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Image quality enhancement of medical images by use of deep learning with a small amount of training data

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Interdisciplinary Science Conference in Okinawa (ISCO 2023) - Physics and Mathematics meet Medical Science -

My career trajectory

Nuclear & Hadron physics

2011. PhD (Physics) in Osaka Univ.

2011-2012. Univ. of Tokyo & Riken

2012-2013. Yonsei Univ. (South Korea)

2013-2015. KEK

2015-2017. Keio Univ.

Postdoc

Medical Physics (Deep learning in medical imagings)

2017-2021. Univ. of Tokyo Hospital

Medical physicist

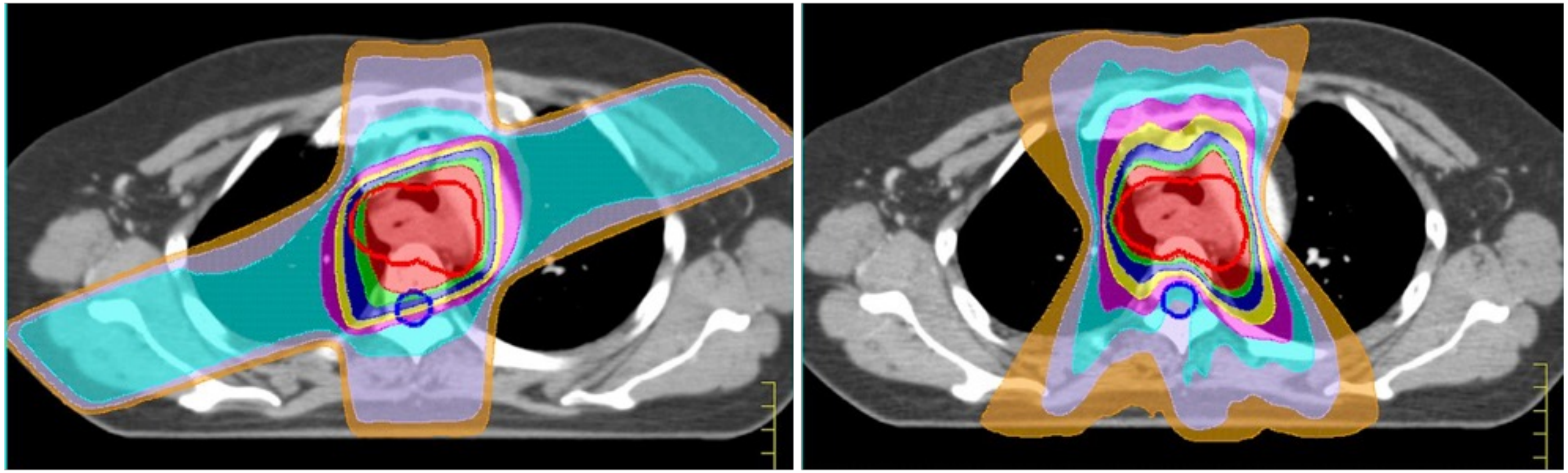
2022-. Hirosaki University

Assistant Prof.

Medical physicist

Conventional 3D-CRT

IMRT
(Optimization calculation)



By using the optimization calculation, the intensity modulated radiation therapy (IMRT) results in a highly conformal dose distribution which covers the target volume with avoiding normal tissue exposure.

Radiotherapy equipment in Univ. of Tokyo Hospital

Radiotherapy units:

Elekta Synergy

Accuray Tomotherapy

CT for registration:

Cone-beam CT (CBCT)

Mega-voltage CT (MVCT)

For precise registration based on image guidance, the image quality of CTs for registration must be ensured. However, the image qualities of these CTs are considerably lower than a normal CT for diagnosis and a planning CT for radiotherapy.

→ We have studied image quality enhancement MVCT by using deep learning.

Cautions

Difficulties in medical fields

- ✓ **Large amount of data for training**

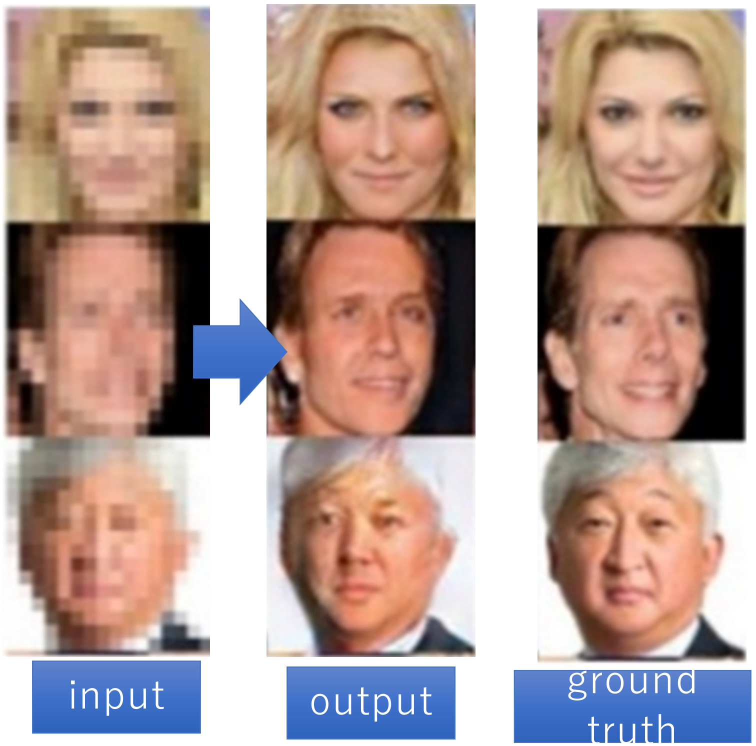
  → **The high cost of acquiring a large data set is limitation to their utilization in medical fields.**

- ✓ **Particularity of medical images**

  - **Safety**
  - **Stability**
  - **Structure preservation in images**

Of the 2,212 AI-based COVID-19 image diagnostic studies that were published in 2020, none of them are suitable for clinical use.

(Roberts et al. Nature Machine Intelligence 2021)



Problems in previous studies

- **Deep learning models such as GAN is developed for natural image processing.**

  → create variety of images

  → change original structure and shape

  → This is undesirable in medical imaging

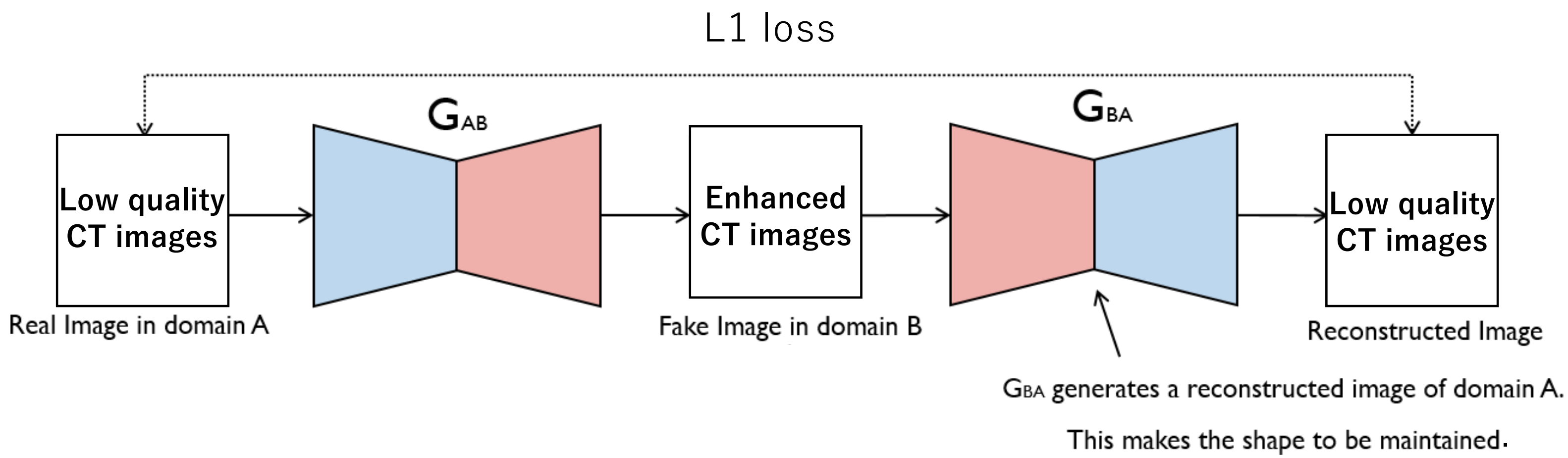
- **Assessment in the absence of the ground truth.**

Solutions

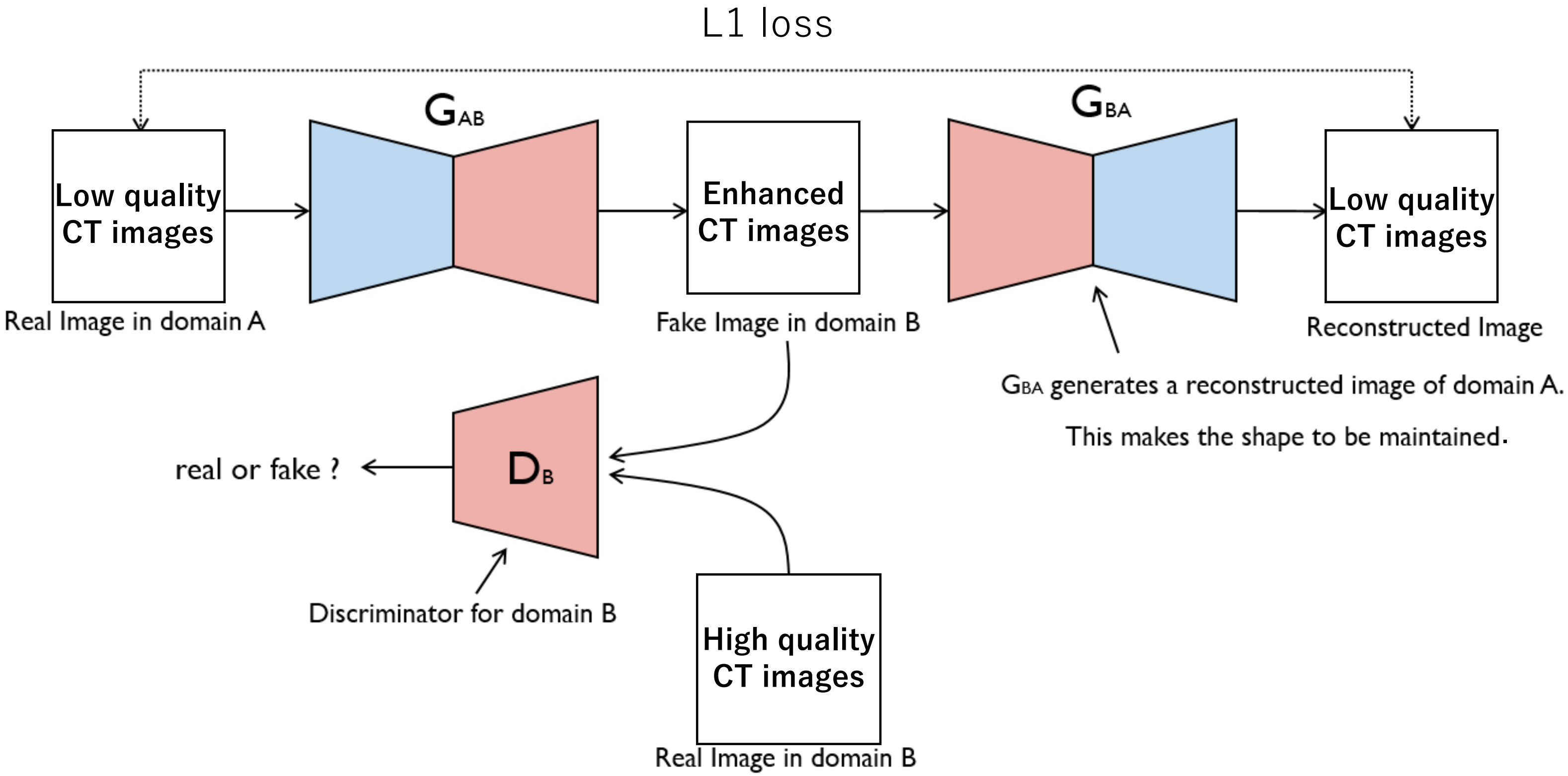
✓ **We extend and improve CycleGAN with several losses for structure preservation.**

✓ **We propose several metrics for evaluating image quality without the ground truth.**

CycleGAN


L1 loss
G_{AB}
G_{BA}
Low quality CT images
Enhanced CT images
Low quality CT images
Real Image in domain A
Fake Image in domain B
Reconstructed Image
G_{BA} generates a reconstructed image of domain A.
This makes the shape to be maintained.

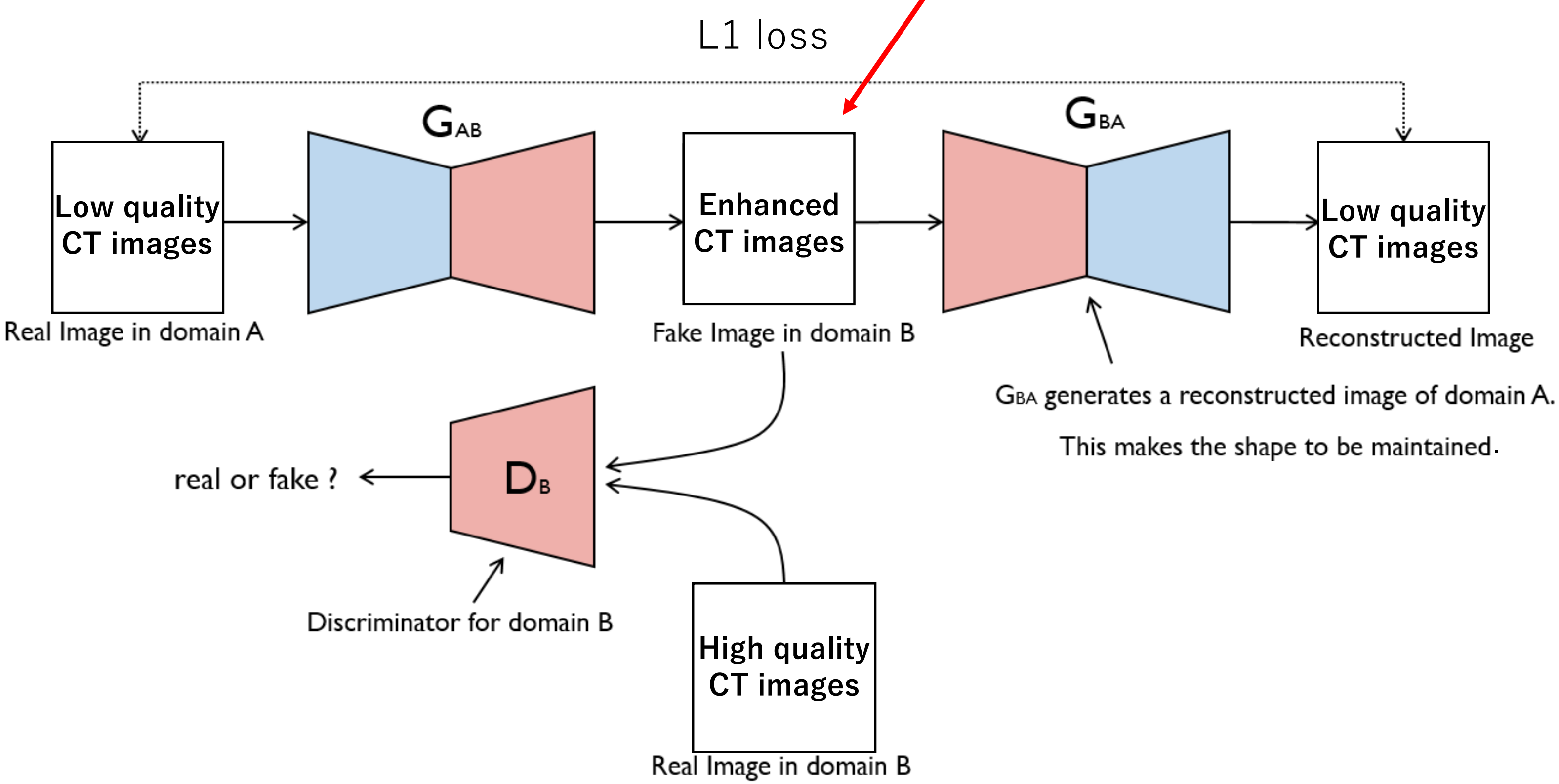
CycleGAN



L1 loss
GAB
GBA
Low quality CT images
Real Image in domain A
Enhanced CT images
Fake Image in domain B
Low quality CT images
Reconstructed Image
GBA generates a reconstructed image of domain A.
This makes the shape to be maintained.
real or fake ?
DB
Discriminator for domain B
High quality CT images
Real Image in domain B

CycleGAN

Structure preservation and stability conditions, such as Perceptual loss and Autoencoder loss, which are need for medical images.

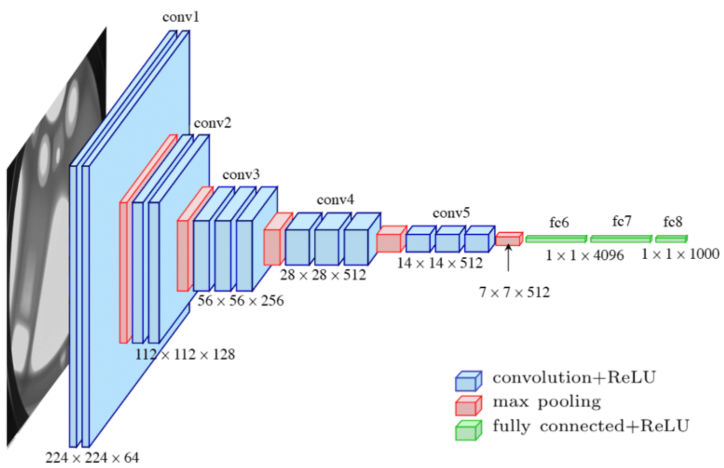


Perceptual loss

$$\mathcal{L}_{\text{percep}} = \frac{1}{whn_{\text{cl}}}\left(\sum_{x\in\mathbf{MV}}||\phi(G_{\text{MV}\rightarrow\text{kV}}(x)) - \phi(x)||^2 + \sum_{y\in\mathbf{kV}}||\phi(G_{\text{kV}\rightarrow\text{MV}}(y)) - \phi(y)||^2\right)$$

ϕ : Output of the second layer of pretrained VGG with ImageNet database

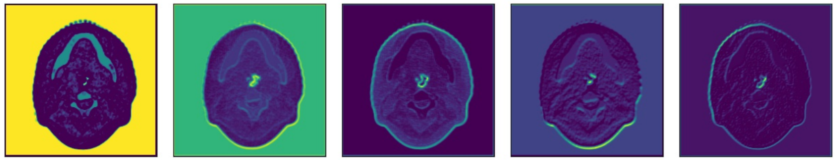
VGG



MV : MVCT images

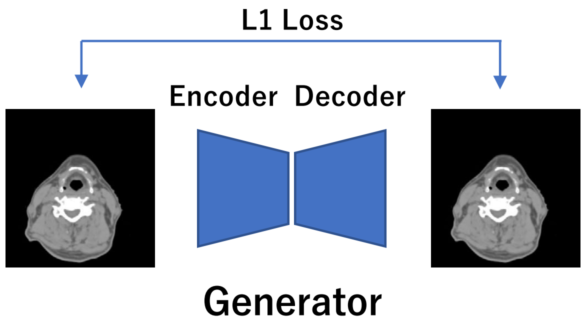
kV : kVCT (PlanCT) images

Examples of ϕ outputs



Auto-encoder loss

$$\mathcal{L}_{\mathrm{autoenc}} = \sum_{x \in \mathbf{MV}} ||x - \mathrm{Dec}_{\mathrm{latent}\to\mathrm{MV}}(\mathrm{Enc}_{\mathrm{MV}\to\mathrm{latent}}(x))||_1 + \sum_{y \in \mathbf{kV}} ||y - \mathrm{Dec}_{\mathrm{latent}\to\mathrm{kV}}(\mathrm{Enc}_{\mathrm{kV}\to\mathrm{latent}}(y))||_1$$



Air region loss

$$\mathcal{L}_{\mathrm{air}} = \sum_{x \in \mathbf{MV}} ||\psi(G_{\mathrm{MV}\to\mathrm{kV}}(x)) - \psi(x)||_1 + \sum_{y \in \mathbf{kV}} ||\psi(G_{\mathrm{kV}\to\mathrm{MV}}(y)) - \psi(y)||_1$$

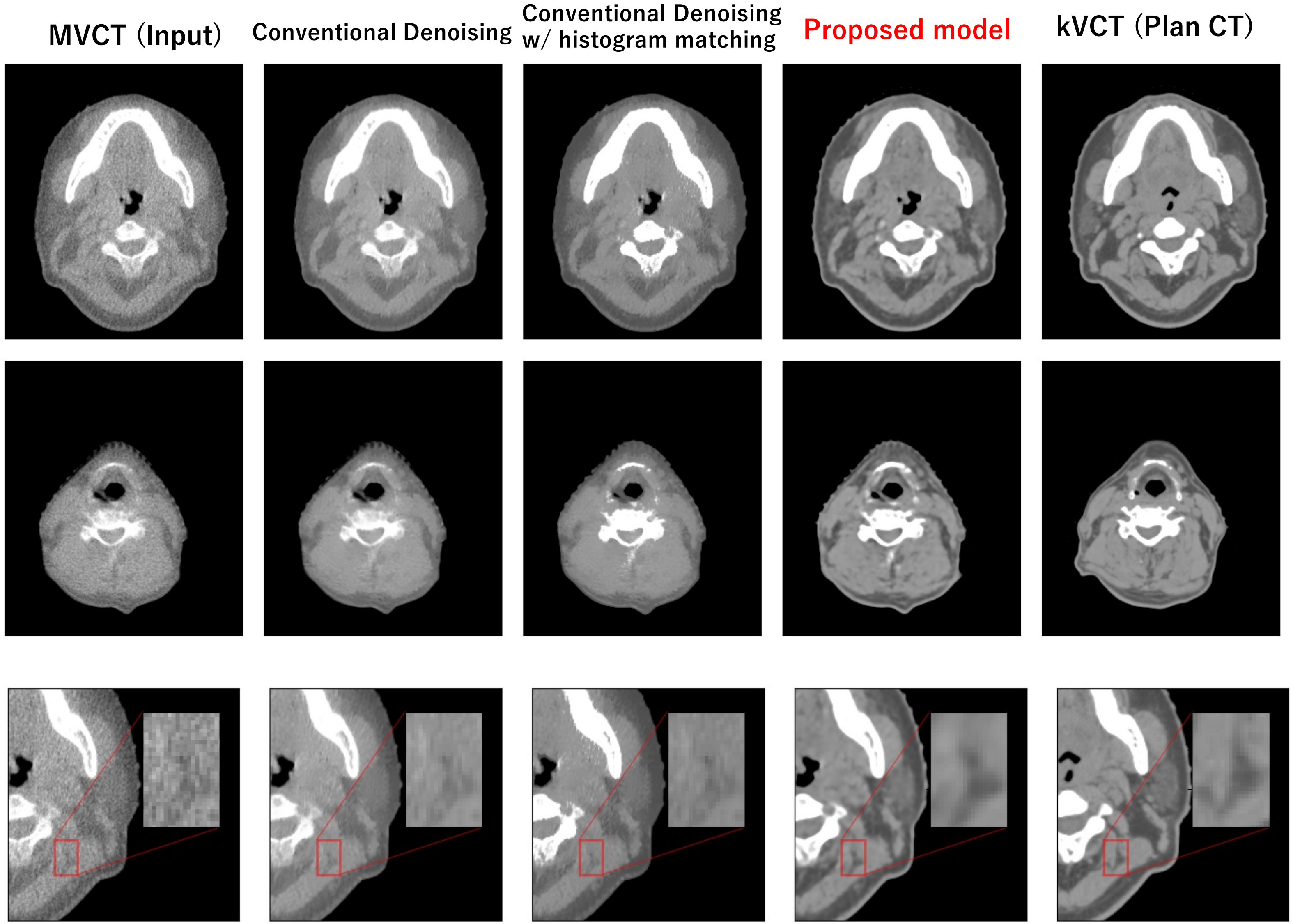
$$\psi(x) = \begin{cases} x & (\text{if } x < C) \\ 0 & (\text{if } x \geq C) \end{cases},$$

$$C = -600 \text{ HU}$$

These loss functions properly regularize model parameters, which leads to structure preservation and stability with small amount of training data.

Visual comparison with conventional denoising methods

S. O., et al., Med. Phys. 49 (6) (2022)



S. O., et al., Med. Phys. 49 (6) (2022)

Proposed evaluation metrics

Metric measuring noise reduction

$$\mathrm{NSelfSSIM}(img) = \mathrm{SSIM}(img, img + \mathrm{Gaussian\ noise})$$

NSelfSSIM

	MVCT	Proposed	PlanCT
Mean	0.9024	0.7079	0.7263
SD	0.0106	0.0794	0.0825

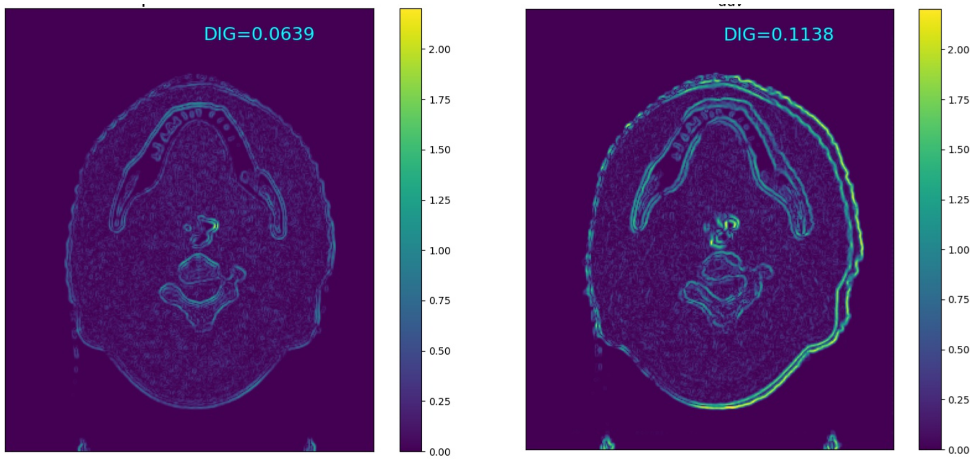
Noise reduction

Metric measuring structure preservation

$$\mathrm{DIG}(x) \quad = \quad ||\mathrm{grad}(x - G_{\mathrm{MV}\to\mathrm{kV}}(x))||^2$$

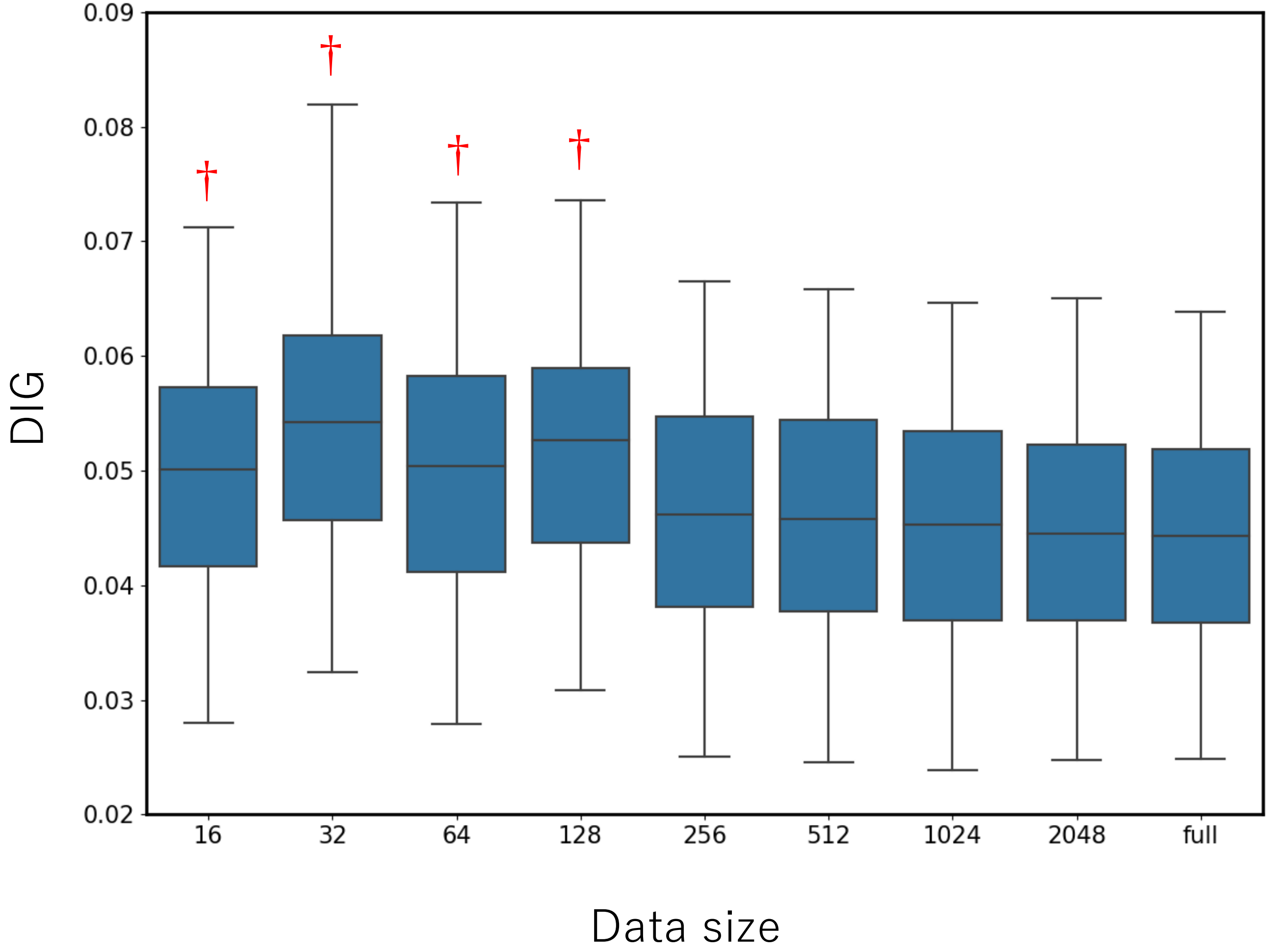
Proposed model

Original CycleGAN



S. O., et al., Med. Phys. 49 (6) (2022)

Data size dependence of DIG



Statistical analysis

Statistical analysis is performed by Fridman’s test ($p < 0.05$) with a post hoc Shirley’s test.

The dagger † indicates $p < 0.05$ in Shirley’s test.

Summary

- We develop a novel low-quality to high quality image translation model based on deep learning, which can be trained using only a few hundred unsupervised images.

- We evaluate the performance of our model with proposed metrics, and show that our model outperforms CycleGAN in terms of structure preservation.