GAN for Unsupervised Learning in Inverse Problems

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한국뇌공학회
심포지엄
"디지털 브레인으로의 진화"

Deep Learning Era in Medical Imaging

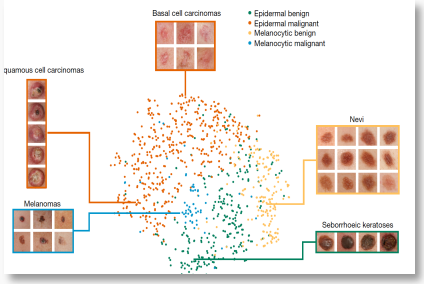
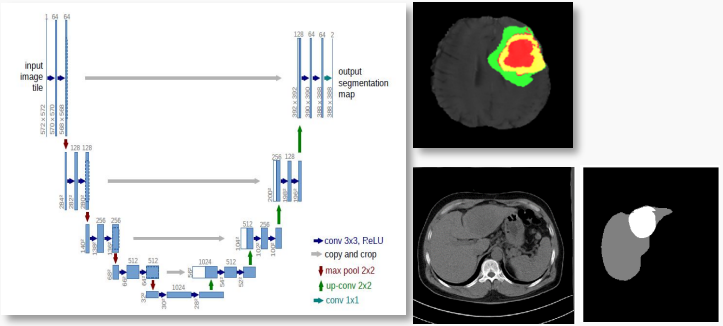
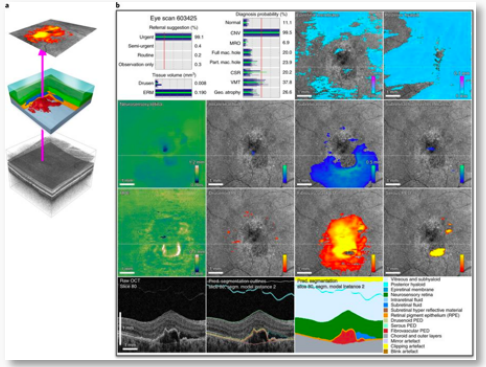


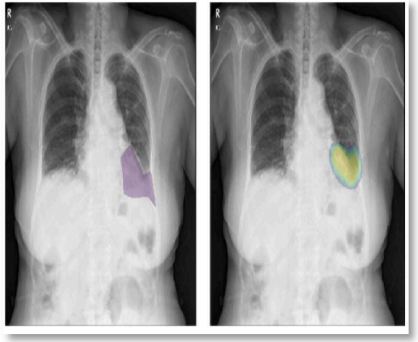
Image segmentation



Ronneberger et al, MICCAI, 2015

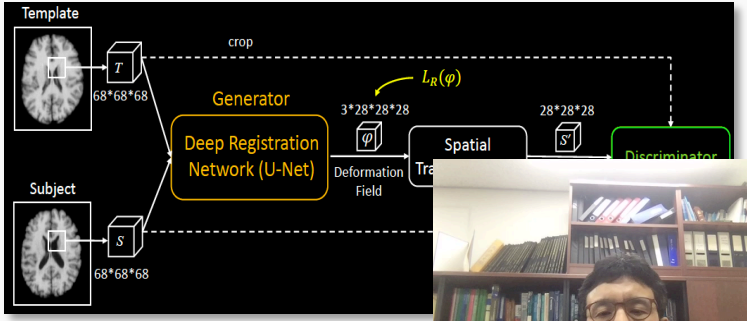


Chest X-ray



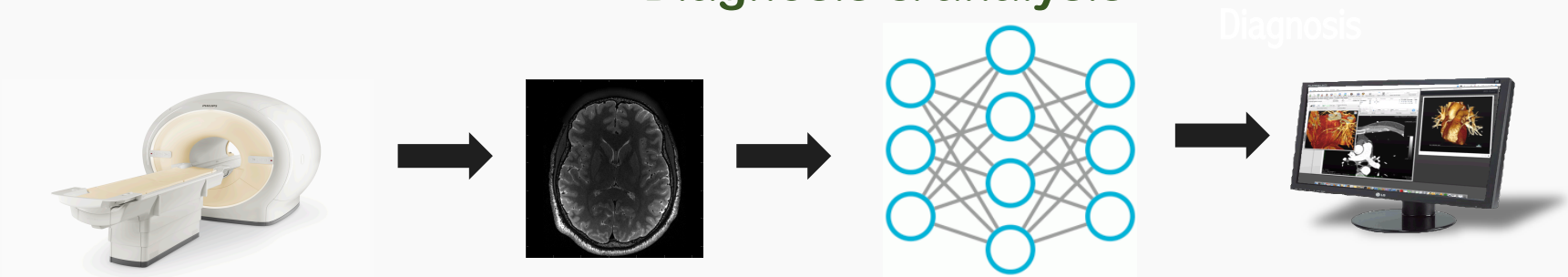
Courtesy of Kyu Hwan Jung @Vuno

Image registration

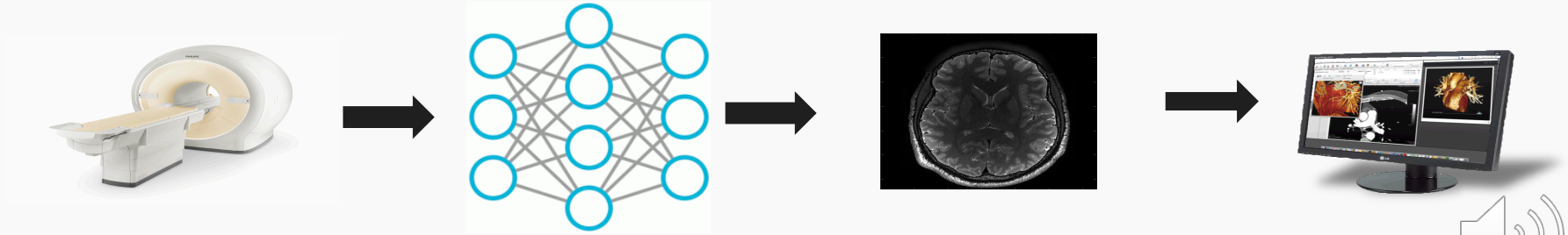


Deep Learning for Inverse Problems

Diagnosis & analysis



New trend of deep learning: inverse problems



Low Dose CT Grand Challenge

National Institute of Biomedical Imaging and Bioengineering

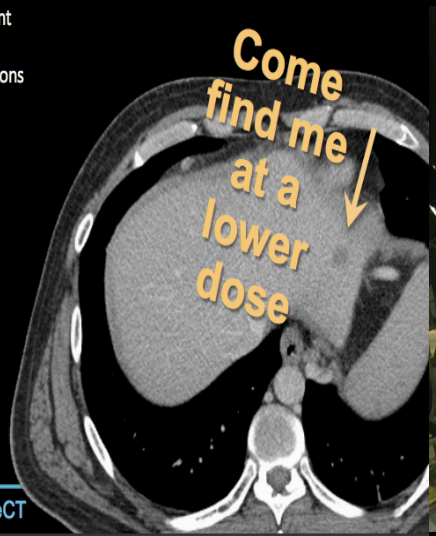
AMERICAN ASSOCIATION of PHYSICISTS IN MEDICINE

MAYO CLINIC

CT Clinical Innovation Center

- Radiologist-selected abdominal CT patient cases (10 training, 20 testing) with noise inserted to simulate lower dose acquisitions
- Projection data converted into an open format (user manual and reading tools provided)

- Apr 2016: Participants submit reconstructed images or denoised images to AAPM website
- Jun 2016: Images read by radiologists at the host site
- Aug 2016: Winners announced at AAPM Annual Meeting



www.aapm.org/GrandChallenge/LowDoseCT

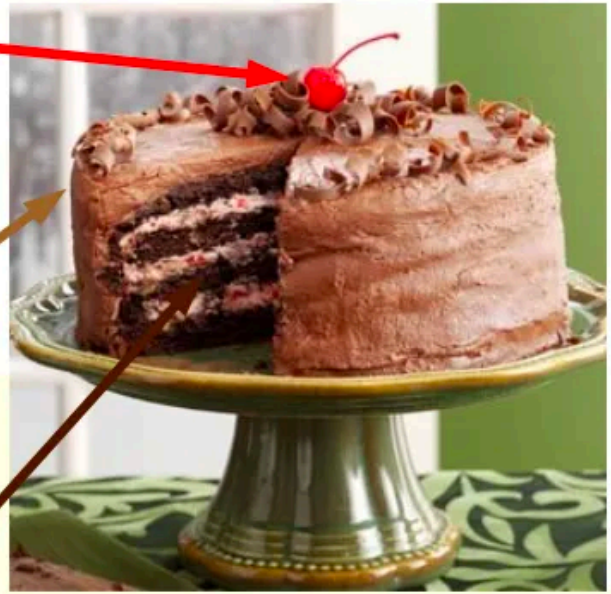

Canon
AiCE
Integrated Intelligence
See through the noise
World's 1st Deep Learning
Reconstruction for CT


GE Healthcare
TrueFidelity
How the best see better.

What if we do not have
label data for training ?

Yann LeCun's Cake Analogy

- "Pure" Reinforcement Learning (cherry)
  - The machine predicts a scalar reward given once in a while.
  - **A few bits for some samples**
- Supervised Learning (icing)
  - The machine predicts a category or a few numbers for each input
  - Predicting human-supplied data
  - **10→10,000 bits per sample**
- Unsupervised/Predictive Learning (cake)
  - The machine predicts any part of its input for any observed part.
  - Predicts future frames in videos
  - **Millions of bits per sample**



- (Yes, I know, this picture is slightly offensive to RL folks. But I'll make it up)

Slide courtesy of Yann LeCun's ICIP 2019 talk

Deep Image Prior (DIP)

Ulyanov et al, CVPR, 2018

$$\min_{\Theta} \|y - HQ_{\Theta}(z)\|^2$$

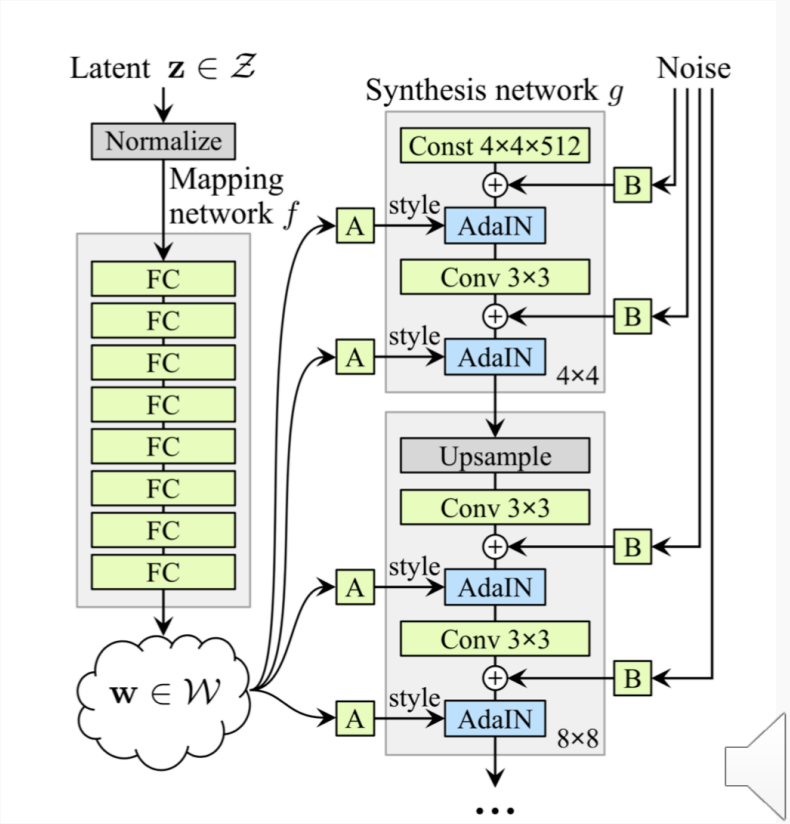
- CNN architecture as a regularization
- Unsupervised learning
- Extensive computation >> PLS

Generative
Adversarial Networks

GAN in 4 years

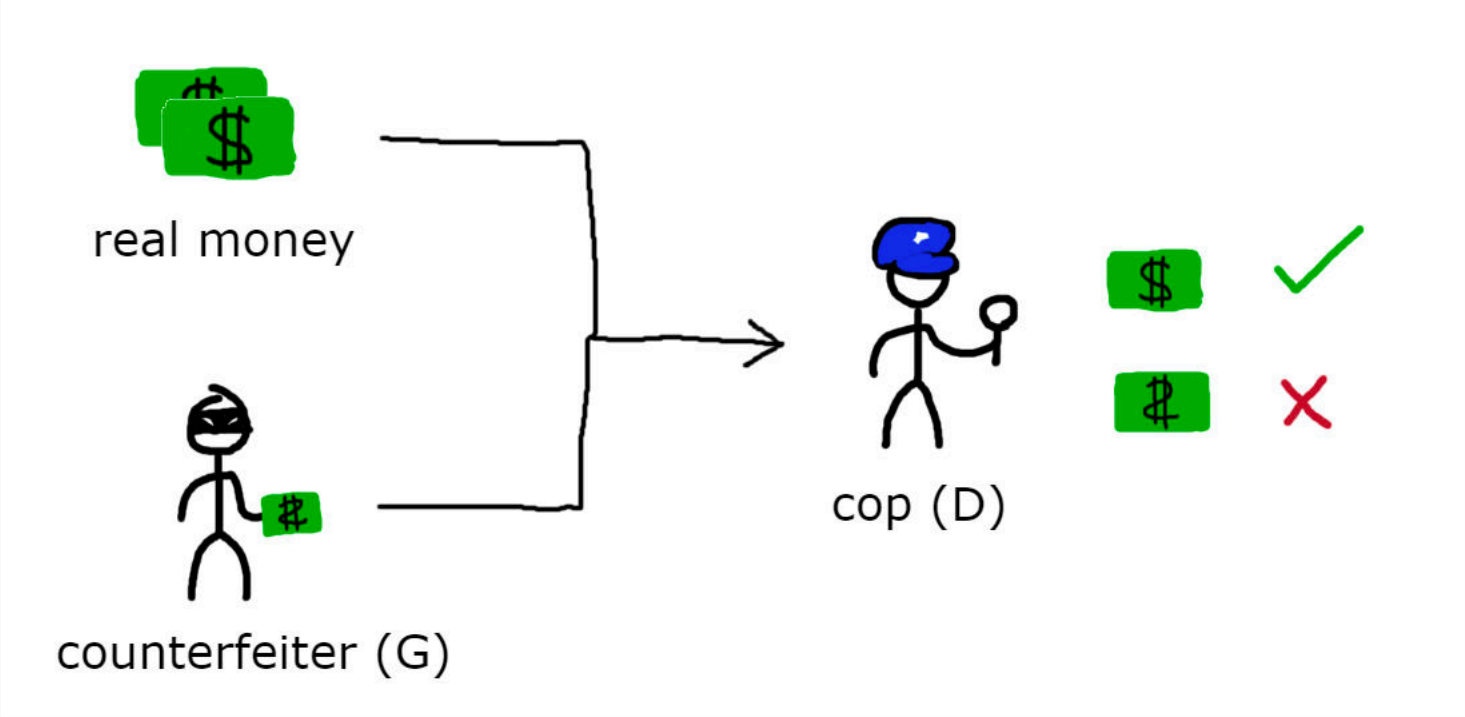
Figure from Ian Goodfollows Twitter

StyleGAN



Karras et al, *CVPR, 2019*

Generative Adversarial Nets (GANs)



https://www.cfml.se/blog/generative_adversarial_networks/

Wasserstein GAN

$$\ell_{W-GAN}(G;\varphi)$$

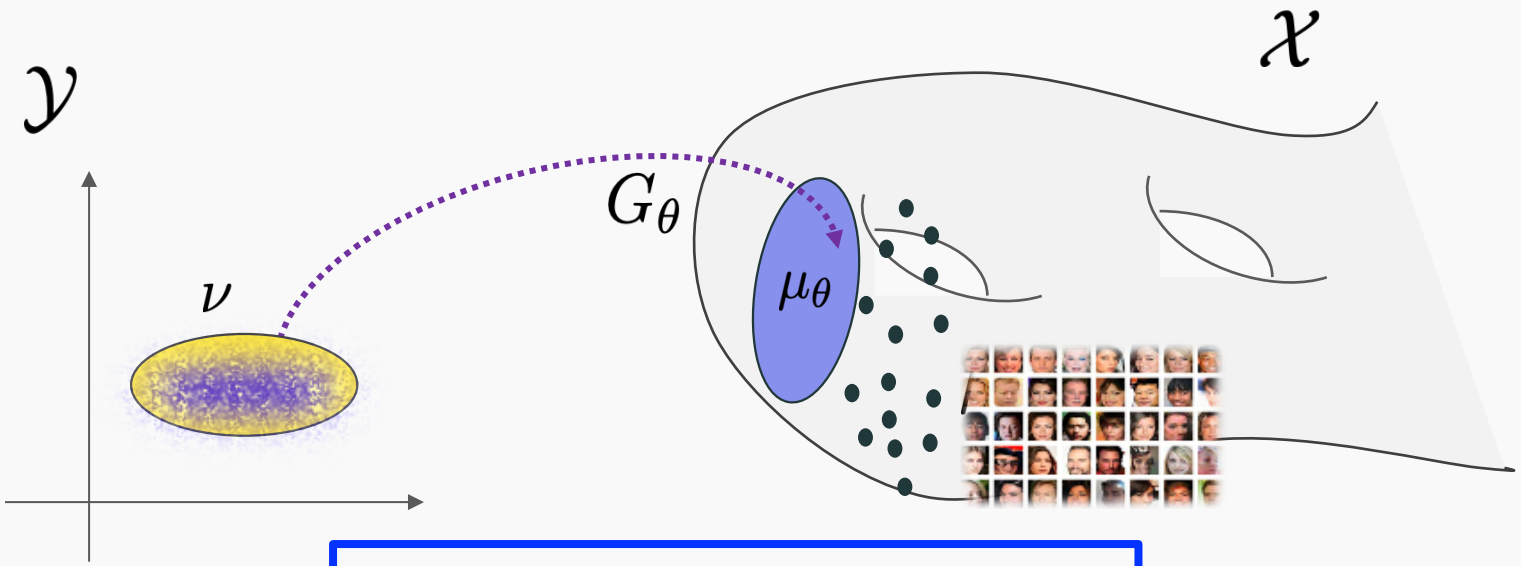
discriminator

generator

$$= \left(\int_{\mathcal{X}} \varphi(x) d\mu(x) - \int_{\mathcal{Z}} \varphi(G(z)) d\zeta(z) \right)$$

Geometry of GAN

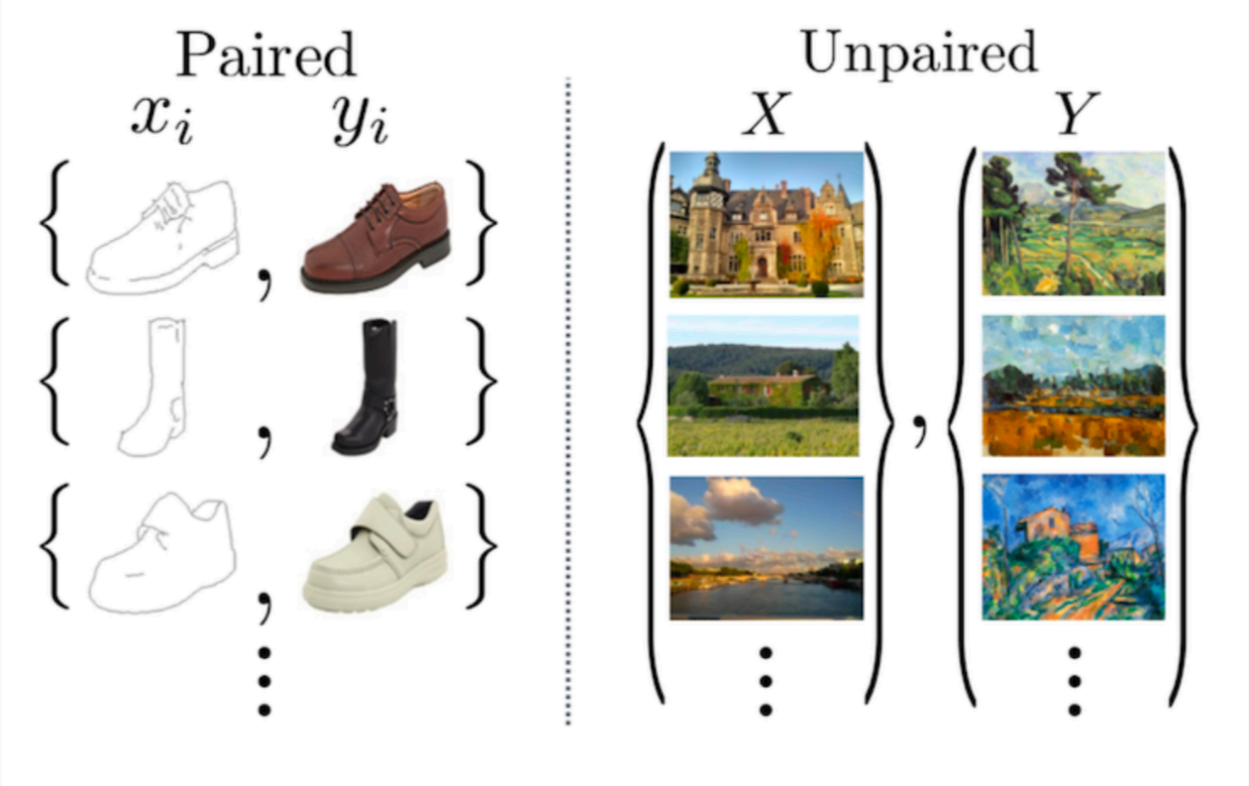
Lei, Na, *arXiv:1710.05488* (2017)



$$\min_\theta \operatorname{dist}(\mu_\theta, \mu)$$

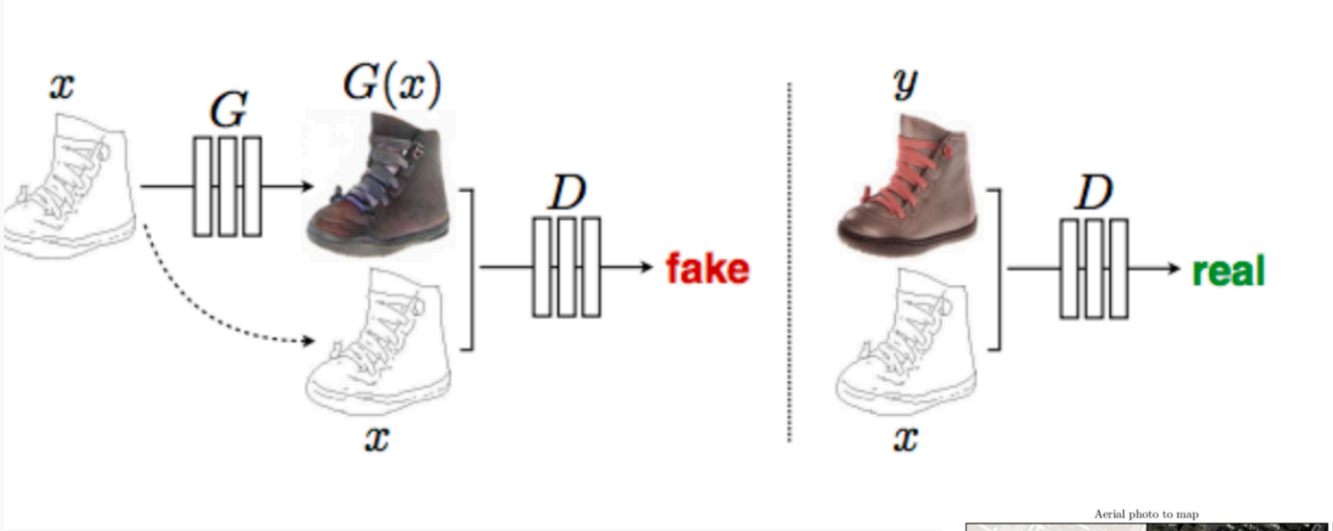
subject to $\mu_\theta = G_{\theta\#}\nu$

Image Translation

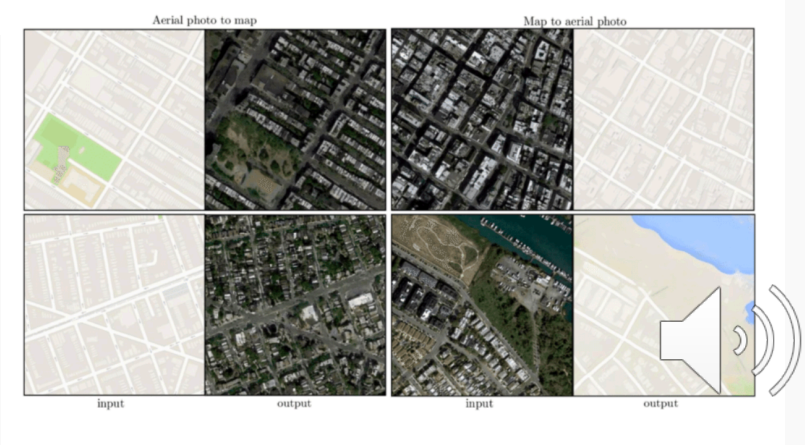


J.-Y. Zhu, et al, CVPR, 2017

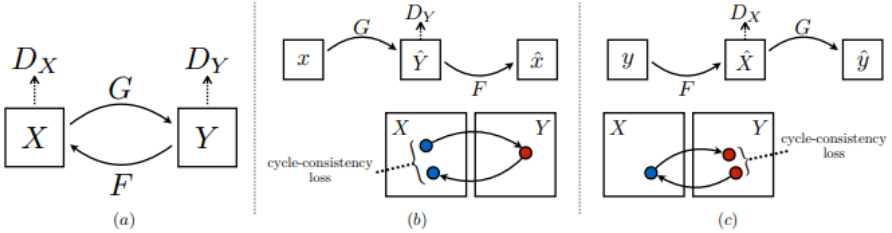
Pix2Pix



P. Isola, et al, CVPR, 2017



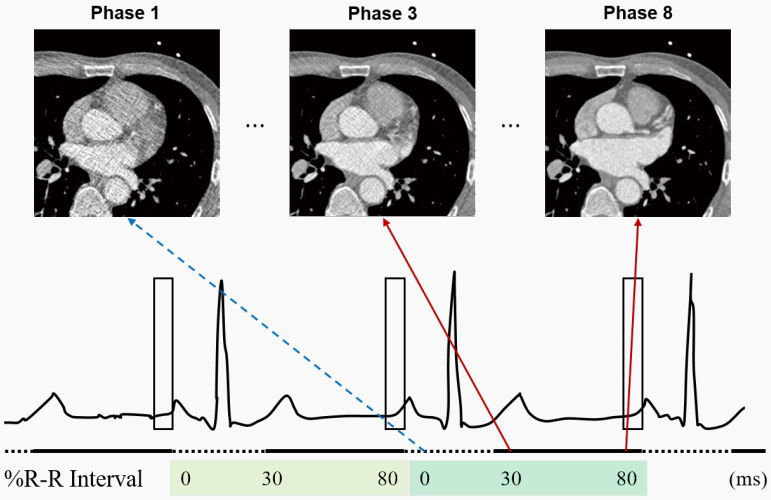
CycleGAN



J.-Y. Zhu, et al, CVPR, 2017

Motivation

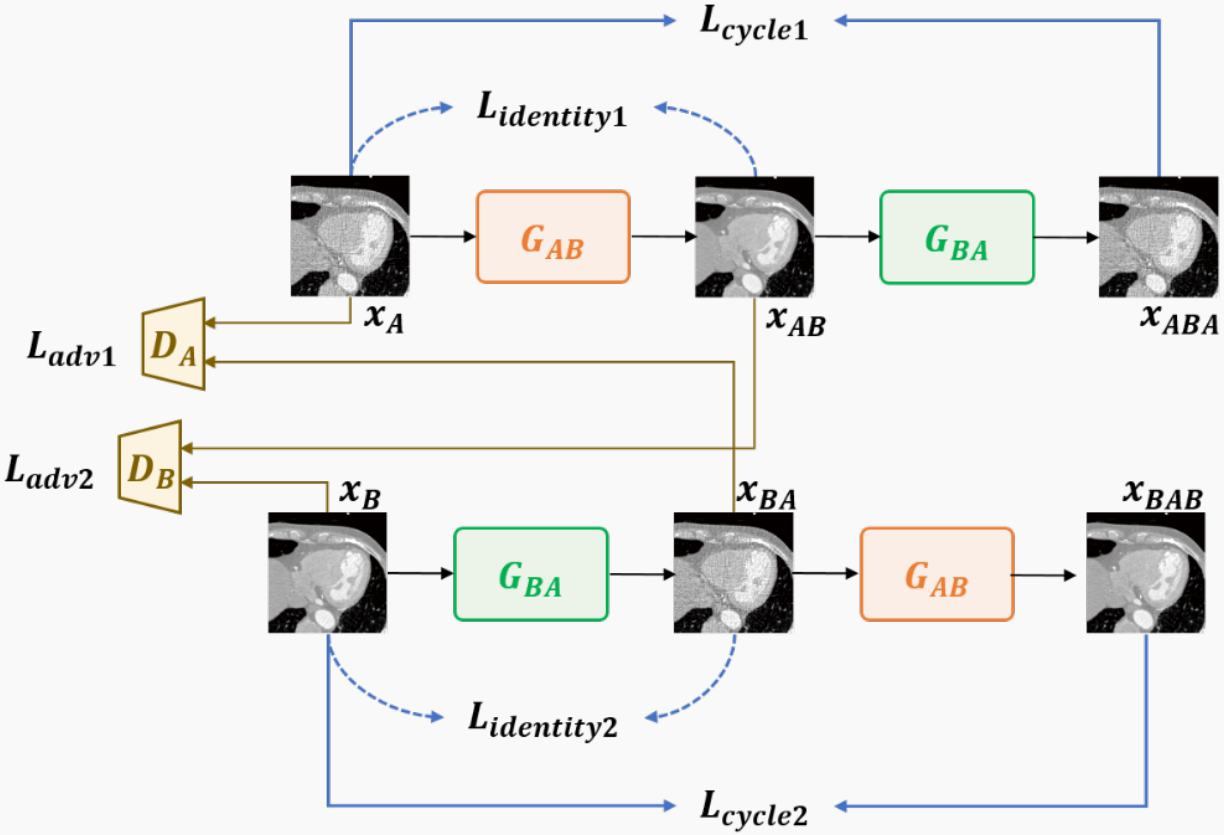
- **Multiphase Cardiac CT denoising**
  - Phase 1, 2: low-dose, Phase 3 ~ 10: normal dose
  - Goal: dynamic changes of heart structure
  - No reference available



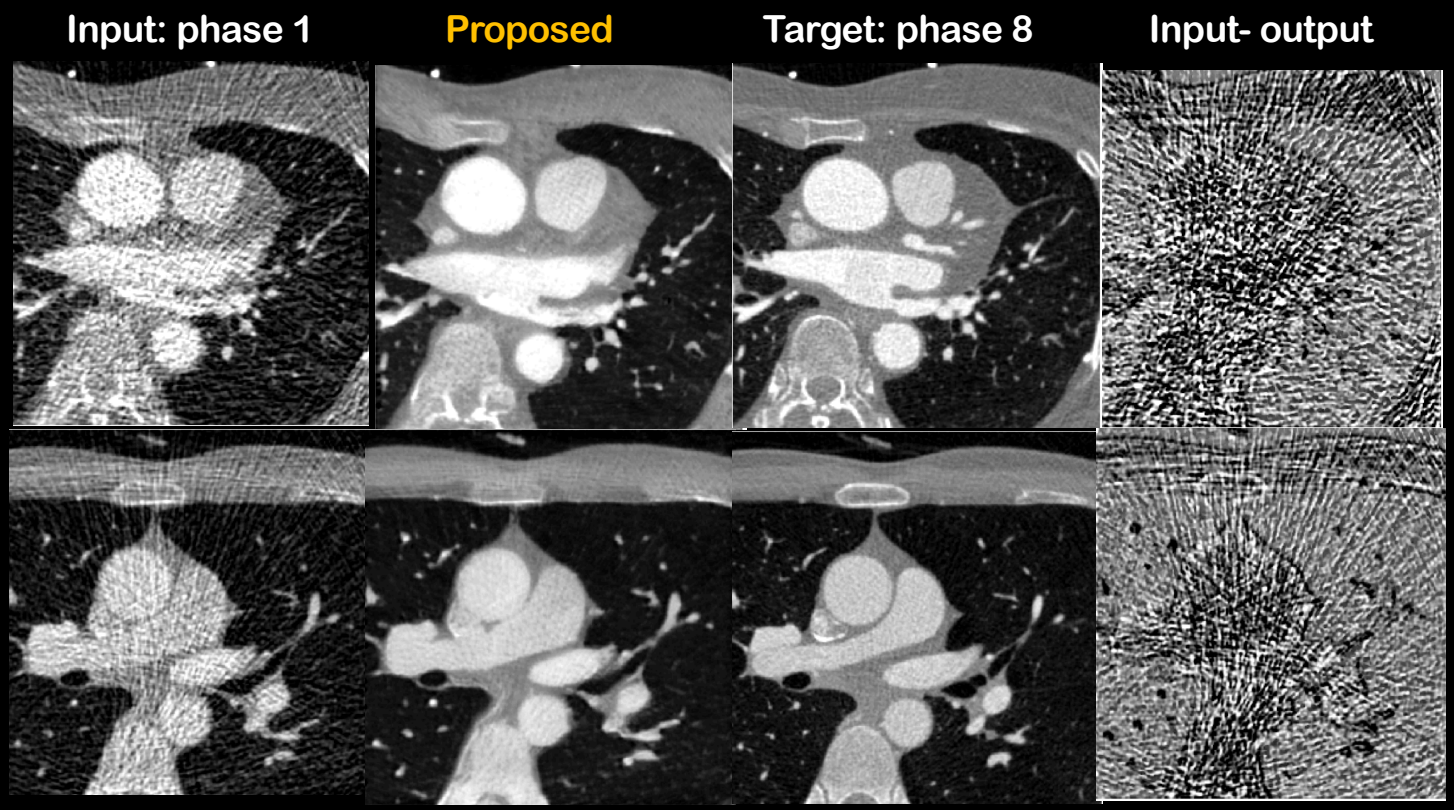
Kang et al, Medical Physics, 2018

Unsupervised Denoising for Low-Dose CT

Kang et al, Medical Physics, 2018



Lose dose (5%) → high dose

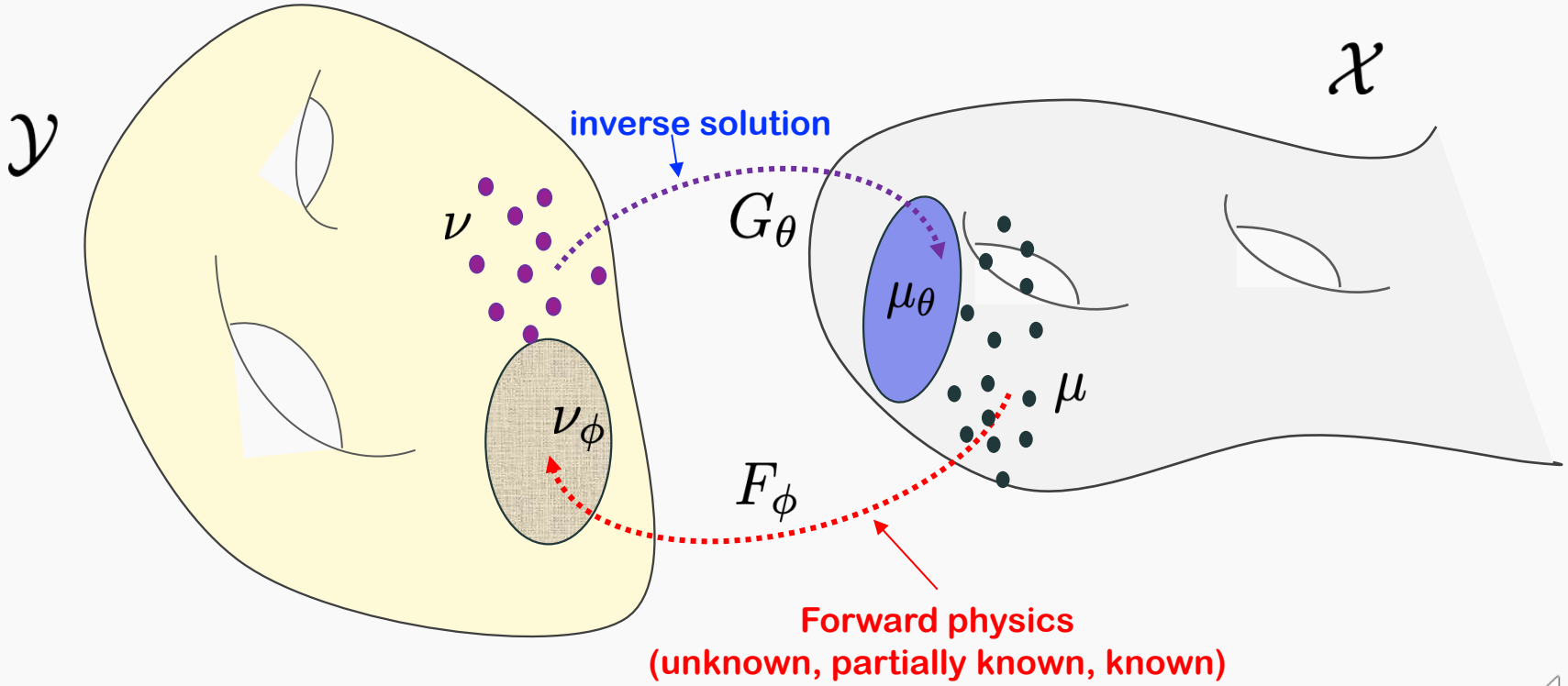


Geometry of CycleGAN

Sim et al, SIAM J. Imaging Sciences, 2020
Khan et al, IEEE TUFFC, 2020
Lee et al, IEEE TCI, 2020

Geometry of CycleGAN

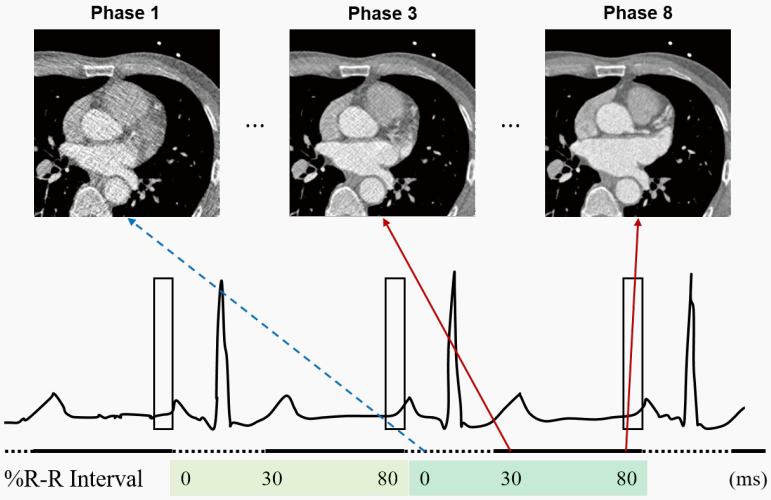
Sim et al, SIIMS, 2020, Lee et al, IEEE TCI, 2020



$$\min_{\theta,\phi} \mathrm{dist}(\mu_\theta, \mu) + \mathrm{dist}(\nu_\phi, \nu)$$

Case 1: Unsupervised Denoising for Low-Dose CT

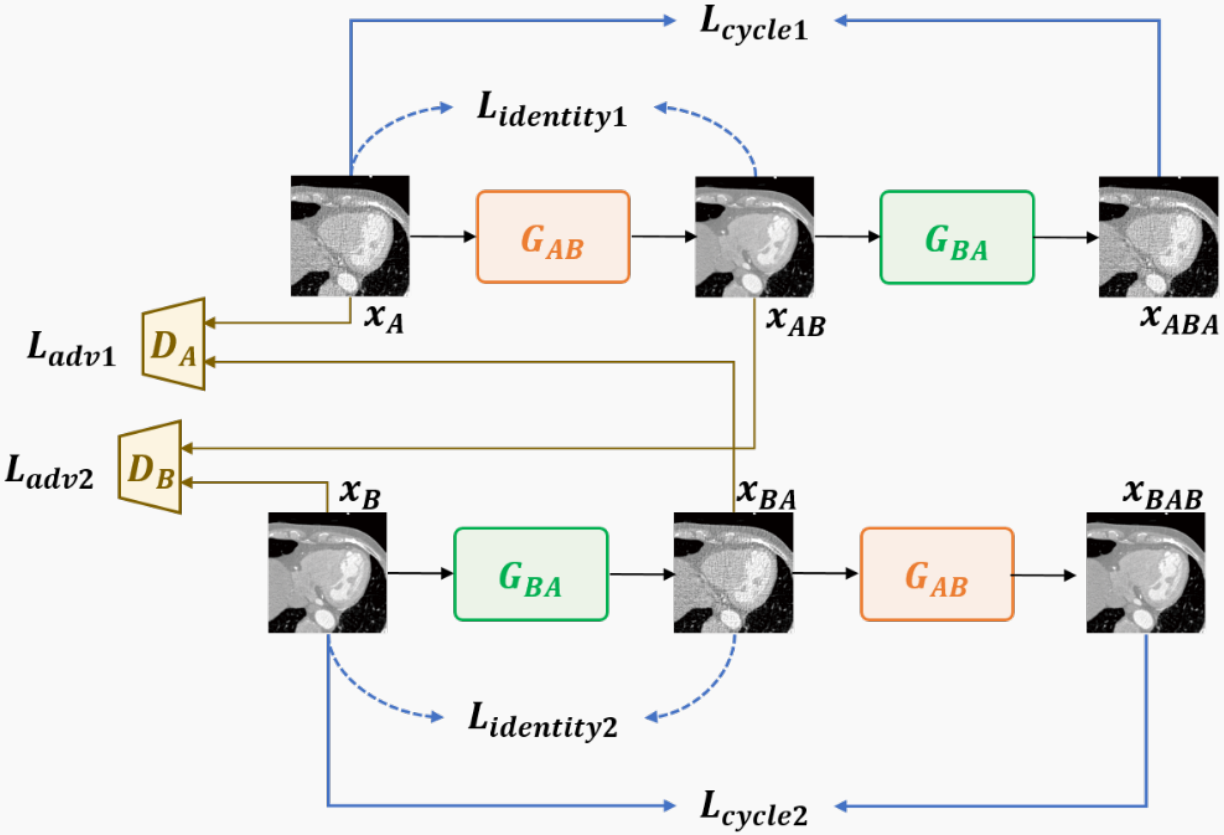
- **Multiphase Cardiac CT denoising**
  - Phase 1, 2: low-dose, Phase 3 ~ 10: normal dose
  - Goal: dynamic changes of heart structure
  - No reference available



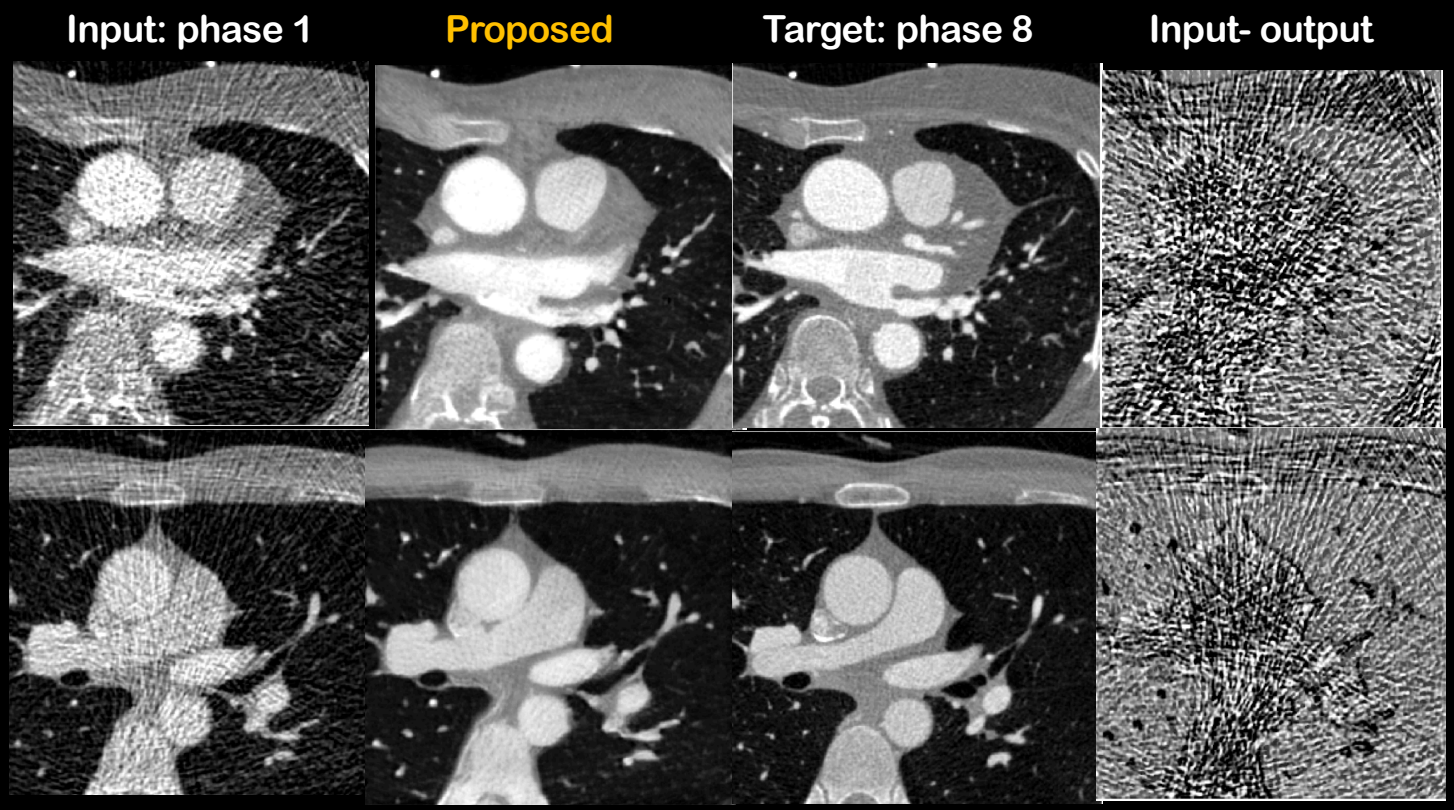
Kang et al, Medical Physics, 2018

Unsupervised Denoising by CycleGAN

Kang et al, Medical Physics, 2019

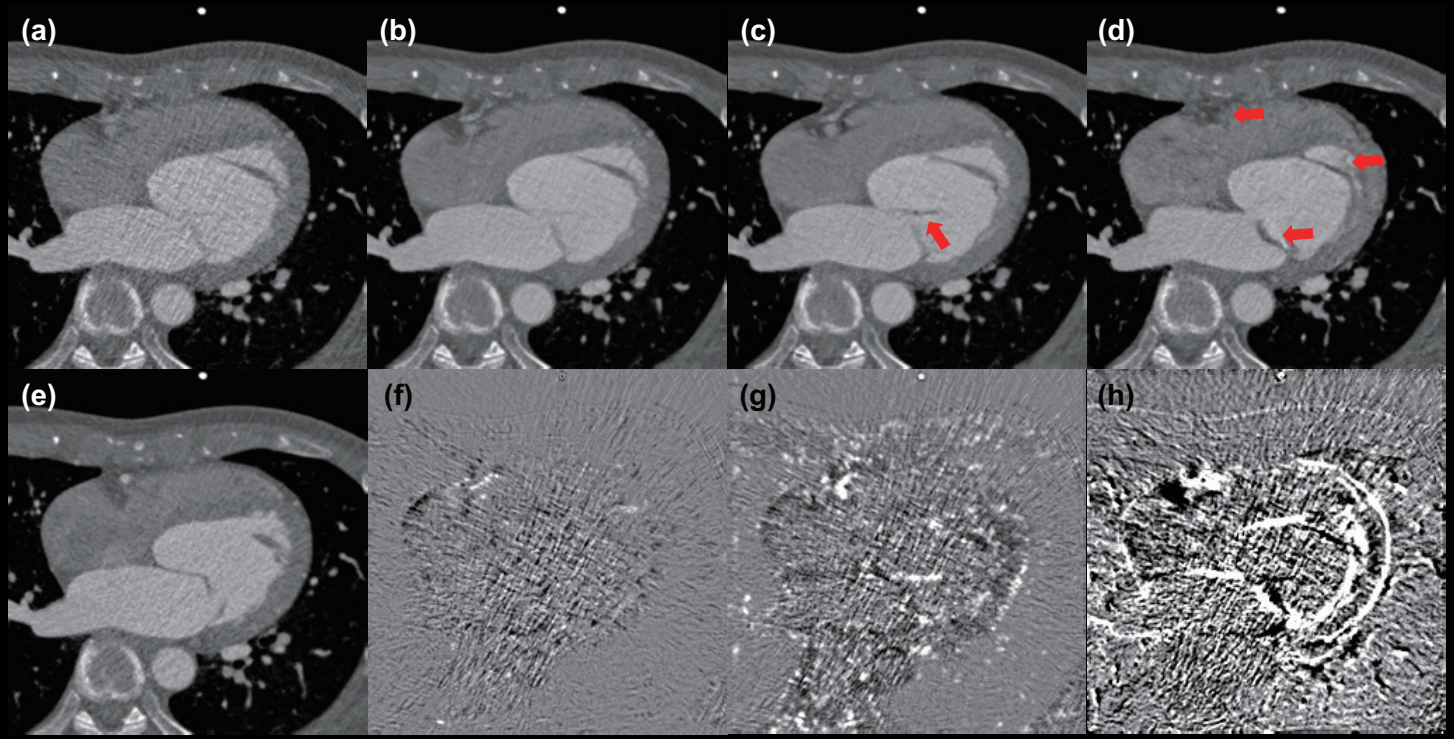


Lose dose (5%) → high dose



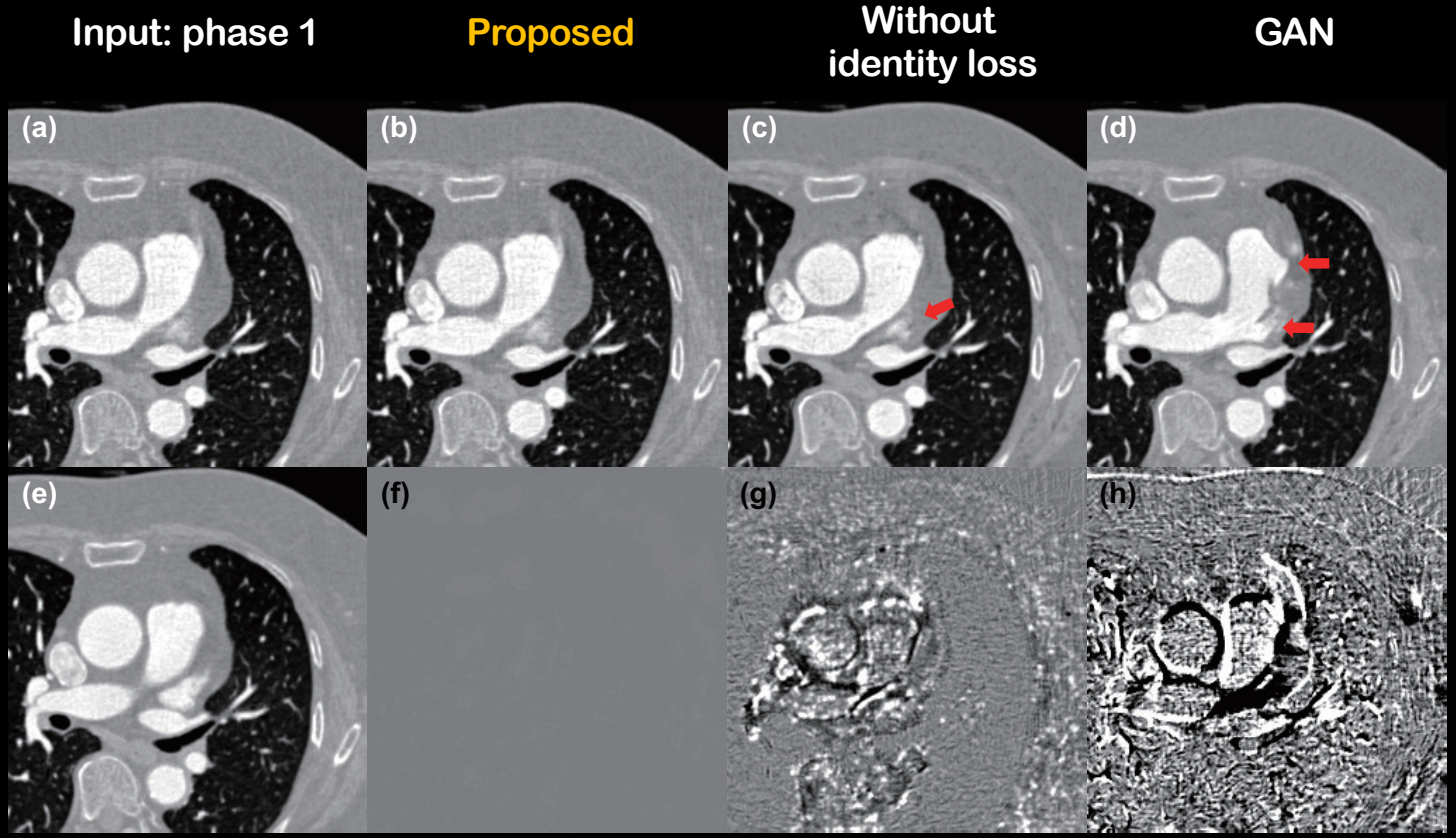
Kang et al, unpublished data

Ablation Study



Kang et al, Medical Physics, 2018

Ablation Study

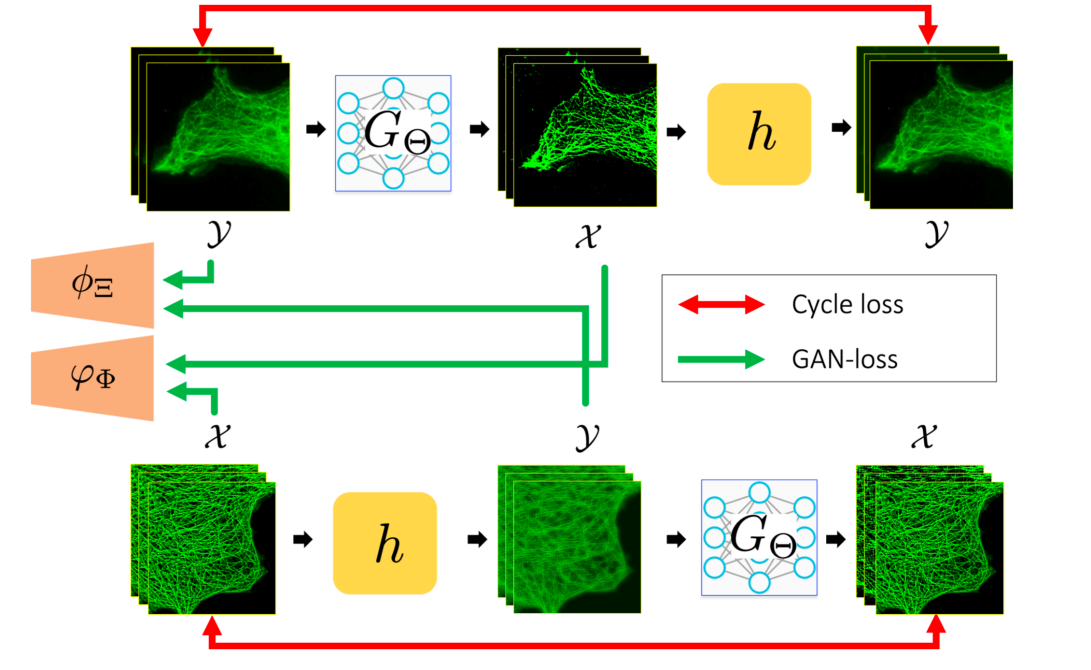


Kang et al, Medical Physics, 2018

Case 2: Unsupervised Deconvolution Microscopy

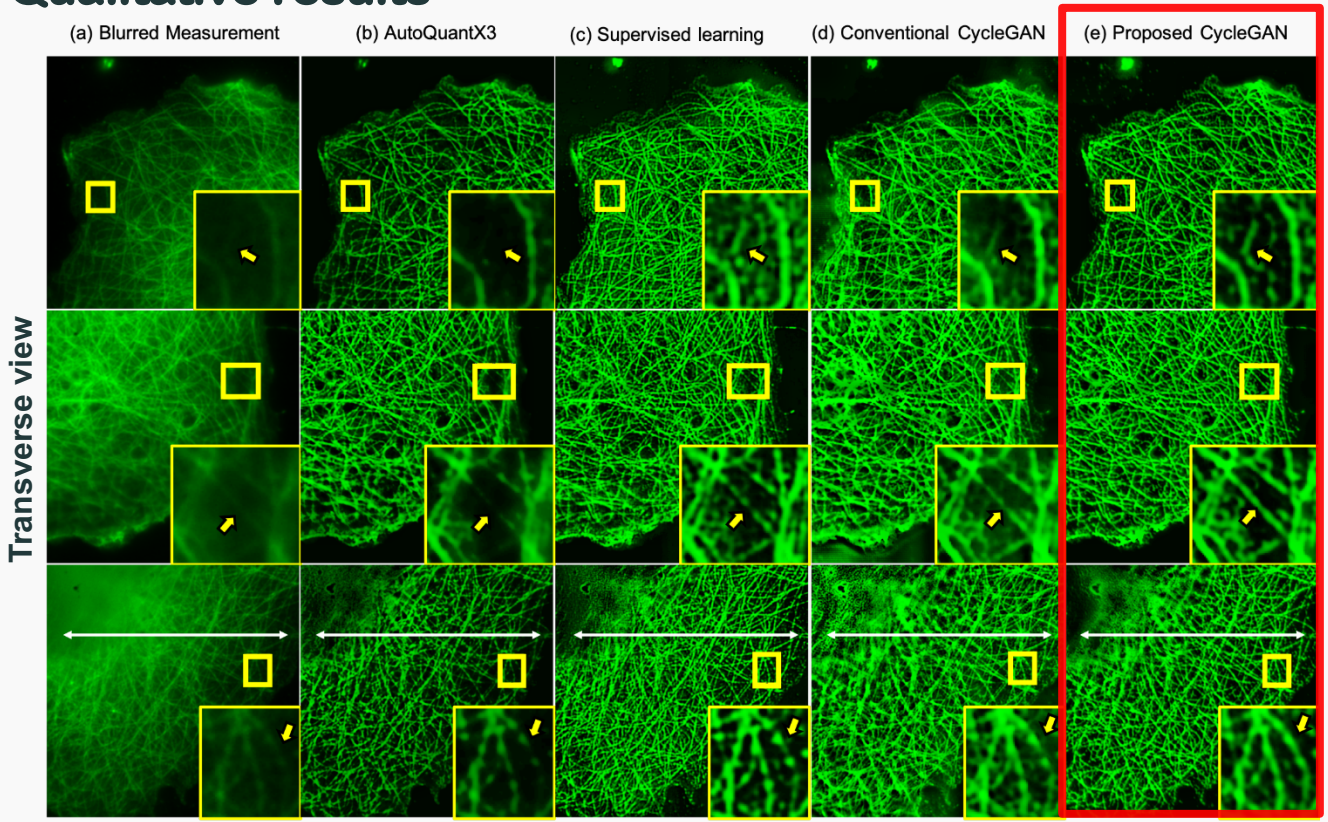
Lim et al, IEEE TCI, 2020

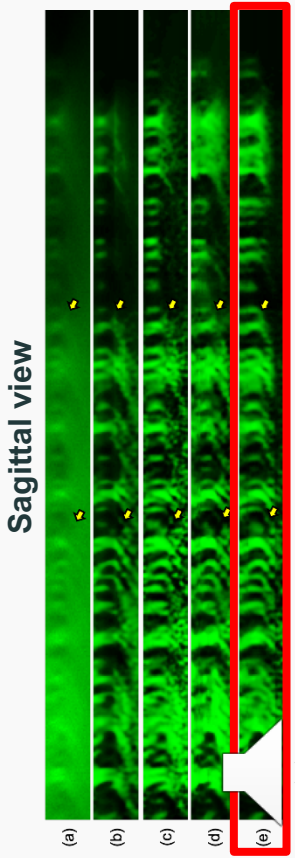
$$c(x, y; \Theta, h) = \|y - h * x\| + \|G_\Theta(y) - x\|$$



Results on Real Microscopy Data

✓ Qualitative results





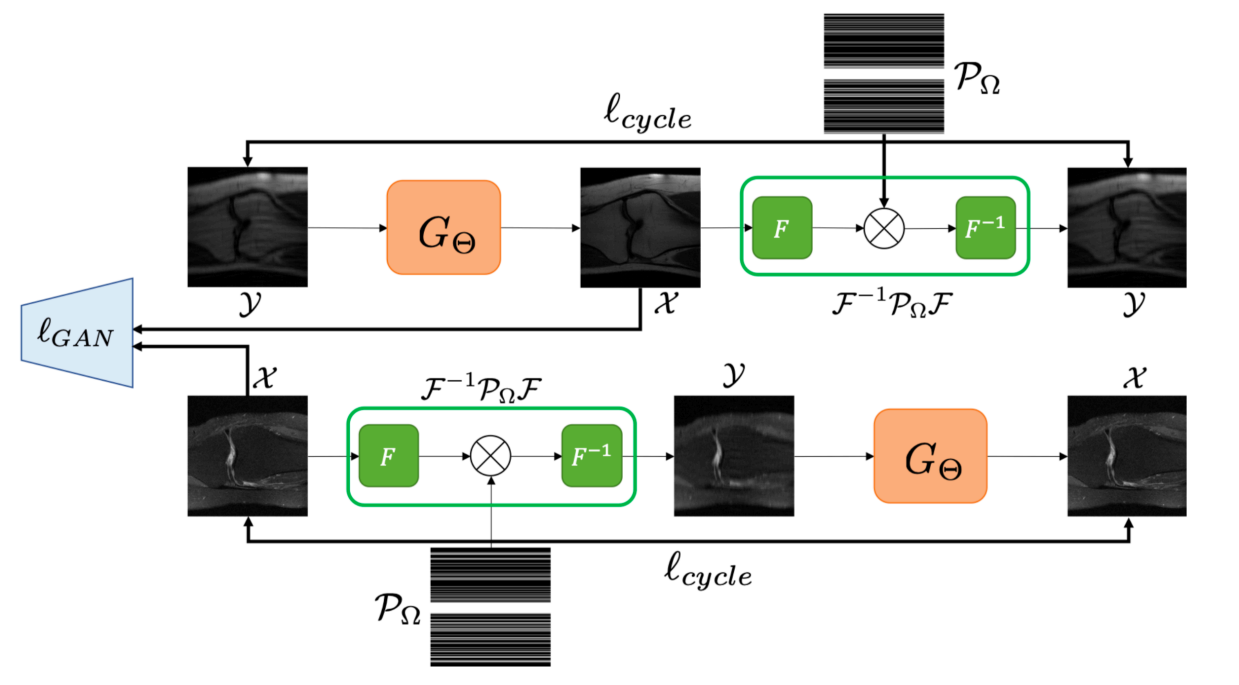
- Runtime for 512 x 512 x 50 volume inference: 15 s

Lim et al, IEEE TCI, 2020

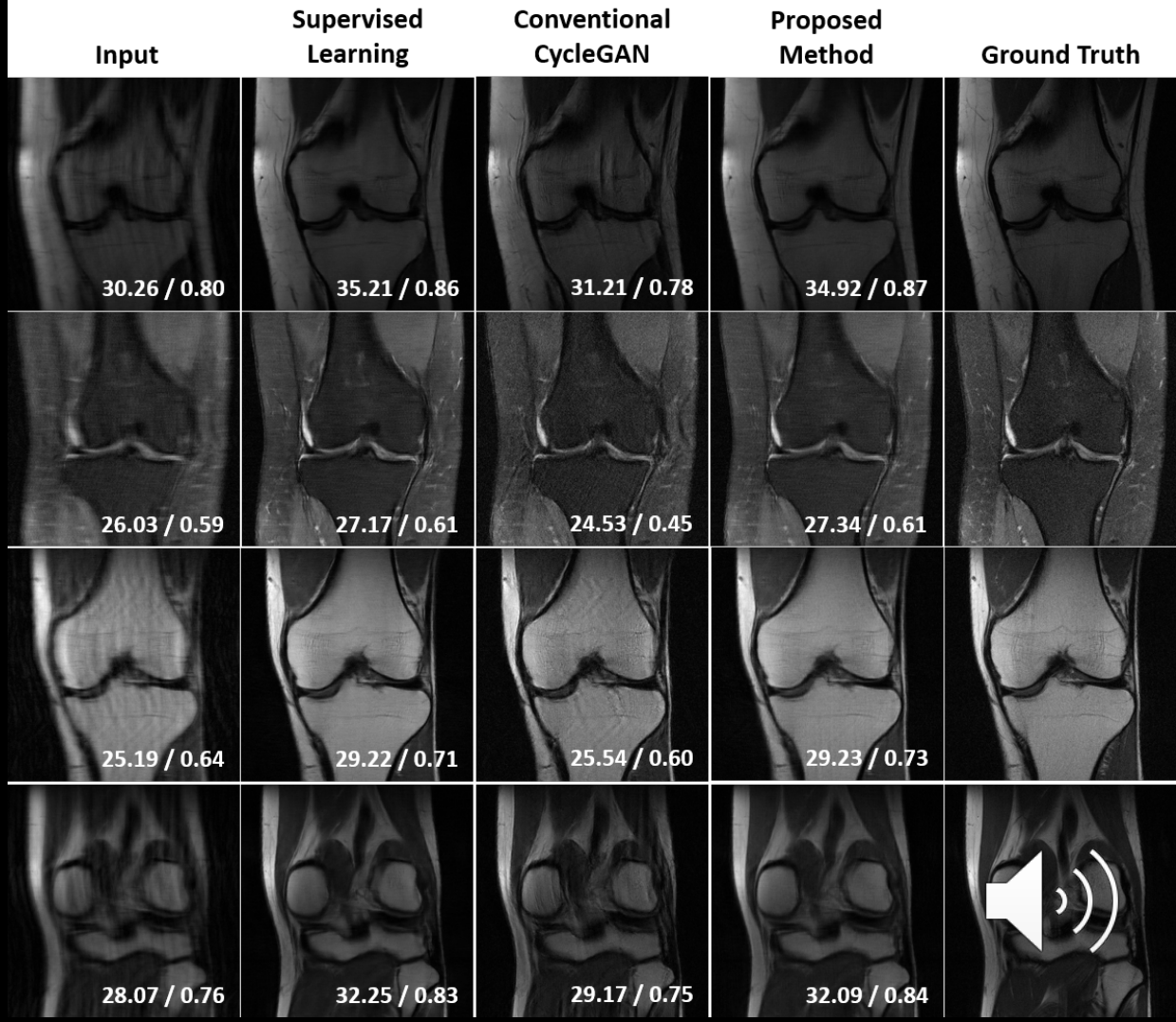
Case 3: Unsupervised Learning for Accelerated MRI

Sim et al, SIAM J. Imaging Sciences, 2020

$$c(x, y; \Theta) = \|y - \mathcal{F}^{-1}\mathcal{P}_\Omega \mathcal{F} x\| + \|G_\Theta(y) - x\|$$



Results on Fast MR Data Set

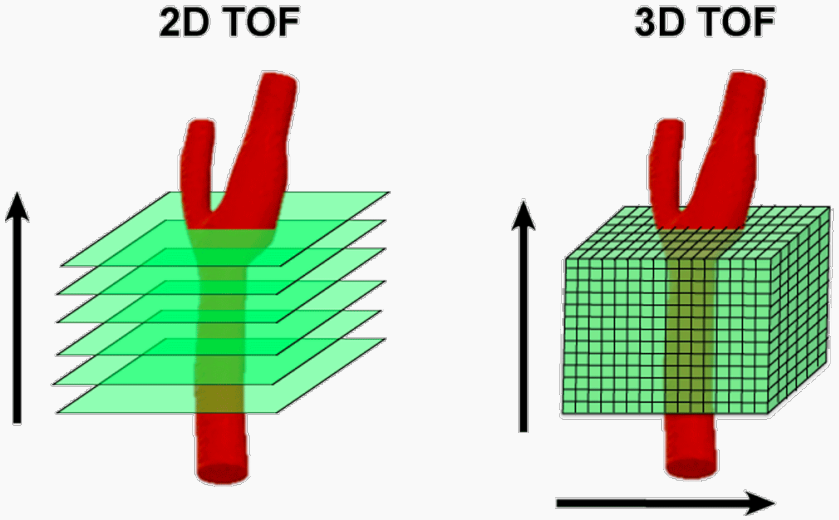


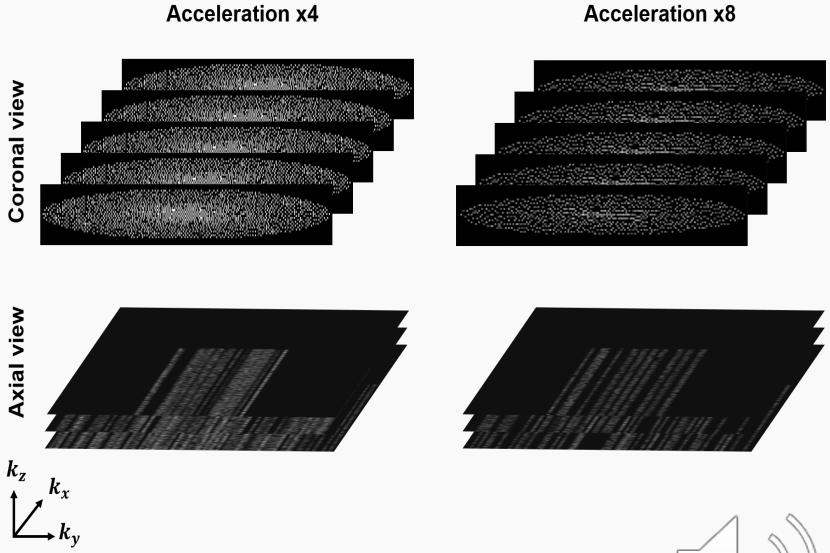
Sim et al, SIAM J. Imaging Science (2020)

Advanced Applications

TOF-MRA

- MR angiography without contrast agent
- 3D volume data → acquisition time is long
- High acceleration is needed → CS, Deep learning

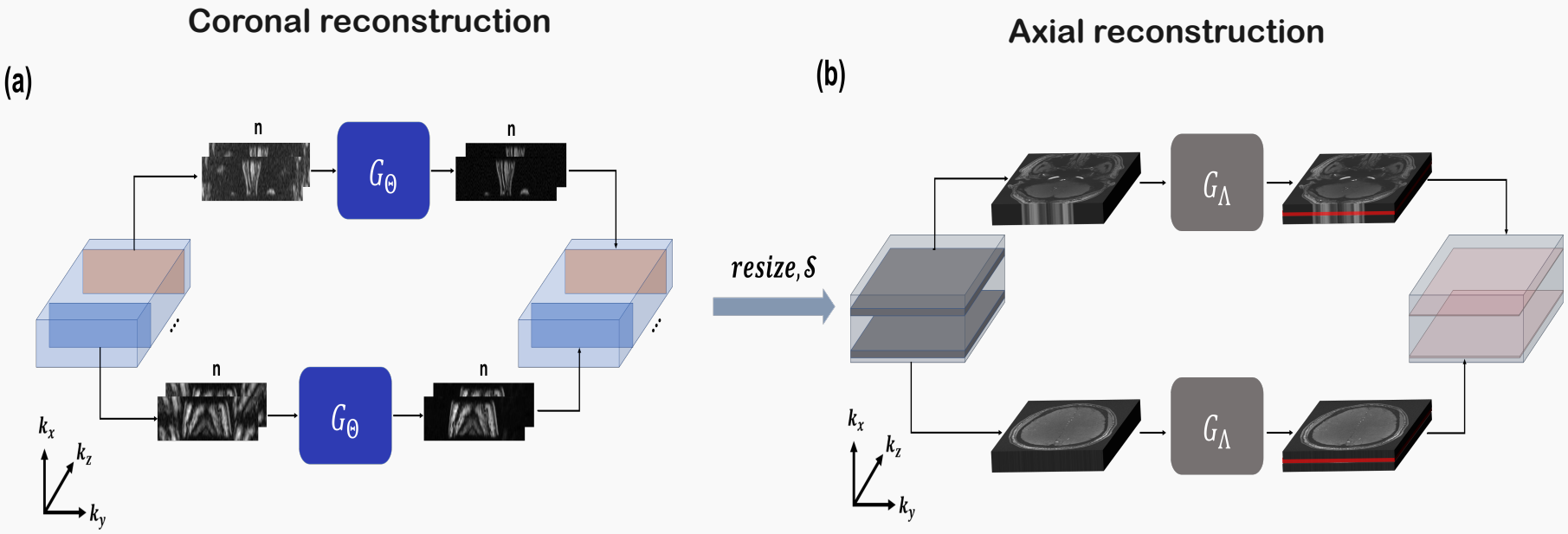




http://mri-q.com/2d-vs-3d-mra.html

Two-Step Unsupervised Learning for TOF-MRA

Chung et al, arXiv:2008.01362 , 2020

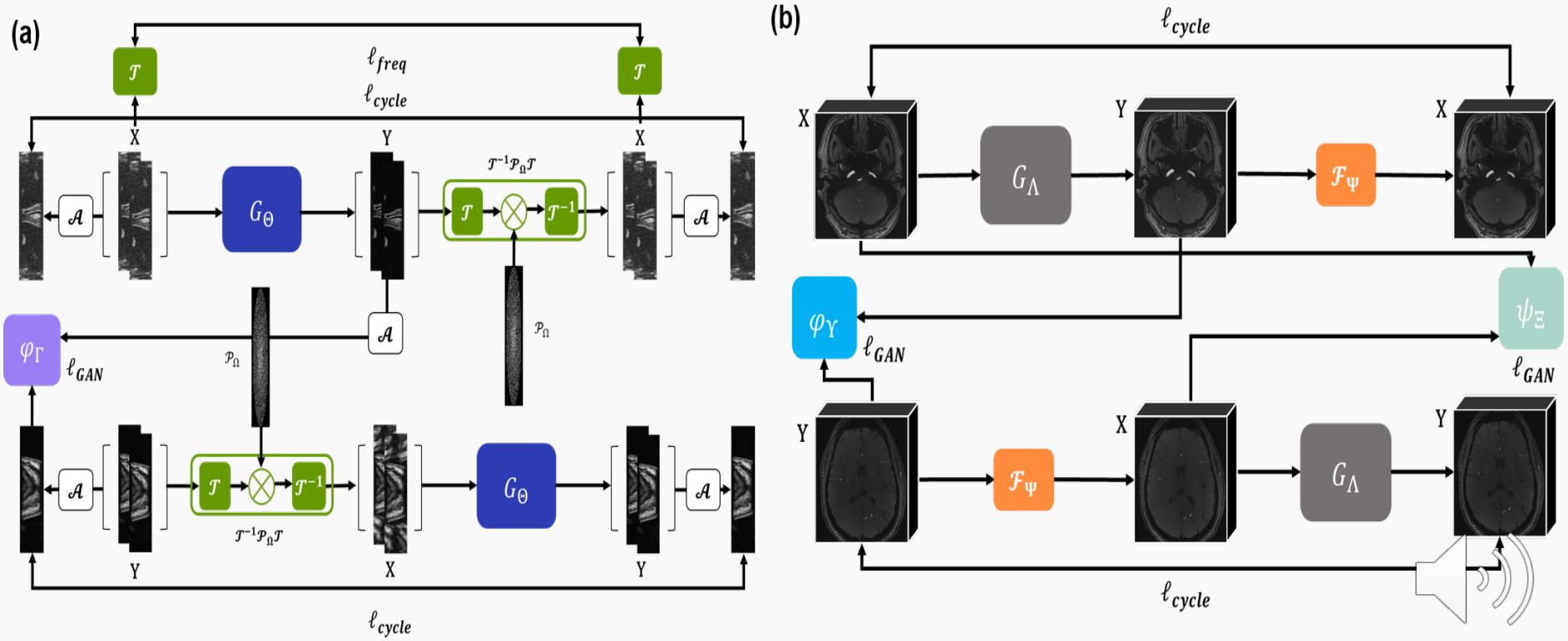


Two-Step Unsupervised Learning for TOF-MRA

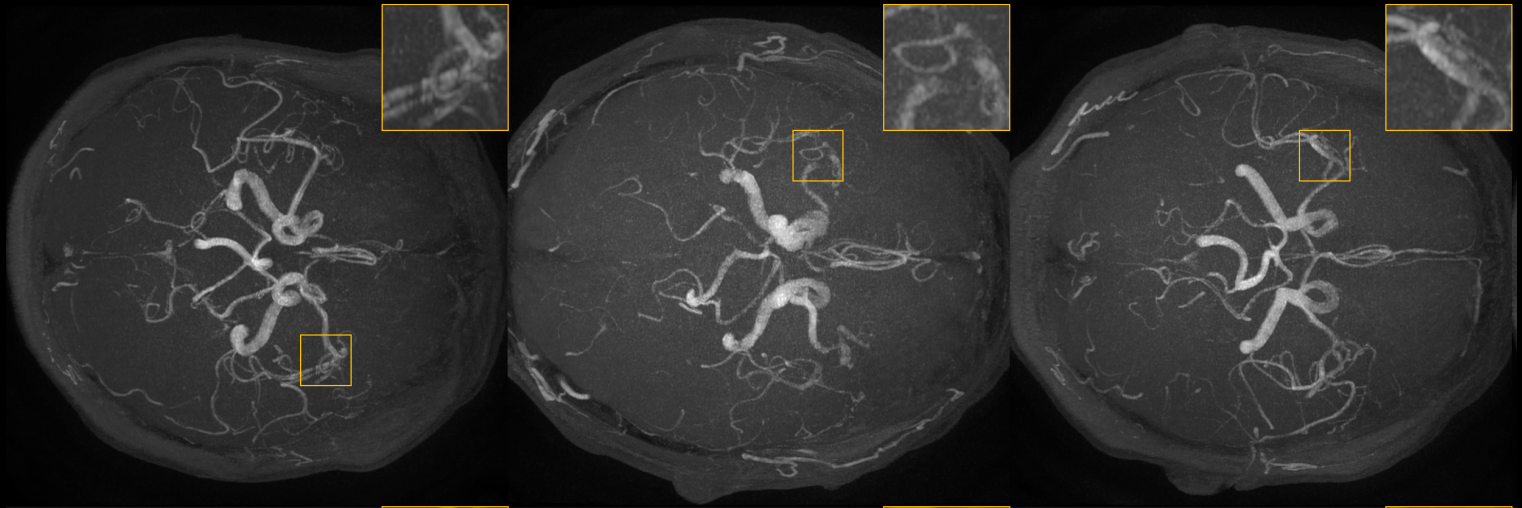
Chung et al, arXiv:2008.01362 , 2020

Coronal reconstruction

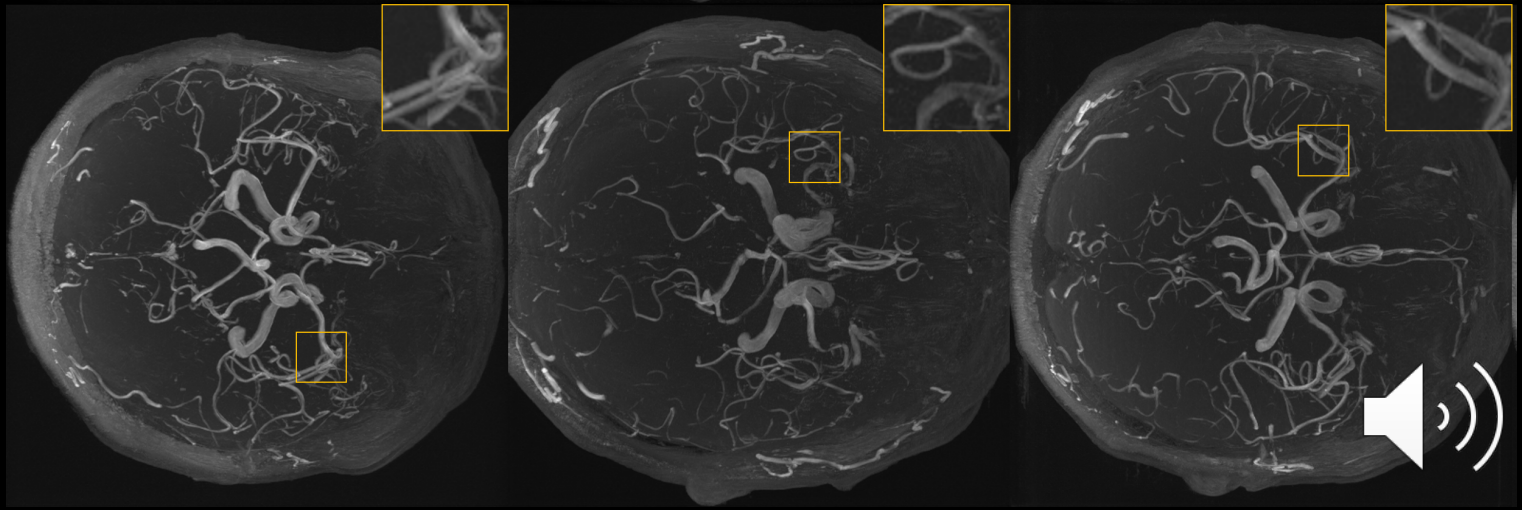
Axial reconstruction

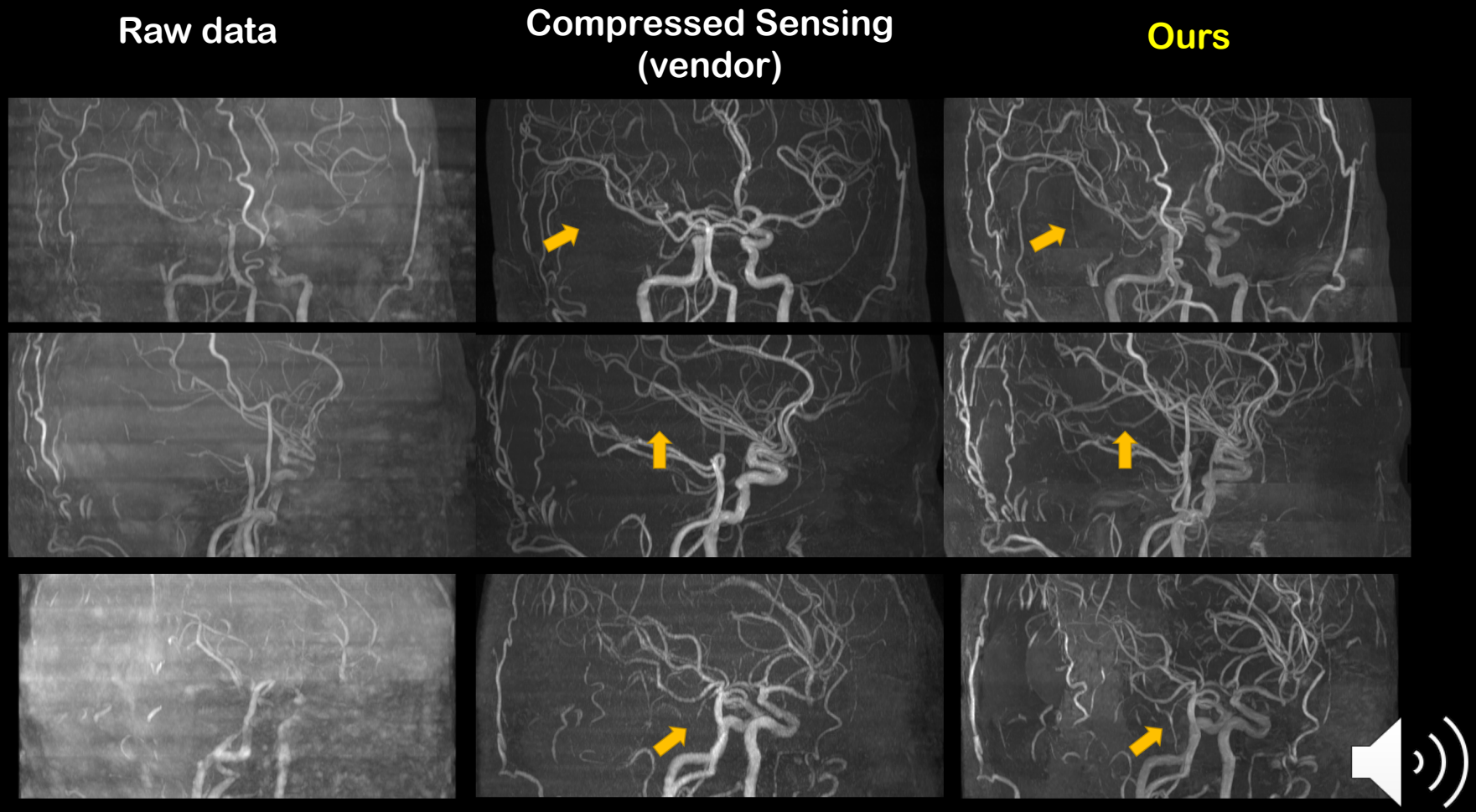


Compressed Sensing (vendor)



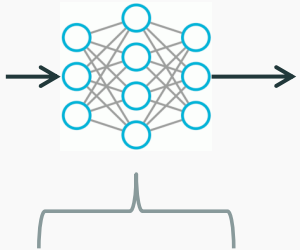
Ours



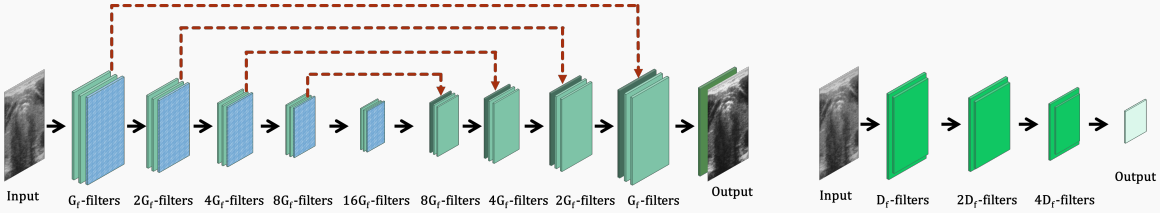

Raw data
Compressed Sensing
(vendor)
Ours

Learning from Low Quality to High Quality US

NPUS050 low-cost portable US system



Alpinion ECUBE 12R high-quality US system



(a) Generator network

(b) Discriminator network

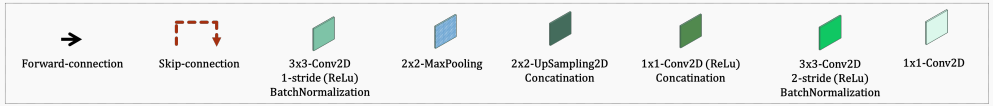
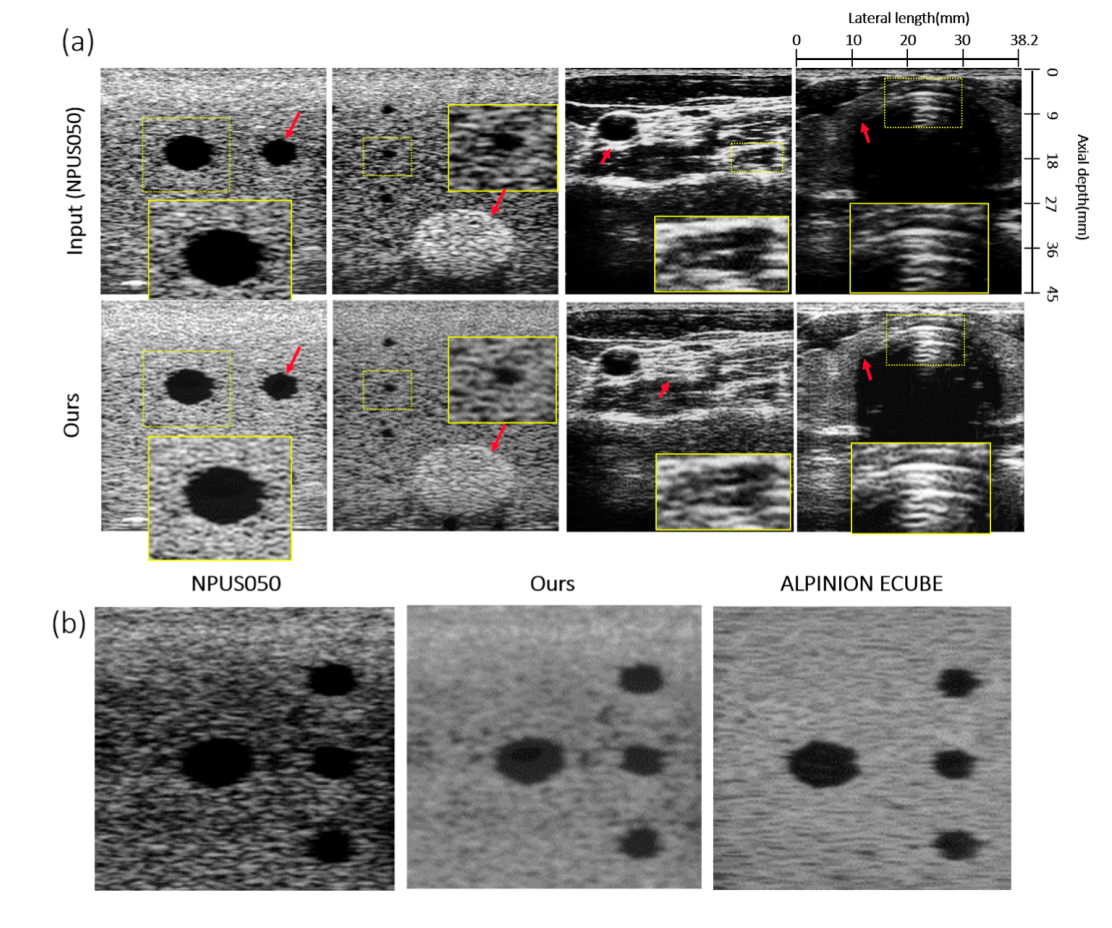
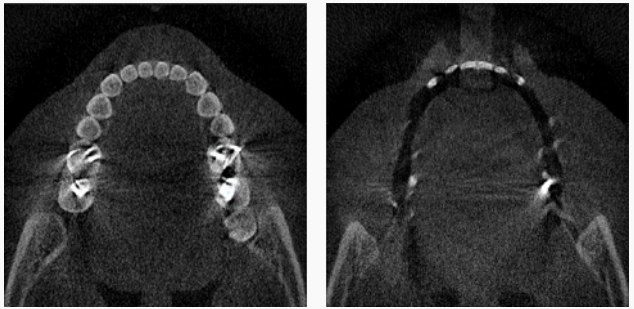


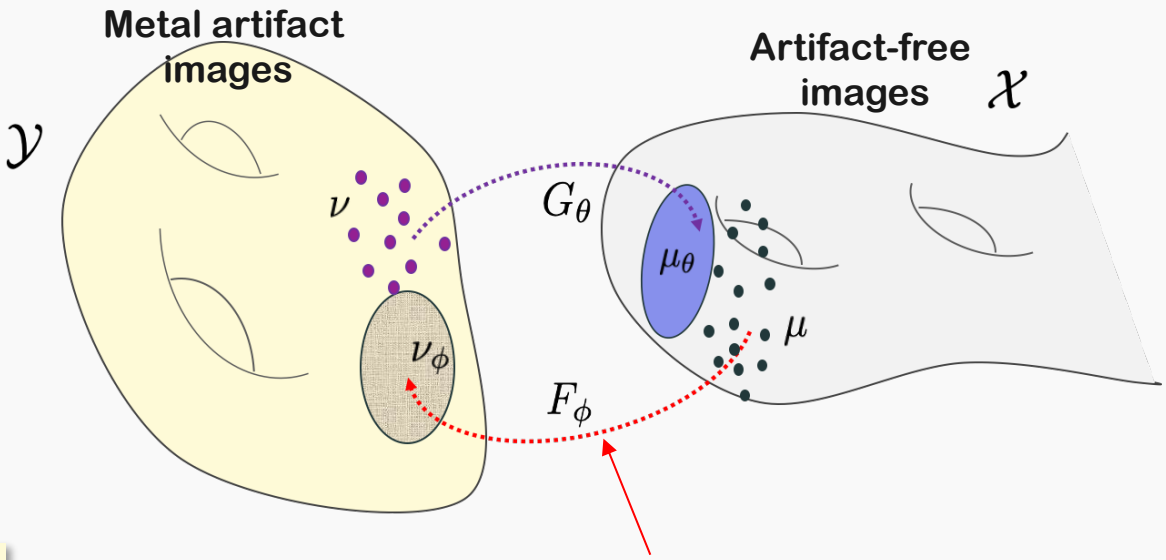
Image translation from low quality to the high-quality system



β-CycleGAN for Unsupervised Metal Artifact Reduction

Lee et al, arXiv:2007.03480, 2020



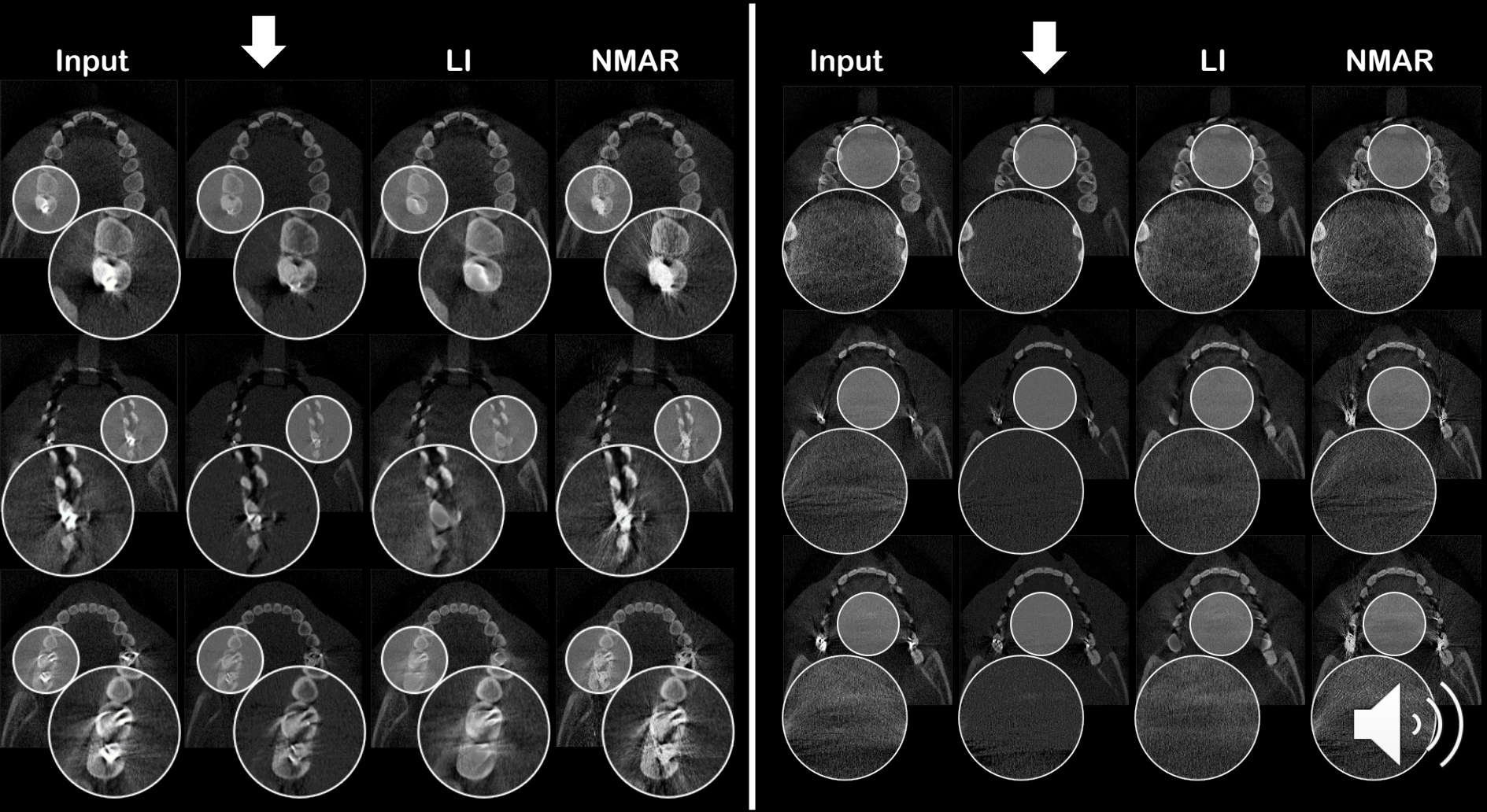


Motivation

- Less focus on the artifact generation
- More emphasis on MAR

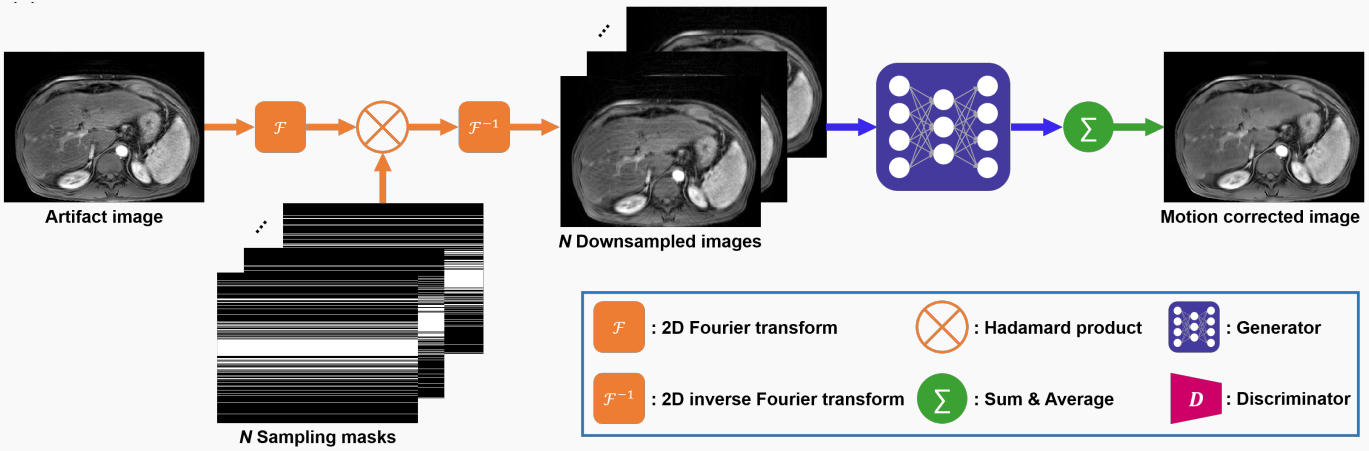
Metal artifact generation physics (beam-hardening, photon starvation, etc.)

→ Highly complicated to lea


Input
LI
NMAR
Input
LI
NMAR

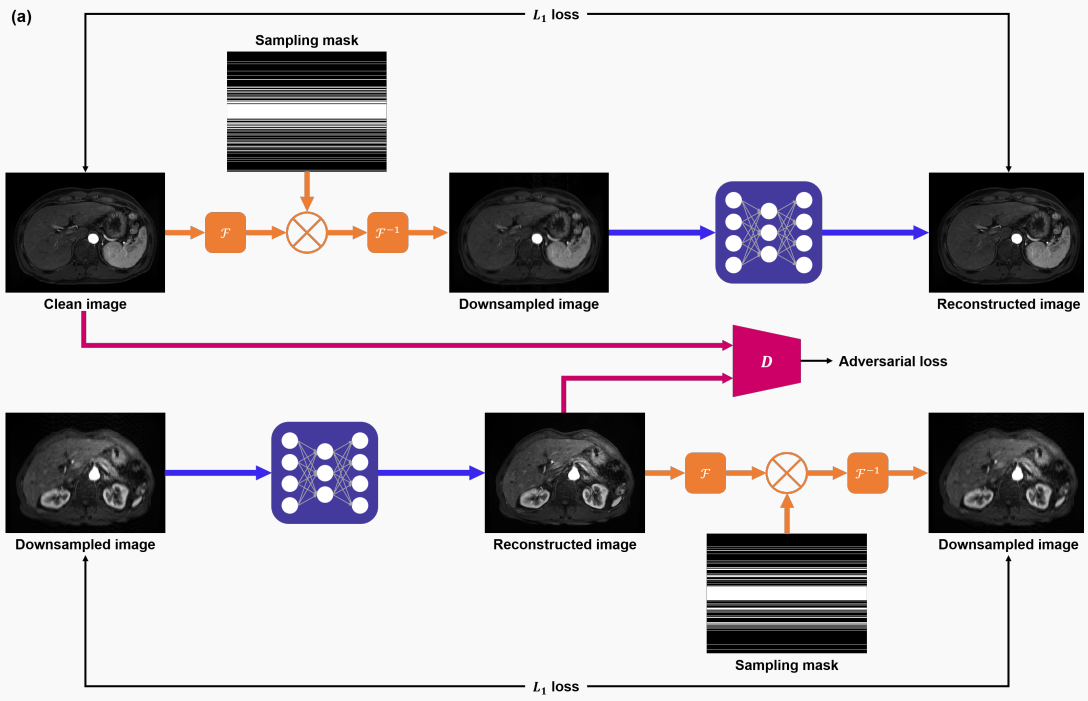
Unsupervised MR Motion Artifact Removal

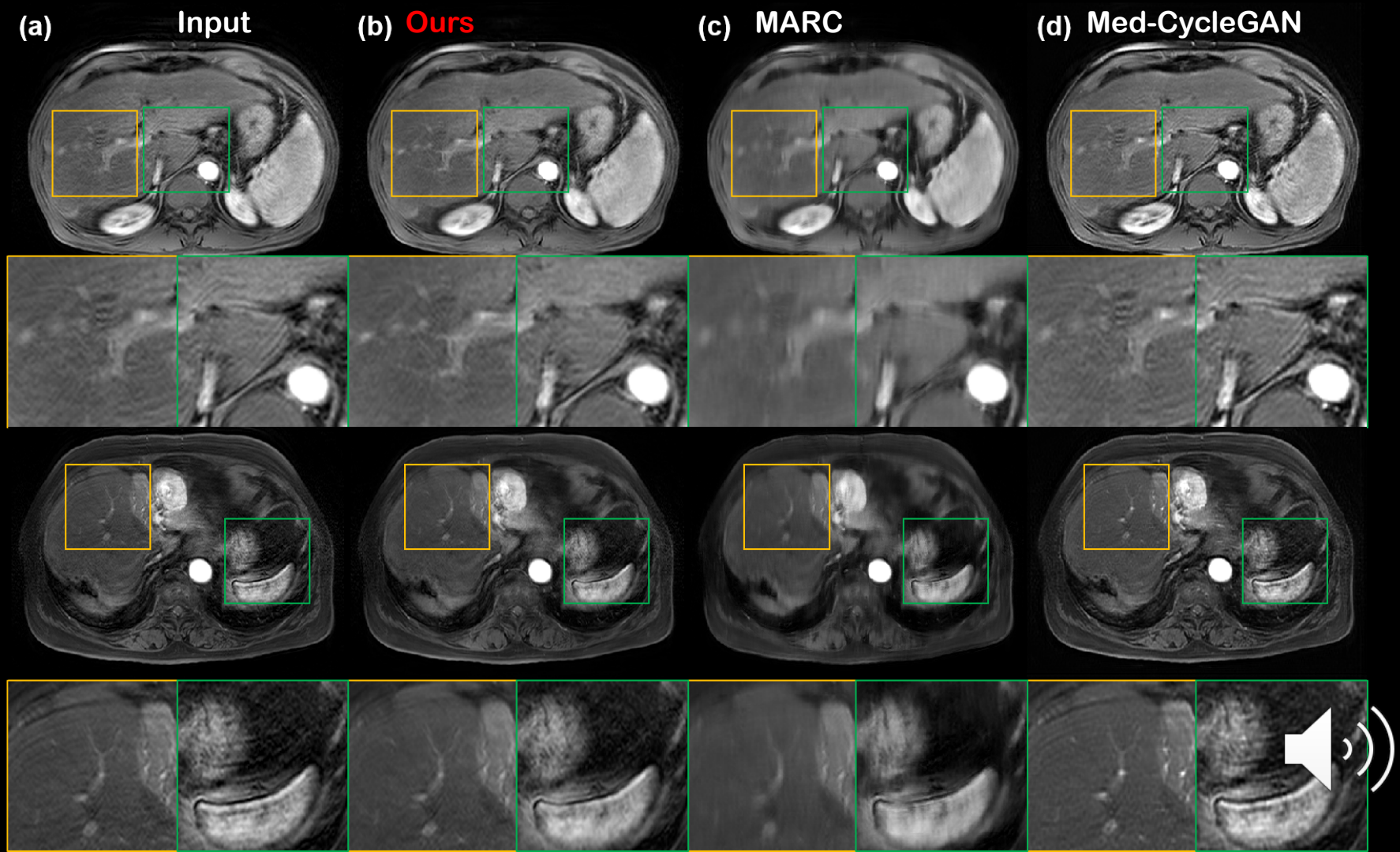
Oh et al, arXiv, 2011.06337.pdf



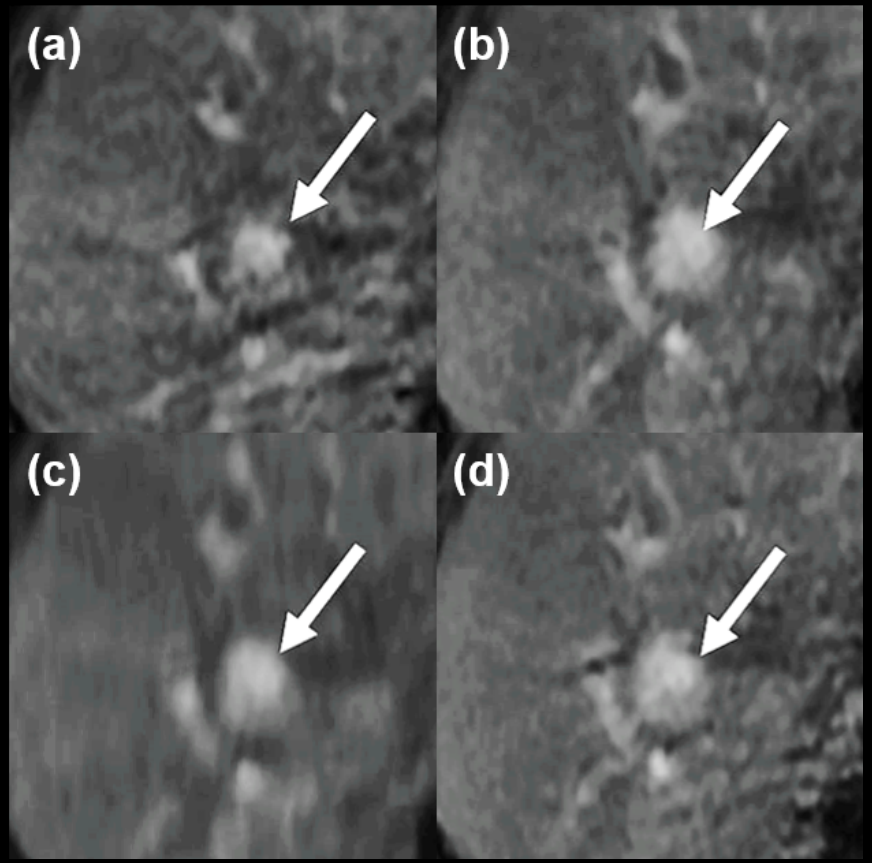
Unsupervised MR Motion Artifact Removal

Oh et al, arXiv, 2011.06337.pdf



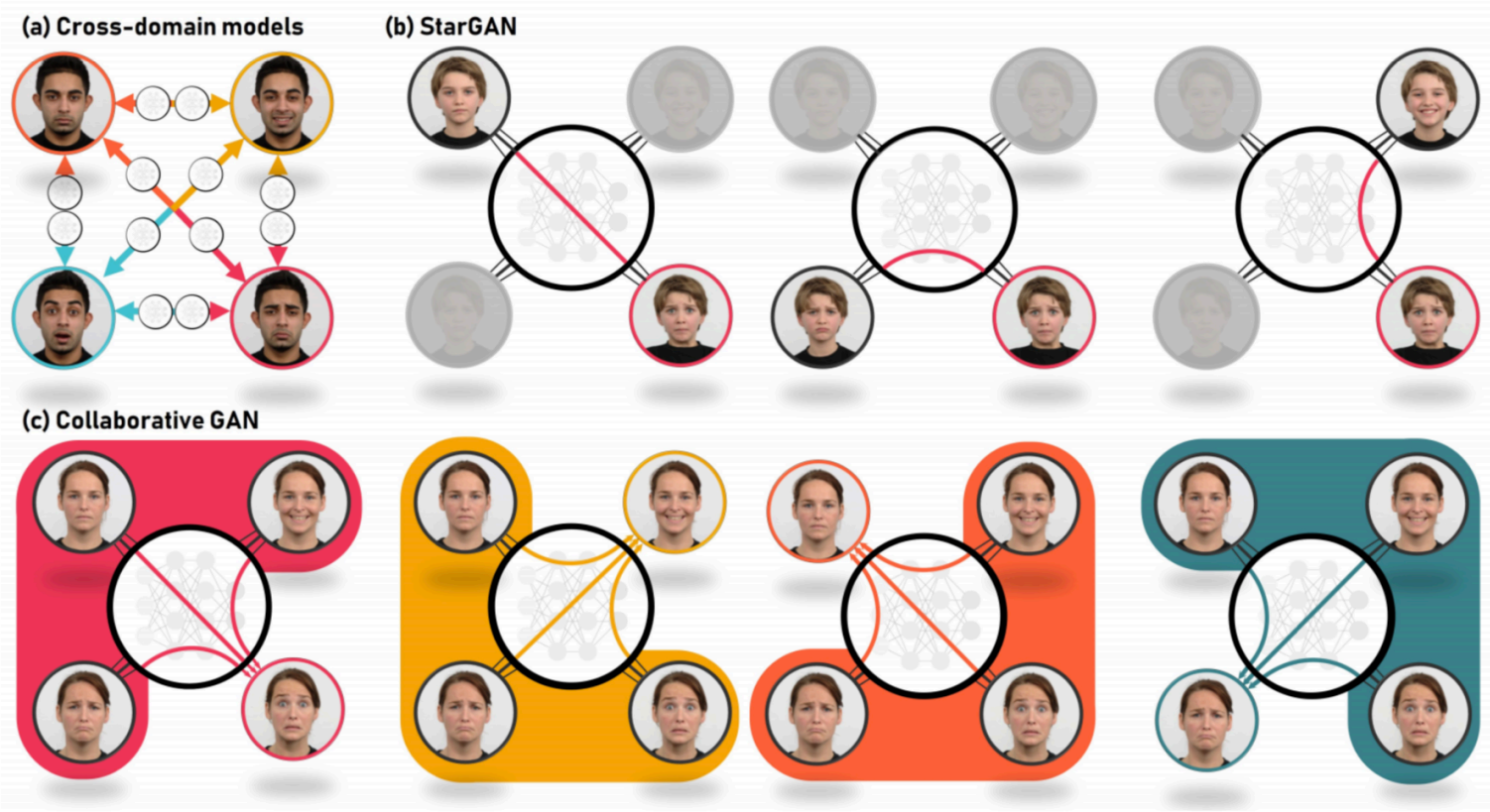

(a) Input
(b) Ours
(c) MARC
(d) Med-CycleGAN

(a) Input (b) Ours (c) MARC (d) Med-CycleGAN



Collaborative GAN (CollaGAN)

Lee et al, *CVPR, 2019*



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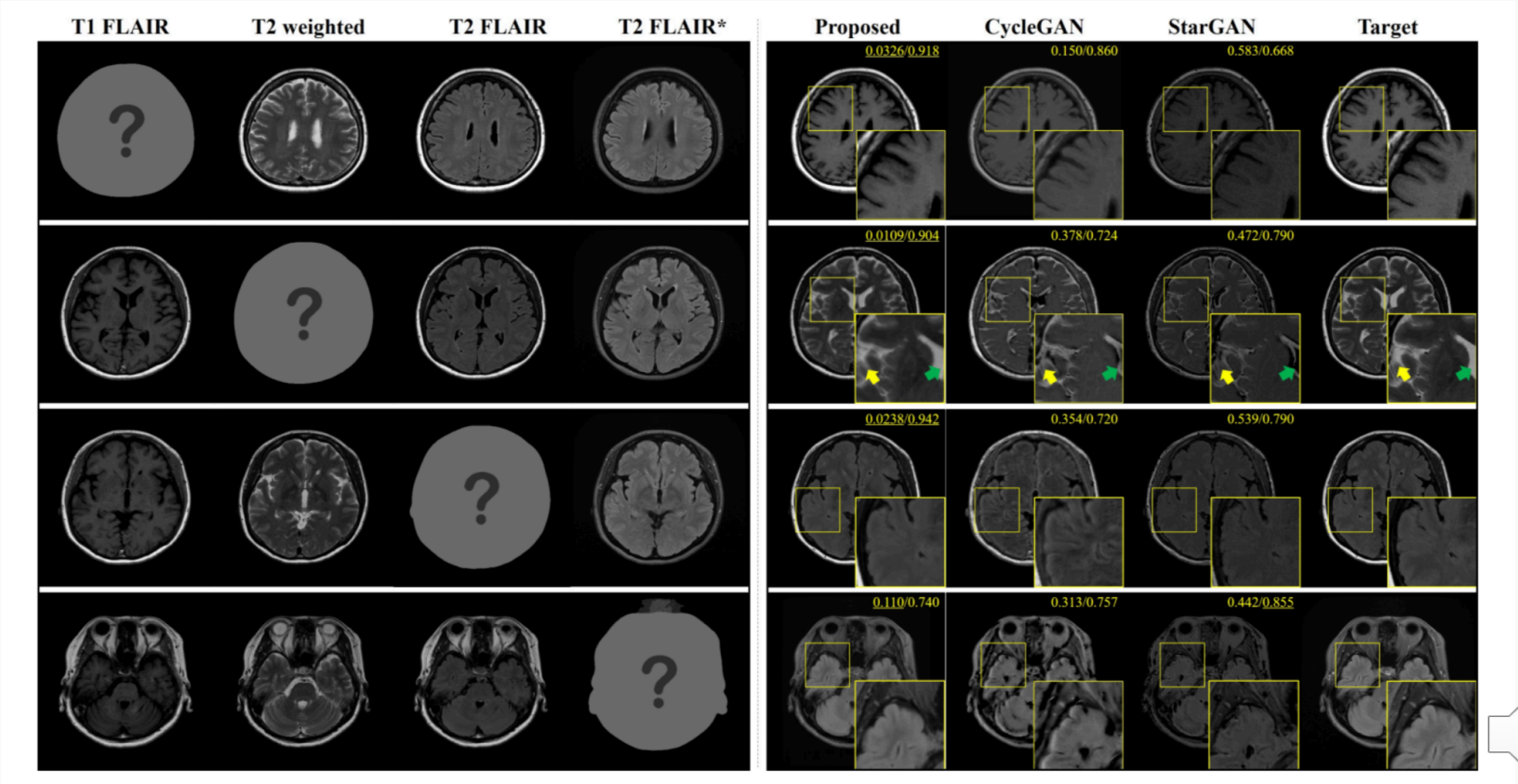
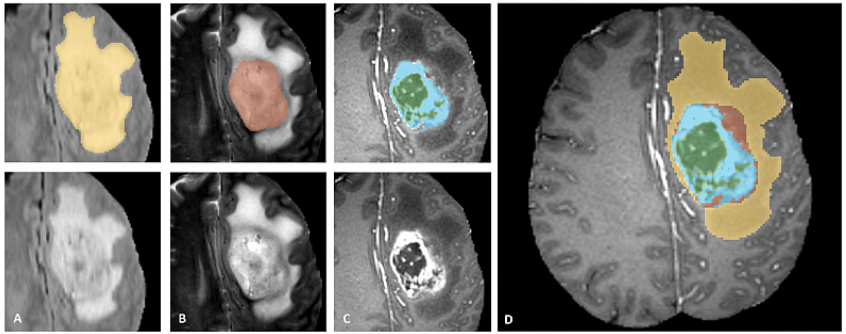


Which Contrast Does Matter ?

Lee et al, *Nature Mach. Intell,* 2020

Quantitative evaluation

- **Segmentation performance on BRATS**[1-2]
  - **BRATS** : Multi modal Brain Tumor image segmentation benchmark[1-2]

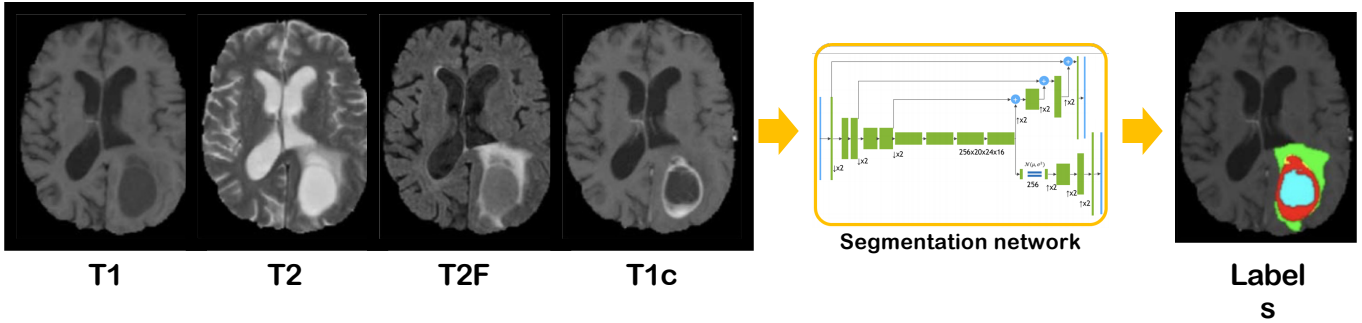


- If the segmentation network works well on the reconstructed image,

  ➔ the reconstruction performance is good.
- **Segmentation** performance = **Quantitative measure** for **CollaGAN**

Quantitative evaluation

- **Five different databases**
  - **Original BraTS**
  - **Substitution by the reconstructed images**



[1] A. Myronenko et al. arXiv:1810.11654, 2018

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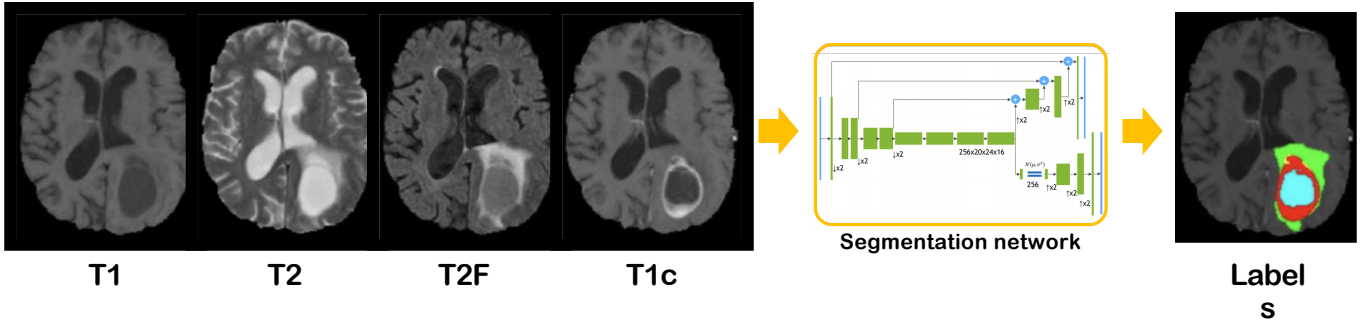

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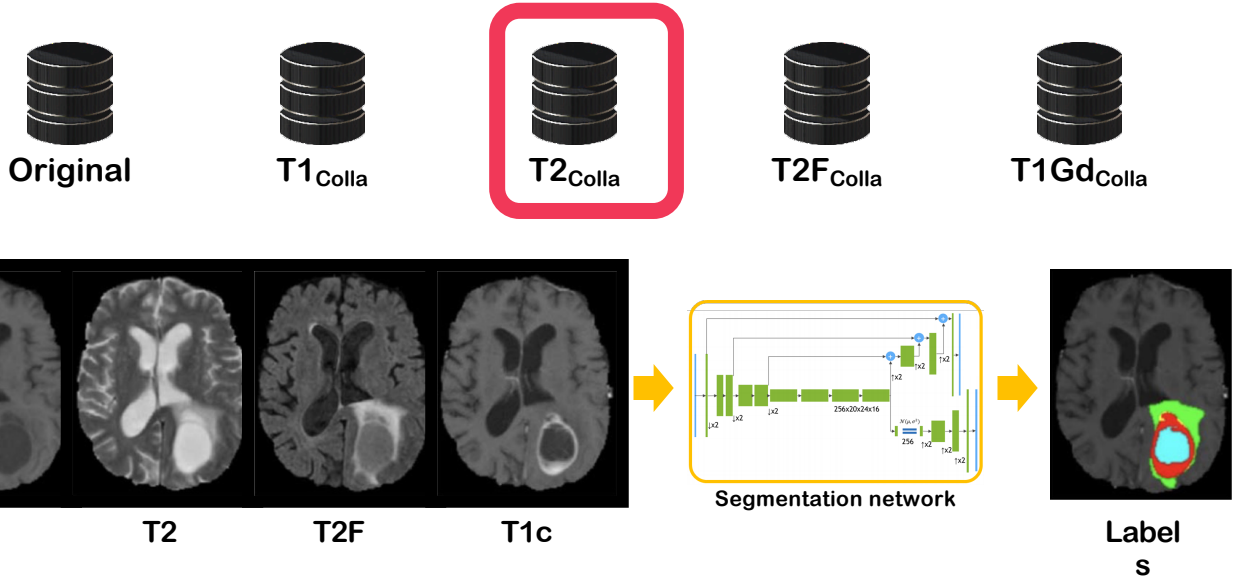

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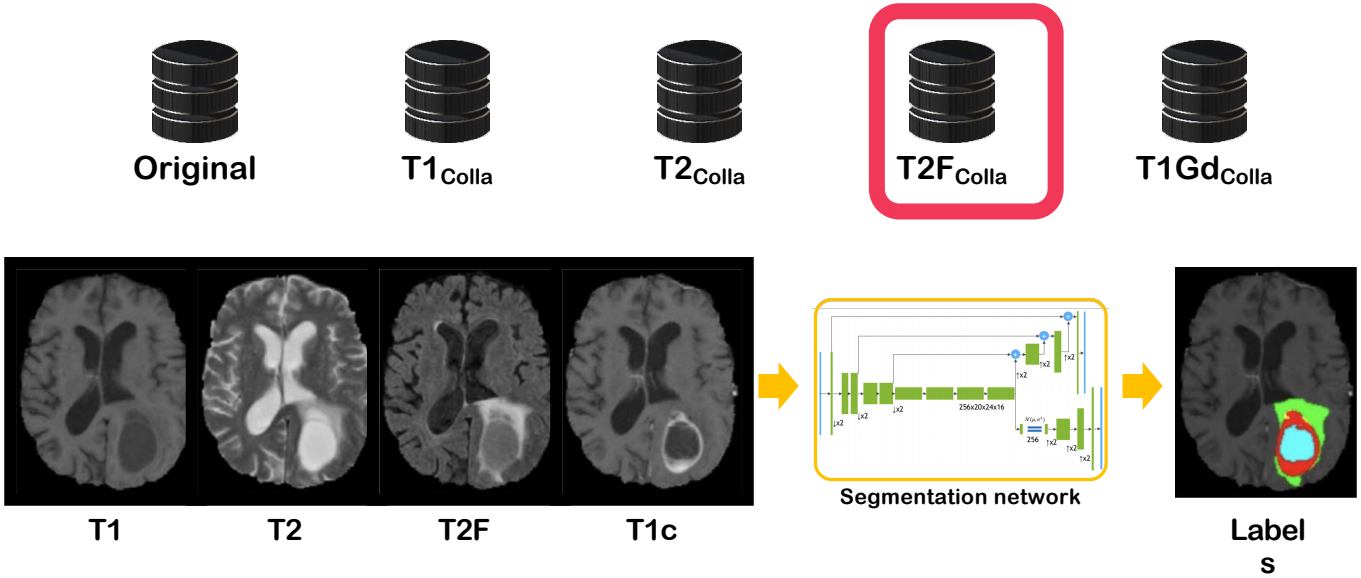

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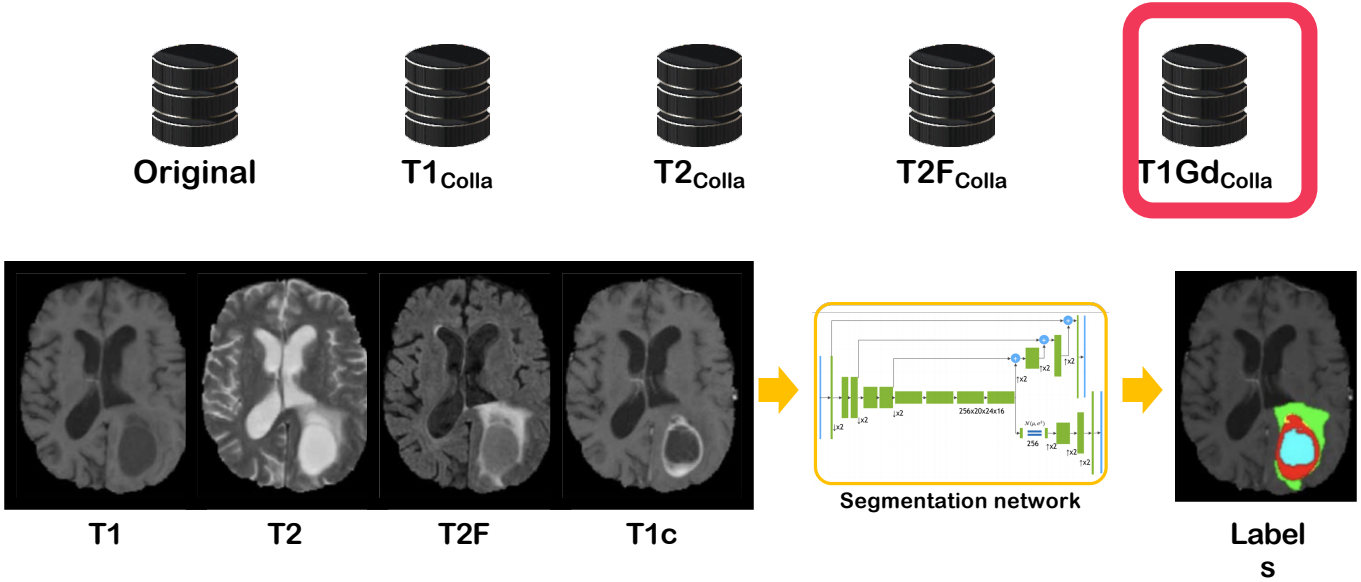

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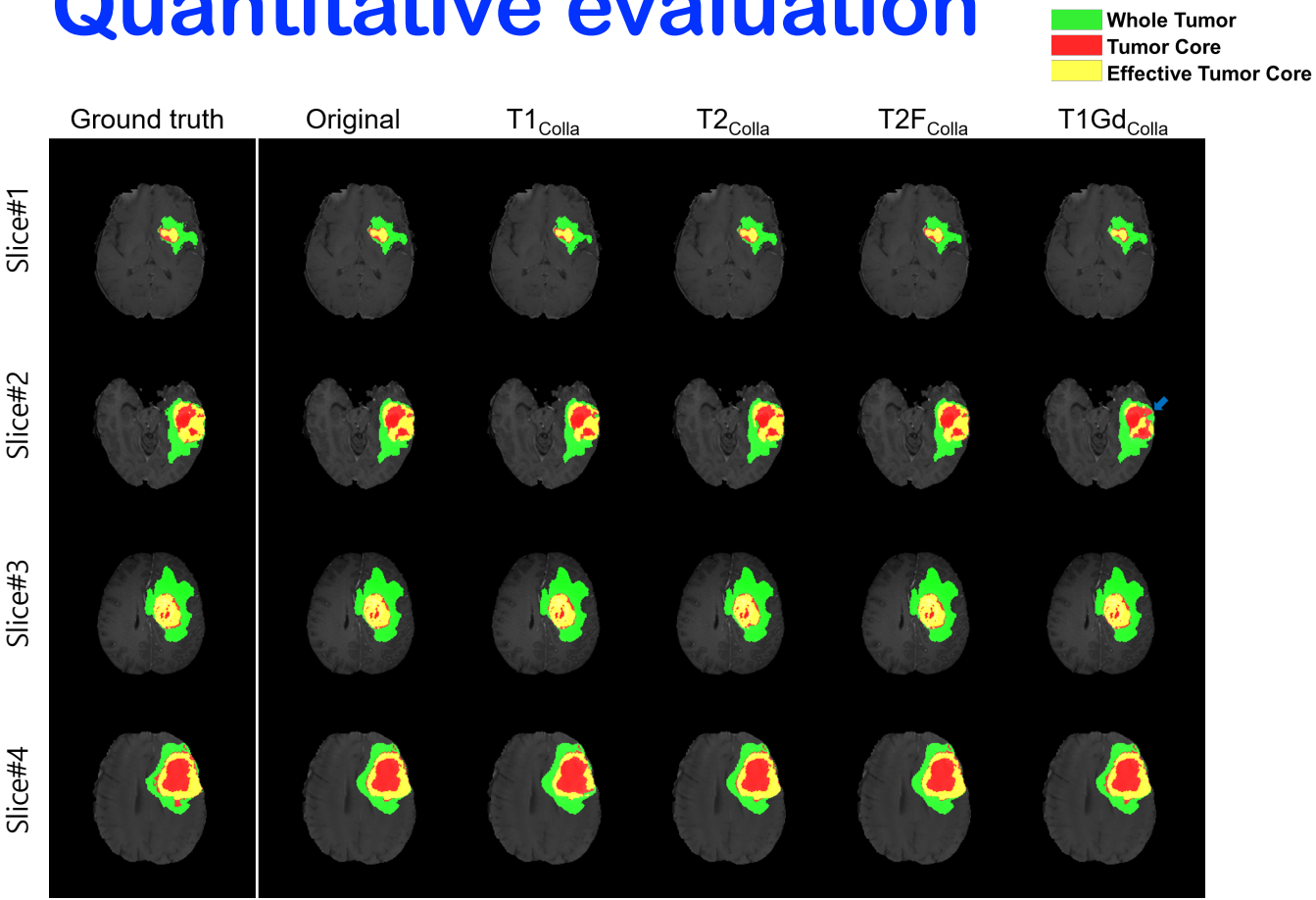
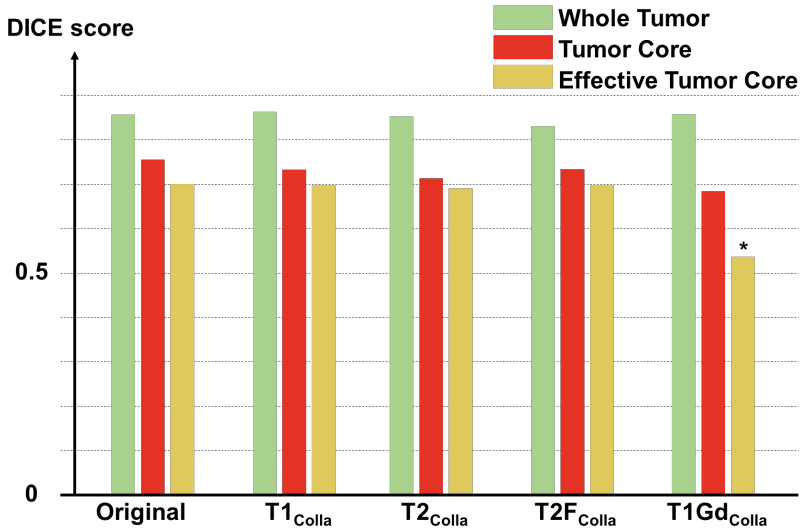
Quantitative evaluation



Quantitative evaluation



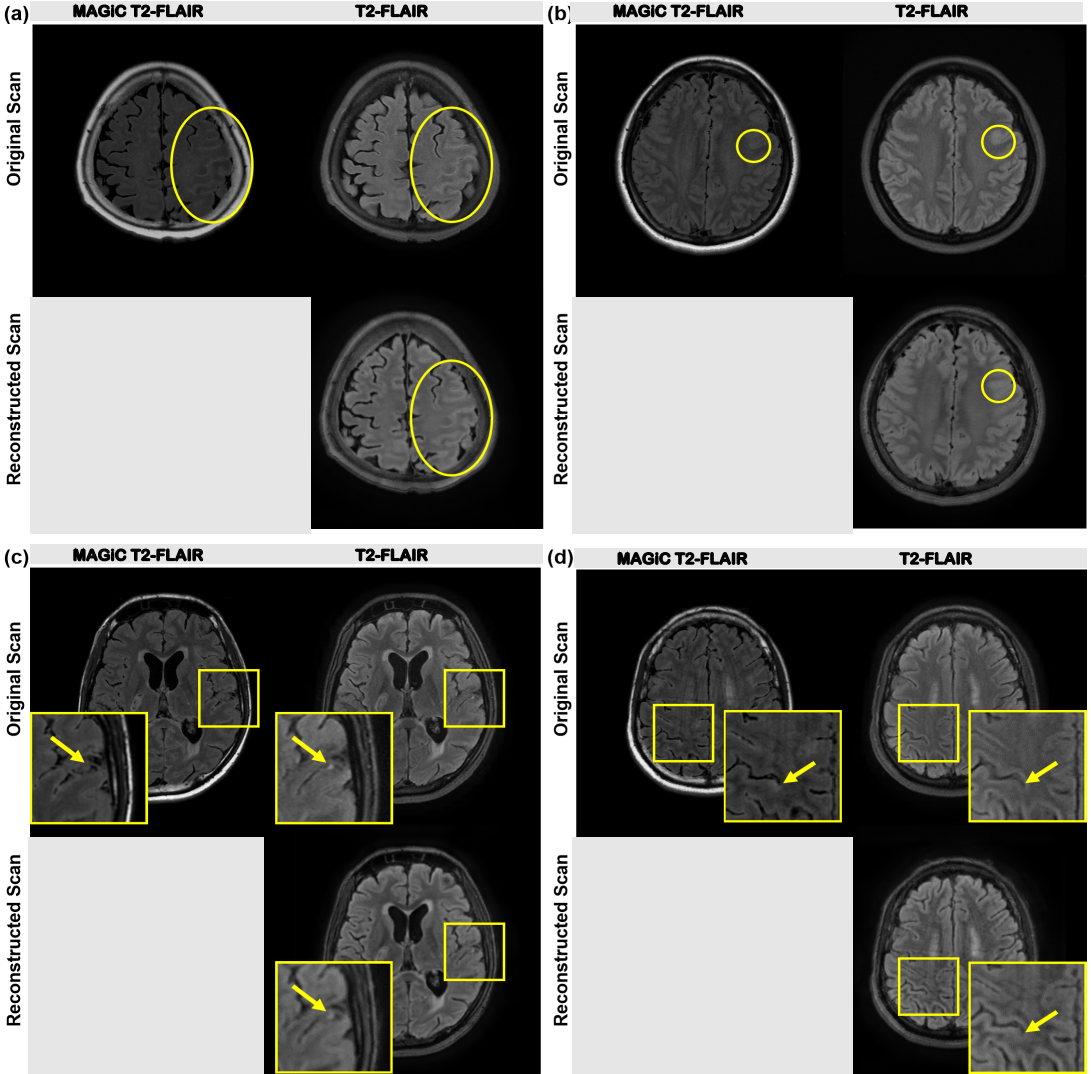
$$Dice(Y_{gt}, Y_{pred}) = \frac{2|Y_{gt} \cap Y_{pred}|}{|Y_{gt}| + |Y_{pred}|}$$

* Inferior performance on Effective Tumor Core from $T1Gd_{Colla}$
- due to the lack of information from the contrast agent

- **CollaGAN reconstructs the missing contrast images very well, quantitatively.**

MAGiC Artifact Corrections

Lee et al, *Nature Mach. Intell,* 2020


(a)
MAGIC T2-FLAIR
T2-FLAIR
Original Scan
Reconstructed Scan
(b)
MAGIC T2-FLAIR
T2-FLAIR
Original Scan
Reconstructed Scan
(c)
MAGIC T2-FLAIR
T2-FLAIR
Original Scan
Reconstructed Scan
(d)
MAGIC T2-FLAIR
T2-FLAIR
Original Scan
Reconstructed Scan

Summary

- GAN is an important topic in AI
- GAN becomes very important topics in medical image reconstruction
- Our theoretical findings
    - CycleGAN is important for unsupervised learning
    - CollaGAN can be used for multi-contrast MR studies
- Geometric view can be generalized for other problems

Questions?