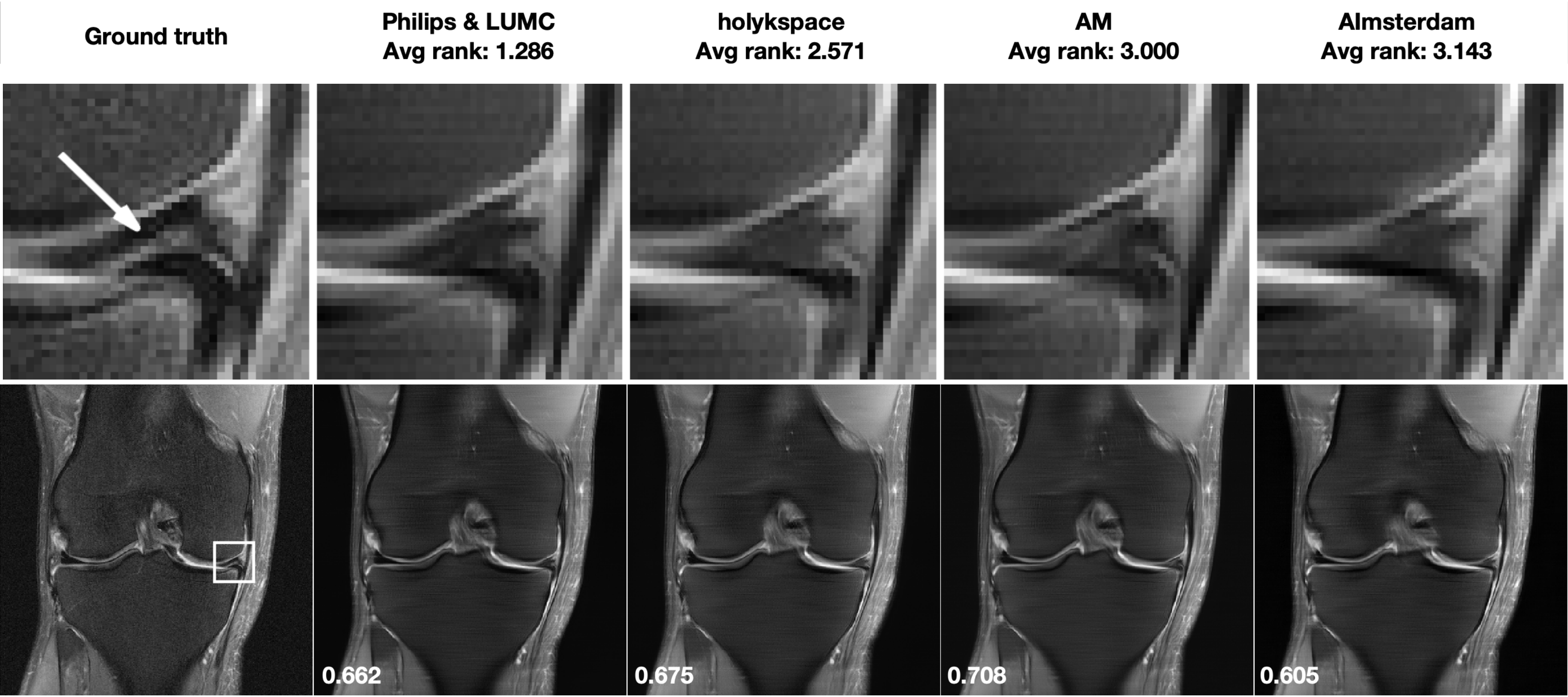


Multi coil R=8 results



https://arxiv.org/abs/2001.02518

Multi coil R=8 results: Pathology



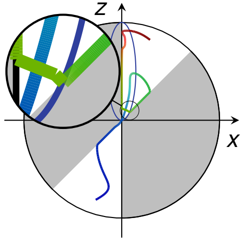
https://arxiv.org/abs/2001.02518

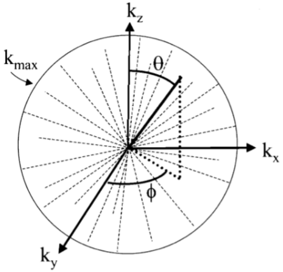
Data acquisition

Hardware

Data acquisition

Pulse sequence design





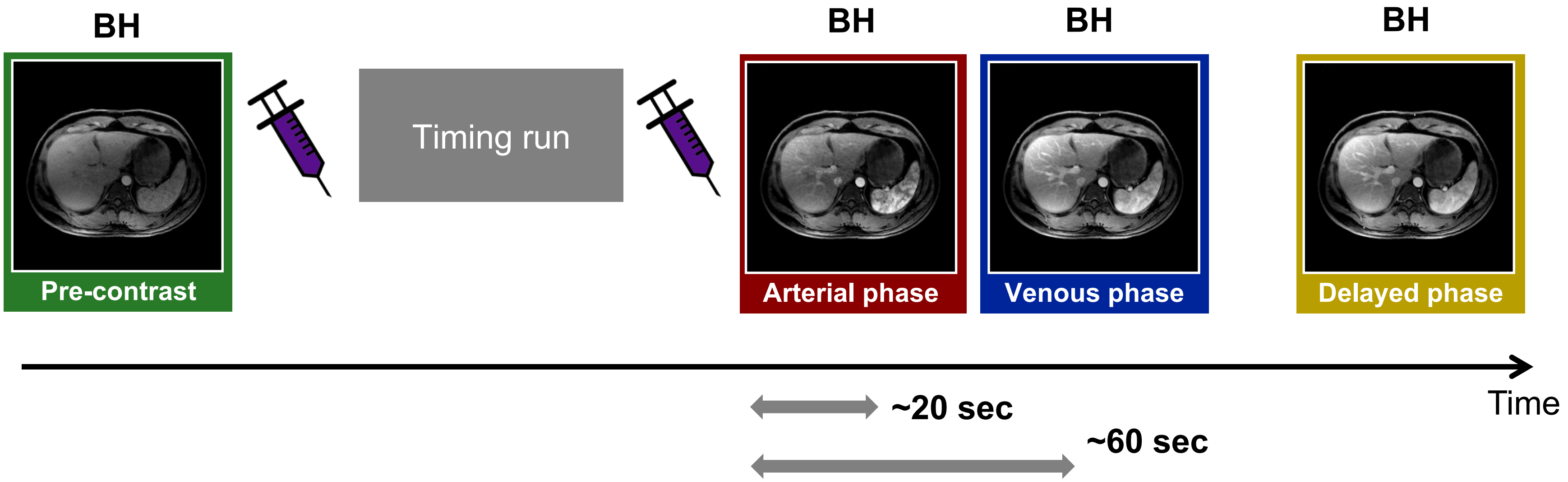
Reconstruction

Classification

Diagnosis

Benign/Malignant

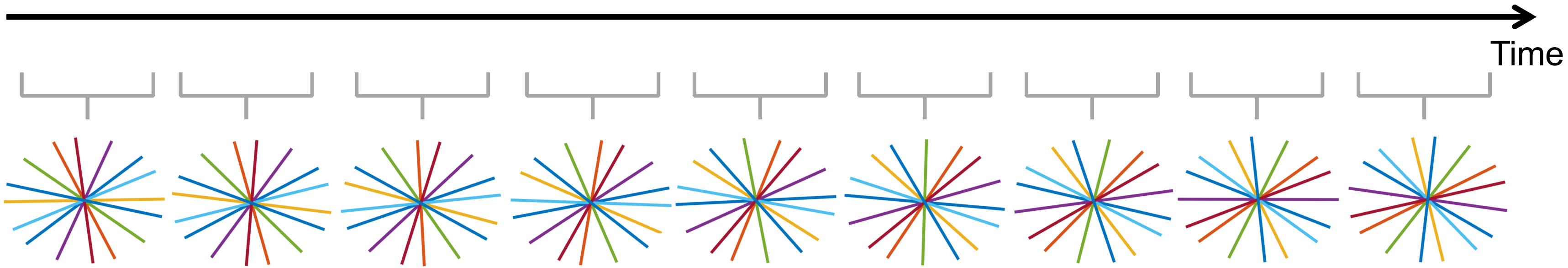
Dynamic data: Contrast enhanced exam



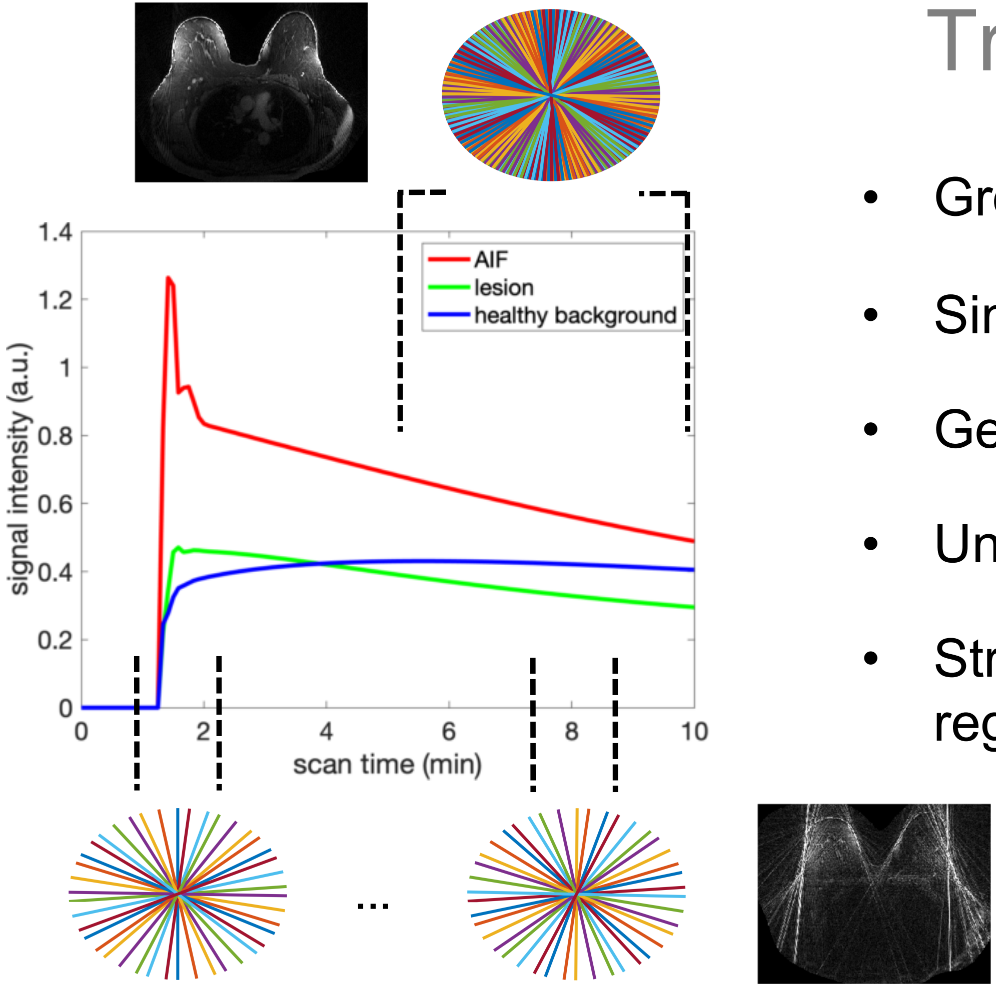
Feng MRM (2014)

Dynamic data: Contrast enhanced exam

Continuous radial acquisition



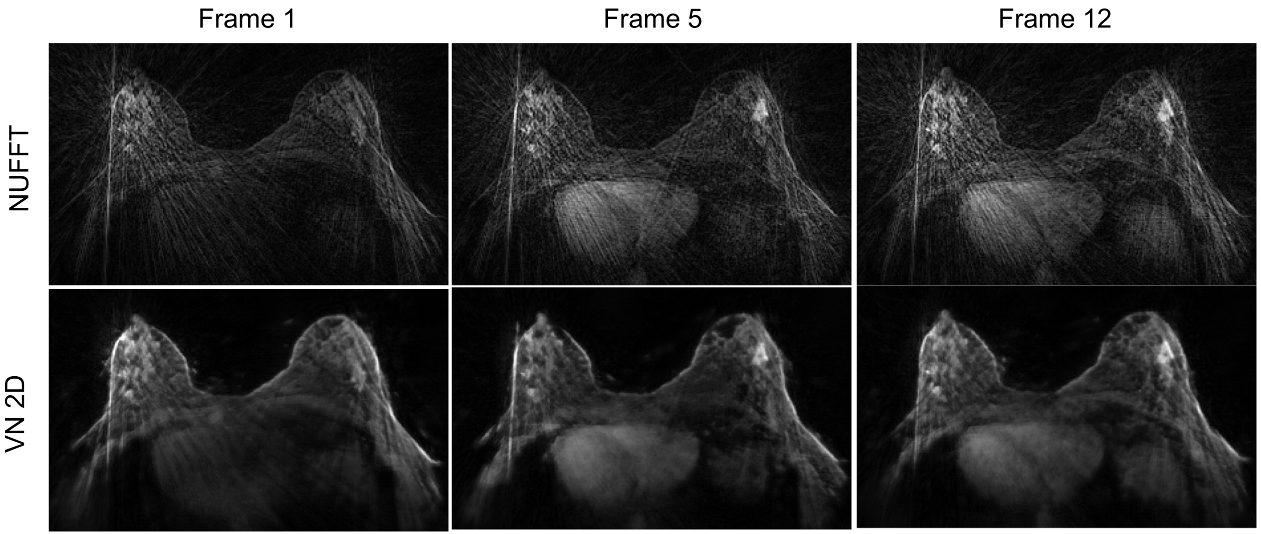
Feng MRM (2014)



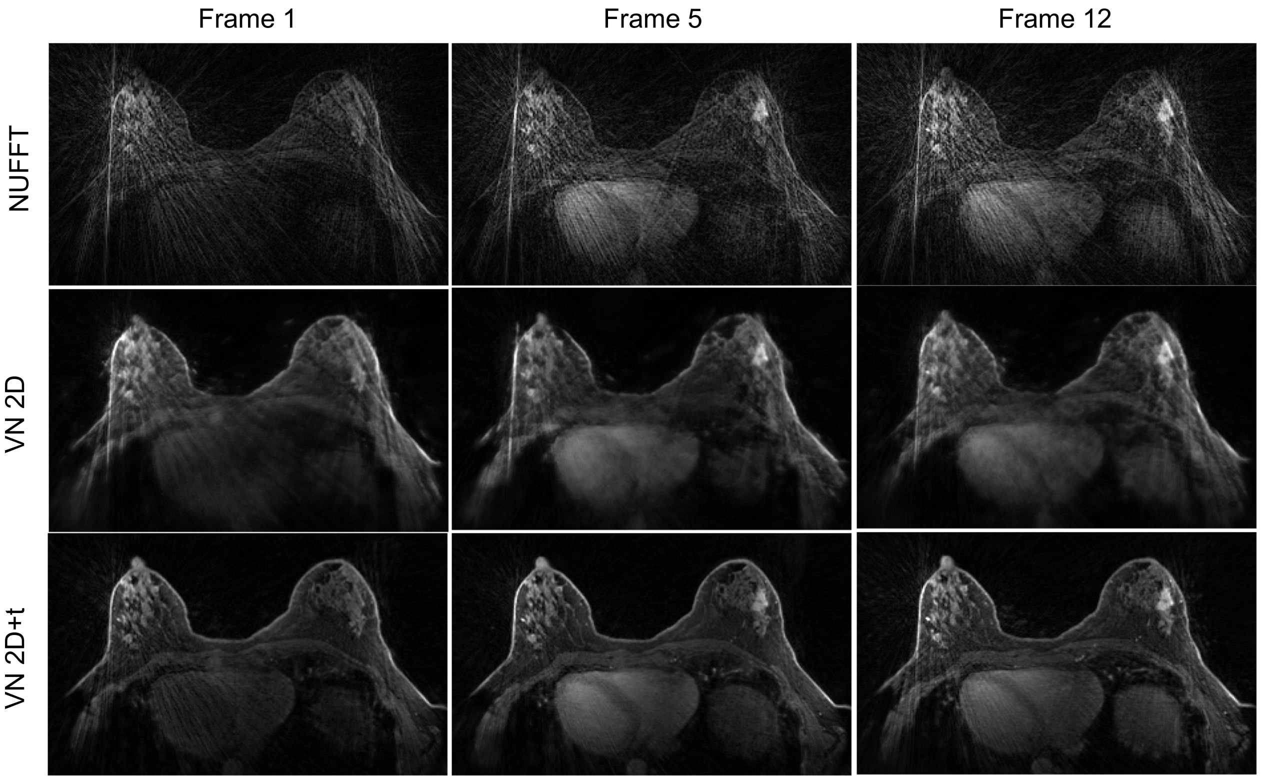
Training design?

- Ground truth?
- Simulations/Transfer learning?
- Generalization?
- Unsupervised learning?
- Structure of spatiotemporal regularizer?

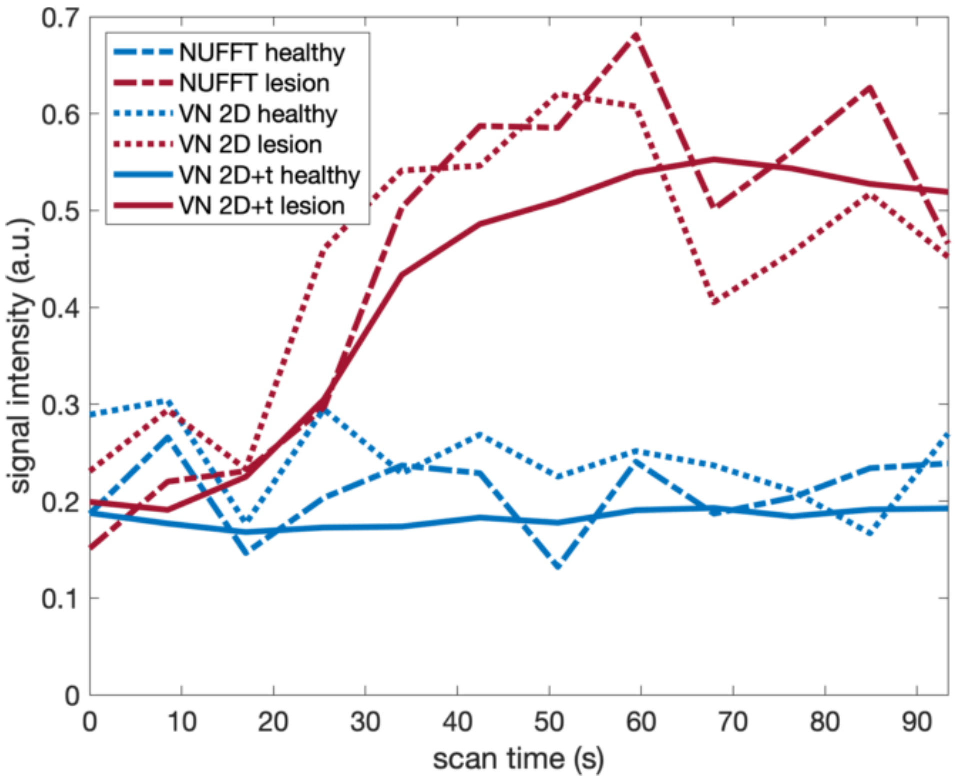
Continuous radial DCE breast cancer MRI

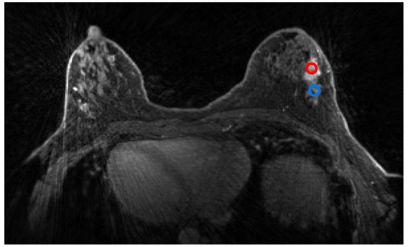


Continuous radial DCE breast cancer MRI



Continuous radial DCE breast cancer MRI





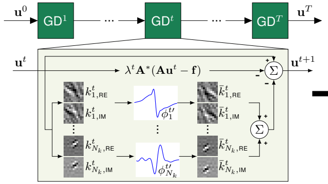
Reconstruction/Classification

Hardware

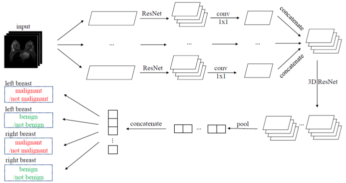
Data acquisition

Pulse sequence design

Reconstruction

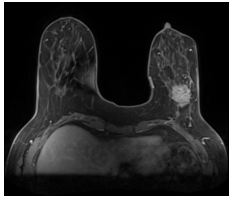


Classification

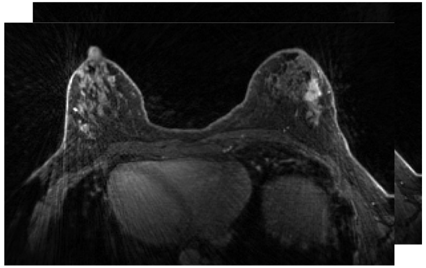


Diagnosis

Benign/Malignant



Diagnostic classification



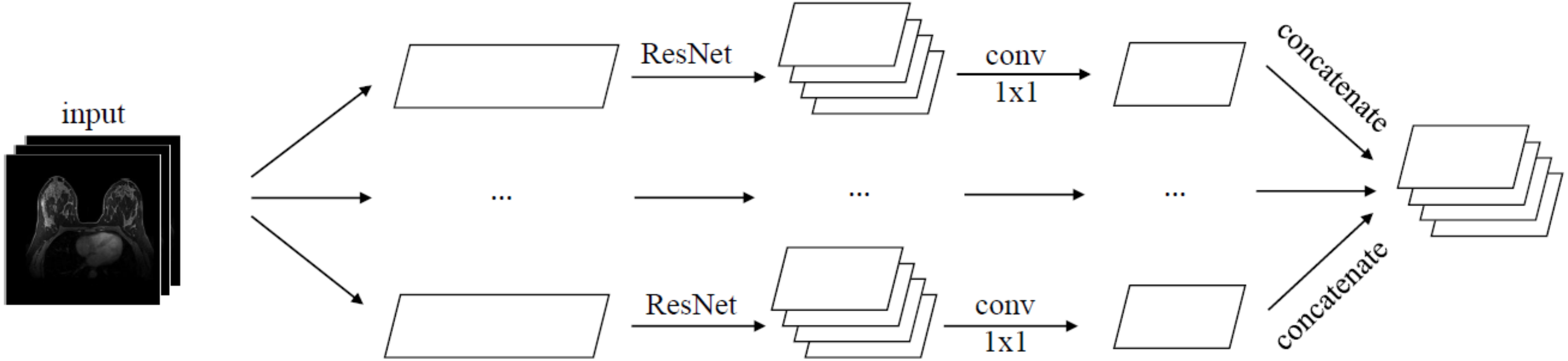
Predict presence of malignant and/or benign lesions in each breast

- 5000 training
- 1500 validation
- 1500 validation

$$\mathcal{L}_{\mathcal{C}}(\Theta_C) = \frac{1}{S}\sum_{s=1}^{S}\sum_{\vartheta\epsilon[L,R]}\sum_{\xi\epsilon[m,b]} -log\,\hat{p}_s^{\vartheta,\xi}\left(u_s^T;\Theta_C\right)$$

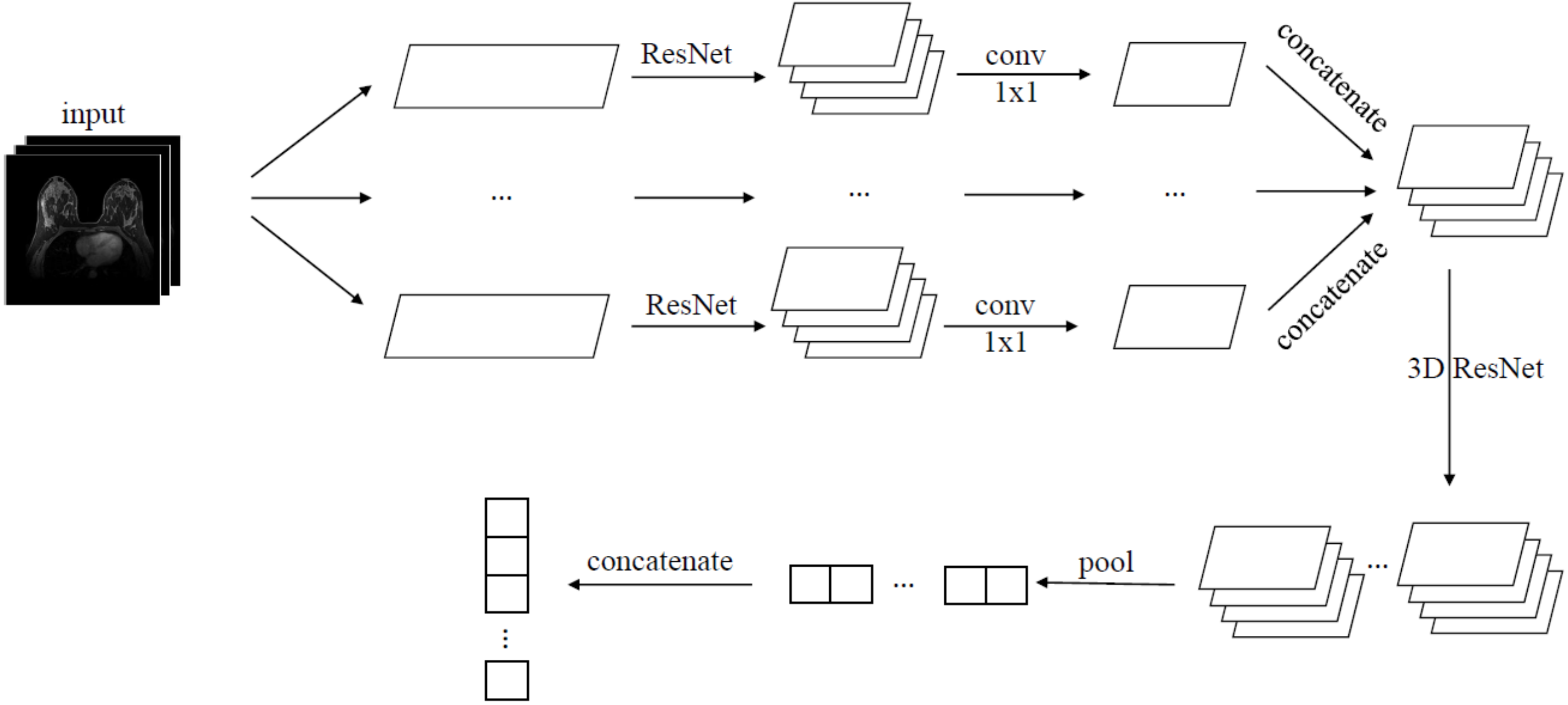
Gong NeurIPS Medical Imaging (2019)

Diagnostic classification



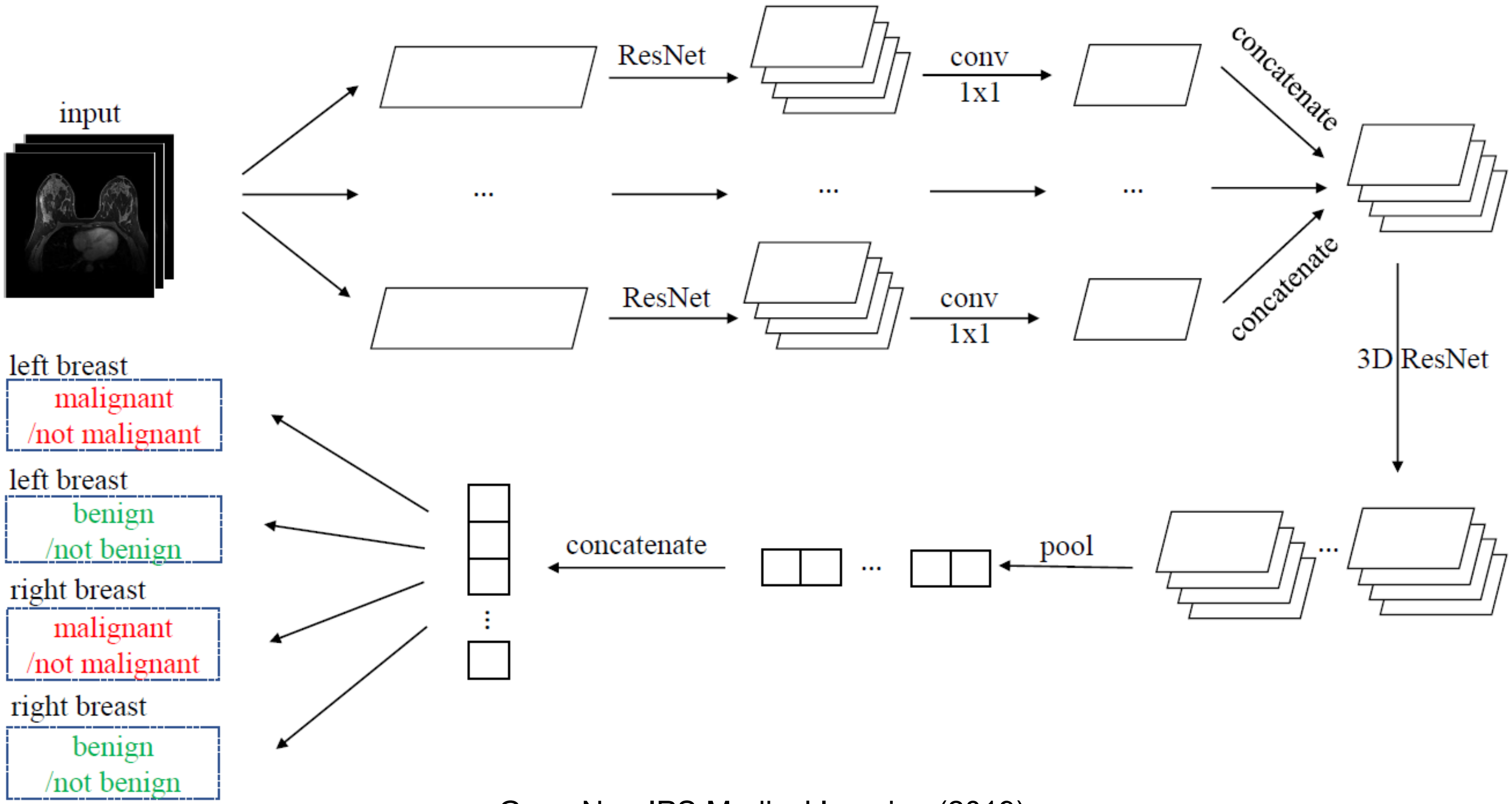
Gong NeurIPS Medical Imaging (2019)

Diagnostic classification



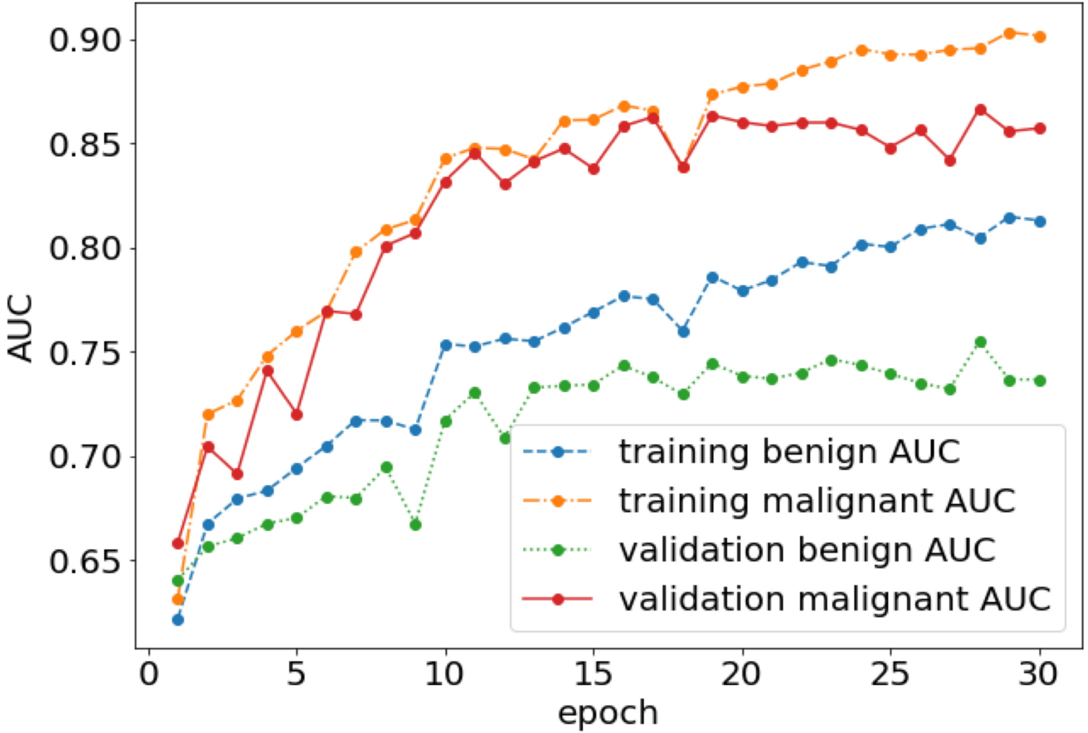
Gong NeurIPS Medical Imaging (2019)

Diagnostic classification



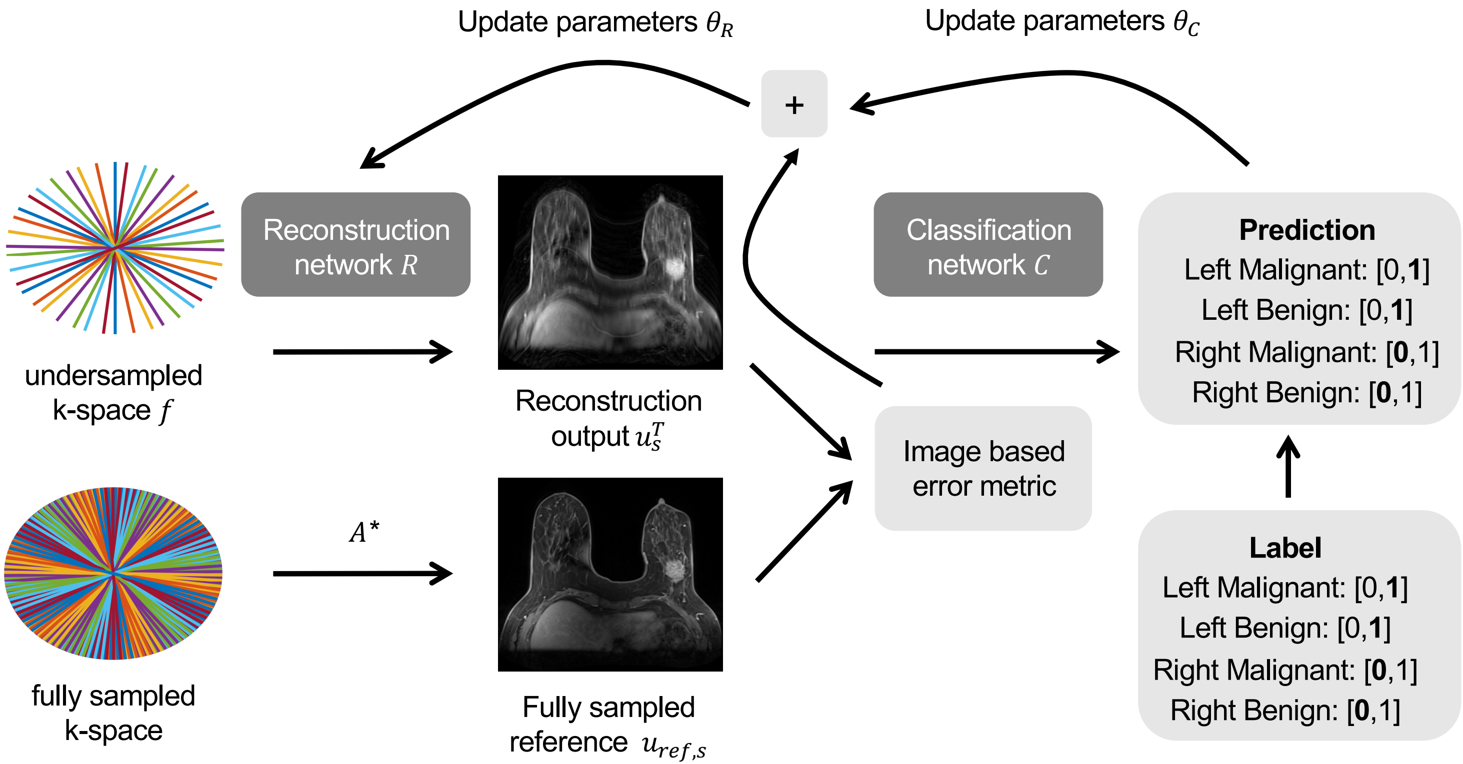
Gong NeurIPS Medical Imaging (2019)

Diagnostic classification



Gong NeurIPS Medical Imaging (2019)

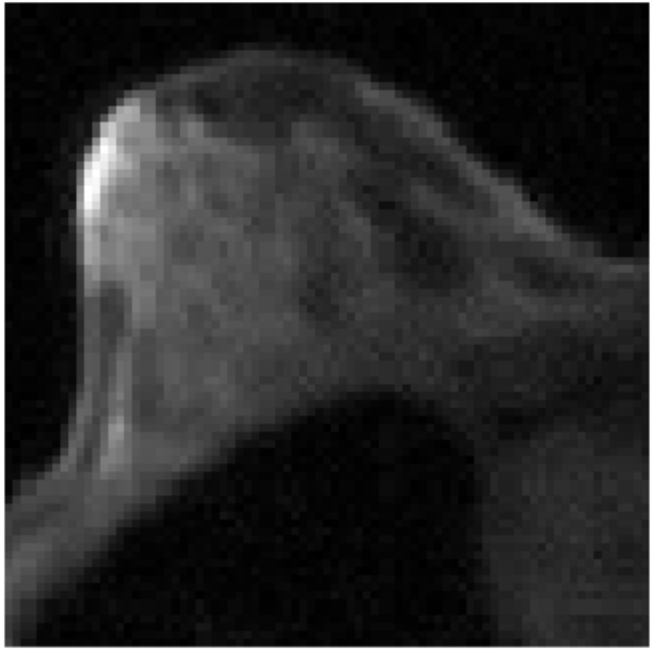
End to end reconstruction and classification



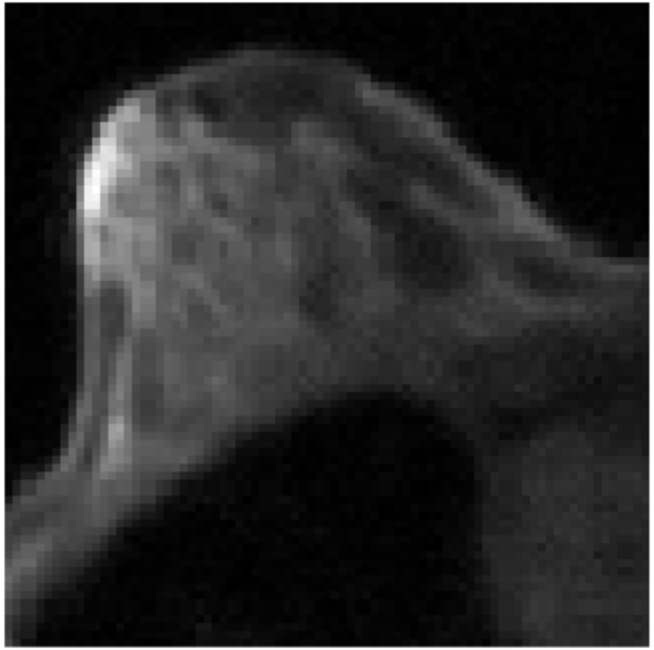
$$\mathcal{L}(\Theta_R, \Theta_C) = \mu \mathcal{L}_{\mathcal{R}}(\Theta_R) + (1 - \mu)\mathcal{L}_{\mathcal{C}}(\Theta_C)$$

End to end reconstruction and classification

Separate



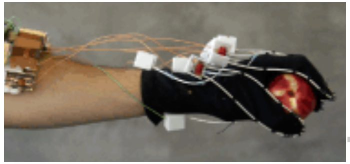
End-to-end

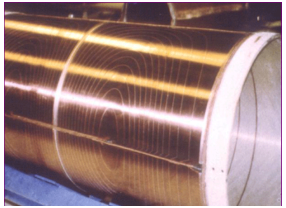


Work in progress :-)

End to end optimization: Reconstruction/Classification

Hardware





Data acquisition

Pulse sequence design

Reconstruction

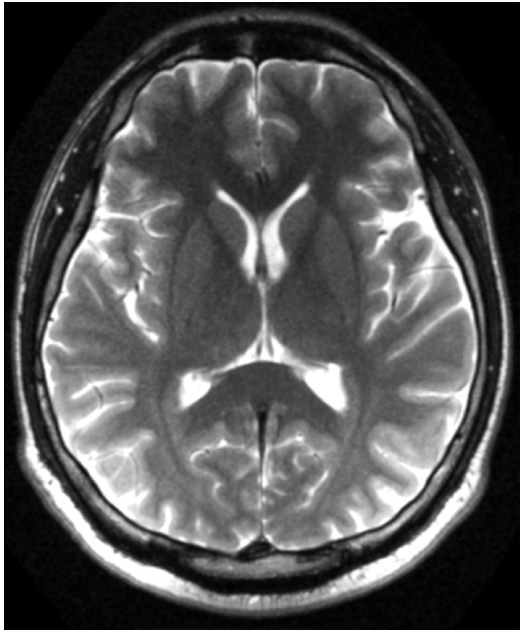
Classification

Diagnosis

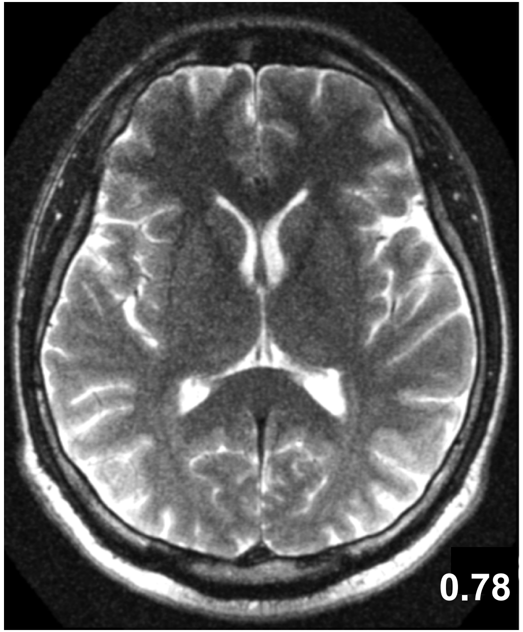
Benign/Malignant

Imaging at lower field strengths: 0.55T system

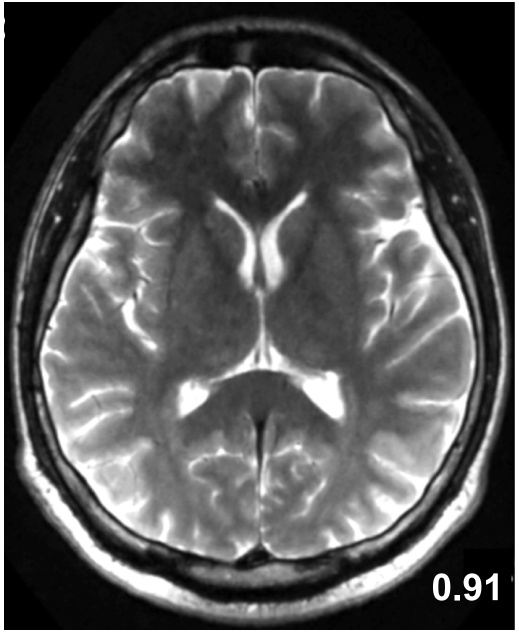
6 averages



1 acquisition IFT



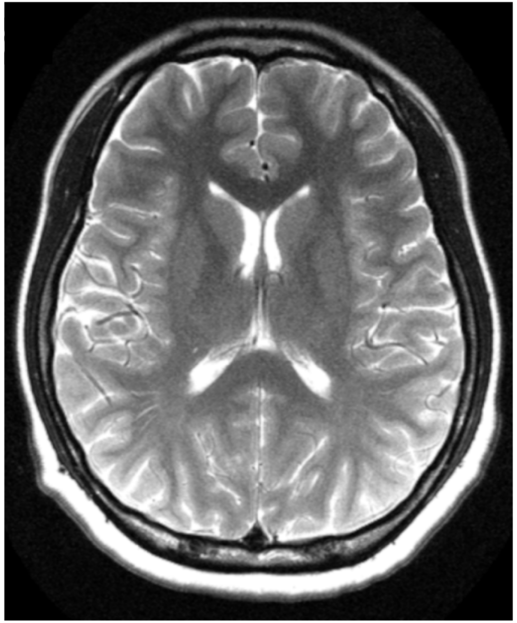
1 acquisition VN reconstruction



Johnson ISMRM Sedona 2020

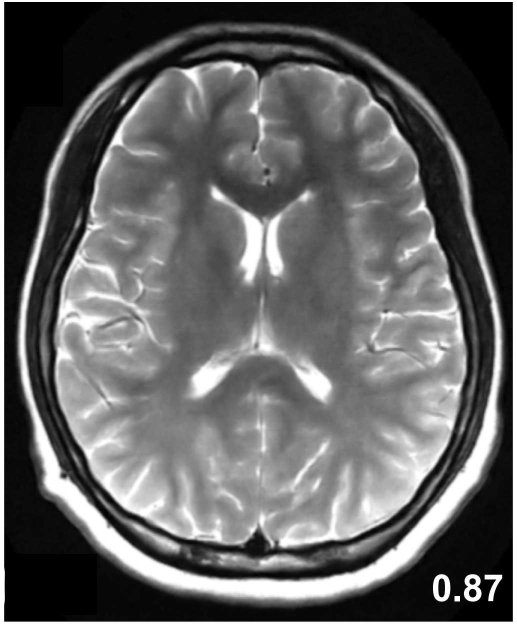
Imaging at lower field strengths: 0.55T system

Fully sampled 6 avgs
(t_{acq}=14.5 mins)



IFT: R=3 single acq
(t_{acq}=0.9 mins)

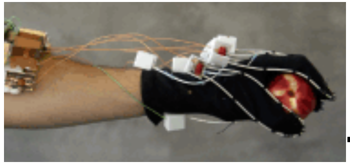
VN: R=3 single acq
(t_{acq}=0.9 mins)

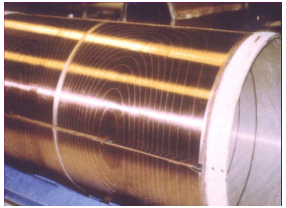


Johnson ISMRM Sedona 2020

Summary: End to end optimization of diagnostic pipeline

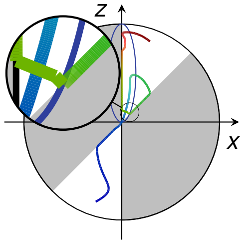
Hardware

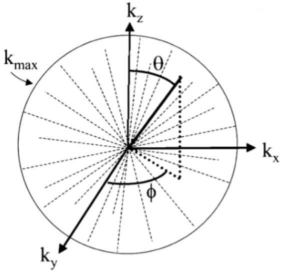




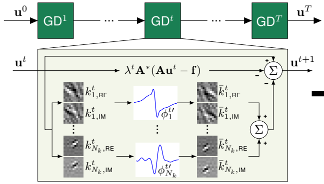
Data acquisition

Pulse sequence design

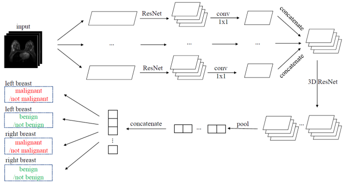




Reconstruction

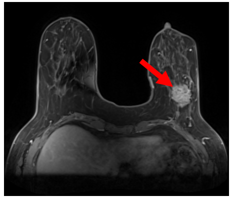


Classification



Diagnosis

Benign/Malignant



Open questions

- Robust enough for clinical routine?
- Integration in clinical workflow?
- Validation: When and how do things go wrong?
- Theory (Math ☺)!

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Thank you!

https://med.nyu.edu/faculty/florian-knoll