

Joint synthesis of WMn MPRAGEand parameter maps using deep

learning and an imaging equation

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Background

- a. The paper deals with a methodological topic in neuroimaging, specifically the synthesis of White Matter nulled (WMn) Magnetization-Prepared Rapid Gradient Echo (MPRAGE) images from existing contrast-weighted MR image
- b. The medical problem being addressed is the limited availability of WMn MPRAGE images in clinical datasets, despite their importance in highlighting certain brain structures, such as thalamic nuclei. This is important for accurate diagnosis and treatment planning in neurological disorders.
- c. The state-of-the-art on this problem involves methods that either directly synthesize WMn MPRAGE images from other contrasts or compute parametric maps to achieve similar results. However, these approaches may have limitations in terms of accuracy, efficiency, or generalizability.
- d. Limitations of existing approaches may include reliance on complex imaging equations, lack of robustness to variations in imaging protocols, or difficulty in obtaining ground truth data for training

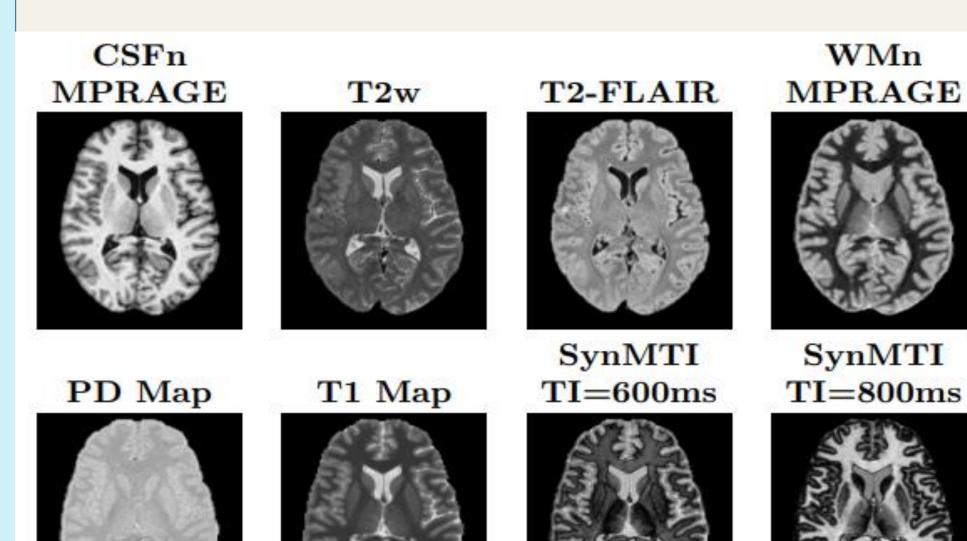


Figure 1: A slice of the preprocessed data and synthetic MTI images.

Objectives and main contributions

The objective of this paper is to develop a deep learning-based method for synthesizing WMn MPRAGE images from existing contrast-weighted MR images, addressing the limitations of current approaches. The principal contribution of the paper lies in its approach to synthesizing WMn MPRAGE images by combining deep learning with imaging equations, technique that not only produces highquality synthetic images but also extracts valuable quantitative parameter maps in the process. This methodology stands out for its ability to generate images that can effectively segment the thalamic nuclei, which is further demonstrated through rigorous validation procedures and comparison with existing methods.

- 1-Innovative Synthesis Technique:
- •The paper introduces a novel method to create White Matter nulled (WMn) MPRAGE images from existing data, addressing a common limitation in clinical datasets.
- They propose a unique two-part model that combines deep learning with imaging equations, allowing for the generation of WMn images from standard contrast-weighted MR images.

2-Integration of imaging equation:

 By incorporating imaging equations into their deep learning model, the authors achieve precise synthesis of MR images with specific acquisition parameters, enhancing image quality and fidelity. Their approach also generates accurate quantitative parameter maps, which previous methods lacked, thereby improving the overall performance of image synthesis.

3-Advanced Training and Evaluation Method: •The authors employ diverse training strategies and loss functions ensuring robust performance and reliability in image generation.

- They utilize cross-validation folds and conduct multiple instances of model training to enhance the consistency and reliability of their results.
- 4-Evaluation in Thalamic Nuclei Segmentation: •The effectiveness of the synthesized images is evaluated through thalamic nuclei segmentation, demonstrating their practical utility in clinical settings.
- Comparison of segmentation results between synthetic and real images provides valuable insights into the accuracy and reliability of the proposed approach.

Method

They adopted a two steps synthesis process: first take T2w and T2w FLAIR images as input to the U-Net then synthesize the corresponding PD and T1 map for each, second, pass them through an imaging equation to generate both CSFn and WMn images.

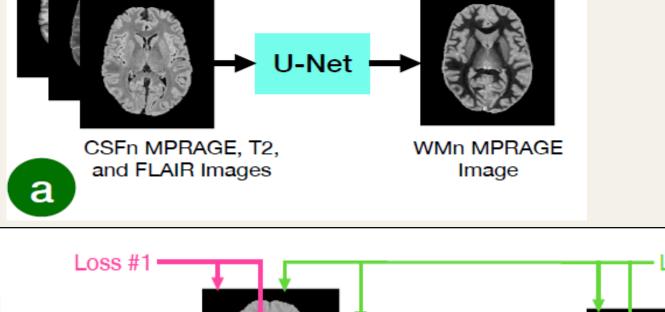
They adopted two strategies when training: 1) supervised with the two MPRAGE images in an end-to-end fashion, therefore this strategy

focuses directly on image synthesis. $\mathcal{L} = c \times \mathcal{L}_{CSFn} + d \times \mathcal{L}_{WMn}$

2) supervised with the PD and T1 maps as well as the two MPRAGE images, this strategy focuses on integrating quantitative parameter maps in the synthesis process.

 $\mathcal{L} = a \times \mathcal{L}_{PDM} + b \times \mathcal{L}_{T1M} + c \times \mathcal{L}_{CSFn} + d \times \mathcal{L}_{WMn}$

In the experiments they compared their model (with the two strategies) with the other 2 methods from literature namely: Umapathy et al. and Moya-Saez et al. Based on PSNR obtained based on PSNR obtained on 3 test subjects.



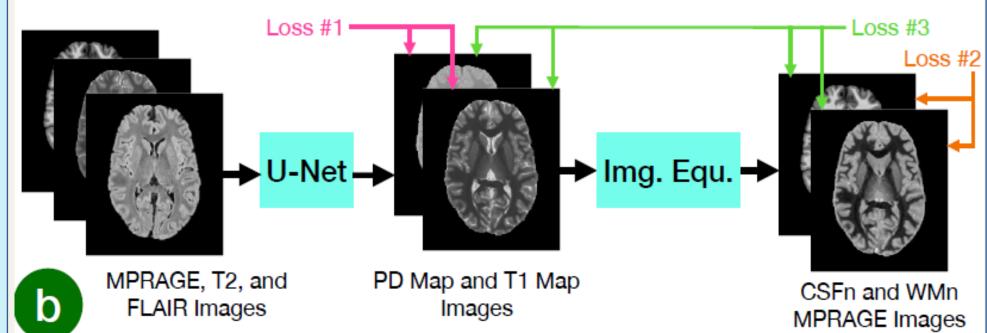


Figure 2: Methods covered in the experiments.

Then to further test the effectiveness of their synthetic process, they use THOMAS software to segment the thalamic nuclei on the synthesized images. they use the the acquired WMn segmentation result as the reference mask since it was proven to be very effective from literature, then they analyse the other segmentation results

namely: acquired CSFn, synthesized WMn (for the 4 methods) and calculated the Dice score for evaluation

Discussion

The use of WMn segmentation results as reference might lead so some biased evaluation of the other segmentations

They mentioned at the beginning of the article the use of both WMn and CSFn images to generate MTI images at different inversion times, but did not do any of that in the experiments. In this case why generating CSFn images if they are not used later.

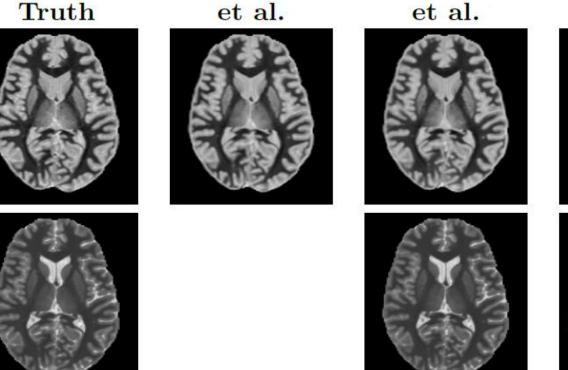
Results

- Successful development of a deep learning-based method for synthesizing WMn MPRAGE images from existing contrast-weighted MR images.
- High-quality synthetic images generated, showing visual similarity and high signal-to-noise ratio compared to ground truth images.
- Synthetic images effectively used in downstream tasks such as thalamic nuclei segmentation, highlighting their potential clinical utility in neuroimaging research and diagnosis.

| Method | Subj. #1 | Subj. #2 | Subj. #3 | $\mathrm{Mean}(\pm \mathrm{SD})$ |
|------------------------------|----------|----------|----------|----------------------------------|
| Umapathy et al. | 28.47 | 28.09 | 27.63 | $28.06(\pm 0.35)$ |
| Moya-Sáez et al. | 28.32 | 25.97 | 26.90 | $27.07(\pm 0.97)$ |
| Proposed method – Strategy 1 | 28.84 | 28.66 | 27.82 | $28.44(\pm0.44)$ |
| Proposed method – Strategy 2 | 28.71 | 28.38 | 27.65 | $28.24(\pm0.44)$ |

Table 1. WMn MPRAGE PSNR (db) for test subjects and their corresponding mean and standard deviation (SD).

Moya-Sáez

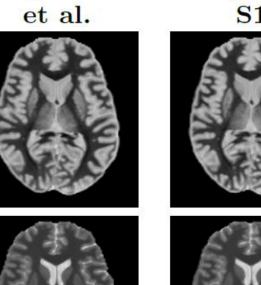


Synthetic,

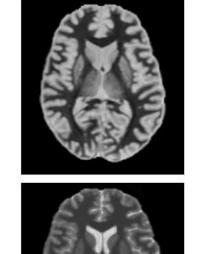
Umapathy

Ground

Acquired

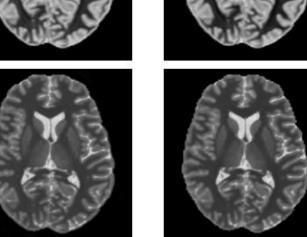


Synthetic,



Synthetic,

Proposed,



Proposed,

Acquired

CSFn

MPRAGE

Figure 3: A slice of WMn MPRAGE images (top) and T1 maps (bottom) for a test subject.

| WMn MPRAGE | Umapathy et al. | Moya-Sáez et al. | Proposed, S1 | Proposed, S2 |
|---------------|-----------------|---------------------|-----------------|-----------------|
| | | | | |
| | | | | |

Synthetic,

Figure 4: A cropped slice of the results from our segmentation experiments, overlayed on the image from which the segmentation was calculated and zoomed in on the thalamus.

Conclusion

In conclusion, the paper highlights the significance of the proposed method in addressing the limitations of existing approaches and advancing MRI imaging techniques in neuroimaging research. It emphasizes the potential clinical utility of synthetic images for improving diagnosis and treatment planning in neurological disorders.

