Pseudo-contrast CTA derived from non-contrast CT using cGANs

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Deep Learning for Medical Imaging

Background

Data-driven decision making is transforming healthcare. However, machine learning models often require significant amounts of data to be trained effectively and produce high-quality outputs. In healthcare, big data is not always available and its a problem to design deep learning models that can generalise. Therefore, generating high-quality synthetic datasets could be an interesting idea for data augmentation. Building a generative model that produces high quality data with low bias is quite challenging. One needs to be cautious and rigorous in the evaluation of the model.

Cardiac contrast-enhanced computed tomography angiography (CTA) is increasingly used to assess heart anatomy and function in various cardiac conditions like coronary artery disease or valvular heart disease. This acquisition process involves ionizing radiation and contrast agent administration, which can harm kidneys and cause allergic reactions. Non-contrast CT (NCCT) scans of the heart primarily evaluate calcification but have limited clinical use. That said they are acquisitions that are made in most of cardiac CT examinations and are safer than their CTA counterpart. Being able to sythesise pseudo-CTA scans from NCCT like in [1], but this time in the cardiac case, could assist radiologists in interpreting CT images, potentially resulting in improved diagnoses, while avoiding invasive acquisitions.

Main contribution

The main contribution of the paper is to present a new application of the cGAN pix2pix [2] to generate **cardiac** pseudo-CTA slices with high contrast derived from non-contrast CT slices.

Dataset

The study comprised of 91 patients with suspected CAD who underwent CTA at a high-volume cardiac imaging facility within a tertiary clinical center. Both the contrast and non-contrast datasets were reconstructed at mid-diastole (60–70% of the cardiac cycle). The dataset was split into two subsets: training ($N_{train} = 72$) and testing ($N_{test} = 19$).

Method

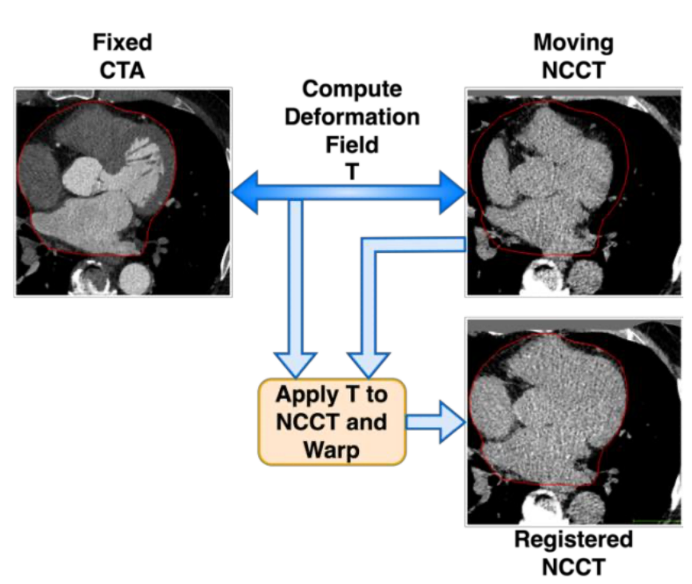

Figure 1: Registrating process

Preprocessing Authors register the NCCT to CTA using multi-resolution B-splines non-rigid transformation. They also homogenize the data in the range $[-1, +1]$. Using

Architecture The generative model is a pix2pix architecture, composed of a generator and a discriminator. The generator is a U-Net based model and the discriminator is a convolutional neural network.

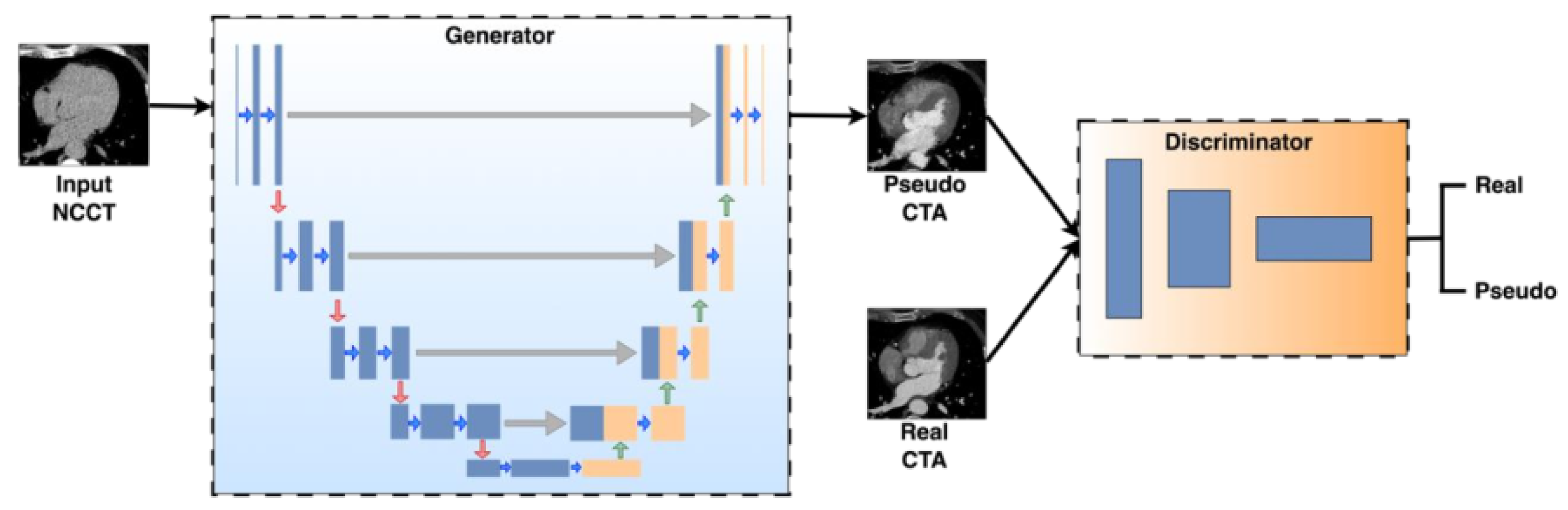

Figure 2. Pix2Pix architecture.

Figure 2: Pix2pix architecture

Loss The loss used to train the networks is composed of three terms :

$$\mathcal{L}_{GAN}(G, D) = \mathbb{E}_{x,y}[\log D(x, y)] + \mathbb{E}_{x,z}[\log D(x, G(x, z))]$$

,

$$\mathcal{L}_{L1}^{heart}(G) = \mathbb{E}[\|y_{heart} - G(x, z_{heart})\|_1]$$

and

$$\mathcal{L}_{L1}^{rest}(G) = \mathbb{E}[\|y_{rest} - G(x, z_{rest})\|_1]$$

Then the criterion is

$$\arg\max_G \arg\min_D \mathcal{L}_{GAN}(G, D) + \alpha \mathcal{L}_{L1}^{heart}(G) + \beta \mathcal{L}_{L1}^{rest}(G)$$

with $\alpha \gg \beta$ to give more importance to the heart region.

Validation and results

The metrics used to evaluate the quality of the synthetic data are Fréchet inception distance (FID). The principle au FID is to compare statistics from features of real and synthetic images computed with the model Inception V3 trained on ImageNet. Authors used ablation studies for hyperparameter tuning and chose the model with the best FID score.

Table 1. Ablation studies for model selection.

Ablation Name	Batch Size	Normalization	Learning Rate G	Learning Rate D	α	β	Optimizer
0004_pix2pix_local	8	Batch	0.0002	0.0002	20	5	Adam
0005_pix2pix_local	8	Batch	0.0002	0.0002	200	50	Adam
0006_pix2pix_local	8	Instance	0.0002	0.0002	20	5	Adam
0007_pix2pix_local	8	Instance	0.0002	0.0002	200	50	Adam
0005_pix2pix_local_001	8	Batch	0.0002	0.0002	1000	100	Adam
0005_pix2pix_local_002	16	Batch	0.0002	0.0002	1000	100	Adam
0005_pix2pix_local_003	16	Batch	0.0001	0.0004	1000	100	Adam
0005_pix2pix_local_004	16	Batch	0.0002	0.0002	1000	100	SGD
0005_pix2pix_local_005	16	Batch	0.0002	0.0002	1000	100	SGD

Figure 3: Ablation study for hyperparameter tuning

Synthetised CTA As we can see above, the model proposed in tha paper seems to improve the contrast of the NCCT.

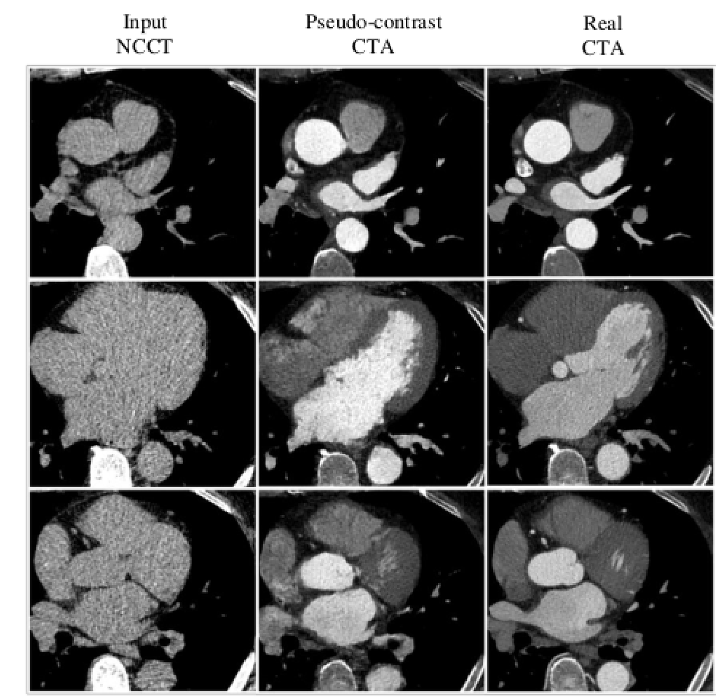

Figure 4: Synthetised images for the test dataset.

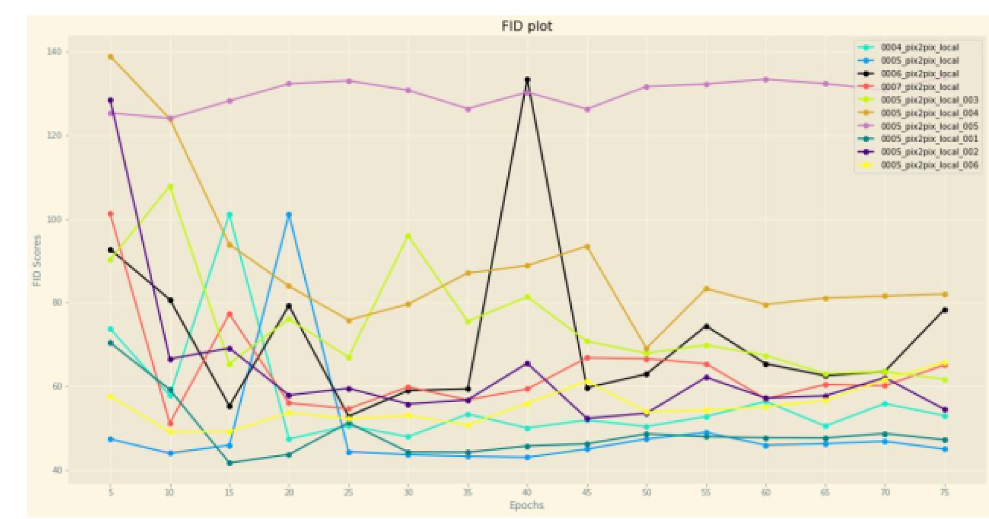

Figure 3. FID at every checkpoint on all the models trained for model selection.

Figure 5: These curves show the FID of each model during an ablation study for model / hyperparameter selection

Between	FID ↓	PSNR (Mean±SD in dB) ↑	MAE (Mean±SD) ↓
NCCT and contrast CTA	57.38	4.17±2.25	100.85±25.99
Pseudo-contrast CTA and contrast CTA	41.78	7.05±1.63	76.89±13.58

Figure 6: Evaluation of their method against no transformation.

Conclusion

The authors share a new application of the pix2pix architecture to add contrast to cardiac NCCT scans. As we can see above, results on the test set seem good, but unfortunately were not evaluated in a real life scenario. As this evaluation was done in [1] for whole chest CTs, we can hope for similar usability in the cardiac case.

References

[1] Cho-Y.J. Ha J.Y. et al. Choi, J.W. Generating synthetic contrast enhancement from non-contrast chest computed tomography using a generative adversarial network. *Nature Sci Rep 11*, 2021.

[2] Jun-Yan Zhu et al. Phillip Isola. Image-to-image translation with conditional adversarial networks. *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2017.