Joint Synthesis of WMn MPRAGE and Parameter Maps Using Deep Learning and an Imaging Equation

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1 Introduction

The paper addresses the challenge of enhancing the contrast in T1-weighted MRI scans to better distinguish thalamic nuclei, essential for diagnosis purposes. It presents a method for synthesising White Matter Nulling (WMn) MPRAGE and its corresponding CSFn MPRAGE images form commonly acquired MRI modalities like T2 w and T2w FLAIR images through integration of deep learning and imaging equation by leveraging quantitative parameter maps (PD and T1 maps) as intermediate steps in the synthesis process [2].

2 Paper positioning with respect to the state of the art

Distinct from existing methods, this paper's methodology synthesizes both WMn and CSFn MPRAGE images by leveraging PD and T1 maps derived from commonly acquired T2w and T2w FLAIR images. It is one step a head the direct synthesis approach of Umapathy et al. [3], which doesn't use intermediate maps, and the method of Moya-Sáez et al. [1], which focuses solely on generating parameter maps without specifically targeting WMn MPRAGE image synthesis. Utilizing a deep learning-based encoder (U-Net architecture), the process starts by synthesizing PD and T1 maps from the input images, then applying an imaging equation to generate the desired MPRAGE images. This end-to-end supervised method ensures that the synthetic images are quantitatively accurate and qualitatively similar to actual WMn MPRAGE images, thus providing significant clinical value, especially for thalamic nuclei segmentation. Thus overcoming limitations of other existing approaches that might require images that are not always available in clinical settings or that are not very efficient in synthesizing WMn MPRAGE images. Therefore, the main contributions of the paper as the authors underline it, is the incorporation of the imaging equation if the deep learning based synthesis process of the WMn images

3 Methodology

The synthesis process introduced by the authors is implemented as a two-part model. The first part involves using T2w and T2w FLAIR images to generate PD and T1 maps via a U-Net architecture. The second part applies an imaging equation to these maps to synthesize both WMn and CSFn MPRAGE images.

They adopted two training strategies as for where to incorporate the guidance during synthesis: one is supervised with the two MPRAGE images in an end-to-end fashion thus focusing directly on image synthesis, here they minimize this loss function: $\mathcal{L}_{\text{total}} = c \times \mathcal{L}_{\text{CSFn}} + d \times \mathcal{L}_{\text{WMn}}$ where $\mathcal{L}$ is the ℓ_1 loss of different terms, here for CSFn and WMn MPRAGE generated images respectively. On the other hand the second strategy is supervised with the PD and T1 maps as well as the two MPRAGE images, focusing on integrating quantitative parameter maps in the synthesis process, in terms of objective function, they are minimizing the following loss function:
$\mathcal{L}_{\text{total}} = a \times \mathcal{L}_{\text{PDM}} + b \times \mathcal{L}_{\text{T1M}} + c \times \mathcal{L}_{\text{CSFn}} + d \times \mathcal{L}_{\text{WMn}}$ where $\mathcal{L}_{\text{PDM}}$ and $\mathcal{L}_{\text{T1M}}$ are loss terms correspondint to parameter maps.

The approach is validated using MR tissue contrast neuroimages from 18 subjects, comparing the performance of the model under both strategies against existing literature methods through metrics like PSNR and Dice scores for thalamic nuclei segmentation using THOMAS software.

3.1 Results

The results highlight that training Strategy 1 yields superior performance in terms of Peak Signal-to-Noise Ratio (PSNR), with the mean PSNR across three test subjects reaching 28.44 dB compared to the Umapathy et al. and Moya-Sáez et al. methods, which achieved mean PSNRs of 28.06 dB and 27.07 dB, respectively . Visually, the synthesized WMn MPRAGE images and T1 maps produced by the proposed method are nearly indistinguishable from the ground truth images.

Additionally, the authors performed thalamic nuclei segmentation using the THOMAS software on both the acquired and synthetic WMn MPRAGE images. The Dice scores, used to evaluate segmentation accuracy, were consistently higher when using the synthetic WMn MPRAGE images generated by Strategy 1 of the proposed method compared to the synthetic images from other methods. Furthermore the authors affirm that in the absence of acquired WMn MPRAGE image it is better to do segmentation using their generated WMn MPRAGE than using acquired CSFn MPRAGE. The results of segmentation acquired CSFn MPRAGE and synthetic WMn MPRAGE are shown in Figure**??**

4 Critical assessment

4.1 Paper strengths

- Novel Method: The paper introduces an innovative two-part model that synthesizes WMn MPRAGE images and parameter maps from commonly acquired MRI images using deep learning and an imaging equation. This approach combines the advantages of both worlds: the flexibility and learning capabilities of deep learning with the precision of model-based imaging equations.
- Rigorous Methodology: The authors employ rigorous methods, including skull stripping, bias field correction, and intensity normalization, to process the MR images before using them to train their model. The use of paired preprocessing to preserve the relative intensities between images is particularly noteworthy, as it ensures that the derived PD and T1 maps are consistent with the input contrasts.
- Rigorous Experiments: Their experiments are methodologically sound, involving cross-validation with three instances of the model to minimize overfitting, and they report comprehensive quantitative results, including PSNR for image quality assessment and Dice scores for segmentation performance.

4.2 Paper weaknesses

- Unexplored Potentials: The paper sets out to improve the segmentation of thalamic nuclei using synthesized WMn MPRAGE images, but it does not fully explore the potential of using both WMn and CSFn images to generate MTI images at different inversion times, despite mentioning this at the beginning of the article. In addition we see that there lacks a state of the art section to clearly situate this work among ohter existing methods.
- Evaluation Method Concerns: The use of acquired WMn segmentation results as the reference standard might introduce bias, in case the THOMAS algorithm gives erroneous segmentation of the reference, in the segmentation results given for other methods.
- Limited Experimentation: While the model shows promise, the experiments are limited to a single cohort of 18 subjects. A broader evaluation across diverse datasets could provide a more robust validation of the method's efficacy. Finally, for reproduciblity and transparency sake, we notice that there are not enough details about the U-Net model model they used or the hyperparametres they used for training neither how they implmented the imaging equation.

4.3 Recommendations for Improvement

- Extensive Validation: Future work should consider a larger, more diverse cohort to validate the model, which would boost the confidence in its generalizability and clinical applicability.

- Comparative Analysis: A deeper exploration of the benefits of generating CSFn images when they are not utilized for MTI image generation in the experiments could provide valuable insights into the model's capabilities and limitations.
- End-to-End Training Exploration: The authors could further investigate the impact of their end-to-end training strategy versus traditional methods that rely on pre-computed parameter maps, which could help clarify the advantages and disadvantages of each approach.
- Finally the authours could either put a reference to their code or give more details on their implementation to allow the reader to explore the methods more in depth and evaluate the validity of the presented results.

References

[1] C. Moya-Sáez et al. A deep learning approach for synthetic mri based on two routine sequences and training with synthetic data. *Computer Methods and Programs in Biomedicine*, 210:106371, 2021.

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[3] L. Umapathy et al. Convolutional neural network based frameworks for fast automatic segmentation of thalamic nuclei from native and synthesized contrast structural mri. *Neuroinformatics*, 20(3):1–14, 2021.