MR-AC using deep learning

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Introduction

To obtain accurate positron emission tomography (PET) images, the emission data recorded need to undergo different corrections before image reconstruction. One of the correction is an attenuation correction (AC).
Hybrid PET/X-ray Computed Tomography (CT) systems provides coregistered CT and PET image volumes. The translation of the CT transmission data into linear AC is trivial and precise.
Due to superior soft tissue contrast offered by magnetic resonance imaging (MRI) and the desire to reduce unnecessary radiation dose, the radiology community's interest to replace CT with MRI has been rapidly growing.
Create a reliable MRI based AC (MR-AC) is a challenging problem.
This project will investigate how to solve it using conditional GANs (cGANs).

Data

The data contains PET/MR and PET/CT scan of a single patient

- 108 coronal slices of both PET/MR scan (Signa PET/MR: GE healthcare) using a two-point Dixon MR sequence performed 120 minutes and a PET/CT scan (mCT: Siemens healthcare). Both MR and CT are 600X600 color images.
- 89 transverse slices of zero-TE (ZTE) MR sequence images as the input images and the corresponding CT images. Both MR and CT are 59X59 color images.

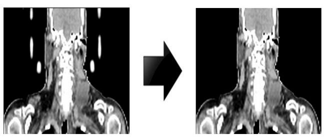

Figure 1: The data were preprocessed to remove artifacts

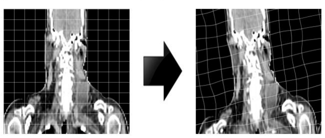

Figure 2: Elastic transformation was used for data augmentation

All the images were then reshaped to be 256X256 color images.

cGANs

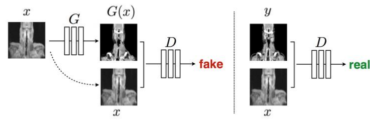

Figure 3: The discriminator, D, learns to classify between fake (synthesized by the generator) and real images. The generator, G,learns to fool the discriminator

The objective :

$$\mathcal{L}_{cGAN}(G,D) = \mathbb{E}_{x,y}[logD(x,y)] + \mathbb{E}_{x,z}[1 - logD(x,G(x,z))]$$

$$\mathcal{L}_{L1}(G) = \mathbb{E}_{x,y,z}||y - G(x,z)||_1$$

$$G^* = \underset{G}{\operatorname{argmin}}\,\underset{D}{\operatorname{argmax}}\,\mathcal{L}_{cGAN}(G,D) + \lambda\mathcal{L}_{L1}(G)$$

Models

Two different architectures were tried for the generator:

- U-net - an encoder-decoder with skip connection.
- FusionNet - a deeper network with residual layers in each U-net level.

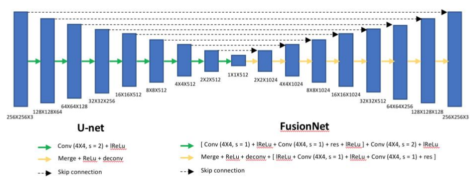

Figure 4: The two Generators architectures

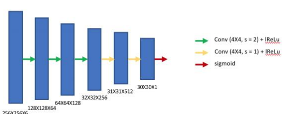

Figure 5: The Discriminator architecture

The networks also used batch normalization, and the two Generator architecture used dropout.

Results

To optimize the network, minibatch SGD and Adam solver ($alpha = 0.0002$, $\beta_1 = 0.5, \beta_2 = 0.999$) were used.

Generator architecture, train data	L_1 norm (train)	L_2 norm (train)	L_1 norm (dev)	L_2 norm (dev)
U-net, prepossessed data	14.266	1023.166	18.291	1313.33
FusionNet, prepossessed data	13.984	939.038	16.276	1113.1
FusionNet, prepossessed and augmented data	11.431	678.669	**15.098**	**936.345**

*The average power of the train set is significantly lower than the dev set.

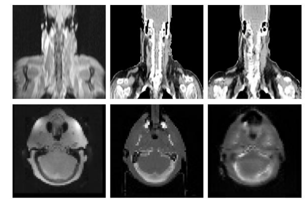

Figure 6: Left: input image - MR. Middle: target image - CT based attenuation. Right: output image - Generator output

Discussion & Future plans

- The dataset is very limited. Using elastic transformation for Data augmentation certainly helped. That being said, it's important to test performance on a new patient's data to evaluate performance.
- Model training is very time consuming (even when using a GPU). Therefore hyperparameter optimization is quite difficult. Due to time limitations, hyperparameter tuning effort was limited, and the results presented here might be further improved.
- The obtained results, using pis2pix default architecture and parameters, are quite impressive. The FusionNet generator further improved those results, As expected from a deeper network.

References

1. X Han. Mr-based synthetic ct generation using a deep convolutional neural network method:. Medical Physics, 44(4):14081419, 2017.
2. Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, and Alexei A Efros. Image-to-image translation with conditional adversarial networks. arxiv, 2016.
3. T. M. Quan, D. G. C. Hildebrand, and W. Jeong. Fusionnet: A deep fully residual convolutional neural network for image segmentation in connectomics. CoRR, abs/1612.05360, 2016.