ECE 5995 Applied Machine Learning Final Project:

T_1 weighted to T_2 weighted upper airway MRI using CycleGAN

Presented by

Rushdi Zahid Rusho

Group 15

May 12nd, 2021

Background and Motivation:

- T1 weighted MRI uses gradient echo (GRE) sequences

  - has short acquisition time TR: ~6 ms

  - commonly used in very fast dynamic imaging

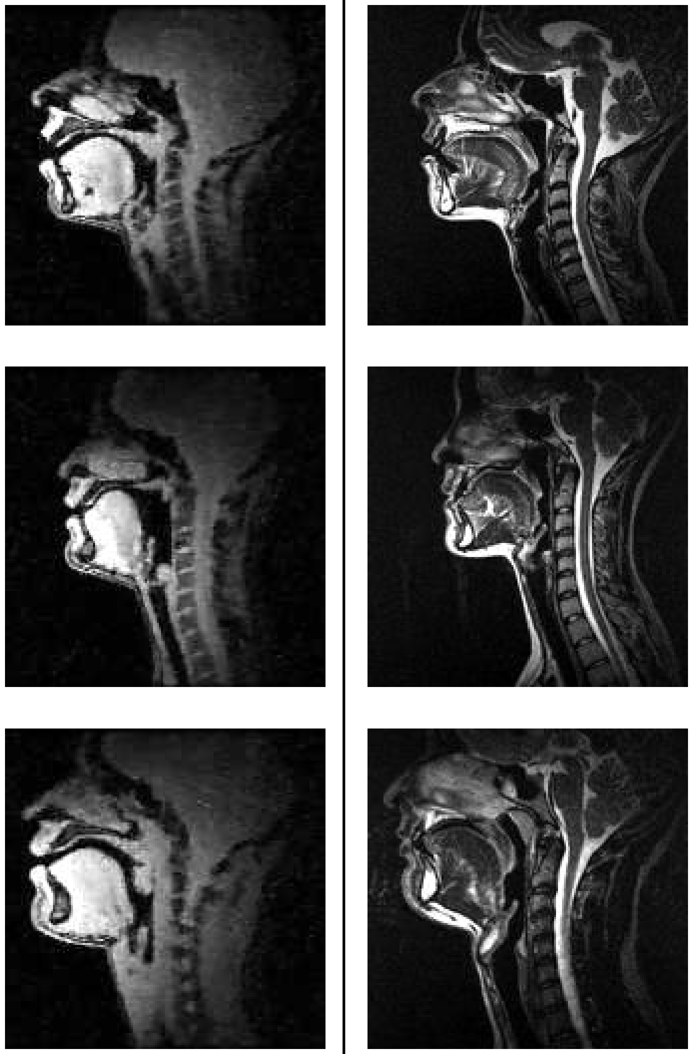
- T2 weighted MRI uses Fast spin echo sequences

  - has long acquisition time TR: ~4600 ms Slow!

  - cannot capture rapid tissue movement because of slow nature

T_1 weighted upper airway MRI

T_2 weighted upper airway MRI



Background and Motivation (cont’d):

However,

- T2 weighted MRI has excellent soft-tissue contrast
- For T2, its easy to identify the boundaries of articulators such as tongue, soft palate, velum, epiglottis and glottis

- The best we can do is to scan for Static T2 weighted images!

T_1 weighted upper airway MRI

T_2 weighted upper airway MRI

Beautiful soft-tissue contrast

Background and Motivation (cont'd):

My goal:

Given T1 weighted images, can I synthesis T2 weighted upper airway images and from them, construct dynamic T2 weighted movies?

?

T_1 weighted upper airway dMRI

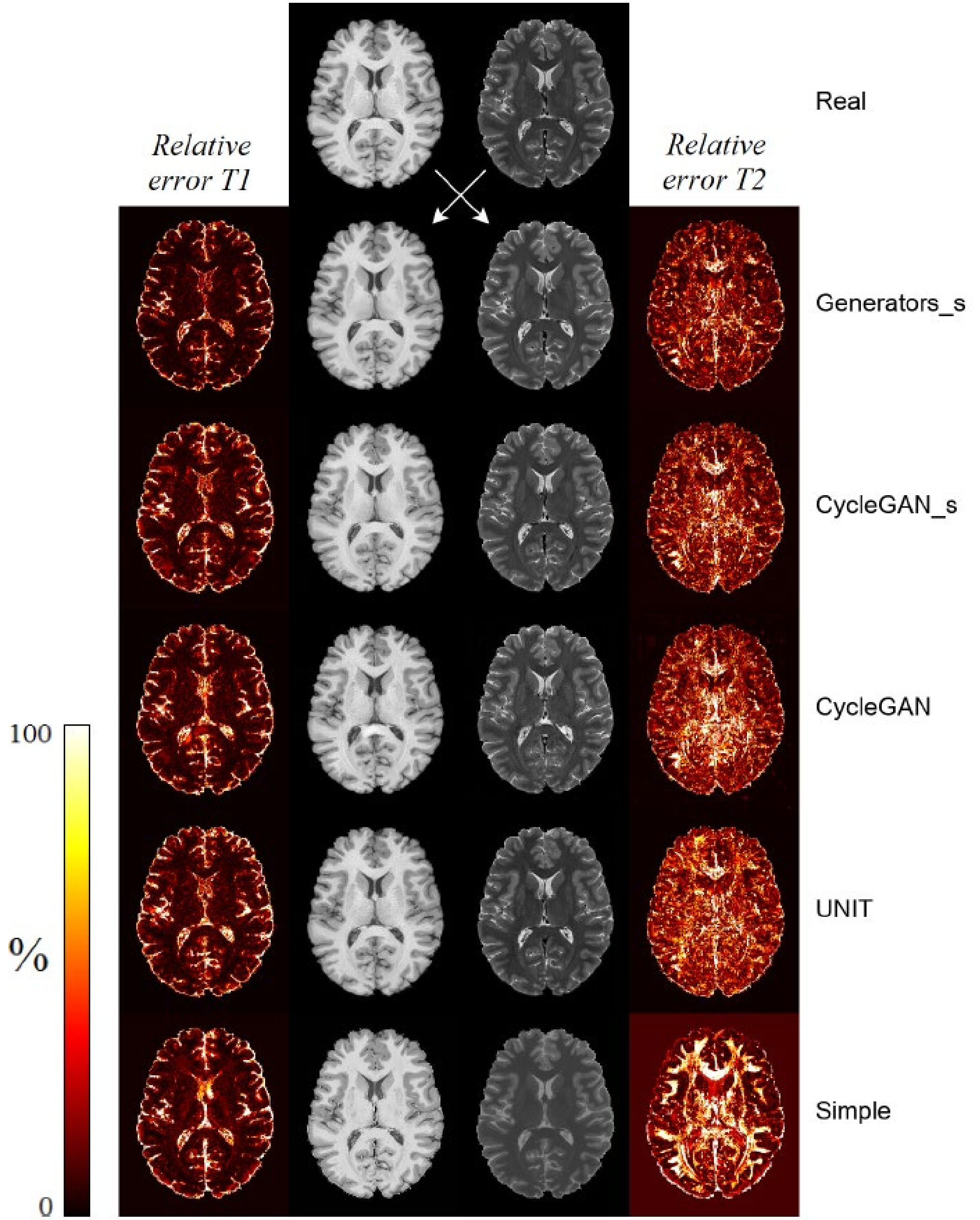
T_2 weighted upper airway dMRI

As a first step: static T1 to static T2

Literature review: state of the art

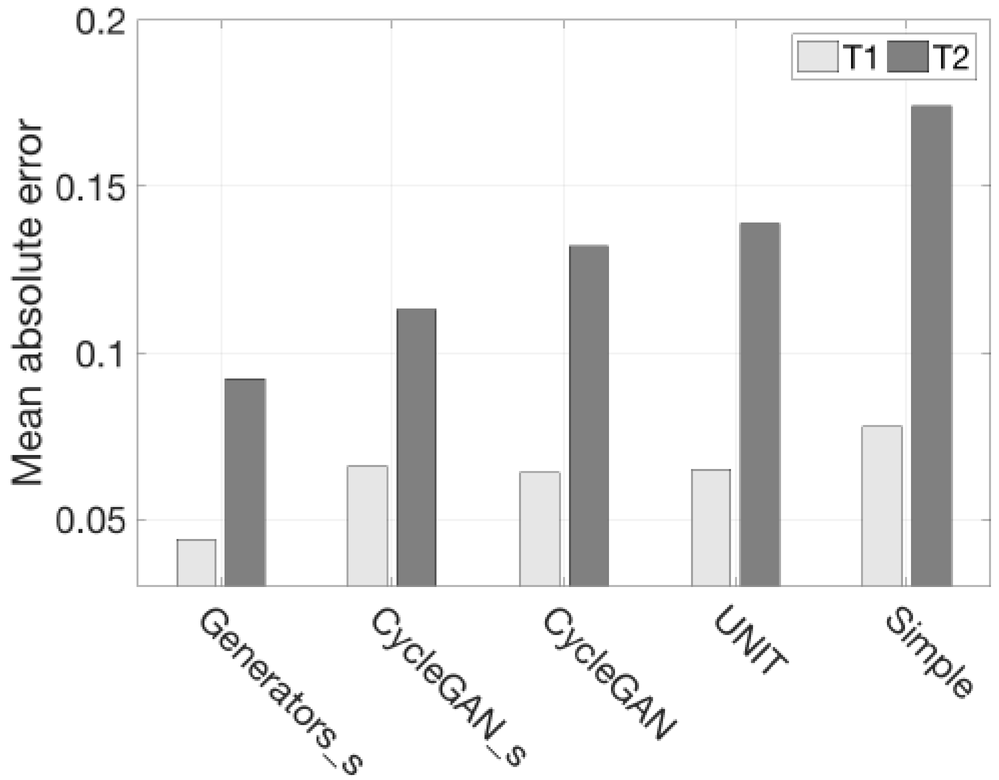
P. Welander et al., 2018 uses,

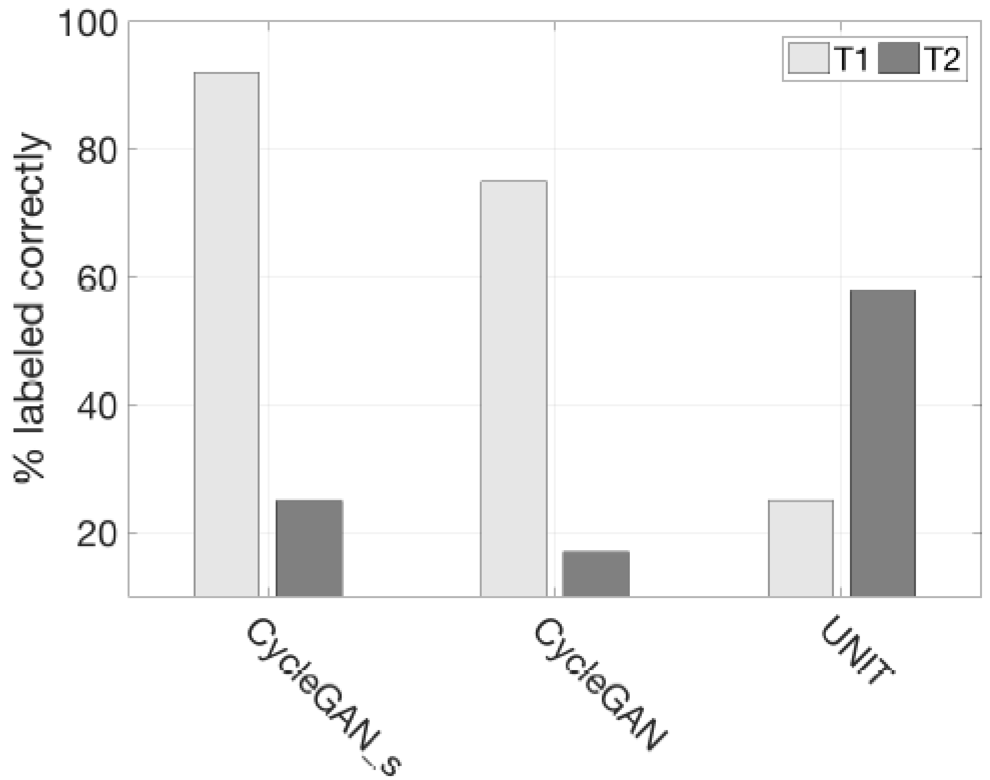
- *Generator_s:* generators of CycleGAN[1] including MAE between ground truth and output; does not include adversarial or cyclic loss
- *CycleGAN_s:* supervised CycleGAN[1] including MAE between ground truth and output
- CycleGAN[1] : applied to paired dataset
- UNIT[2]: applied to unpaired dataset
- A *Simple* base line model: only two convolutional layers



[1] J.-Y. Zhu et al. 2017
[2] M.-Y. Liu et al. 2017

Literature review: state of the art (Cont'd)





P. Welander et al., 2018

Literature review: state of the art (Cont’d)

Heran Yang et al. 2018 uses structure-constrained CycleGAN for unpaired Brain MR-to-CT Synthesis

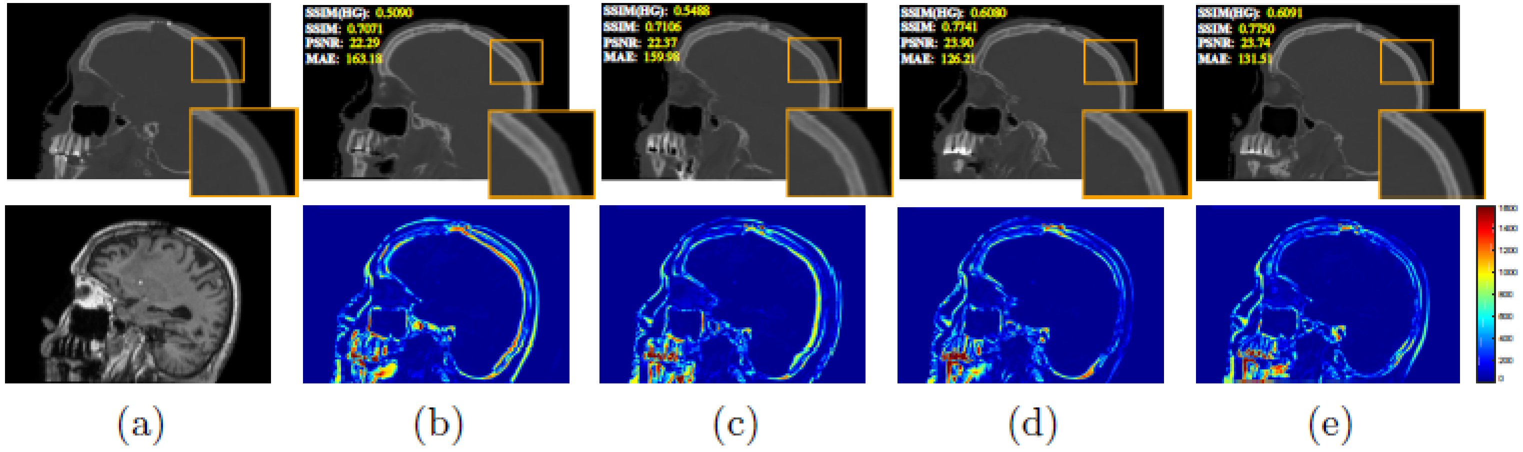
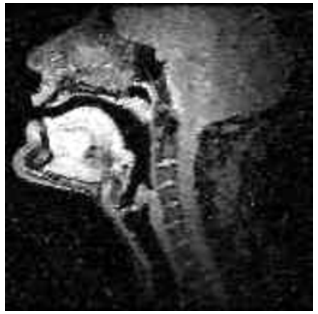


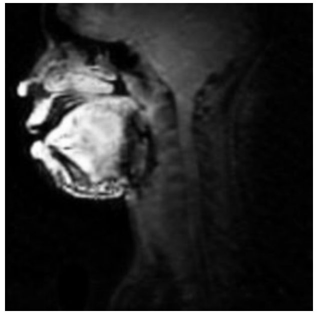
Fig. 5: Visual comparison of synthetic CT images using different methods. For one test subject, we show (a) the ground-truth CT image and input MR image; the synthetic CT image and its difference image (compared to ground-truth CT image) generated by (b) cycleGAN, (c) cycleGAN (PBS), (d) cycleGAN (paired), and (e) proposed method. The small text in each sub-image is the corresponding accuracy on this test subject.

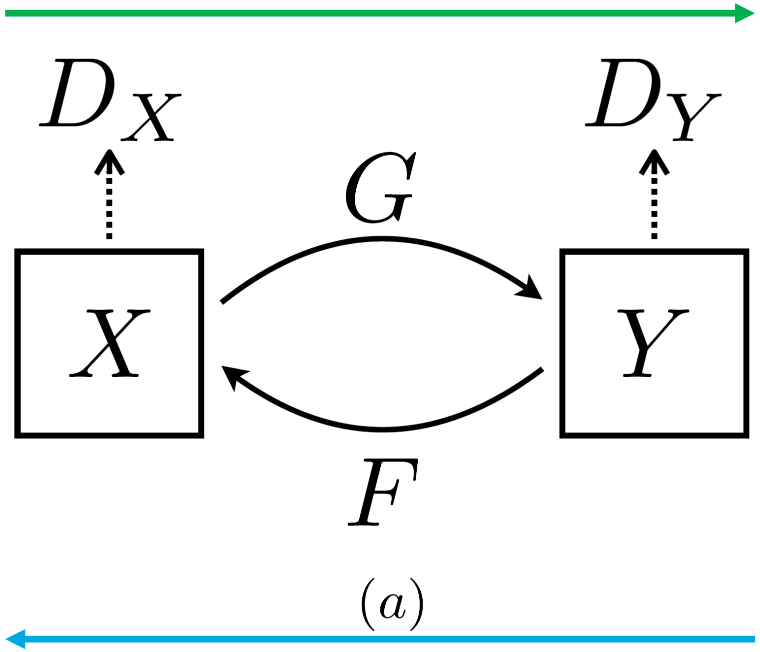
Proposed Work and Theory:

I will implement CycleGAN[1] to unpaired T1-T2 weighted upper airway MRI dataset

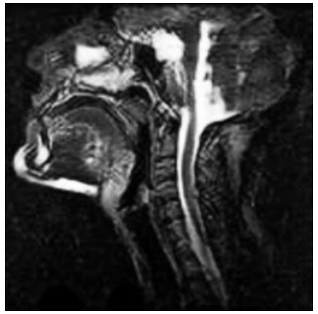
X:T1

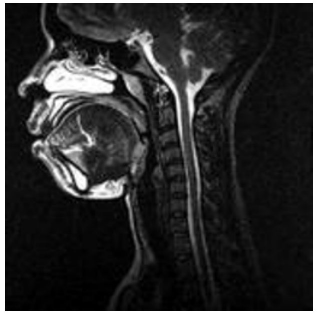






Y:T2





$$L_{GAN}(G, D_Y, X, Y) = E_{y\sim p_{data(y)}}[\log D_Y(y)] + E_{x\sim p_{data(x)}}[\log(1 - D_Y(G(x)))]$$

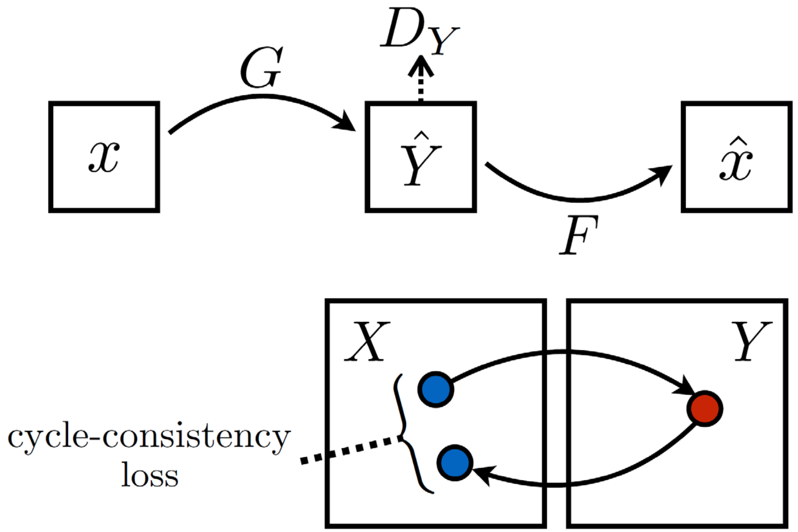
$$L_{GAN}(F, D_X, Y, X) = E_{x\sim p_{data(x)}}[\log D_X(x)] + E_{y\sim p_{data(y)}}[\log(1 - D_X(G(y)))]$$

Adversarial losses

[1] J.-Y. Zhu et al. 2017

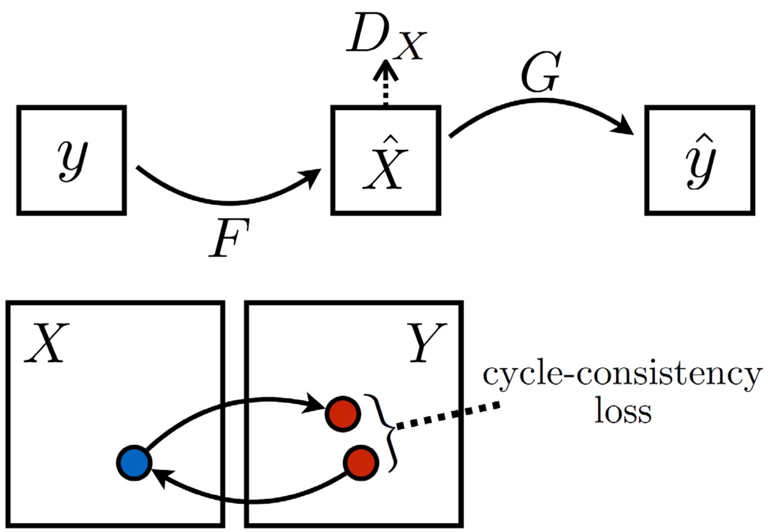
Proposed Work and Theory: CycleGAN

Cycle consistency losses



(b)

$$L_{cyc-Forward}(G,F) = E_{x \sim p_{data(x)}}[\|F(G(x)) - x\|_1]$$



(c)

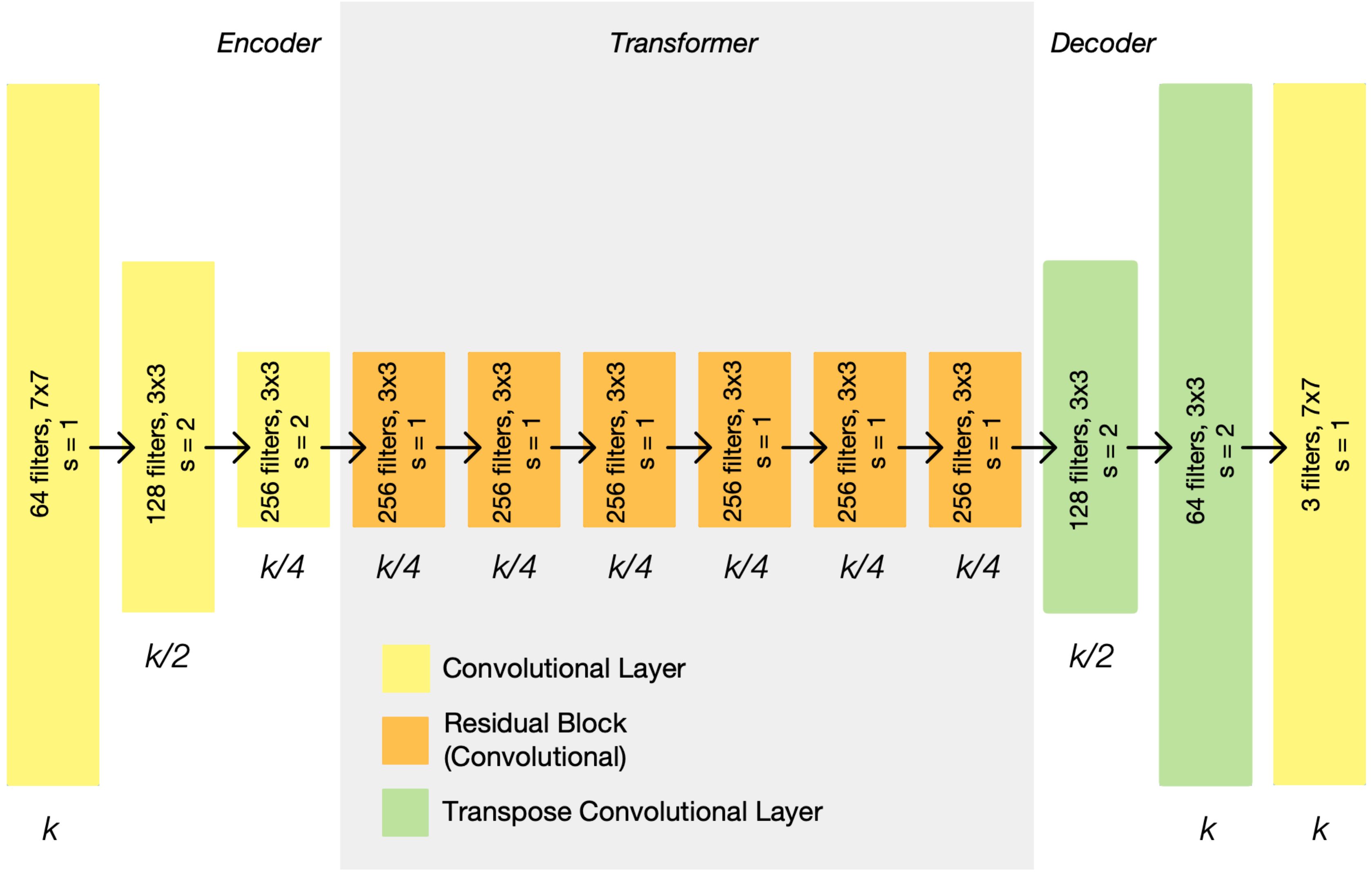
$$L_{cyc-Backward}(G,F) = E_{y \sim p_{data(y)}}[\|G(F(y)) - y\|_1]$$

Total loss in CycleGAN

$$\boxed{\begin{aligned}\mathcal{L}(G, F, D_X, D_Y) =& \mathcal{L}_{\text{GAN}}(G, D_Y, X, Y) \\ &+ \mathcal{L}_{\text{GAN}}(F, D_X, Y, X) \\ &+ \lambda \mathcal{L}_{\text{cyc}}(G, F),\end{aligned}}$$

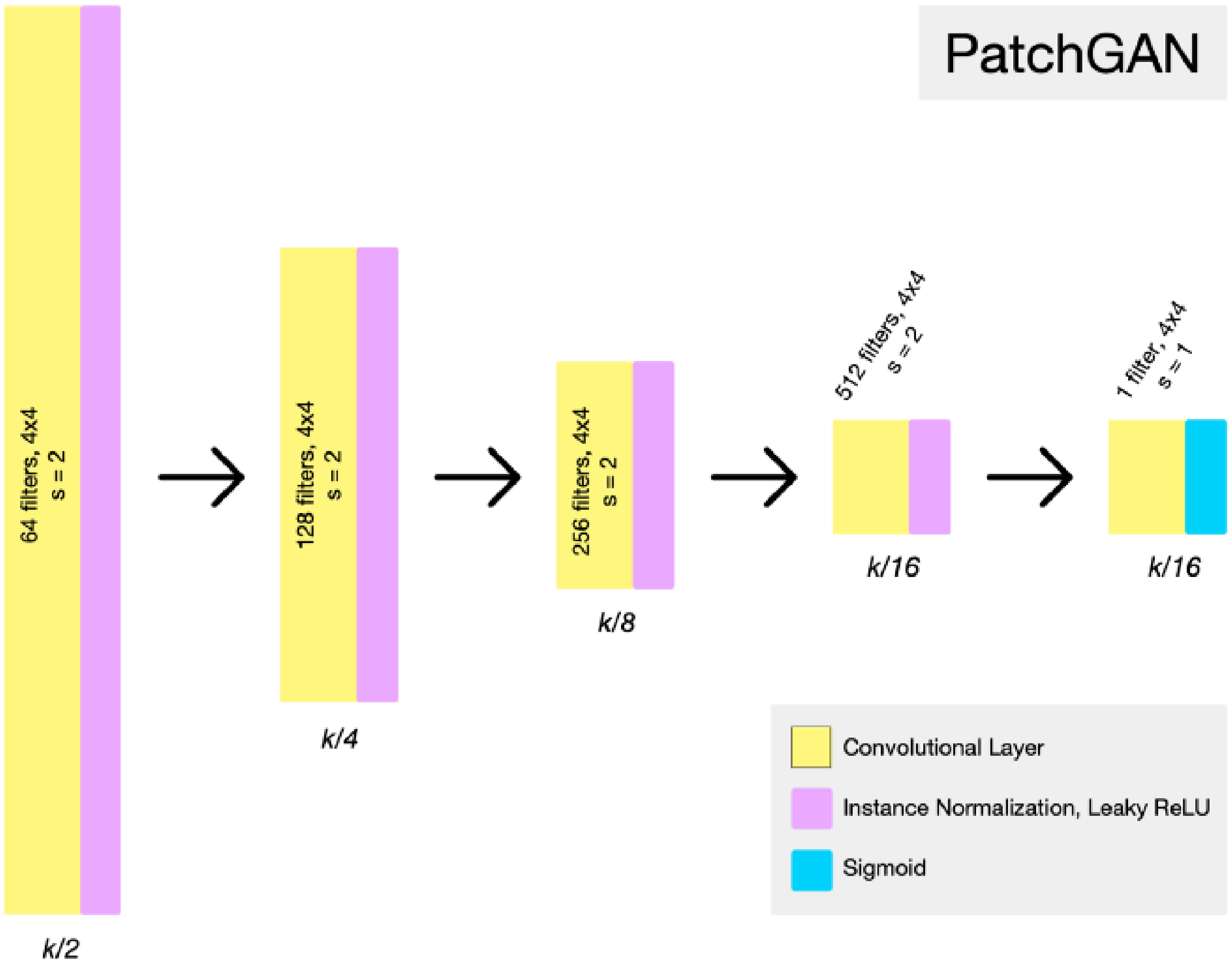
[1] J.-Y. Zhu et al. 2017

Proposed Work and Theory: Generator Architecture



Adopted from: Sarah Wolf, 2018

Proposed Work and Theory: Discriminator Architecture



Adopted from: Sarah Wolf, 2018

Dataset preparation:

Open source Multi-speaker dataset for Upper airway from USC[1]

→ Contains T1 and T2 weighted images from 75 subjects

T1 weighted images:

- FOV: 200×200 mm^2
- Resolution: 1.25×1.25 mm^2
- image matrix size: 160×160

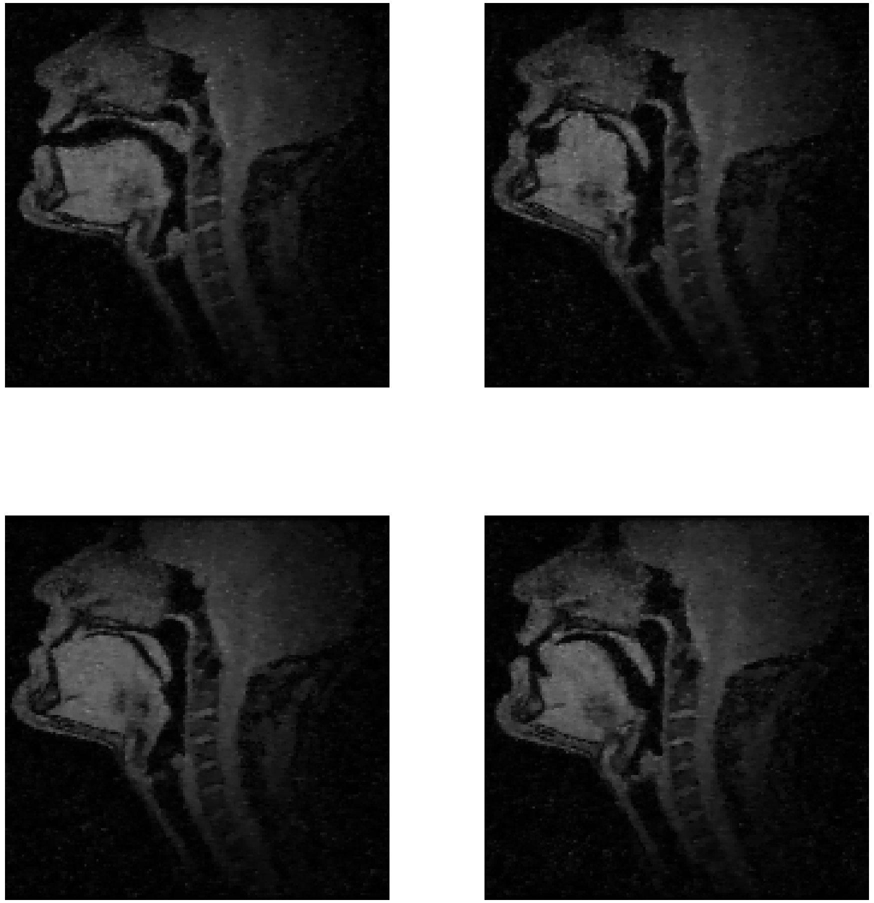
T2 weighted images:

- FOV: 300×300 mm^2
- Resolution: 0.5859×0.5859 mm^2
- image matrix size: 512×512

[1] Y. Lim et al. 2021

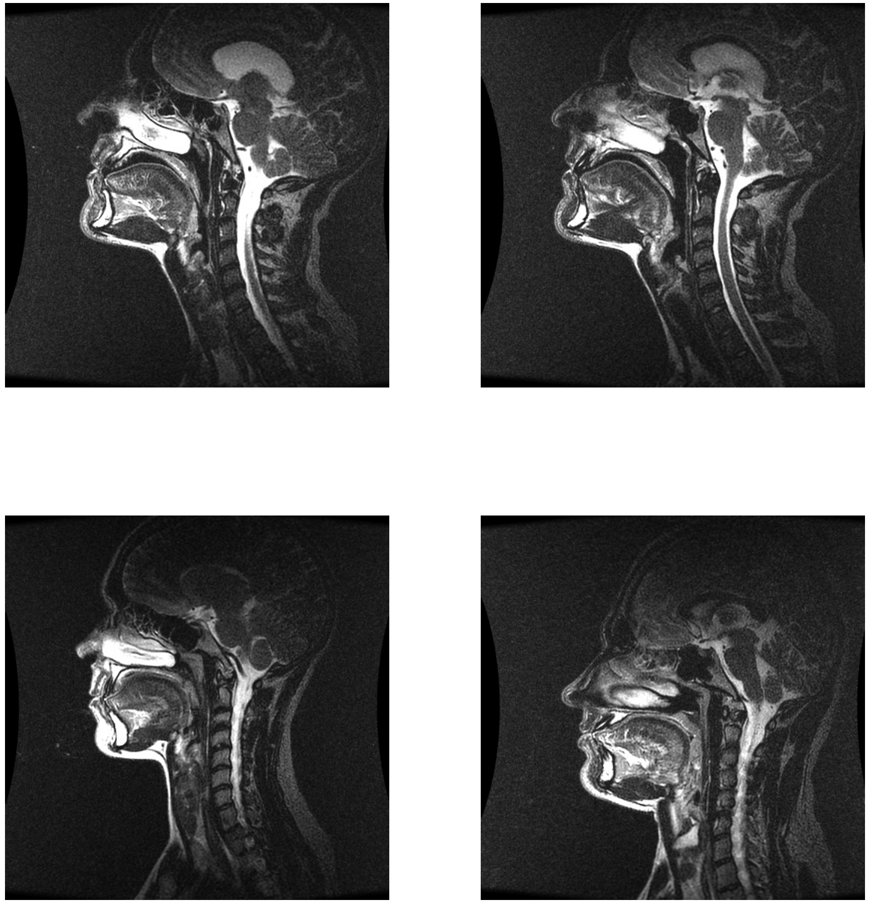
Dataset preparation:

T1 different postures (varies with subject and specific tasks)



Sustained sound, breath, tip, hold, clench

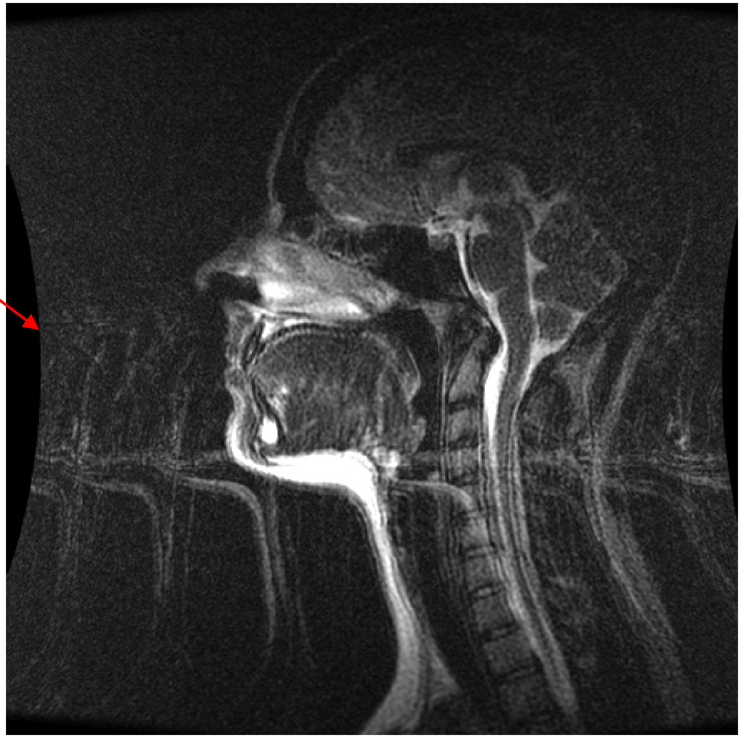
T2 resting posture only (varies with subjects)



[1] Y. Lim et al. 2021

Dataset preparation: some T2 images contain artifacts

Gradient nonlinearity correction

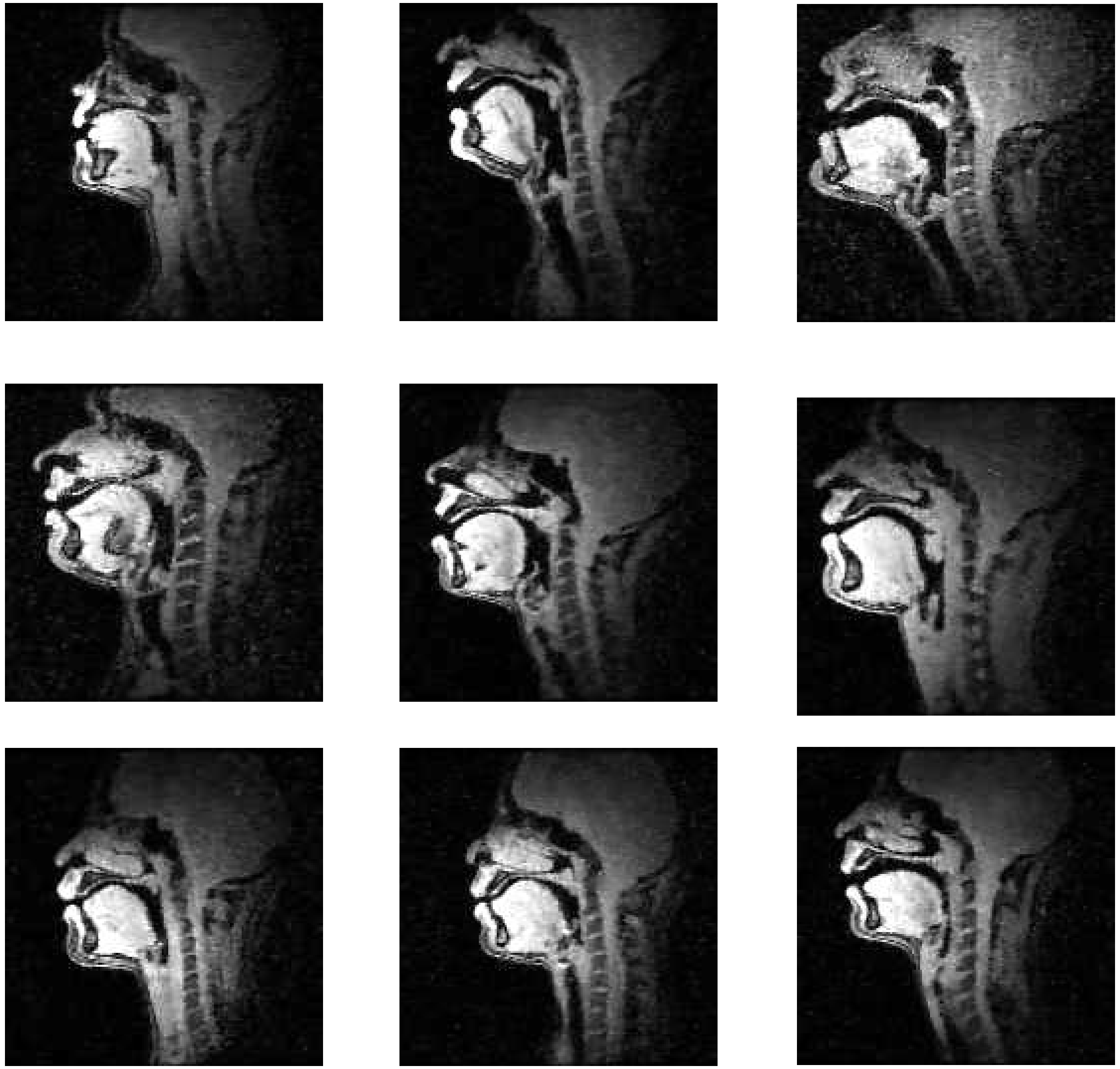


Motion artifacts

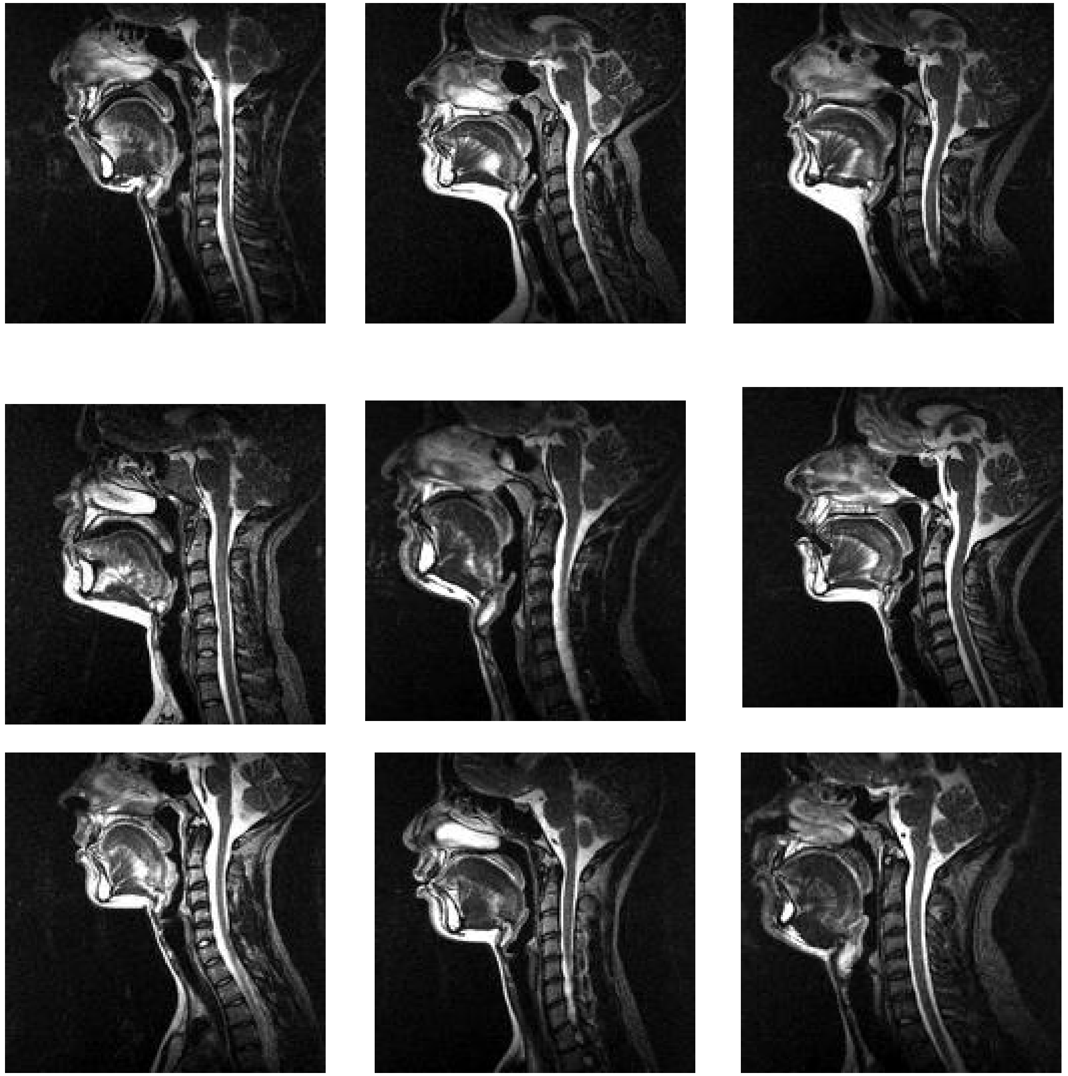
[1] Y. Lim et al. 2021

Dataset preparation: Crop, resize and normalize

Random T1 image dataset after adjustments



Random T2 image dataset after adjustments



Dataset preparation: Training and test sets

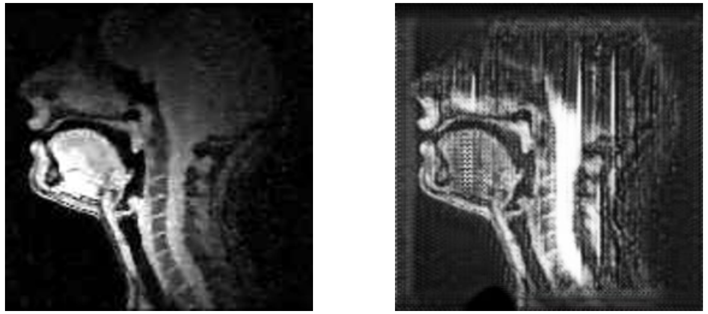
- Total 284 T1 weighted images of which 248 training and 36 testing images
- Total 115 T2 weighted images of which 100 training and 15 testing images

Code implementation:

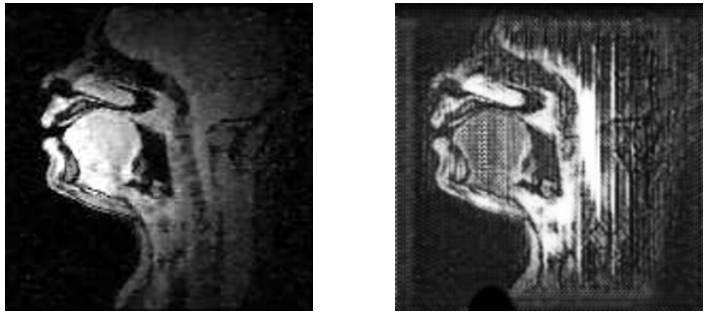
- pyTorch
- ARGON cluster HPC from UIOWA
- GPU: NVIDIA 1080ti
- Average training time per epoch ~80 sec (total 400 epochs)

Results: (T1 to T2)

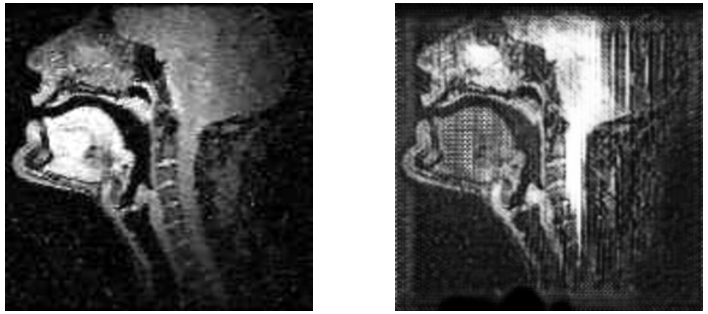
Results after 200 epoch



sub54

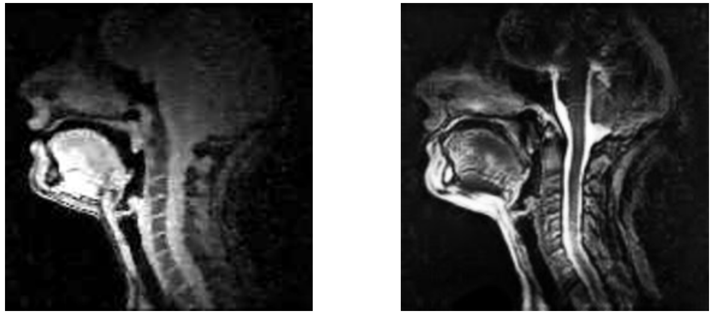


sub59

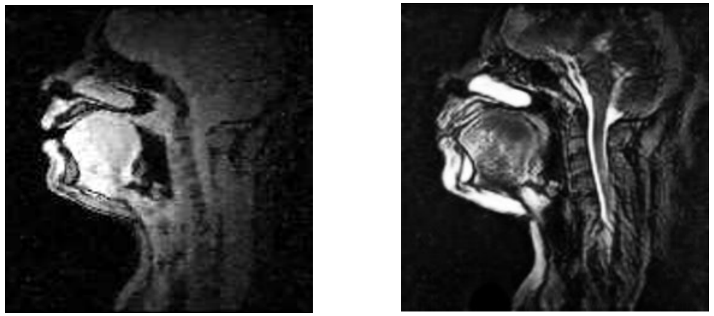


Sub 06

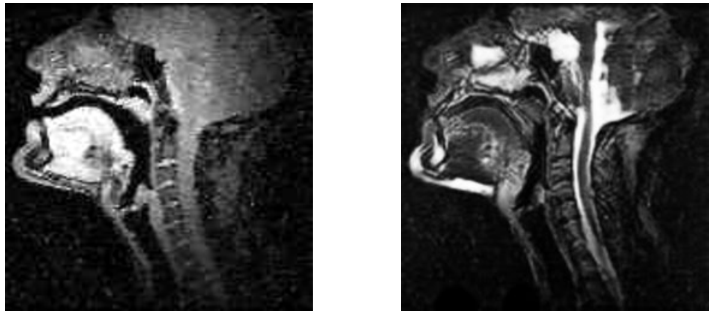
Results after 400 epoch



sub54

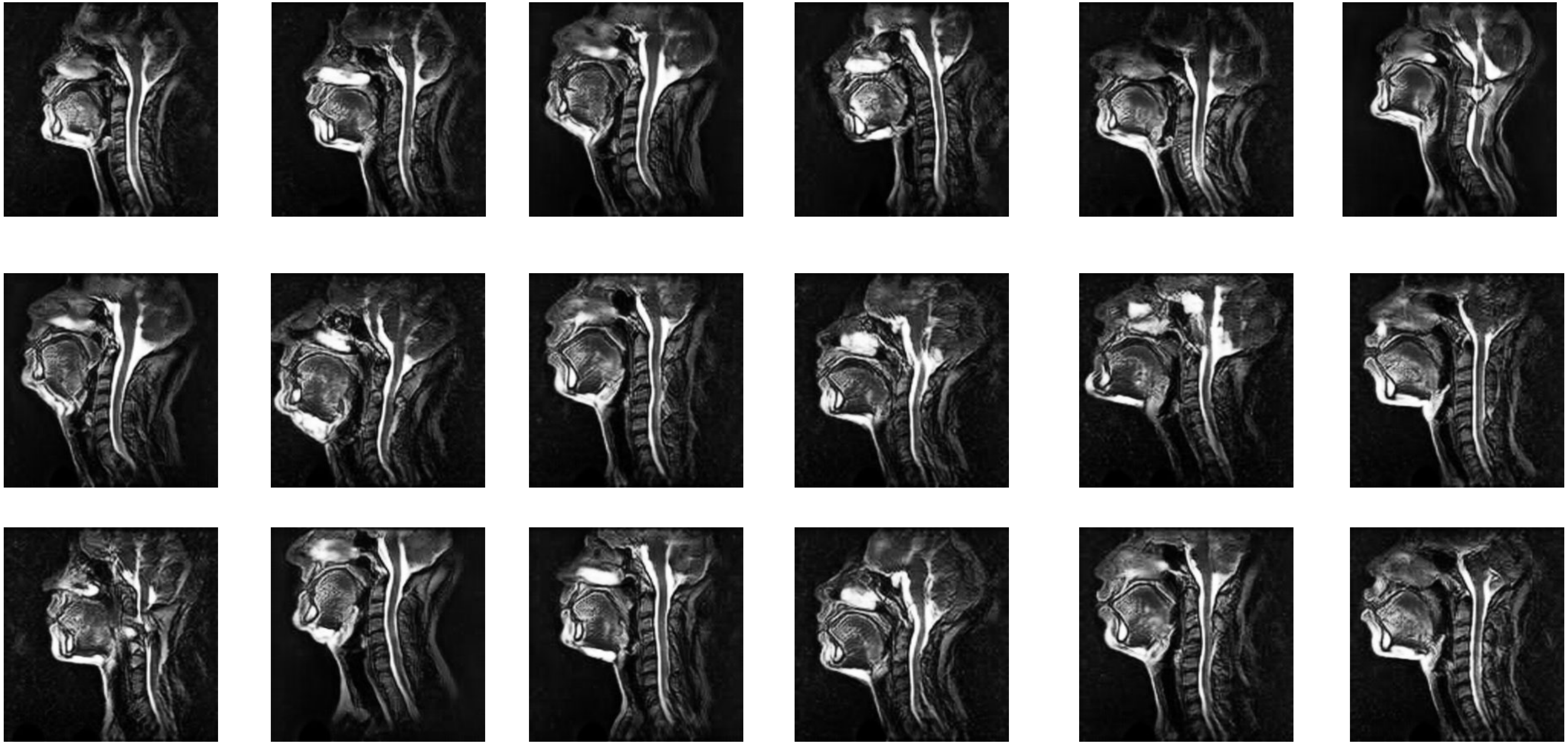


sub59



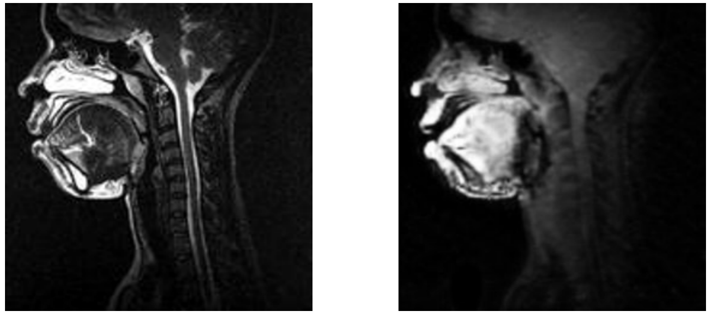
Sub 06

Results: Some fake T2 images generated by cycleGAN

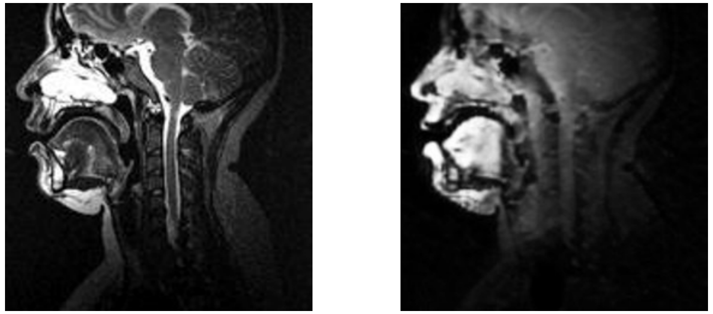


Results: (T2 to T1)

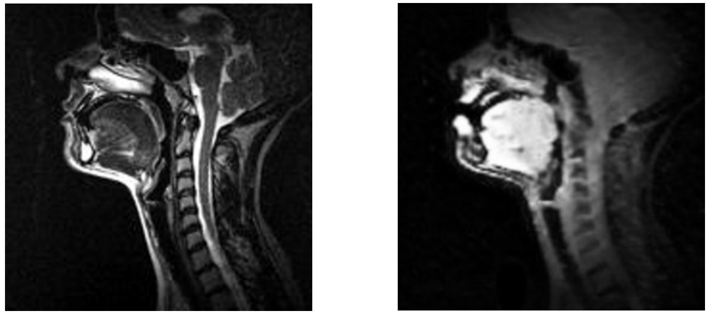
Results after 400 epoch



sub44

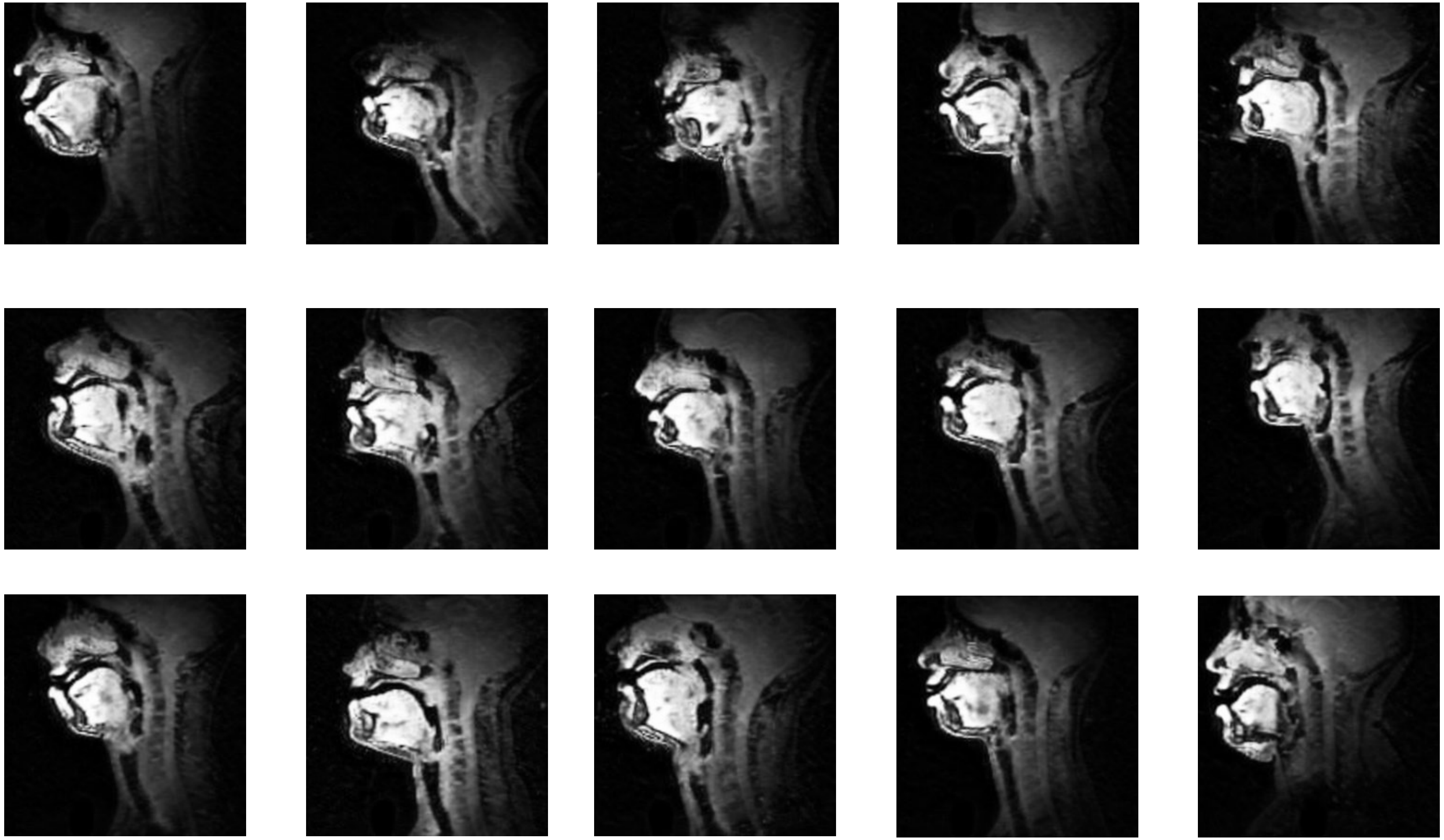


sub42



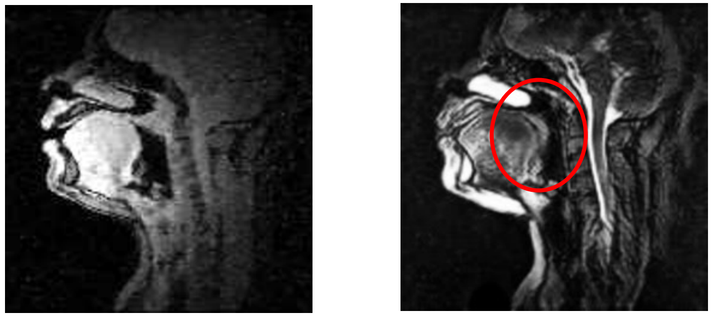
Sub31

Results: Some fake T1 images generated by cycleGAN

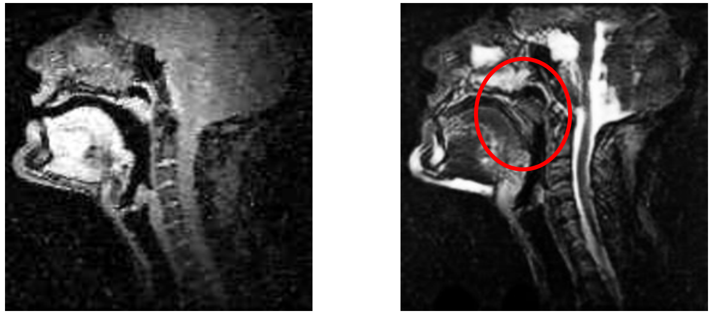


Discussion:

sub54



sub59



Sub06

Future work:

- Collect new dataset from our UIOWA facility
- Do some literature review
- May need custom loss functions for the task
- May add structure-consistency loss to constrain structural consistency between input and synthetic images.
- Check the style transfer (velum position transfer) from styleGAN
- May be use paired dataset instead of unpaired dataset

Thank you