#0465

Reconstruction of multi-shot diffusion-weighted MRI using unrolled network with U-nets as priors

Yuxin Hu[1], Xinwei Shi[1], Qiyuan Tian[2], Hengkai Guo[3], Minda Deng[4], Miao Yu[1], Catherine Moran[5], Grant Yang[1], Jennifer A McNab[5], Bruce Daniel[5,6], and Brian Hargreaves[1,5,6]

[1]Department of Electrical Engineering, Stanford University, Stanford, CA, United States
[2]Athinoula A. Martinos Center for Biomedical Imaging,
Department of Radiology, MGH, Boston, MA, United States
[3]ByteDance AI Lab, Beijing, China
[4]Department of Applied Physics, Stanford University, Stanford, CA, United States
[5]Department of Radiology, Stanford University, Stanford, CA, United States
[6]Department of Bioengineering, Stanford University, Stanford, CA, United States

Declaration of Financial Interests or Relationships

Speaker Name: Yuxin Hu

I have the following financial interest or relationship to disclose with regard to the subject matter of this presentation:

Company Name: GE Healthcare
Type of Relationship: Research Support

Diffusion-weighted imaging

- Single-shot imaging (fast, motion insensitive)
  - Limited resolution and SNR
  - Heavy distortion
- Multi-shot imaging
  - Motion-induced phase variations

Reconstruction of multi-shot DWI

- Shot locally low-rank (shot-LLR)
  - ✓ A relaxed model without phase estimation
  - ✓ Robust to motion
  - ❖ Slow (1 ~ 2 minutes per image)…

Hu, Yuxin, et al. *MRM* 2019.

Reconstruction of multi-shot DWI

- Shot locally low-rank (shot-LLR)
  - ✓ A relaxed model without phase estimation
  - ✓ Robust to motion
  - ❖ Slow (1 ~ 2 minutes per image)…

- Deep learning reconstruction
  - ✓ Fast
  - ❖ Black-box
  - ❖ Ghost artifacts (global) in multi-shot EPI

Reconstruction of multi-shot DWI

- Shot locally low-rank (shot-LLR)
  - ✓ A relaxed model without phase estimation
  - ✓ Robust to motion
  - ❖ Slow (1 ~ 2 minutes per image)…

- Deep learning reconstruction
  - ✓ Fast
  - ❖ ~~Black-box~~ -> unrolled network, with the forward model
  - ❖ ~~Ghost artifacts (global)~~ -> CNN in k-space and image space

Image reconstruction

$$\min_x ||Ax - y||_2^2 + \boxed{\lambda r(x)}$$

A: encoding operator (sampling, FT, sensitivity encoding)
x: image to be estimated
y: acquired data
r(x): regularization term (l1, l1-wav, l2, LLR, TV...)

Optimization algorithm

Given x_0, A, y
For k from 0 to N:
Gradient update:
$x_{k+1/2} = x_k - lA^T(Ax_k - y)$
Proximal operator:
$x_{k+1} = P_{r,\lambda}(x_{k+1/2})$

Unrolled ISTA/FISTA/ADMM

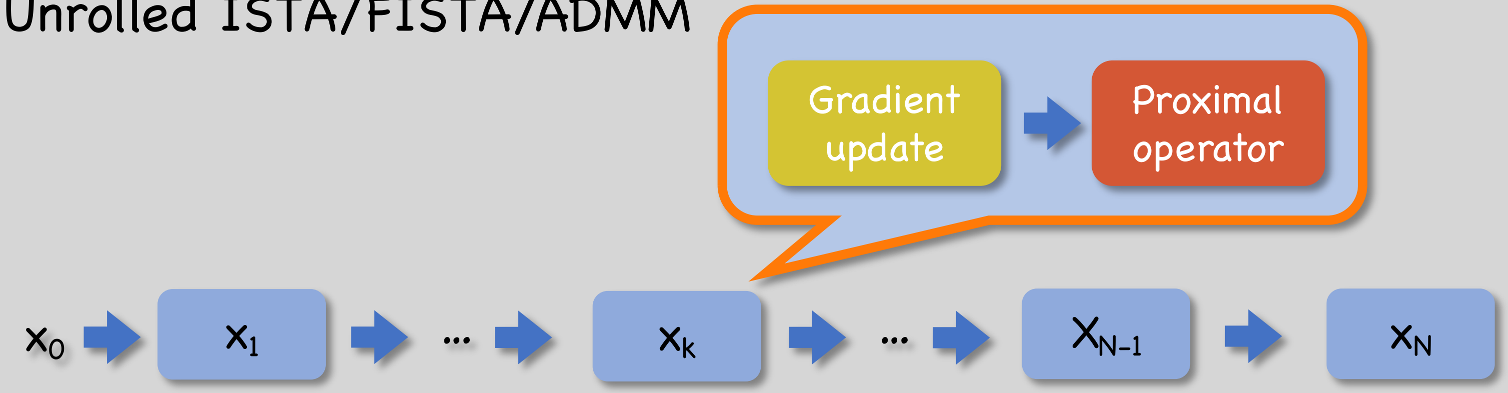


Image reconstruction

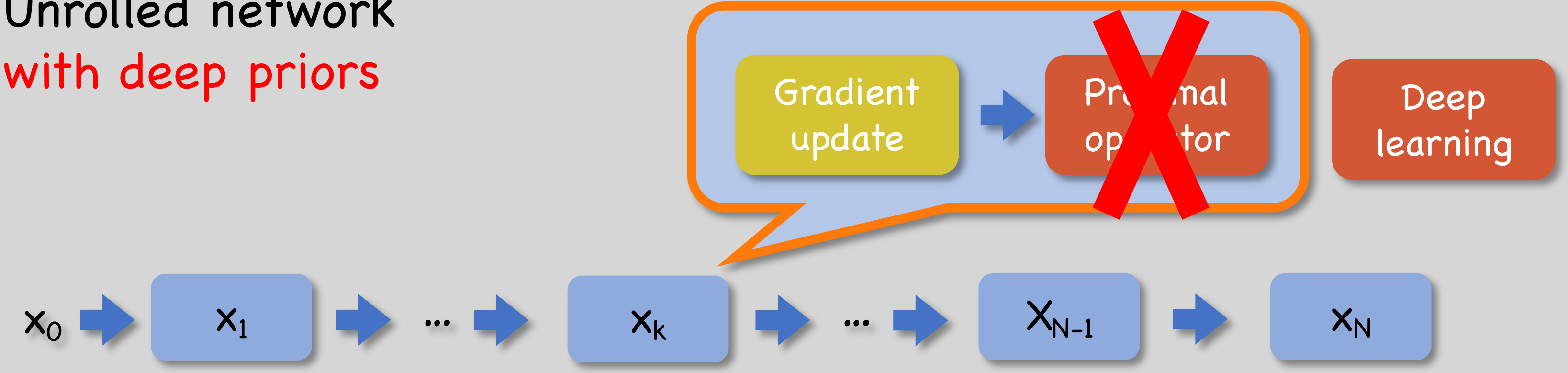
$$\min_{x} ||Ax - y||_2^2 + \cancel{\lambda r(x)}$$

A: encoding operator (sampling, FT, sensitivity encoding)
x: image to be estimated
y: acquired data
~~r(x): regularization term (l1, l1-wav, l2, LLR, TV...)~~

Optimization algorithm

Given x_0, A, y
For k from 0 to N:
  Gradient update:
    $x_{k+1/2} = x_k - l A^T(Ax_k - y)$
  ~~Proximal operator:~~
    $\cancel{x_{k+1} = P_{r,\lambda}(x_{k+1/2})}$
    $x_{k+1} = CNN_k(x_{k+1/2})$

Unrolled network
with deep priors



DL Reconstruction of multi-shot DWI

Data (k-space data and sensitivity map)

6 volunteers / 1734 images	2 volunteers / 48 images

Zero-filled and normalized

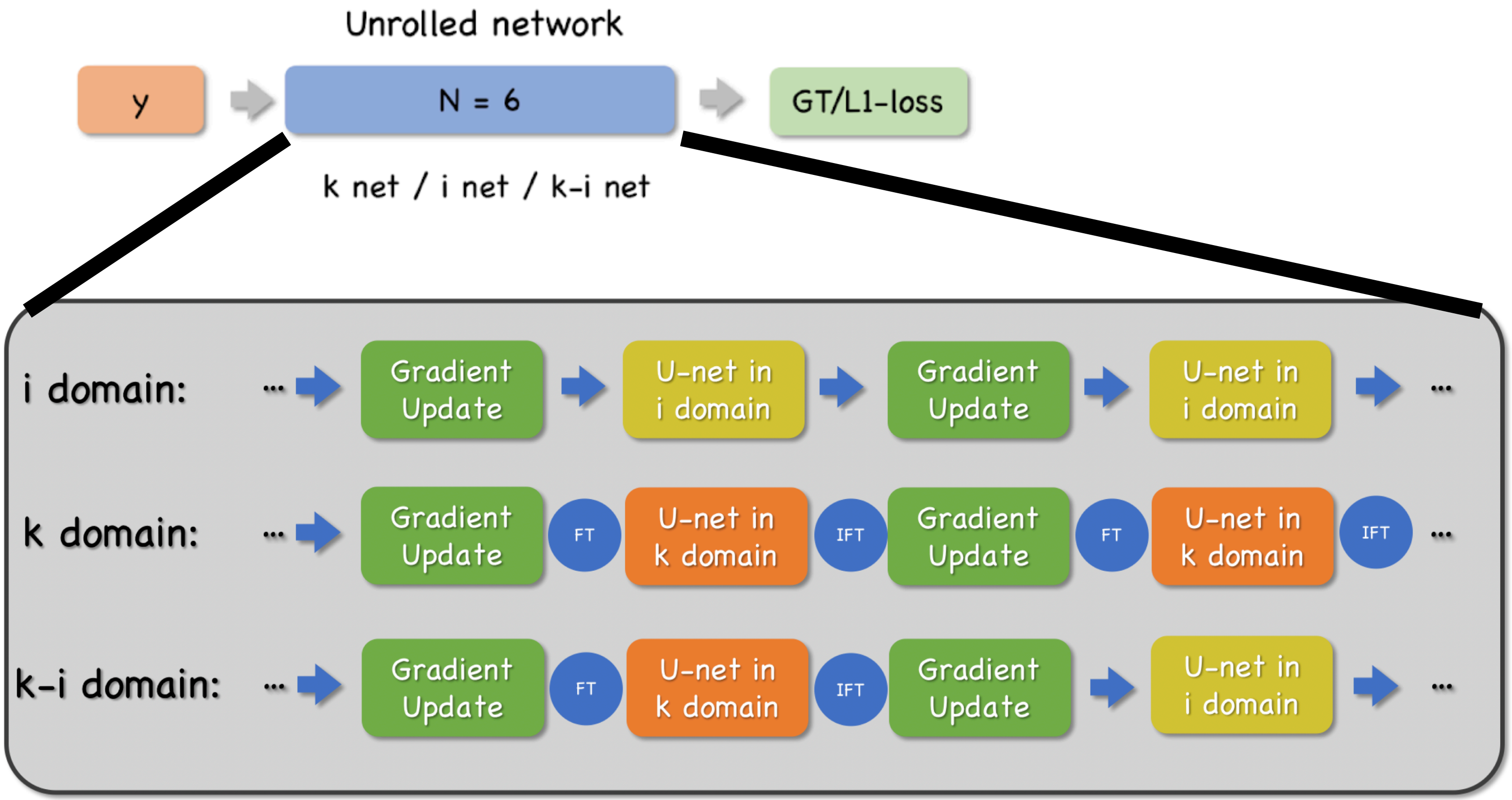
Network structure

Unrolled network

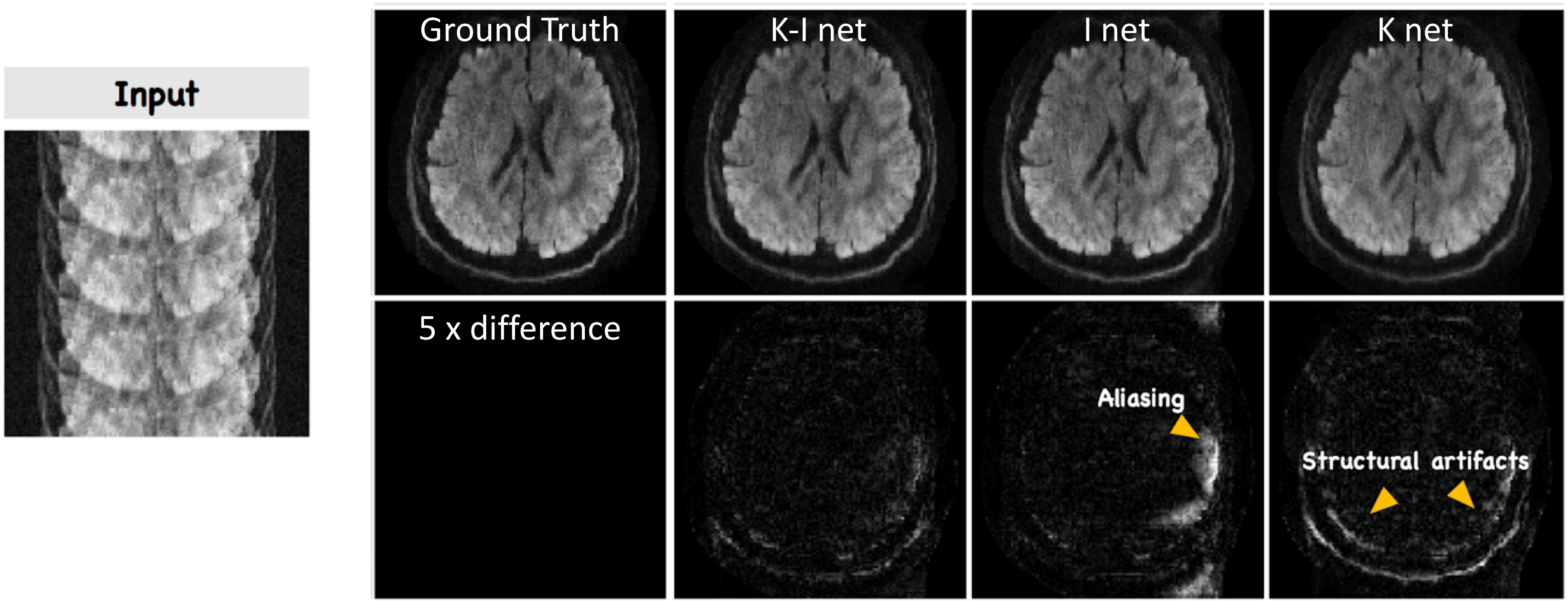
y → N = 6 → GT/L1-loss

k net / i net / k-i net

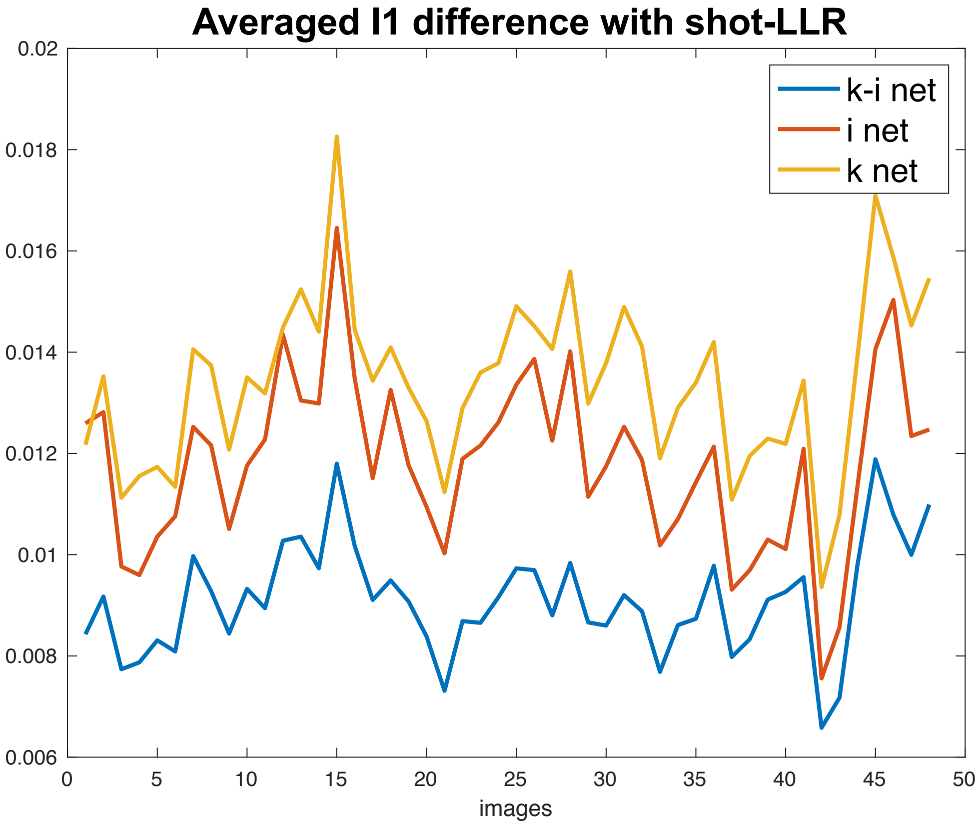
DL Reconstruction of multi-shot DWI



Results


Input
Ground Truth
K-I net
I net
K net
5 x difference
Aliasing
Structural artifacts

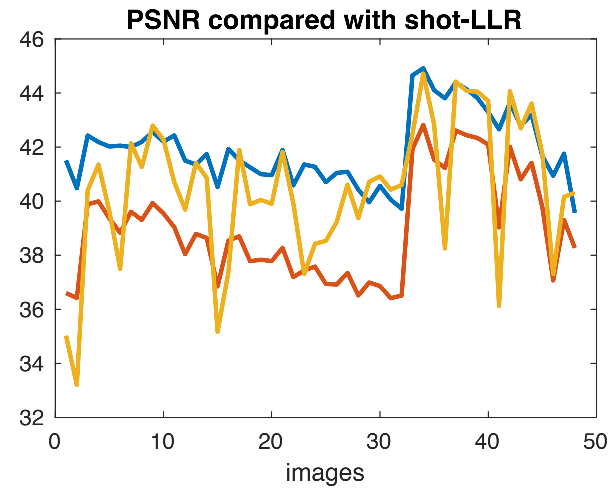
Results

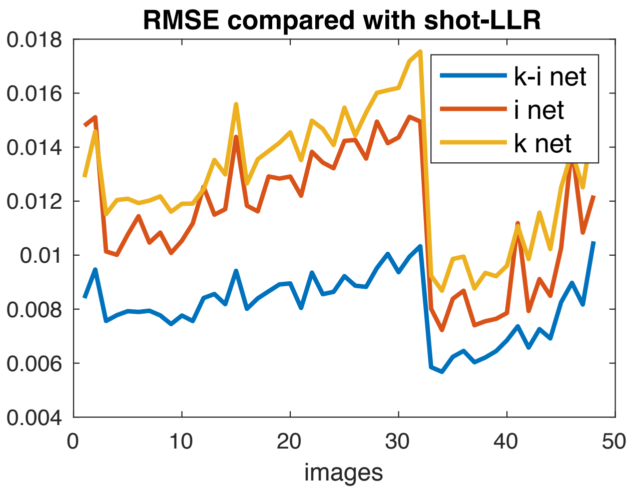


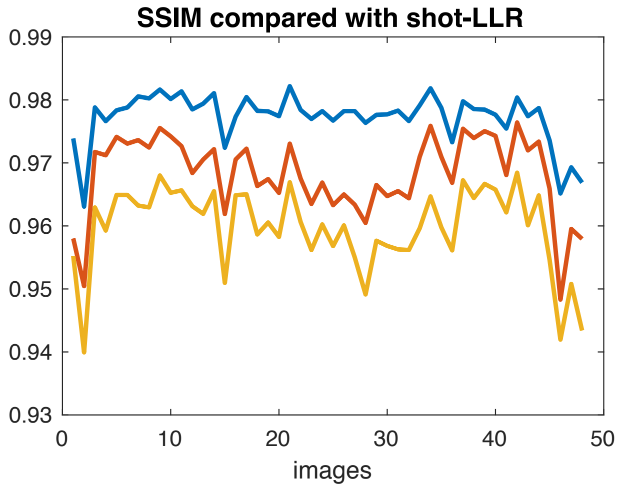
~ 1% difference for most of the test images using K-I net

DL takes less than 1s per image

#0465



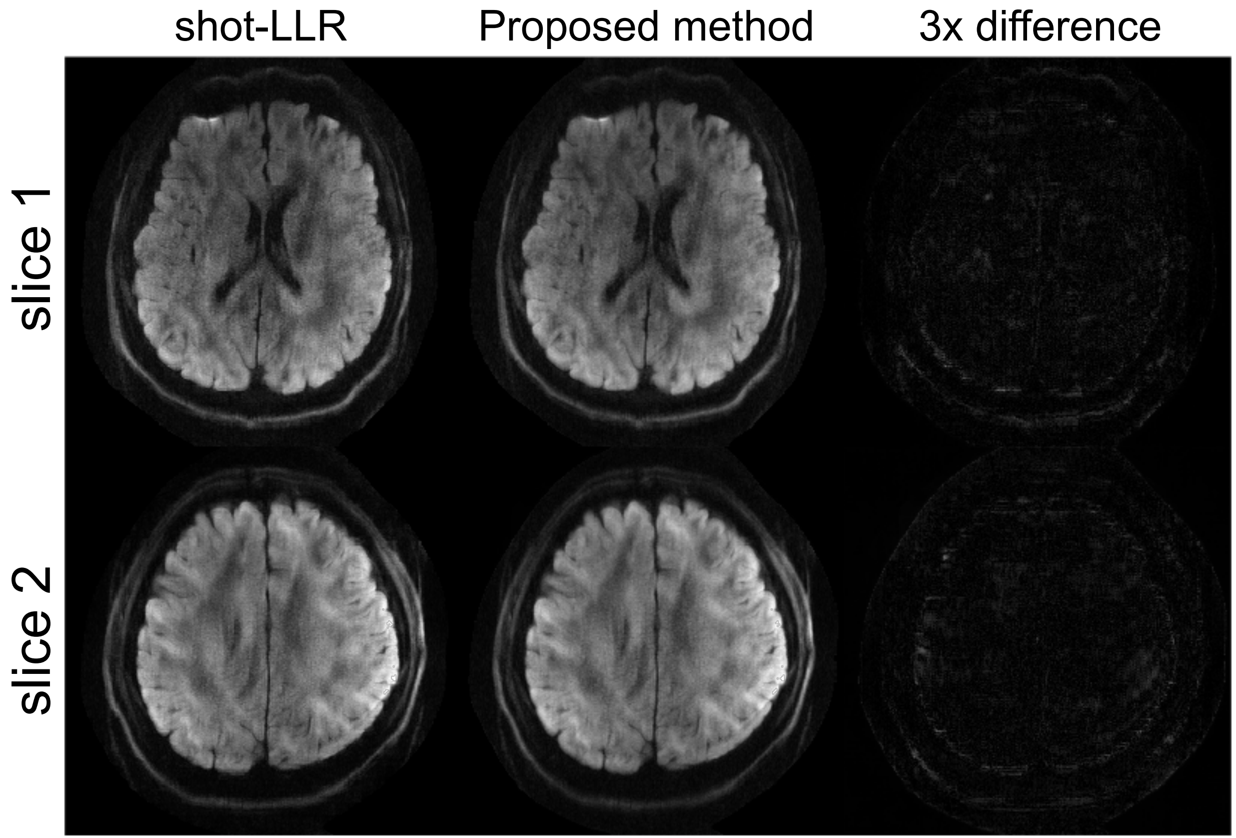




~ 1% difference for most of the test images using K-I net

DL takes less than 1s per image

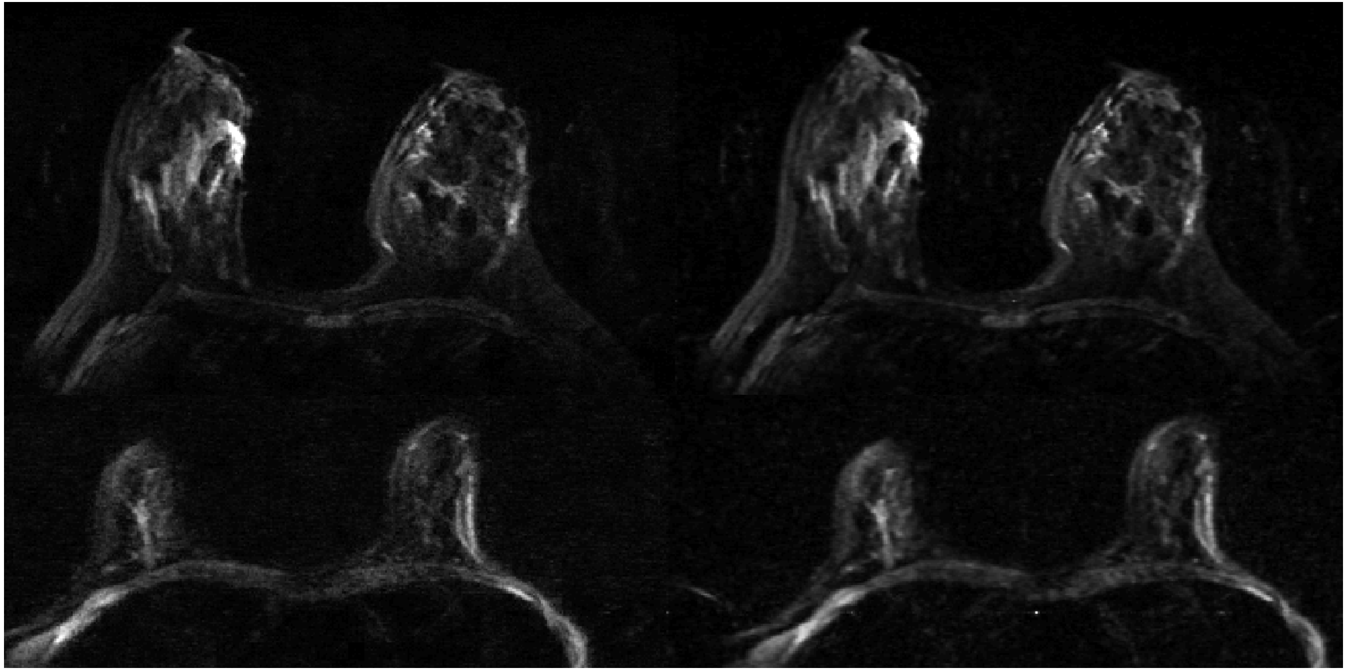
Results



Applied to 4-shot breast data

Coil compressed 4-shot breast data (1 x 1 x 5 mm^3)

Shot-LLR | Unrolled network



Summary

A faster recon method for multi-shot DWI by DL

- Including gradient updates
- Alternating inputs in k-space and image space
- Other applications: breast