Conditional GAN is All You Need for MR2CT

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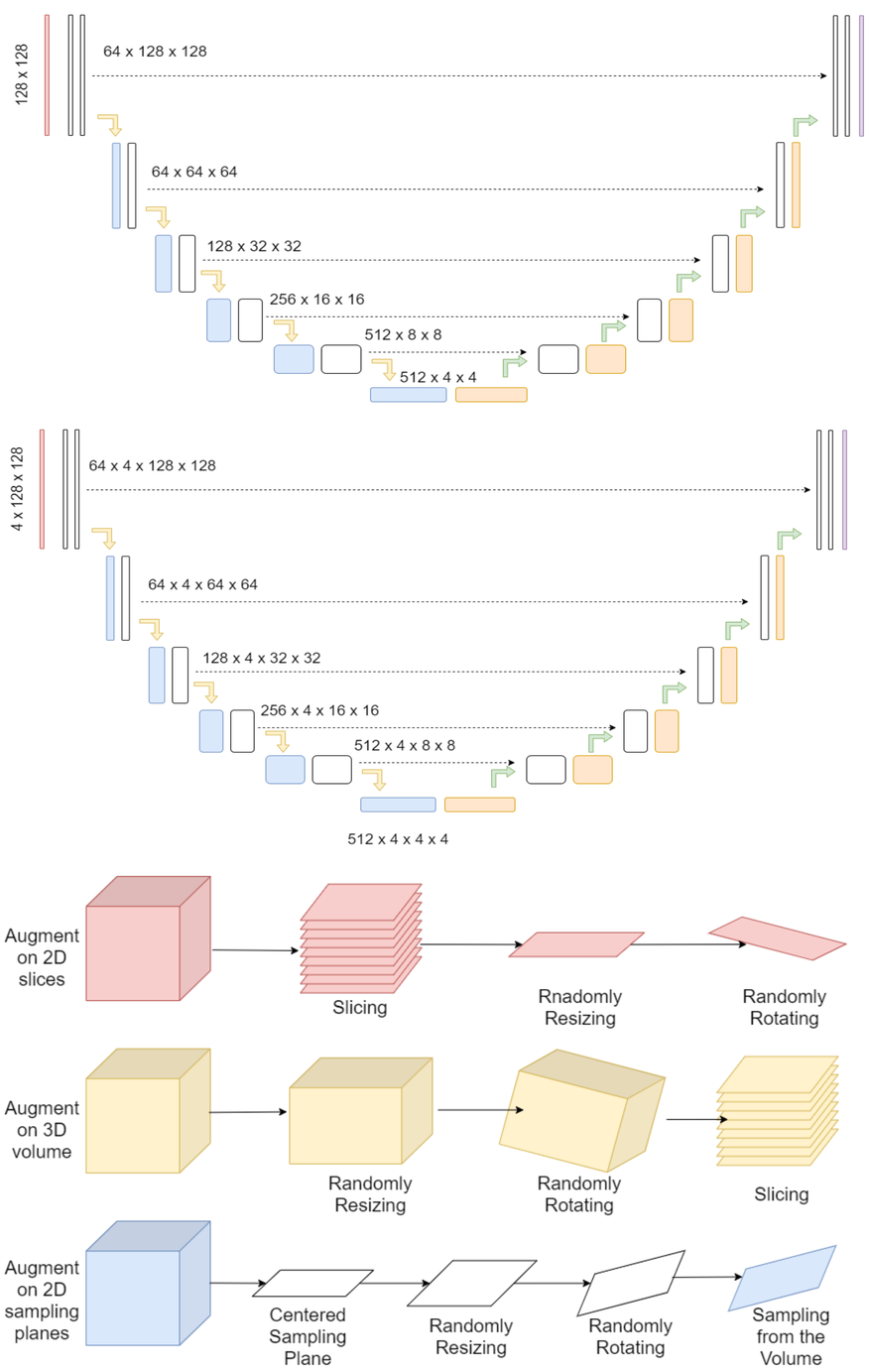
Motivation and Objectives

- While convolutional networks have seen a decline in focus due to emerging methodologies, their performance relative to other methods for the MR2CT task remains inadequately investigated. To ensure an unbiased comparison, we evaluate both techniques under consistent conditions.
- There exists a debate concerning the superiority of 3D networks over their 2D counterparts. In this study, we examine the performance of 2D, 2.5D, and 3D networks.
- Data augmentation for medical images, especially in 2D networks, presents challenges. Traditional techniques might merely segment images along the z-axis, subsequently applying augmentations to each section. In our research, we introduce an innovative sampling plane augmentation approach designed to address this limitation effectively.

Methods and Materials



The structure of the 2D network

The structure of the 2.5D network

Different data augmentation strategies used for medical imaging in DL.

Historically, data augmentation techniques have been designed to operate either on 2D slices or the entire 3D volume. While the 2D slice approach is straightforward to implement, its augmentation is limited to individual slices. On the other hand, the true 3D augmentation technique, although comprehensive, applies uniform augmentation across all slices within a given volume, compromising the element of randomness. In our approach, we suggest randomly augmenting the sampling plane. This method seeks to integrate the benefits of both aforementioned strategies.

Key Results

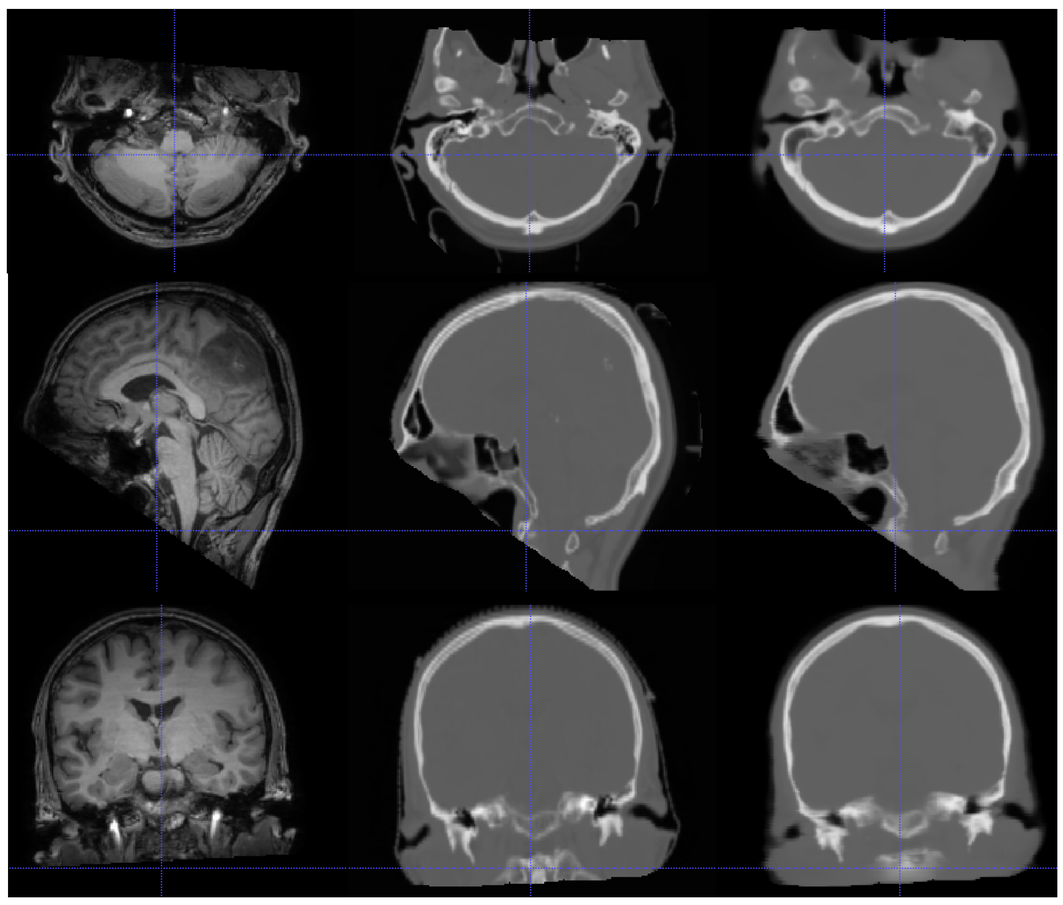
- Given the anatomic difference, we train **separate networks** for brain and pelvis.
- For each region, the dataset is split by **150/30** for training and validation.
- Each model is trained **100 epochs** and then evaluated on the validation set.

Table 1. Evaluation of different augmentation parameters on brain.

Net width	Rotation	Resizing	MAE	PSNR
Thin	[0, 0]	[0, 0]	82.03	23.20
Thin	[-5, 5]	[-30, 30]	80.94	24.33
Thin	[-10, 10]	[-30, 30]	80.75	24.35
Thin	[-20, 20]	[-30, 30]	80.19	24.41
Thin	[-30, 30]	[-30, 30]	79.70	24.45
Thin	[-30, 30]	[-5, 5]	81.10	24.34
Thin	[-30, 30]	[-10, 10]	82.52	24.24
Thin	[-30, 30]	[-20, 20]	80.03	24.47
Thin	[-30, 30]	[-30, 30]	79.07	24.46
Wide	[-30, 30]	[-30, 30]	77.94	24.60

Table 2. Evaluation of different input dimension and shapes.

Dim	Batch size	Input size	MAE	PSNR
2D	64	256 * 256	72.15	25.32
2D	64	128 * 128	74.08	25.20
2.5D	16	4 * 128 * 128	67.58	25.90
2.5D	8	8 * 128 * 128	69.32	25.72
2.5D	4	16 * 128 * 128	69.69	25.71
3D	16	16 * 64 * 64	70.58	25.66
3D	16	32 * 32 * 32	72.97	25.47



MR real CT syn CT

Figure 1. Visualization of an exemplar case.

Conclusion

- Convolutional networks continue to be effective in the task of MR-based CT synthesis.
- The 2.5D network demonstrates superior performance for the conditional GAN, surpassing both 2D and 3D networks.
- Data augmentation is imperative for medical imaging datasets. Our novel augmentation technique focuses on the sampling plane, as opposed to individual sampled slices, with its effectiveness validated through experiments.

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