Few Labeled Atlases are Necessary for Deep-Learning-Based Segmentation

Hyeon-Woo Lee, Mert R. Sabuncu, Adrian V. Dalca

Code available at voxelmorph.mit.edu

Introduction

- Biomedical image segmentation in the scenario of only a few *labeled* brain MR images
- Proposed a straightforward implementation of semi-supervised learning-based registration for multi-atlas segmentation (MAS)
- Through empirical study, performance of a supervised segmentation with augmentation via random deformations was evaluated

Motivation

Traditional approaches
- Supervised deep learning-based method with large labeled datasets
- Acquiring a large set of paired manual segmentation maps is challenging
- MAS with unsupervised registration

Contributions
- Multi-atlas segmentation with **semi-supervised registration**
- Improves current MAS performance
- Evaluated the performance of SOTA 3D segmentation methods

Method

Registration loss
- Semi-supervised registration

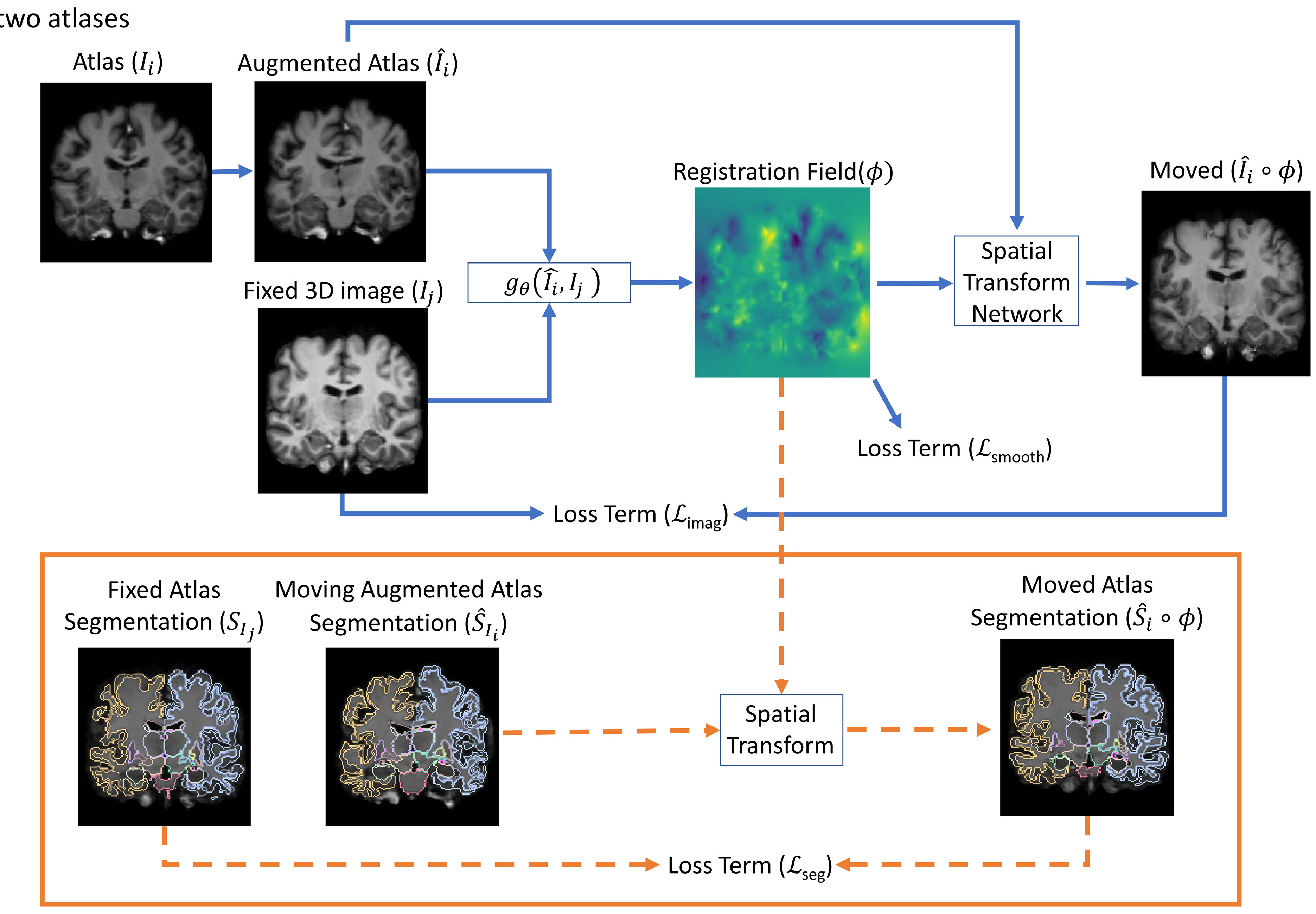
$$\mathcal{L}(\theta; I_i, I_j^*) = \underbrace{\mathcal{L}_{img}(I_j, I_i \circ g_\theta(I_j, I_i))}_{\text{Dissimilarity (NCC)}} + \lambda \underbrace{\mathcal{L}_{smooth}(g_\theta(I_j, I_i))}_{\text{Smoothness}} + \gamma \underbrace{\mathcal{L}_{seg}((S_{I_j}, S_{I_i} \circ g_\theta(I_j, I_i))}_{\text{Dice overlap of two atlases}}$$

- Dice loss is optional and only appears in semi-supervised registration

Spatial Data Augmentation
- $\{I_i, S^i\}_{i=1}^N$ small dataset of labeled *atlases*
- Randomly deform $\{I_i, S^i\}_{i=1}^N$ with smooth random deformation field
- Synthesized data to train MAS and supervised-learning based model

Multi-atlas segmentation with label fusion
- Warp labeled atlases and N_I augmented atlases to each test subject.
- Propagate the segmentation probabilities then majority voting for each voxel

Supervised-learning based segmentation
- Using same U-Net structure as registration network
- Categorical Cross-Entropy
- Augmentation with random deformation



Supervised atlas-to-atlas registration 10 percent of the training iterations

Experiments

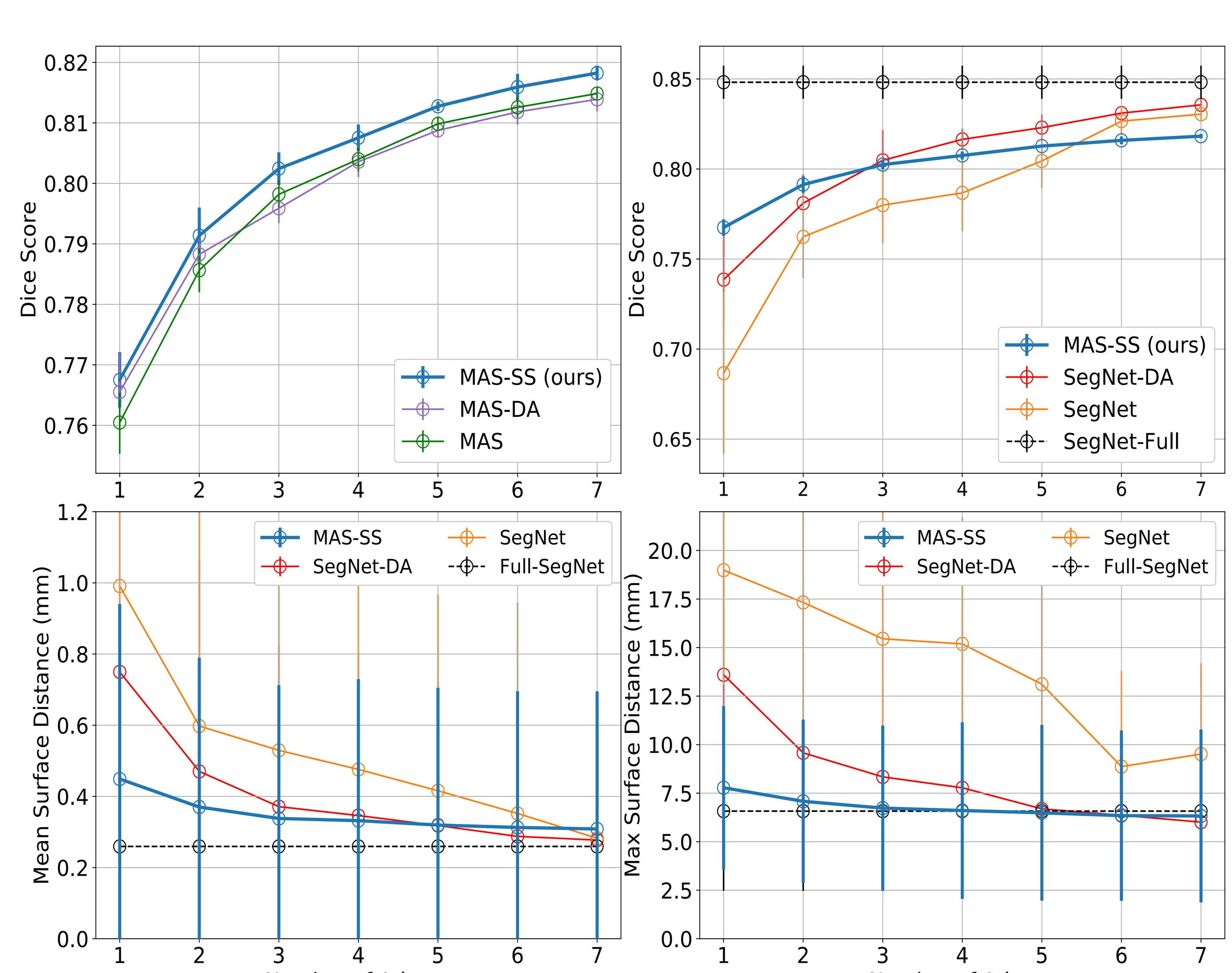
Data
- 8 public datasets used for registration (unlabeled images)
- 18 images from Buckner40 (labeled images)

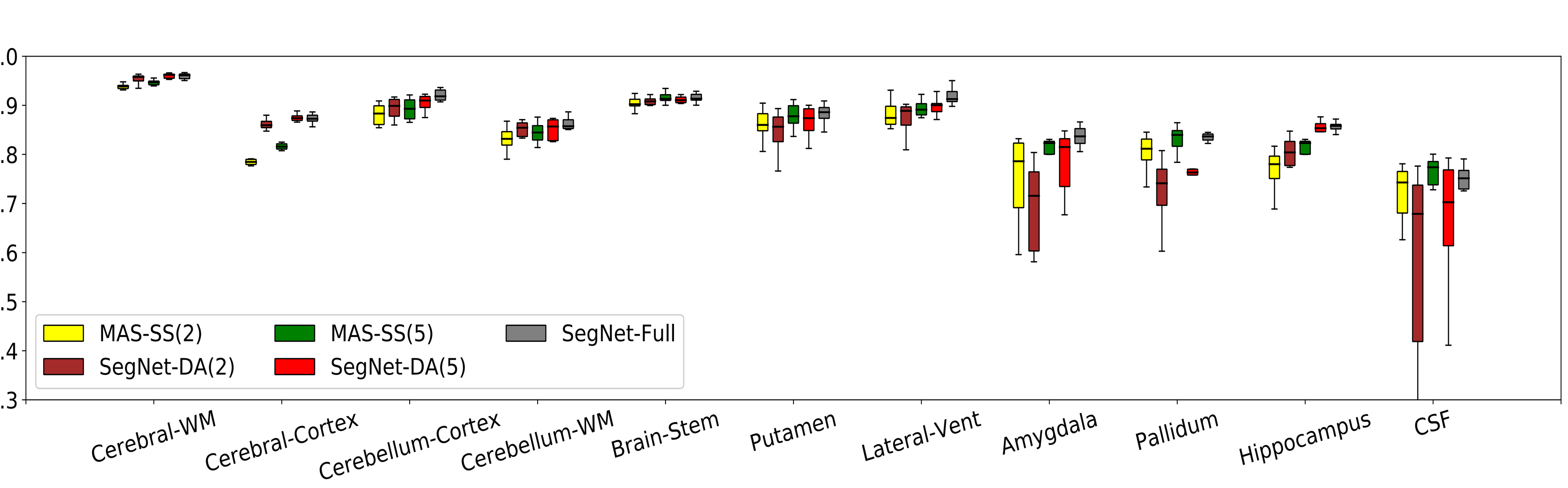
Experiment setup
- N = 1…7 labeled scans randomly picked from labeled training sets
- 29 subcortical structures

Metrics
- Volume overlap of segmentations with Dice (higher the better)
- Surface distance (SD) of all structures in mm (lower the better)
- Surface distance is likely to highlight spurious segmentations

Models for evaluation
- SegNet (supervised-learning method using U-Net as backbone)
- SegNet-DA (SegNet with random deformation augmentation)
- SegNet-Full (SegNet that trained with all the training images)
- MAS (Multi-atlas segmentation with unsupervised registration)
- MAS-SS (our proposed method, MAS with semi-supervised registration)

Results
- For all methods, can achieve good segmentations with few labeled images
- Data augmentation significantly improves SegNet performance in terms of Dice
- MAS methods have higher Dice than SegNet when atlases is less than three
- MAS-SS performs significantly better in terms of both mean and max surface
- MAS-SS preserve anatomical topology





FreeSurfer | MAS-SS (n=2) | SegNet-DA (n=2) | MAS-SS (n=5) | SegNet-DA (n=5) | SegNet-Full