Paper Presentation

Group 10: Cross Modality Medical Image Synthesis and Registration through Machine Learning

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LABORATORY FOR Computational Sensing + Robotics

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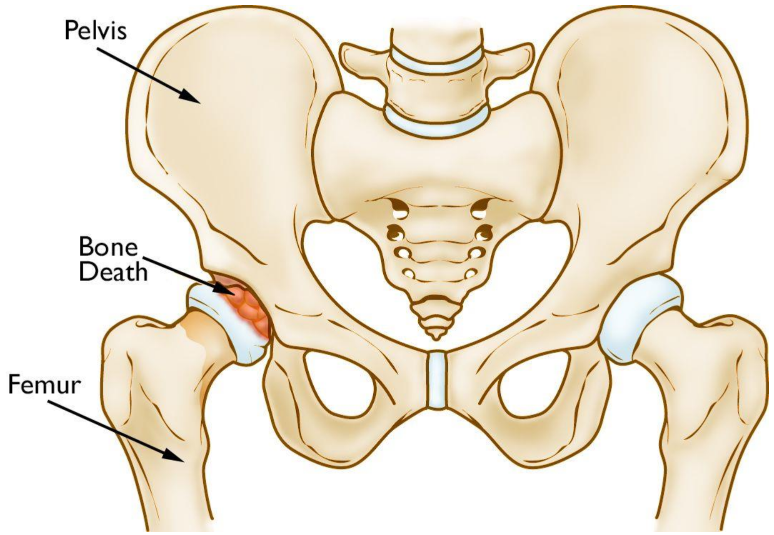
Project recap - Background

- Core Decompression for Osteonecrosis
  - Drilling several holes into the femoral head to relieve pressure in the bone and create channels for new blood vessels to nourish the affected areas of the hip
  - X-rays provides images of dense structures (like bones) and intraoperative x-ray shots are taken to monitor the surgical procedure.



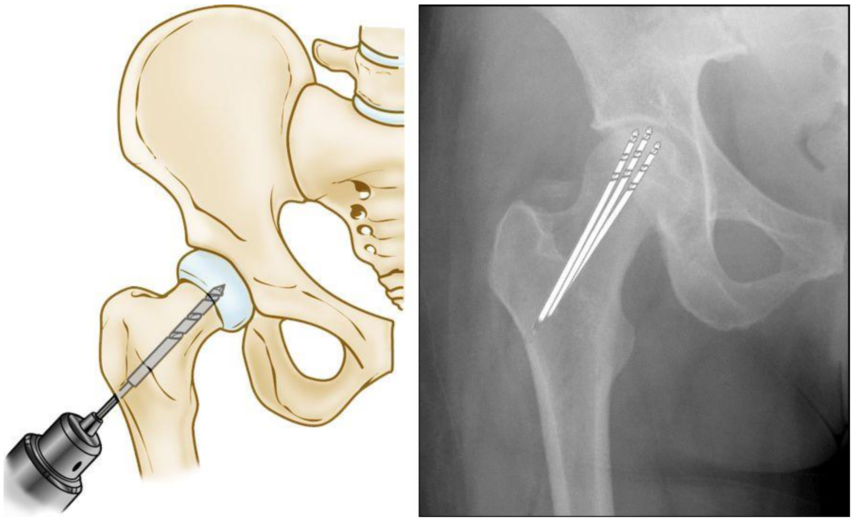
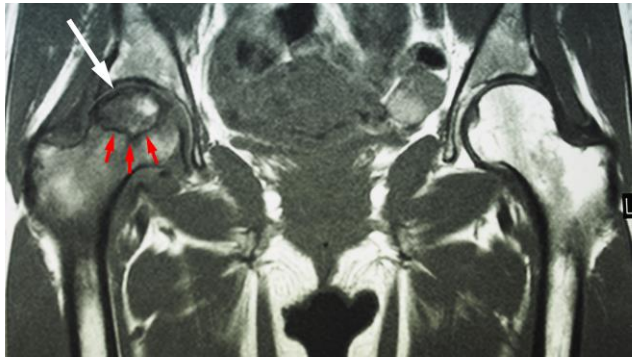


Image source (Left and right image): [1] orthoinfo - aaos. Retrieved February 16, 2021

Project recap - Project Goal

- Motivation
  - Surgeons also rely on preoperative MR scans for tool trajectory planning for core decompression surgery, but there is no easy way for them to visualize the planned paths in the intra-operative X-ray shots
- Project Goal
  - We would like to convert the annotations of segmentation of the necrotic tissues and the drill insertion paths from preoperative MR images to intraoperative x-rays would be helpful for surgeons.



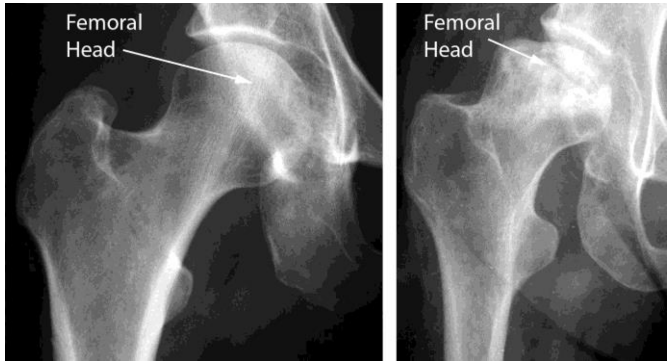


Image source (Left and right image): [1] orthoinfo - aaos. (n.d.). Retrieved February 16, 2021

Paper Overview

Cross-modality image synthesis from unpaired data using CycleGAN: Effects of gradient consistency loss and training data size

Yuta Hiasa, Yoshito Otake, Masaki Takao, Takumi Matsuoka, Kazuma Takashima, Jerry L. Prince, Nobuhiko Sugano, Yoshinobu Sato

- Introduction of gradient consistency loss to CycleGAN loss functions to improve the boundaries in synthesized images
- Accuracy of synthesized images was investigated by adjusting the number of training data and the implementation of gradient consistency loss

Paper: Background

- CT is commonly used in orthopedic procedures, while MRI is used along with CT to identify muscle structures and diagnose osteonecrosis due to its superior soft tissue contrast [1].
- Image synthesis has been performed through patch-based learning [2] as well as deep learning, including convolutional neural networks (CNN) and generative adversarial networks (GAN).
- Previous CycleGAN approaches focus on more consistent field-of-view (FOV), while the entire hip region has larger variation in the anatomy and the pose.

Paper: Dataset

- 302 unlabeled MR volumes
  - T1-weighted
  - matrix size: 256×256
  - field of view: 320×320 mm
  - slice thickness: 2 mm
- 613 unlabeled + 20 labeled CT volumes
  - matrix size: 512×512
  - field of view: 360×360 mm
  - slice thickness: 2mm

MR
dataset

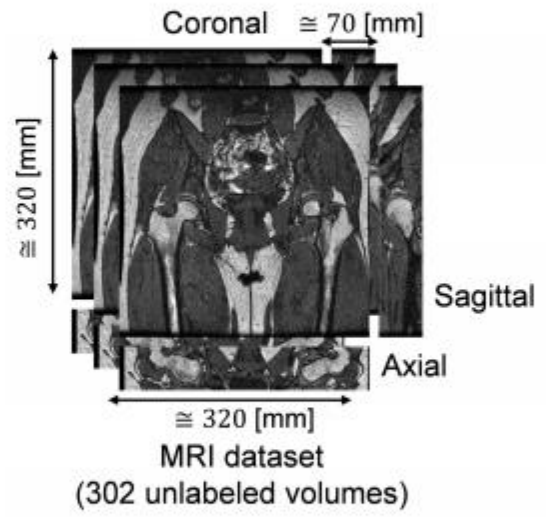


Image reference: [1] Y. Hiasa

CT
dataset

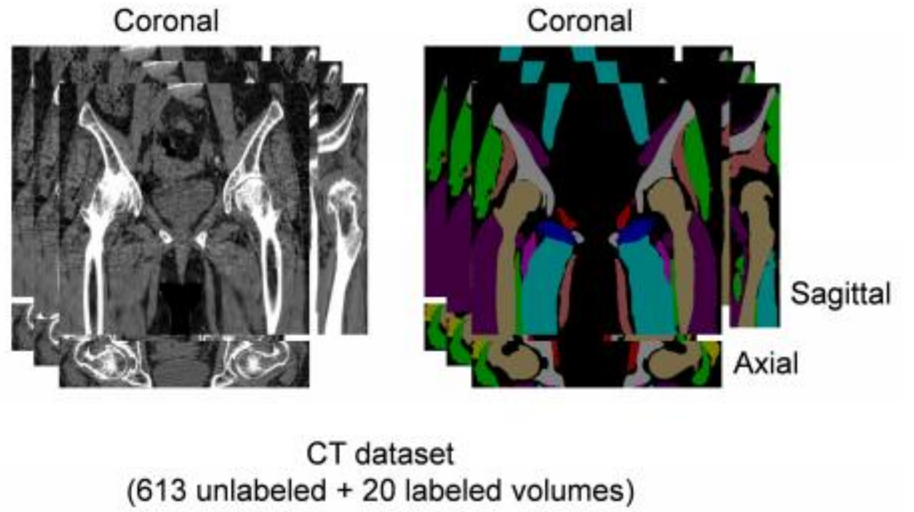


Image reference: [2] Y. Hiasa

Paper: CycleGAN Workflow

- Generator networks
  - G_{CT} : translates MR to CT
  - G_{MR} : translates CT to MR
- Discriminator networks
  - D_{MR} : distinguish real and fake MR
  - D_{CT} : distinguish real and fake CT
- Loss functions
  - $\mathcal{L}_{CT}, \mathcal{L}_{MR}$: adversarial losses
  - $\mathcal{L}_{Cycle}$: cycle consistency loss
  - $\mathcal{L}_{GC}$: gradient correlation loss

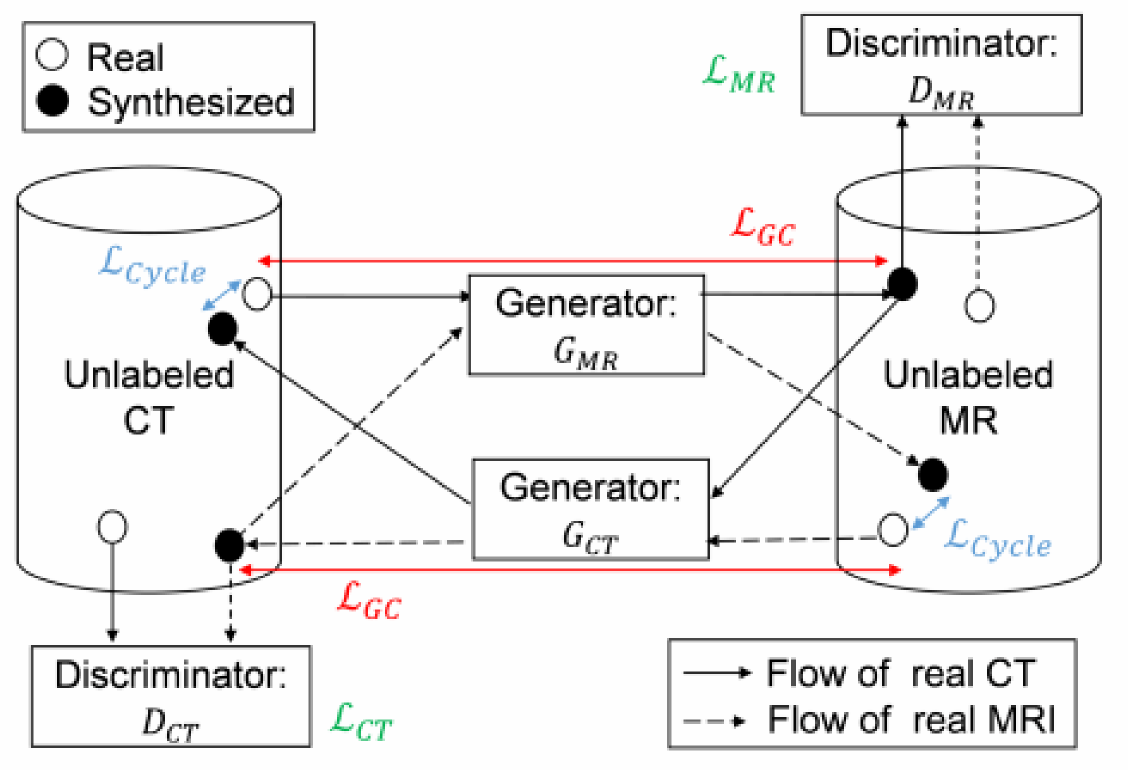


Image reference: [2] Y. Hiasa

Paper: CycleGAN loss

- Adversarial losses
  - Generators create synthesized images, while the discriminators attempt to distinguish between the real and synthesized images by maximizing the adversarial losses

$$\mathcal{L}_{CT} = \sum_{x \in I_{CT}} \log D_{CT}(x) + \sum_{y \in I_{MR}} \log(1 - D_{CT}(G_{CT}(y))),$$
$$\mathcal{L}_{MR} = \sum_{y \in I_{MR}} \log D_{MR}(y) + \sum_{x \in I_{CT}} \log(1 - D_{MR}(G_{MR}(x))),$$

x: Input CT
y: Input MR

- Cycle consistency loss
  - Compare the real image and the reconstructed images from synthesized images
  - Prevent convergence where generators creates same set of images

$$\mathcal{L}_{Cycle} = \sum_{x \in I_{CT}} |G_{CT}(G_{MR}(x)) - x| + \sum_{y \in I_{MR}} |G_{MR}(G_{CT}(y)) - y|$$

x: Input CT
y: Input MR

Paper: Gradient consistency loss

- Gradient correlation (GC) is a similarity metric in medical image registration. The value is defined to be the normalized cross correlation (NCC) between two images.

$$GC(A,B) = \frac{1}{2}\{NCC(\nabla_x A, \nabla_x B) + NCC(\nabla_y A, \nabla_y B)\}$$

$$\text{where, } NCC(A,B) = \frac{\sum_{(i,j)}(A-\bar{A})(B-\bar{B})}{\sqrt{\sum_{(i,j)}(A-\bar{A})^2}\sqrt{\sum_{(i,j)}(B-\bar{B})^2}}$$

- Gradient consistency loss is formulated as:

$$\mathcal{L}_{GC} = \frac{1}{2}\{\sum_{x \in I_{CT}}(1 - GC(x, G_{MR}(x))) + \sum_{y \in I_{MR}}(1 - GC(y, G_{CT}(y)))\}$$

- Overall loss function:

$$\mathcal{L}_{total} = \mathcal{L}_{CT} + \mathcal{L}_{MR} + \lambda_{Cycle}\mathcal{L}_{Cycle} + \lambda_{GC}\mathcal{L}_{GC}$$

Paper: Evaluation method

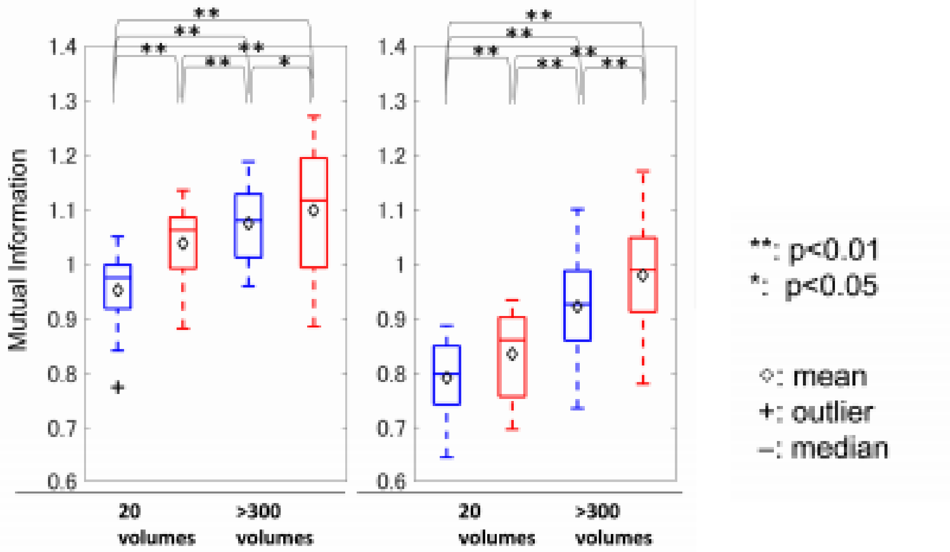
- Variable: Training dataset size
    1. 20 MR volumes + 20 CT volumes
    2. 302 MR volumes + 613 CT volumes
- Variable: Implementation of gradient consistency (GC) loss
    1. with GC loss implemented
    2. without GC loss implemented
- Evaluation methods:
    - Data with ground truth (paired CT and MR images):
        - mean absolute error (MAE)
        - peak-signal-to-noise ratio (PSNR) [dB] (increases when mean squared error decreases)
    - Data without ground truth:
        - Mutual Information (MI)
    - Quantitative evaluation on segmentation

Paper: Results

- MAE and PSNR:
  - Average MAE decreases and PSNR increases when there are more training volumes and when GC is implemented

		20 volumes		>300 volumes	
		w/o GC	/w GC	w/o GC	/w GC
MAE	Patient #1	30.121	30.276	26.899	26.388
	Patient #2	26.927	26.911	22.319	21.593
	Patient #3	33.651	32.155	29.630	28.643
	Average ± SD	30.233 ± 2.177	29.781 ± 1.777	26.283 ± 1.367	25.541 ± 1.129
PSNR	Patient #1	14.797	14.742	15.643	15.848
	Patient #2	15.734	15.628	17.255	17.598
	Patient #3	14.510	14.820	15.674	15.950
	Average ± SD	15.014 ± 0.330	15.063 ± 0.380	16.190 ± 0.273	16.465 ± 0.296

- Mutual information (MI):
  - Increased training data and implementation of GC both yield improvements



	20 volumes	>300 volumes		20 volumes	>300 volumes
w/o GC	0.952 ±0.068	1.074 ±0.068	w/o GC	0.791 ±0.077	0.922 ±0.105
w/ GC	1.037 ±0.077	1.098 ±0.111	w/ GC	0.835 ±0.080	0.979 ±0.117

Between CT and Synthesized MR — Between MR and Synthesized CT

Image reference: [2] Y. Hiasa

Paper: Results

- With gradient consistency loss implemented, the shape of the femoral head and the adductor muscles would be more likely preserved.

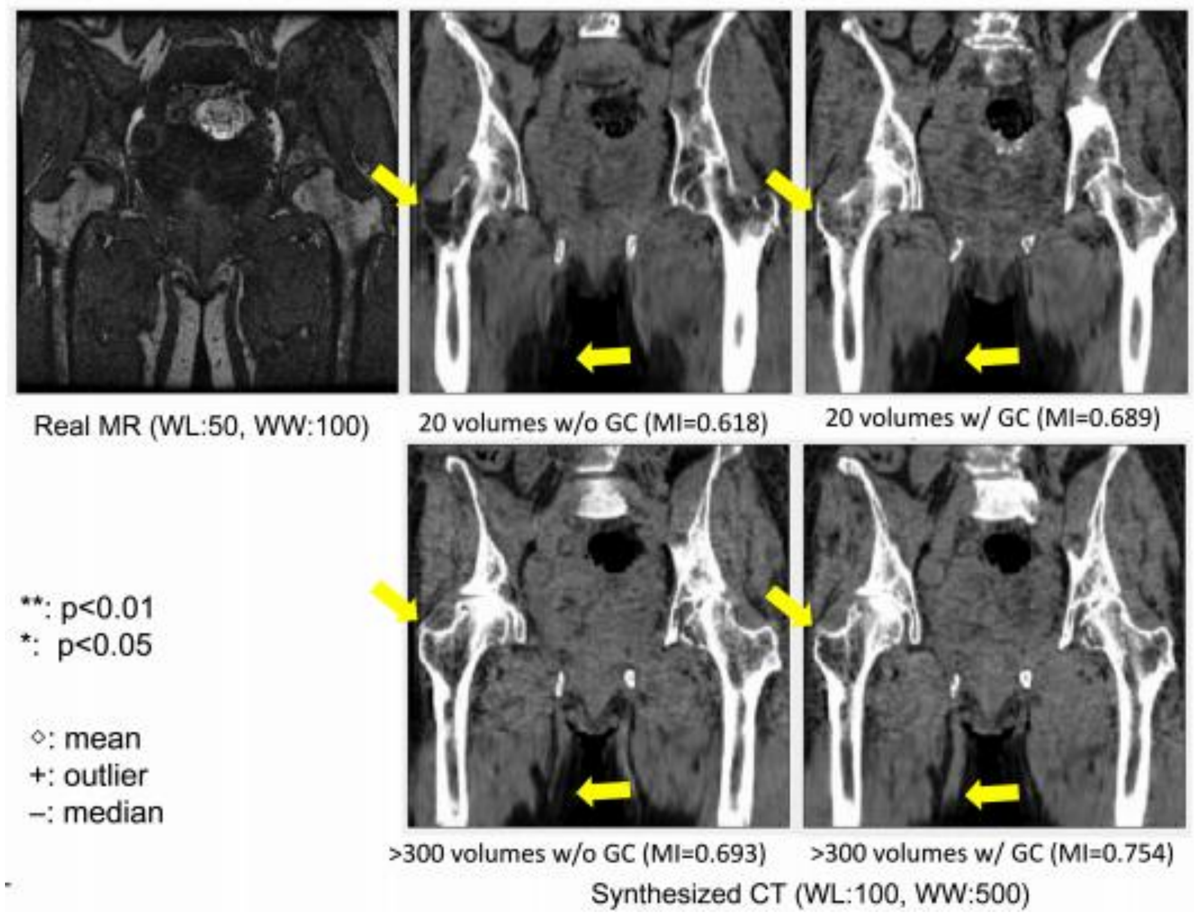
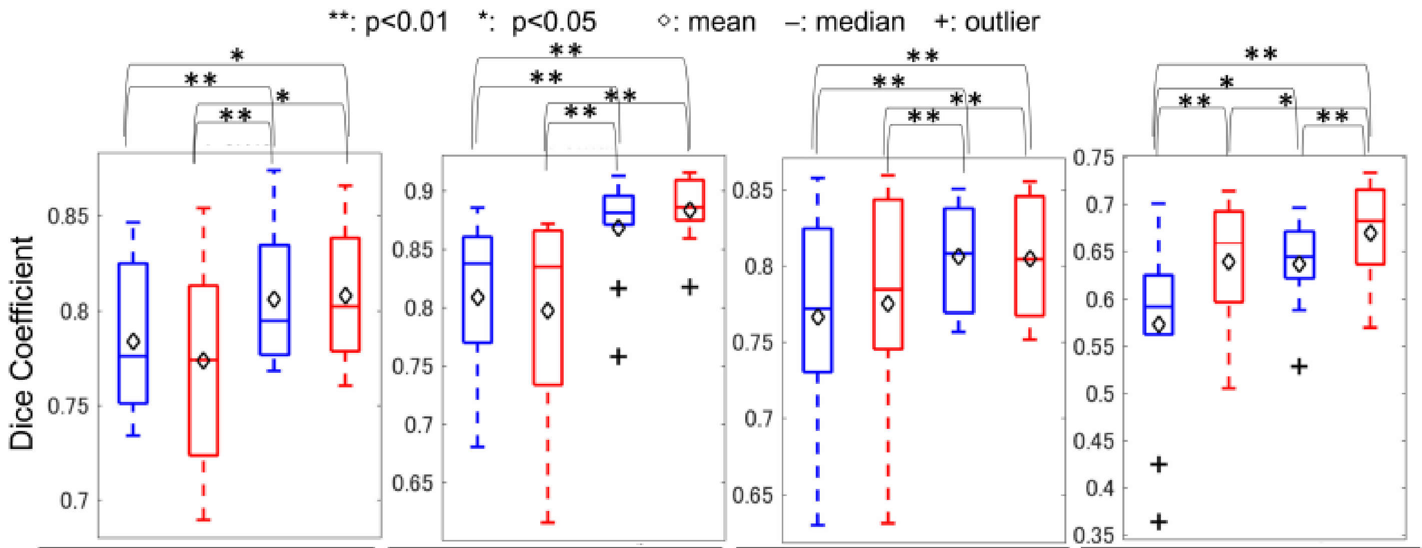


Image reference: [2] Y. Hiasa

Paper: Results

- Quantitative evaluation on segmentation



	(a) Pelvis: 20 volumes	(a) Pelvis: >300 volumes	(b) Femur: 20 volumes	(b) Femur: >300 volumes	(c) Gluteus medius: 20 volumes	(c) Gluteus medius: >300 volumes	(d) Gluteus minimus: 20 volumes	(d) Gluteus minimus: >300 volumes
w/o GC	0.784 ±0.041	0.806 ±0.036	0.809 ±0.073	0.868 ±0.047	0.767 ±0.066	0.806 ±0.036	0.573 ±0.106	0.637 ±0.049
w/ GC	0.774 ±0.055	0.808 ±0.036	0.797 ±0.085	0.883 ±0.029	0.775 ±0.070	0.804 ±0.040	0.639 ±0.067	0.669 ±0.054

(a) Pelvis (b) Femur (c) Gluteus medius (d) Gluteus minimus

Image reference: [2] Y. Hiasa

Paper: Conclusions

- Main contributions:
  - introduction of gradient consistency loss in CycleGAN
  - quantitative and qualitative evaluation of the dependency of both image synthesis accuracy and segmentation accuracy on a large number of training data
- Future work:
  - patients with implants are excluded in the dataset for the cycleGAN training
  - development of a method that effectively incorporates information in unlabeled CT and MR volumes to improve segmentation accuracy

Paper: Critiques

- Good:
  - Clearly explained model and clear math for all the loss functions involved
  - Made full use of available data (paired/unpaired volumes and few labeled volumes) to provide quantitative and qualitative evaluation of the results

- Bad:
  - Effect of implementation of GC loss is not significant. The balancing weights for GC loss was set to a constant throughout the paper.
  - No publicly available code implementations, which may be difficult for researchers to reproduce the results

Paper: Relevance to project

- Understanding the loss functions involved in CycleGAN
- Provides insights to modification of network losses
- Understanding the evaluation and testing methods

Reference

1. Osteonecrosis of the Hip - OrthoInfo - AAOS.url:https://orthoinfo.aaos.org/en/diseases--conditions/osteonecrosis-of-the-hip
2. Hiasa, Y., Otake, Y., Takao, M., Matsuoka, T., Takashima, K., Carass, A., . . . Sato, Y. (2018). Cross-Modality image synthesis From UNPAIRED data Using CycleGAN. *Simulation and Synthesis in Medical Imaging,* 31-41. doi:10.1007/978-3-030-00536-8_4

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