Applied Deep Learning and Generative Models in



• Healthcare



Session 5: Medical Image Synthesis

Date: Feb 15 2025

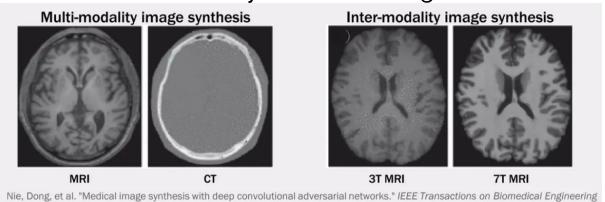
Instructor: Mahmoud E. Khani, Ph.D.

Medical image synthesis

 An approach to modeling a mapping from given images to unknown images

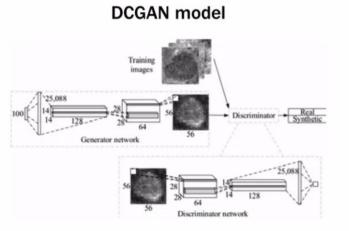
Necessity

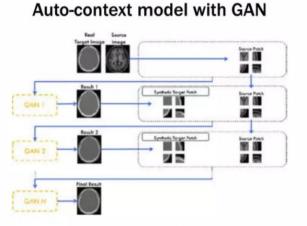
- Potential risk of radiation exposure for multiple acquisition of medical images (ec. CT, PET)
- Not always accessible modalities for every patient
- Alignment issue on the analysis of multi-images

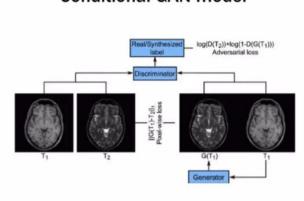


Deep learning approaches for image synthesis

- Image generation by solving the min-max problem with generator and discriminator
- Useful for the dataset that does not have ground-truth images







Conditional GAN model

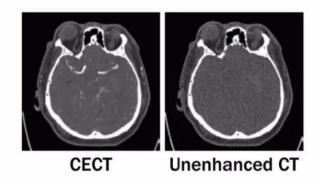
CT image synthesis from CECT

CECT and unenhanced CT

- CECT: highlight specific tissues or parts of body by contrast agent
- Useful for diagnosis by extracting certain organ (ex. bone)

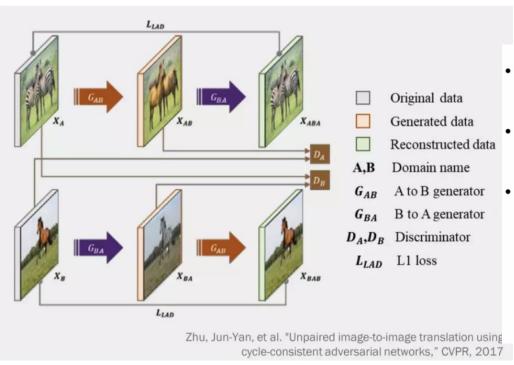
Challenge

- Not aligned CT & CTEC: not have ground-truth images
- Only have to change the enhanced blood vessels
- Do not generate or remove certain organs/tissues



Motivation: CycelGAN

One-to-one mapping using cycling constraint



- Two Generators

 Generate the unknown image from source image
- Two Discriminators
 Distinguish between real and fake images
- Loss function

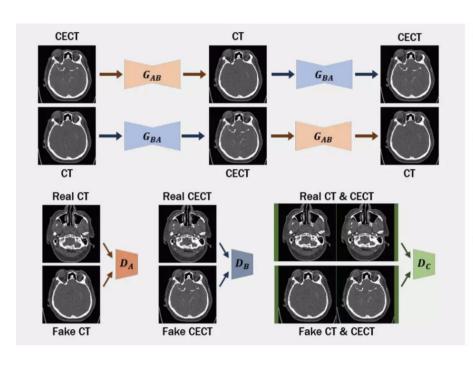
$$\frac{\min\limits_{G_{AB},G_{BA}} \max\limits_{D_{A},D_{B}} L(G_{AB},G_{BA},D_{A},D_{B})}{L(G_{AB},G_{BA},D_{A},D_{B})}$$

$$= L_{GAN}(G_{AB},D_{A}) + L_{GAN}(G_{BA},D_{B})$$

$$+ \lambda_{1}L_{cyclic}(G_{AB},G_{BA}) + \lambda_{2}L_{identity}(G_{AB},G_{BA})$$

Overall framework

Improved cycleGAN with residual learning



Residual learning for generators

Prevent loss of medical information CNN

Two Generators

 G_{AB} : CECT \rightarrow CT (generate synthetic CT)

 $G_{BA}: CT \rightarrow CECT$ (generate synthetic CECT)

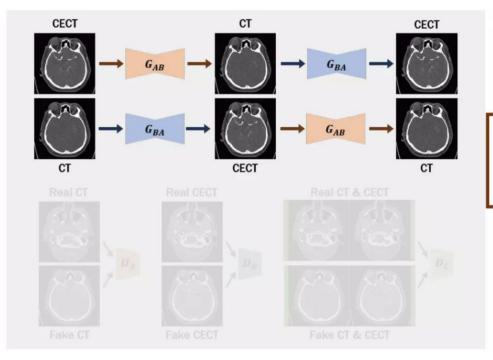
Three Discriminators

 D_A : Distinguish real and fake CT

 D_B : Distinguish real and fake CECT

D_C: Distinguish real and fake pair of CT & CECT

Overall framework



Residual learning for generators

Prevent loss of medical information



Two Generators

 G_{AB} : CECT \rightarrow CT (generate synthetic CT)

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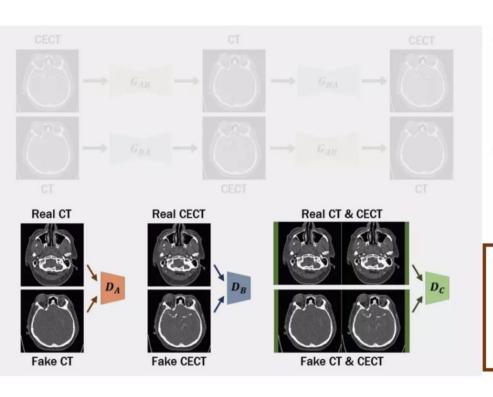
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Overall framework



Residual learning for generators

Prevent loss of medical information



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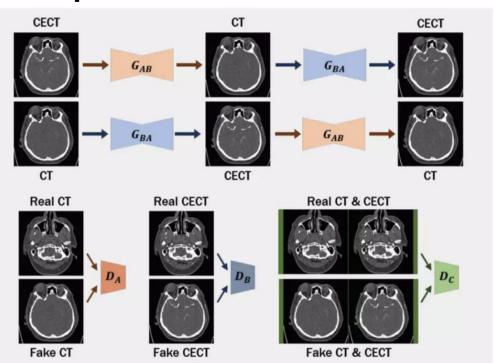
Three Discriminators

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 Training networks by solving the optimization problem



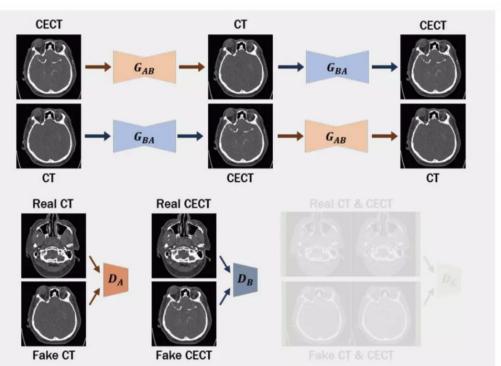
$$\min_{G_{AB},G_{BA}} \max_{D_A,D_B,D_C} L(G_{AB},G_{BA},D_A,D_B,D_C)$$

$$L(G_{AB},G_{BA},D_A,D_B,D_C)$$

$$= L_{GAN}(G_{AB},D_A) + L_{GAN}(G_{BA},D_B) + L_{GAN'}(G_{AB},G_{BA},D_C)$$

 $+ \lambda_1 L_{cyclic}(G_{AB}, G_{BA}) + \lambda_2 L_{identity}(G_{AB}, G_{BA})$

 Training networks by solving the optimization problem

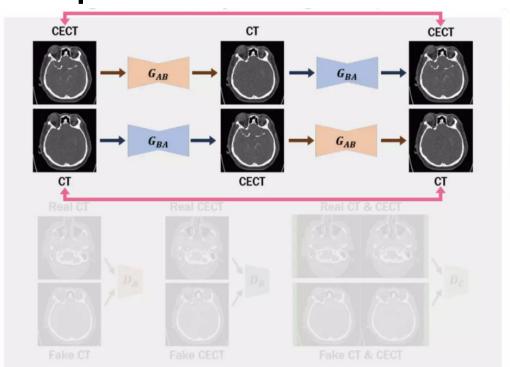


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\min_{G_{AB},G_{BA}} \max_{D_{A},D_{B},D_{C}} L(G_{AB},G_{BA},D_{A},D_{B},D_{C})
L(G_{AB},G_{BA},D_{A},D_{B},D_{C})
= \frac{L_{GAN}(G_{AB},D_{A}) + L_{GAN}(G_{BA},D_{B})}{L_{Cyclic}(G_{AB},G_{BA}) + \lambda_{2}L_{identity}(G_{AB},G_{BA})}
```

- Adversarial loss, $L_{GAN}(G_{AB}, D_A)$
 - Produce realistic images
 - Apply to input x

$$\min_{G_{AB}} \mathbb{E}_{x_{A} \sim P_{A}} [(D_{A} (G_{AB}(x_{A})) - 1)^{2}]
\min_{D_{A}} \frac{1}{2} \mathbb{E}_{x_{B} \sim P_{B}} [(D_{A}(x_{B}) - 1)^{2}] + \frac{1}{2} \mathbb{E}_{x_{A} \sim P_{A}} [D_{A} (G_{AB}(x_{A}))^{2}]$$

 Training networks by solving the optimization problem



$$\min_{G_{AB},G_{BA}} \max_{D_{A},D_{B},D_{C}} L(G_{AB},G_{BA},D_{A},D_{B},D_{C})$$

$$L(G_{AB},G_{BA},D_{A},D_{B},D_{C})$$

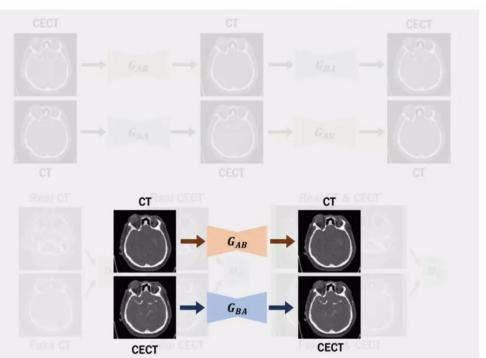
$$= L_{GAN}(G_{AB},D_{A}) + L_{GAN}(G_{BA},D_{B}) + L_{GAN'}(G_{AB},G_{BA},D_{C})$$

$$+ \lambda_{1}L_{cyclic}(G_{AB},G_{BA}) + \lambda_{2}L_{identity}(G_{AB},G_{BA})$$

• Cyclic loss, $L_{cyclic}(G_{AB}, G_{BA})$ Guarantee one-to-one mapping of CT & CECT

$$\mathbb{E}_{x_{A} \sim P_{A}} \left[\| G_{BA} (G_{AB} (x_{A})) - x_{A} \|_{1} \right] + \mathbb{E}_{x_{B} \sim P_{B}} \left[\| G_{AB} (G_{BA} (x_{B})) - x_{B} \|_{1} \right]$$

 Training networks by solving the optimization problem



$$\min_{G_{AB},G_{BA}} \max_{D_{A},D_{B},D_{C}} L(G_{AB},G_{BA},D_{A},D_{B},D_{C})$$

$$L(G_{AB},G_{BA},D_{A},D_{B},D_{C})$$

$$= L_{GAN}(G_{AB},D_{A}) + L_{GAN}(G_{BA},D_{B}) + L_{GAN'}(G_{AB},G_{BA},D_{C})$$

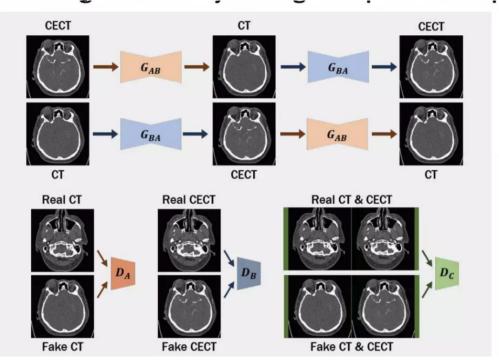
$$+ \lambda_{1}L_{cyclic}(G_{AB},G_{BA}) + \lambda_{2}L_{identity}(G_{AB},G_{BA})$$

• Identity loss, $L_{identity}(G_{AB}, G_{BA})$

Preserve medical information between CT & CECT

$$\mathbb{E}_{x_A \sim P_A}[\|G_{BA}(x_A) - x_A\|_1] + \mathbb{E}_{x_B \sim P_B}[\|G_{AB}(x_B) - x_B\|_1]$$

 Training networks by solving the optimization problem

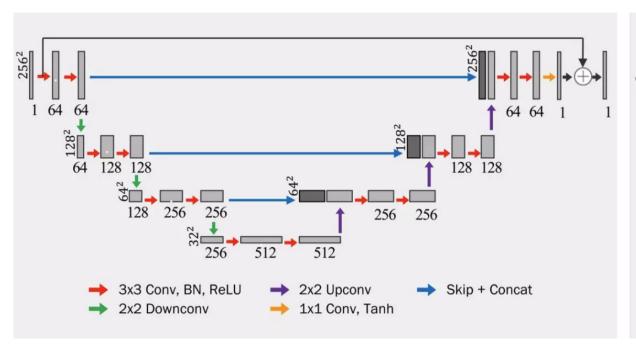


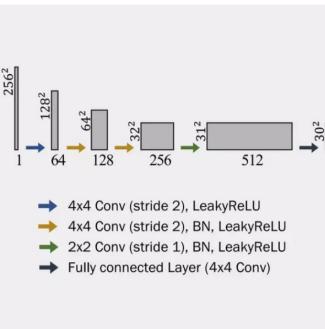
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L(G_{AB},G_{BA},D_{A},D_{B},D_{C})
= \frac{L_{GAN}(G_{AB},D_{A}) + L_{GAN}(G_{BA},D_{B}) + L_{GAN'}(G_{AB},G_{BA},D_{C})}{+ \lambda_{1}L_{cyclic}(G_{AB},G_{BA}) + \lambda_{2}L_{identity}(G_{AB},G_{BA})}
```

Minimize our designed loss function
 (adversarial loss + cyclic loss + identity loss)

Network architecture

- Generator (UNet)
- Discriminator





Experiments (Next session)

Dataset

- Head CT & CECT scans
 - 10 paris of CT & CTECT scans
 - 8 scans for training / 2 scans for test