A soft segmentation approach for new multiple sclerosis lesion detection

Uzay Macar[1,2*], Enamundram Naga Karthik[1,2*], Charley Gros[1,2], Andréanne Lemay[1,2], Julien Cohen-Adad[1,2,3]

[1]NeuroPoly Lab, Institute of Biomedical Engineering, Polytechnique Montreal, Canada
[2]MILA - Québec AI Institute, Montréal, QC, Canada
[3]Functional Neuroimaging Unit, CRIUGM, Université de Montréal, Montreal, Canada

Introduction

Segmenting new lesions can help choose the best treatment early on. However, visually identifying new lesions in longitudinal MRI data is time-consuming and error-prone.

Successful deep learning (DL) methods exist for segmenting present [1,2] and new [3] MS lesions. Yet, challenges such as out-of-distribution generalization still remain.

We describe a soft segmentation approach inspired from [4] for automatically detecting new MS lesions. This approach fuels the pipelines we submitted for the MSSEG-2 challenge.

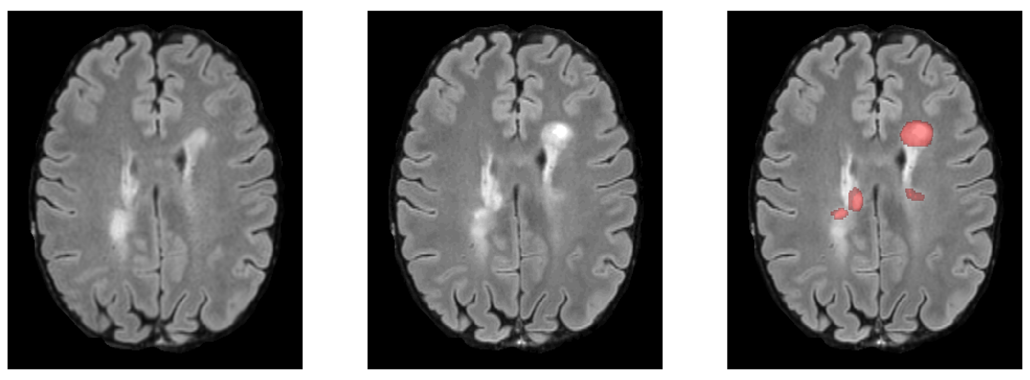

Figure 1: FLAIR images extracted from the dataset. Left: Session 1, Center: Session 2, Right: Session 2 overlaid with red ground-truth (GT) of new MS lesion segmentations.

Background

Soft Segmentation

Most DL-based segmentation pipelines are trained and evaluated with binary GTs (0 and 1 voxel values), which fail to capture uncertainty in voxel values [1], inter-expert ambiguity [5], and partial volume information (PVE) [6].

Soft GTs are formed from binary GTs during preprocessing (e.g. co-registration) and data augmentations (e.g. affine transformations) mainly due to interpolation.

SoftSeg [4] uses soft GTs instead of binary GTs in training, and reports improvements in lesion segmentation. Soft GT-trained models have better calibrated outputs. Additionally, normalized ReLU is preferred for the final activation function as opposed to sharper alternatives such as sigmoid.

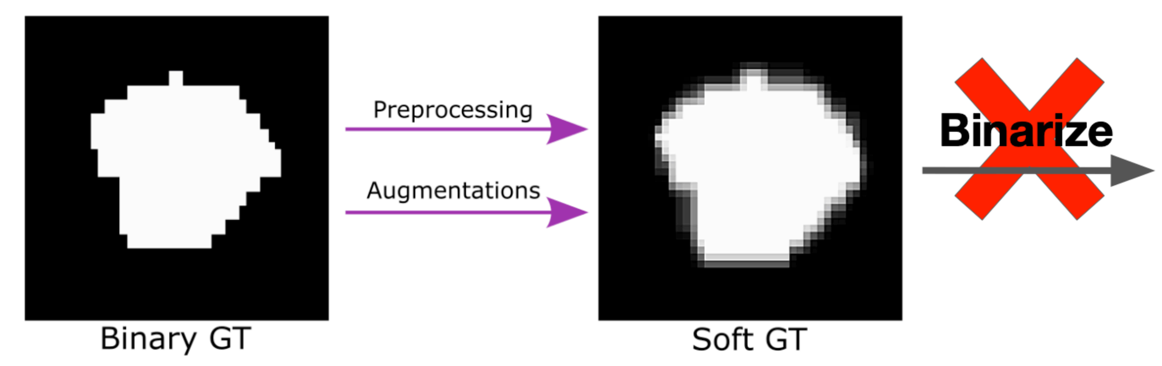

Figure 2: The main idea for soft segmentation is not binarizing the GTs after preprocessing and data augmentations. This introduces "softness" into training.

Methods

Our proposed solution consists of (i) a **robust preprocessing stage** with two-step co-registration, (ii) replacing binary GTs with **soft GTs** in training, and (iii) using **normalized ReLU** instead of sigmoid as the final activation function.

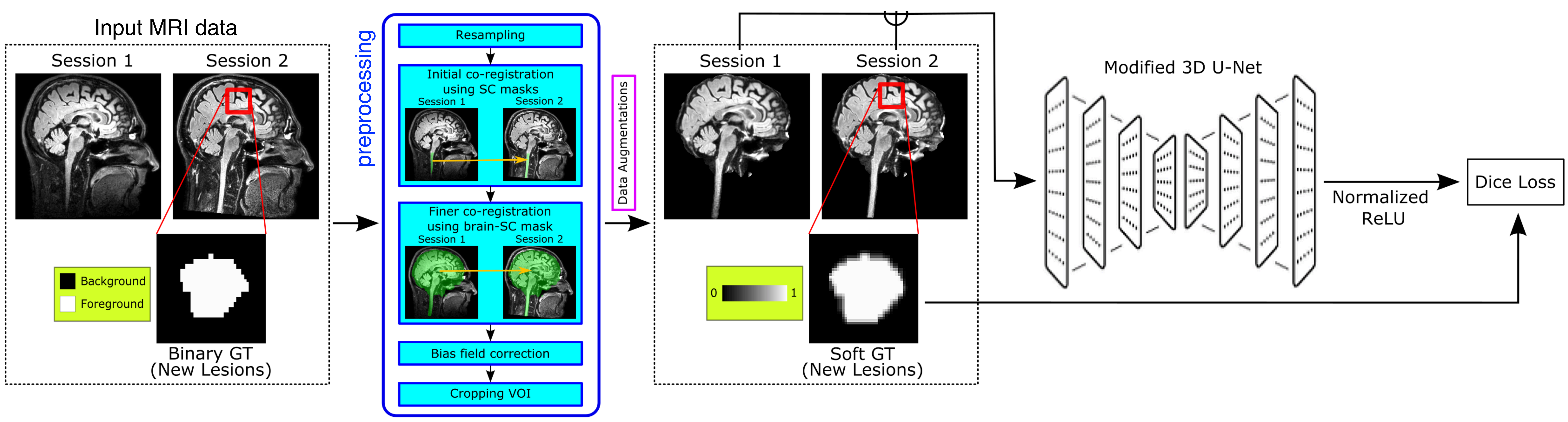

Figure 3: General methodology adopted for new MS lesion segmentation. Raw longitudinal data is passed through a preprocessing stage and augmentations which yield soft GTs. Two sessions are concatenated and propagated through a multi-channel Modified 3D U-Net. The soft GT is utilized in the loss function.

Preprocessing

Our preprocessing pipeline is fully automatic. Initially, images and GTs were resampled to 0.5mm isotropic resolution. We extracted spinal cord (SC) from *both sessions,* and performed an **initial** co-registration on *session 1* (ref: *session 2*) using SC masks.

We extracted the brain from *session 2,* and created a dilated and binarized joint brain-SC mask. A **finer** co-registration was then performed on *session 1* (ref: *session 2*) using brain-SC mask. We applied N4 bias field correction on *both sessions* masked by brain-SC mask. Finally, *both sessions* are cropped so that they only include volume-of-interest. A quality-control visualization is available at this link: https://bit.ly/3nMpXFM.

Modified 3D U-Net

Different from 3D U-Net [7], Modified 3D U-Net has (i) smaller filter sizes to prevent overfitting, (ii) instance norm. instead of batch norm. due to small batch sizes in 3D, (iii) LeakyReLU instead of ReLU between convolutional blocks, and (iv) normalized ReLU instead of sigmoid as the final activation function. The implementation can be found in ivadomed [8].

Batch size	4
Subvolume size	128x128x128 pixels^3
Learning Rate	3e-5
Dropout Rate	0.5
Loss	Dice loss
Num. Epochs	100
Sampling Strategy	Balanced

Table 1: Training parameters for Modified 3D U-Net

Pipelines

The pipelines submitted for the MSSEG-2 challenge are:

- **Pipeline #1: Modified 3D U-Net**
- **Pipeline #2: Ensemble of 3D U-Nets**
  Three Modified 3D U-Nets & One Attention 3D U-Net [9]
- **Pipeline #3: Attention 3D U-Net with Monte-Carlo (MC) Dropout**
  Attention 3D U-Net = Modified 3D U-Net + attention gates
  Used dropout during inference and averaged 10 MC samples as the final output [10]

Conclusion

For the MSSEG-2 challenge, we adopted a preprocessing stage with two-step co-registration, and Modified 3D U-Net trained with a **soft segmentation** approach.

Our code for this work can be found at: https://github.com/ivadomed/ms-challenge-2021.

Future work will focus on developing better sampling strategies to tackle the class imbalance problem.

Contact: uzay.macar@polymtl.ca

References

[1] Nair T, Precup D, Arnold DL, Arbel T. *Med Image Anal.* 2020;59: 101557. **[2]** Gros C, De Leener B, Badji A, Maranzano J, Eden D, Dupont SM, et al. *Neuroimage*. 2019;184: 901–915. **[3]** Krüger J, Opfer R, Gessert N, Ostwaldt A-C, Manogaran P, Kitzler HH, et al. *Neuroimage Clin.* 2020;28: 102445. **[4]** Gros C, Lemay A, Cohen-Adad J. *Med Image Anal.* 2021;71: 102038. **[5]** Carass A, Roy S, Gherman A, Reinhold JC, Jesson A, Arbel T, et al. *Sci Rep.* 2020;10: 8242. **[6]** Chaves H, Dorr F, Costa ME, Serra MM, Slezak DF, Farez MF, et al. *J Neuroradiol.* 2021;48: 147–156. **[7]** Çiçek Ö, Abdulkadir A, Lienkamp SS, Brox T, Ronneberger O. *arXiv [cs.CV]*. 2016. Available: http://arxiv.org/abs/1606.06650. **[8]** Gros C, Lemay A, Vincent O, Rouhier L, Bourget M-H, Bucquet A, et al. *J Open Source Softw.* 2021;6: 2868. **[9]** Oktay O, Schlemper J, Folgoc LL, Lee MJ, Heinrich, M, Misawa K, Mori K, McDonagh SG, Hammerla N, Kainz B, Glocker B, Rueckert D. *arXiv [cs.CV].* Available: https://arxiv.org/abs/1804.03999. **[10]** Gal Y, Ghahramani Z. *arXiv [stat.ML]*. 2016. Available: https://arxiv.org/abs/1506.02142