Deep Learning Reconstruction Methods for Dosimetry and Acceleration

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Overview

- What? Why?
- Examples
  - Digital Breast Tomosynthesis reconstruction
  - Cone Beam CT reconstruction
  - MRI reconstruction

Our rationales for deep learning based reconstruction

- Speed (neural networks have fast inference)
  - Real time adaptive MR-guided radiotherapy
    - Lower scan time
    - Faster inference (reconstruction)
- Ability to learn a data manifold
  - Dosimetry
    - Digital Breast Tomosynthesis
    - Cone-beam CT for prefraction adaptation

Reconstruction is an inverse problem

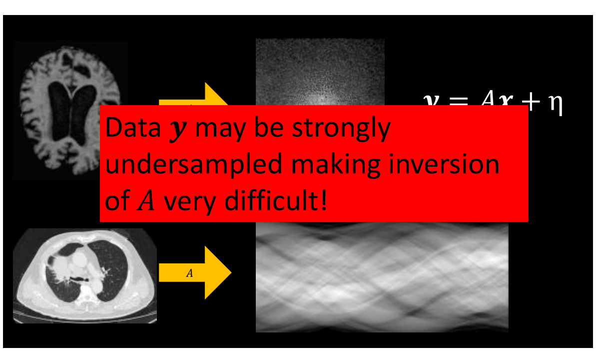
$$\overset{\text{Measurements}}{\boldsymbol{y}} = \overset{\text{Forward operator}}{A}\underset{\text{Object}}{\boldsymbol{x}} + \overset{\text{Noise}}{\eta}$$

Reconstruction is an inverse problem

$$\boldsymbol{y} = A\boldsymbol{x} + \eta$$

Goal: find B such that $\boldsymbol{x} \approx B\boldsymbol{y}$

We will use a neural network for this.



Deep Learning and Reconstruction

- Several approaches can be envisioned
  - Standard reconstruction algorithm + deep learning filtering
  - Directly from measured data to output
  - Model-based, combining learning with model knowledge

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  - Standard reconstruction algorithm + deep learning filtering
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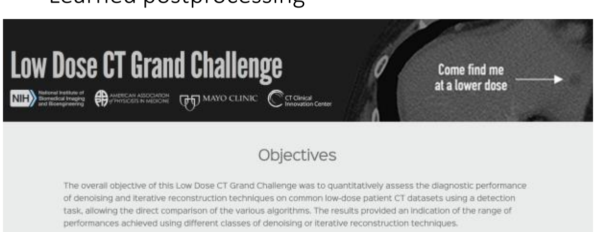
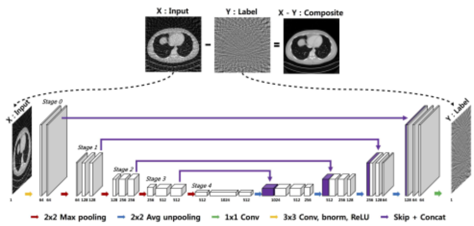
  - **Model-based, combining learning with model knowledge**

Learned postprocessing



Learned postprocessing



Fully learned approach (Automap)

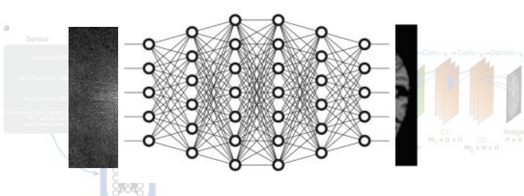

LETTER

doi:10.1038/nature25988

Image reconstruction by domain-transform manifold learning

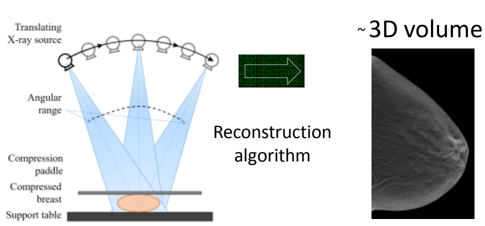
Bo Zhu[1,2,3], Jeremiah Z. Liu[4], Stephen F. Cauley[1,2], Bruce R. Rosen[1,2] & Matthew S. Rosen[1,2,3]

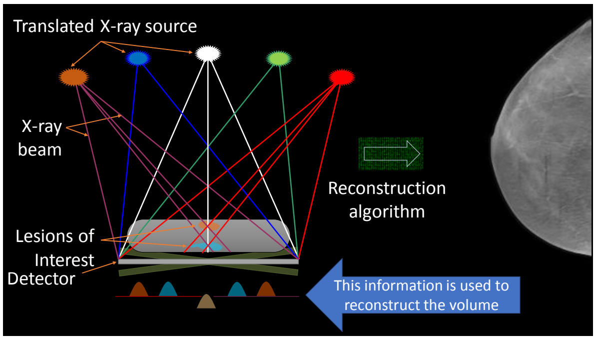
Fully learned approach (Automap)



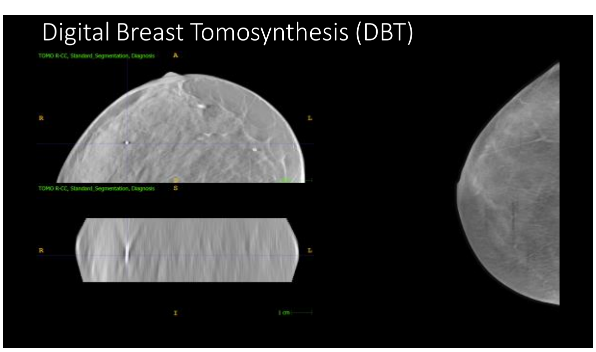
Breast Dosimetry

Digital Breast Tomosynthesis (DBT)




Translated X-ray source
X-ray beam
Lesions of Interest
Detector
Reconstruction algorithm
This information is used to reconstruct the volume


Courtesy of Dr. Ritse Mann


Digital Breast Tomosynthesis (DBT)

Most deep learning reconstruction methods are *supervised*

$$\boldsymbol{x} \approx B\boldsymbol{y}$$

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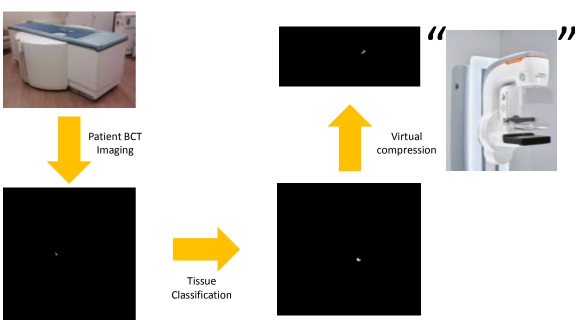
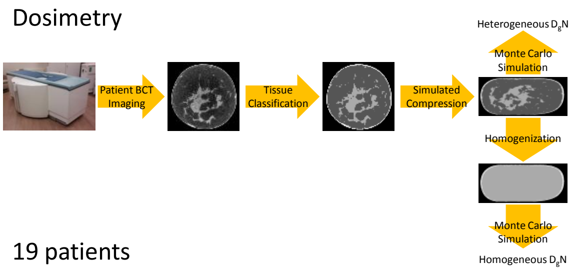
So how to get the ground truth if this is what we have ?



Dosimetry

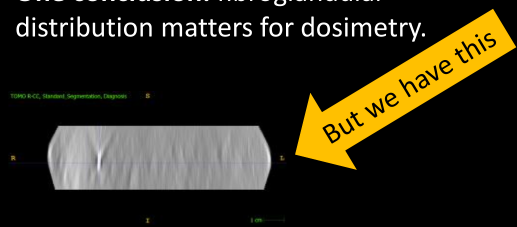


19 patients

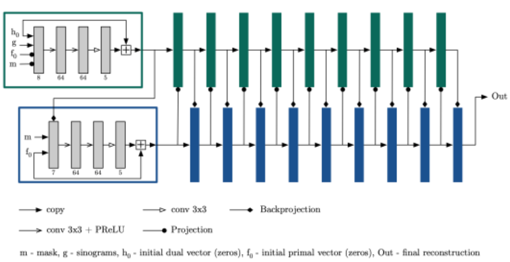
Sechopoulos et al, Medical Physics, 2012, 39(8), 5050-5059

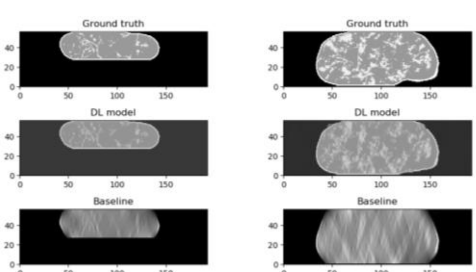
Digital Breast Tomosynthesis (DBT)

One conclusion: fibroglandular distribution matters for dosimetry.



Learned primal dual (Adler et al. 2018)

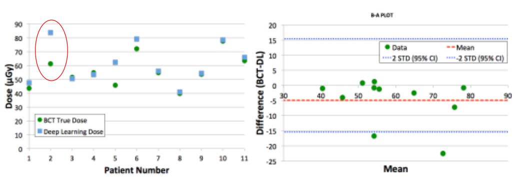




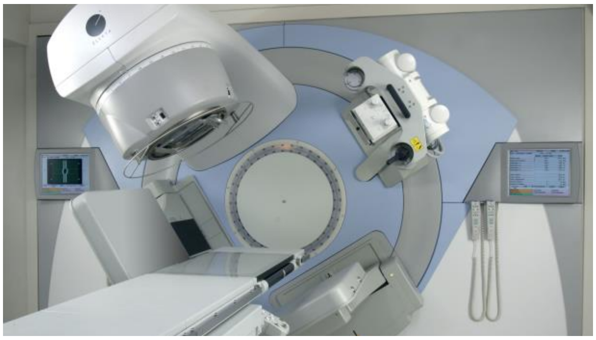
Average Glandular Dose

$$\frac{\text{Amount of energy deposited by x-rays in glandular tissue}}{\text{Amount of glandular tissue}}$$

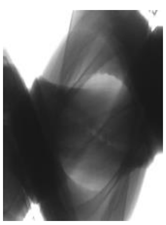
DBT reconstruction for dosimetry



Cone-beam CT reconstruction



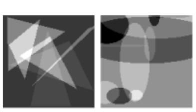
Goal

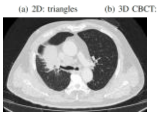


y

x

Ground truth





x

The ASTRA Toolbox

The ASTRA Toolbox is a MATLAB and Python toolbox of high-performance GPU primitives for 2D and 3D tomography.

We support 2D parallel and fan beam geometries, and 3D parallel and cone beam. All of them have highly flexible source/detector positioning.

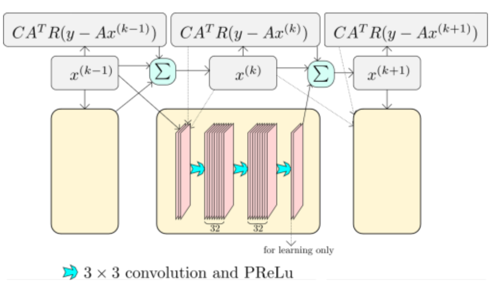
y

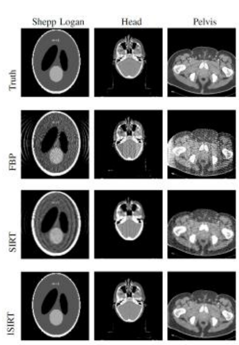
Goal for reconstruction in adaptive radiotherapy

- Proper soft-tissue contrast to target malignant tissue
- Calibrated units for radiotherapy dose calculations
- Needs to scale to clinically relevant sizes, and have *fast* inference

This would enable day-by-day adaptive radiotherapy

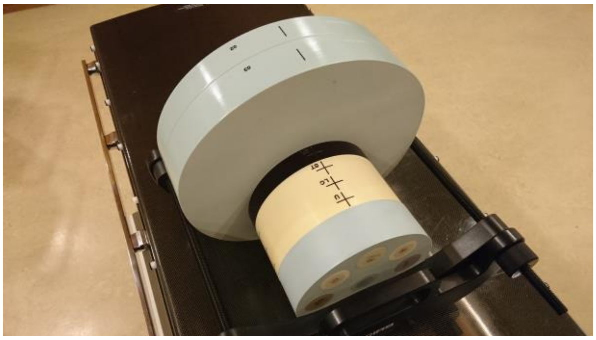
Learned SIRT



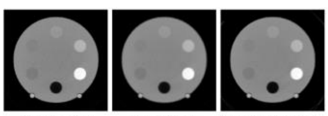


Model trained on lung CTs Generalizes well

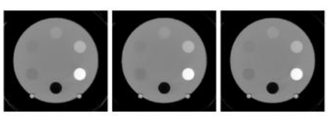
Cone beam geometry reflecting Elekta Synergy with 60 projections



Generalizes well to real measurements



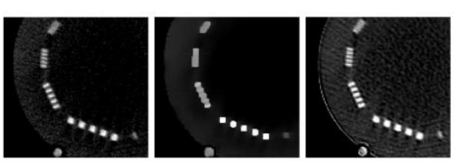
(a) FPB no filter (b) FBP h=0.8 (c) SIRT 250 iterations



(d) ISIRT, low noise model (e) ISIRT, highnoise model (f) ISIRT, patient model

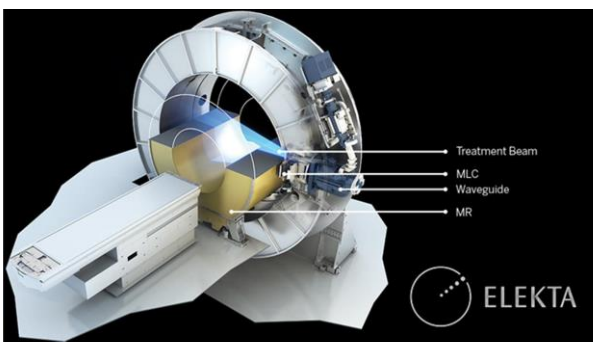
Experiment	CNR	FWHM (cm)
FBP (no filter)	1.81	0.14
FBP (h=0.8)	3.95	0.27
SIRT (100 iterations)	21.76	0.40
SIRT (250 iterations)	13.67	0.28
SIRT (1000 iterations)	6.67	0.24
ISIRT (low noise model)	27.16	0.25
ISIRT (mid noise model)	33.17	0.24
ISIRT (high noise model)	34.52	0.22
ISIRT (Patient model)	17.11	0.23

Generalizes well to real measurements



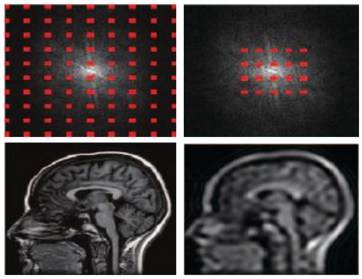
(a) SIRT 250 iterations (b) ISIRT, highnoise model (c) ISIRT, patient model

MRI reconstruction



The highest sampled Frequency (Bandwidth) Determines the Image Resolution

Images from: https://people.eecs.berkeley.edu/~mlustig/CS/CSMRI.pdf



High bandwidth | Low bandwidth

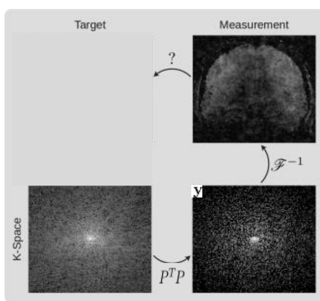
MRI Process

MR samples acquired in the spatial frequency domain, aka. k-space

Proper image is retrieved by sampling at the Nyquist-rate, i.e. “fully sampled”

Scanning time is reduced by acquiring partial measurements

Corruption process given by the forward model: $\mathbf{y} = P\mathscr{F}\mathbf{x} + \mathbf{n}$



Same story, use deep learning.

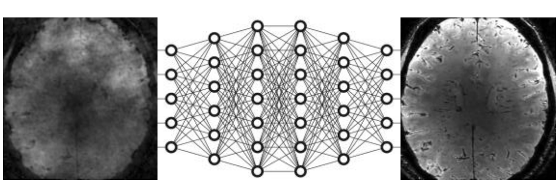
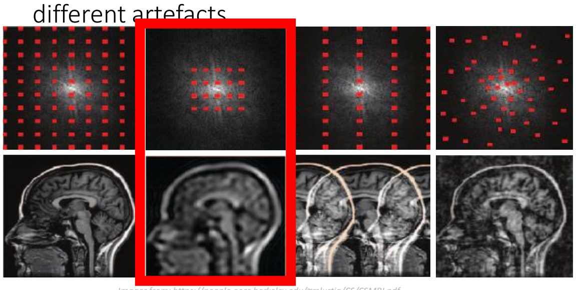


Image from shutterstock user: all_is_magic

How to speed up? Different sampling, different artefacts



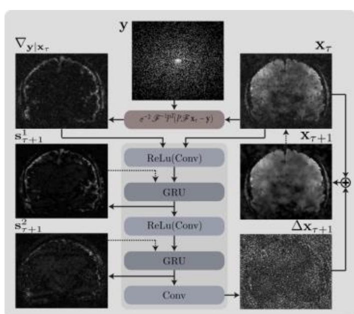
Images from: https://people.eecs.berkeley.edu/~mlustig/CS/CSMRI.pdf

Recurrent inference machines

- Combine convolutional layers and GRU cells
- Maintain two internal states
- And T external states (reconstructions)

MSE averaged over all T external states used for training:

$$L(\mathbf{x}_T) = \frac{1}{nT}\sum_{t=1}^{T}\|\mathbf{x}_t - \mathbf{x}\|_2^2$$

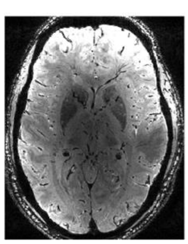


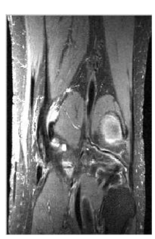
Putzky & Welling, ICLR 2017

Data Used

1.0mm transversal T1-weighted brain images from 3T scanner

0.7mm coronal T2*-weighted brain images from 7T scanner





0.6x0.5mm T2-weighted knee images from 3T scanner at all angles http://mridata.org/fullysampled/knees

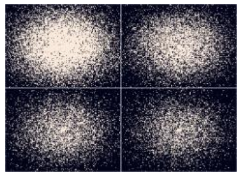
Model trained on all data, and cross validated

For acceleration factors 2x, 3x, 4x, and 5x on Gaussian distribution

SSIM, NRMSE, and PSNR were used as a metrics of reconstruction quality

Compared with

- U-net postprocessing
- Compressed Sensing



Hyun, arXiv 2017
Lustig, Signal Processing 2008

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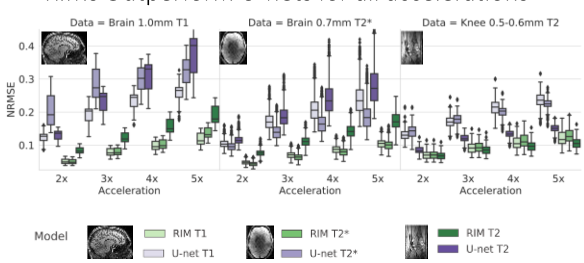
RIMs Outperform U-nets for all accelerations



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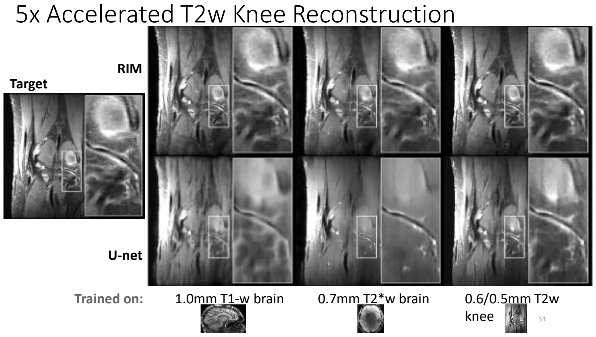
5x Accelerated T2w Knee Reconstruction



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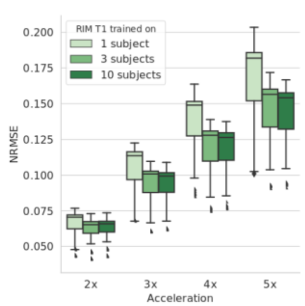
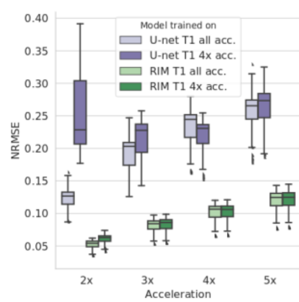
You do not need a lot of data



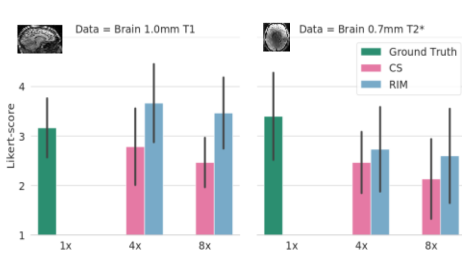
Insensitivity to acceleration factor

The RIM and U-net were trained with masks at 4x acceleration

And tested on random acceleration factors sampled from U(1.5, 5.2)



Ratings by neuroradiologist



Likert-scale:
5: Excellent
4: Very Good
3: Good
2: Fair
1: Poor

Questions?