Optimizing the generation of pseudo-CT from MRI based on a highly efficient 3D neural network

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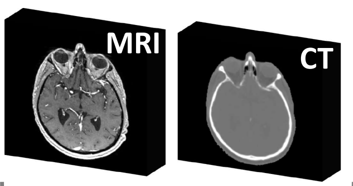
Introduction

Magnetic Resonance Imaging (MRI) has become increasingly popular these last few years, since it offers an excellent soft tissue contrast. This imaging modality is required during a brain tumor radiotherapy treatment to complement Computed Tomography (CT) imaging. Yet, this dual acquisition implies an image registration, process which was proved to induce errors up to 2mm (1) and thus to increase margins. As a result, the generation of pseudo Computed Tomography (pCT) from MRI appears to be of most interest for an optimized patient safety. This study aimed at evaluating key parameters: the training set size, MRI input sequences namely T1 weighted MRI (T1) or contrast enhanced T1 MRI (T1-Gd), MRI standardizations namely Histogram-Based (HB) (2), Zero Mean-Unit Variance (ZMUV) (3), White Stripe (WS) (4), No Standardization (NS), N4 bias field filter application (5) and network architectures, i.e. HighResNet (default) (6) and 3D Unet (7), impacts on the pCT quality.

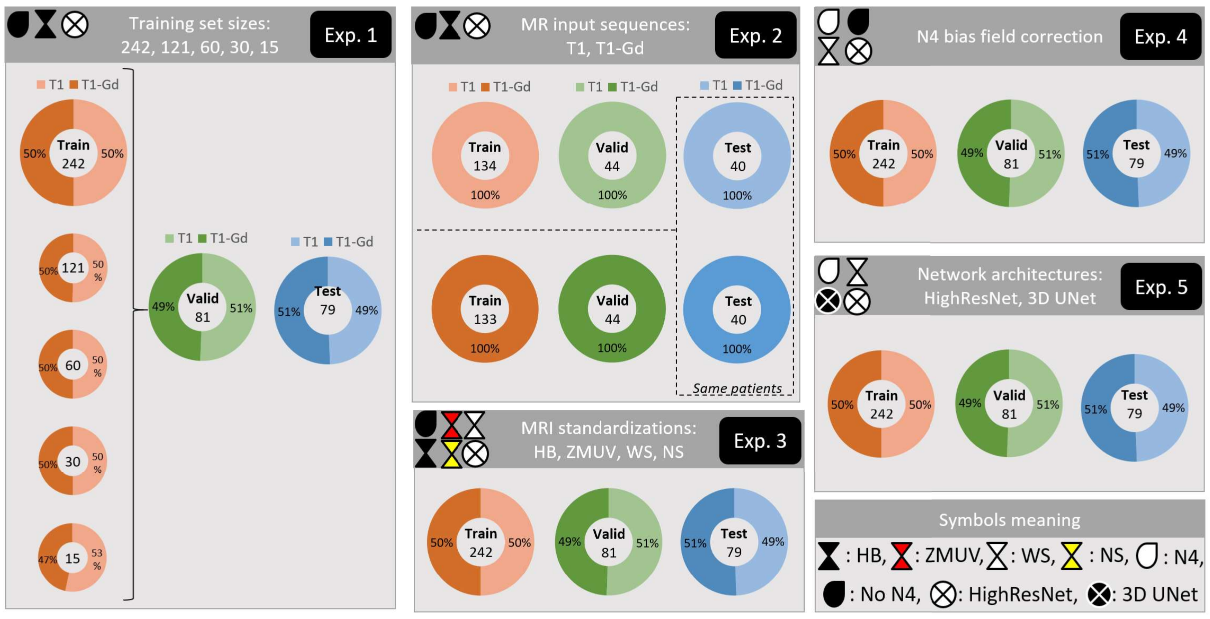
Material and Methods

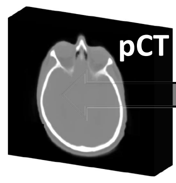


201 couples of CT/T1 and 201 CT/T1-Gd

Preprocessing:

- Rigid registration
- Linear resampling to 1mmx1mmx1mm voxels
- Hounsfield Units (HU) and MRI intensities clip





- Mean Absolute Error (MAE) defined as: $\frac{1}{N} \times \sum_{i=1}^{N} |Intensity\ CT(i) - Intensity\ pCT(i)|$

With N the total number of voxels. MAE was computed in the whole head, air, bone and water areas.

- Dosimetry: Transfer of the initial plan on the pCT. Pencil beam dose calculation performed with iPlan (BrainLab). Calculations of differences in Dose Volume Histograms (DVH) of the planning target volume and 3D global gamma indexes (1%/1mm, 2%/2mm, 3%/3mm) without dose threshold.
- Wilcoxon tests to assess the significance of the observed differences. Threshold set to 0.05.

Results and Discussion

- Experiment 1 proved that generating pCT with all the available cases for training resulted in higher pCT quality (Figure 1).
- Regarding experiment 3, obtained pCT with the HB standardization, are presented in Figure 2. WS slightly outperformed HB, ZMUV and NS in terms of MAE only (Table 1).
- Experiments 2, 4, 5 led to similar performances regardless of the adopted approach (Table 1).

	Head MAE	Head MAE p-values	3%/3mm gamma index	3%/3mm gamma index p-values
Experiment 2	T1 : 84HU +/- 25HU T1-Gd : 87HU +/- 28HU	**p-value = 0.0047**	T1 : 99.84% +/- 0.18% T1-Gd : 99.85% +/- 0.18%	**p-value = 0.044**
Experiment 3	HB : 92HU +/- 23HU ZMUV : 83HU +/- 22HU WS : 78HU +/- 22HU NS : 96HU +/- 23HU	**p-values WS/HB, WS/ZMUV, WS/NS < 0.0001**	HB : 99.86% +/- 0.16% ZMUV : 99.83% +/- 0.19% WS : 99.85% +/- 0.17% NS : 99.86% +/- 0.18%	p-values WS/HB, WS/ZMUV, WS/NS > 0.14
Experiment 4	Without N4 : 78HU +/- 22HU With N4 : 81HU +/- 22HU	**p-value < 0.0001**	Without N4 : 99.85% +/- 0.17% With N4 : 99.83% +/- 0.19%	**p-value = 0.012**
Experiment 5	HighResNet : 81HU +/- 22HU 3D UNet: 90HU +/- 21HU	**p-value < 0.0001**	HighResNet : 99.83% +/- 0.19% 3D UNet: 99.74% +/- 0.24%	**p-value < 0.0001**

Table 1: Head Mean Absolute Error (MAE), 3%/3mm gamma indexes and p-values for experiments 2, 3, 4 and 5.

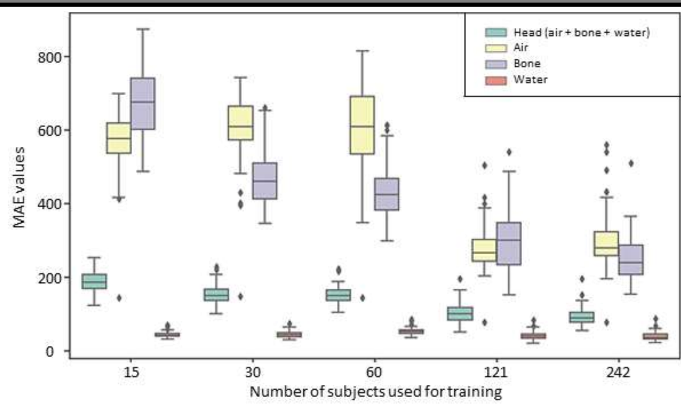


Figure 1: Evolution of the MAE when modifying the number of subjects in the training set during experiment 1.

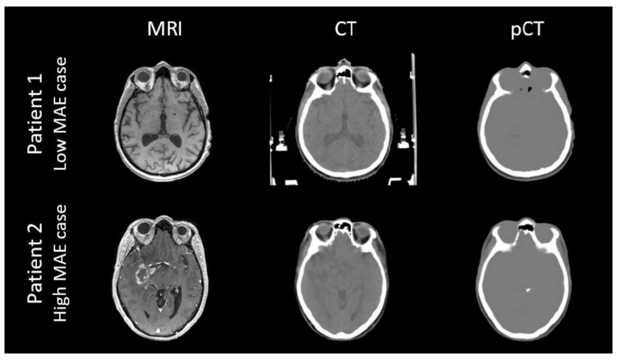


Figure 2: MRI, original CT and pCT with soft tissues windows and levels respectively for Patient 1 (Head MAE = 64HU) and Patient 2 (Head MAE = 110HU) derived from experiment 3 with HB standardization.

Conclusion

The goal of the study was to evaluate the impact of key generation parameters on pCT quality. Results, derived from experiments based on a large cohort composed of 402 patients, proved that the largest training set size provided the best quality pCT. Regarding the MR input sequence, standardization, bias field application and network architecture, no major dosimetry differences were obtained suggesting the clinical equivalence of the studied approaches. Future work will include the generation of pCT combined with a segmentation task and the extension of the presented model to another anatomical site, such as pelvis.

Acknowledgement and References

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