Self-Supervised Super-Resolution for Anisotropic MR Images with and Without Slice Gap

Samuel W. Remedios[1,2], Shuo Han[3], Lianrui Zuo[4,5], Aaron Carass[4]
Dzung L. Pham[6], Jerry L. Prince[4], and Blake E. Dewey[7]

Dept. of Radiology and Imaging Sciences, Clinical Center[2],
National Institutes of Health, Bethesda, MD, USA
Laboratory of Behavioral Neuroscience, National Institute on Aging[5],
National Institutes of Health, Baltimore, MD, USA

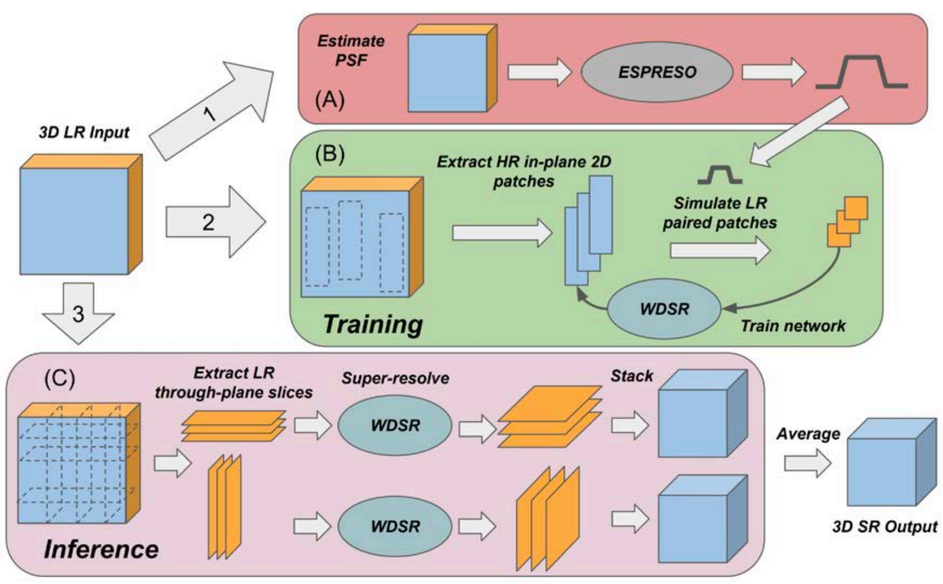
Dept. of Computer Science[1], Biomedical Engineering[3], Electrical and Computer Engineering[4]
Johns Hopkins University, Baltimore, MD, USA

Dept. of Radiology and Radiological Sciences[6],
Uniformed Services University of the Health Sciences, Bethesda, MD, USA
Dept. of Neurology[7],
Johns Hopkins School of Medicine, Baltimore, MD, USA

Introduction

- **Background:** Anisotropic magnetic resonance (MR) volumes are common clinically, but isotropic volumes are often needed for automated neuroimage processing
- **Challenge:** Super-resolution (SR) techniques estimate high-resolution (HR) volumes from low-resolution (LR) ones, but deep learning methods are prone to domain shift and existing methods do not model slice gaps
- **Solution:** We propose a zero-shot self-supervised approach for super-resolution which models slice gap, building on a previous approach SMORE[1]

Method



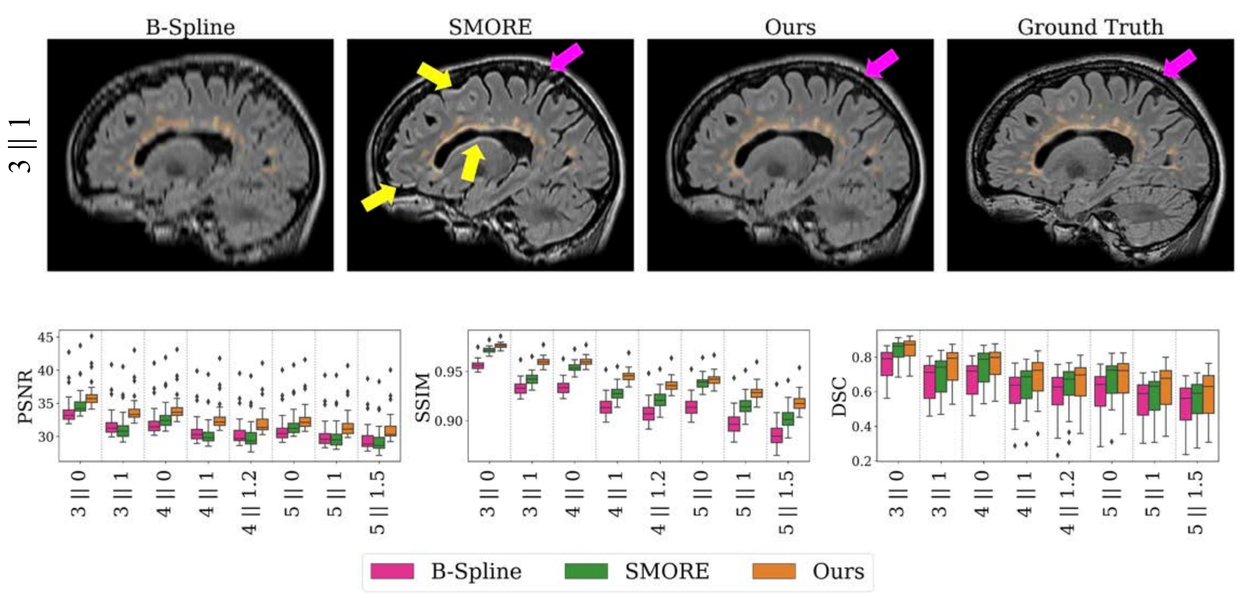
$$\underbrace{\lfloor (N+p)\tilde{s} \rceil}_{\text{Pre-network interpolation}} \times \overbrace{\lfloor s \rceil}^{\text{Pixel shuffle scaling}} - \underbrace{\lfloor ps \rceil}_{\text{Remove scaled padding}} = \overbrace{\lfloor Ns \rceil}^{\text{Ideal number of SR slices}}$$

T_2-FLAIR Experiment

➢ Dataset

- 30 T_2-FLAIR volumes from the 3D-MR-MS[3] dataset
- Downstream task: MS lesion segmentation with a pre-trained U-net

➢ Results

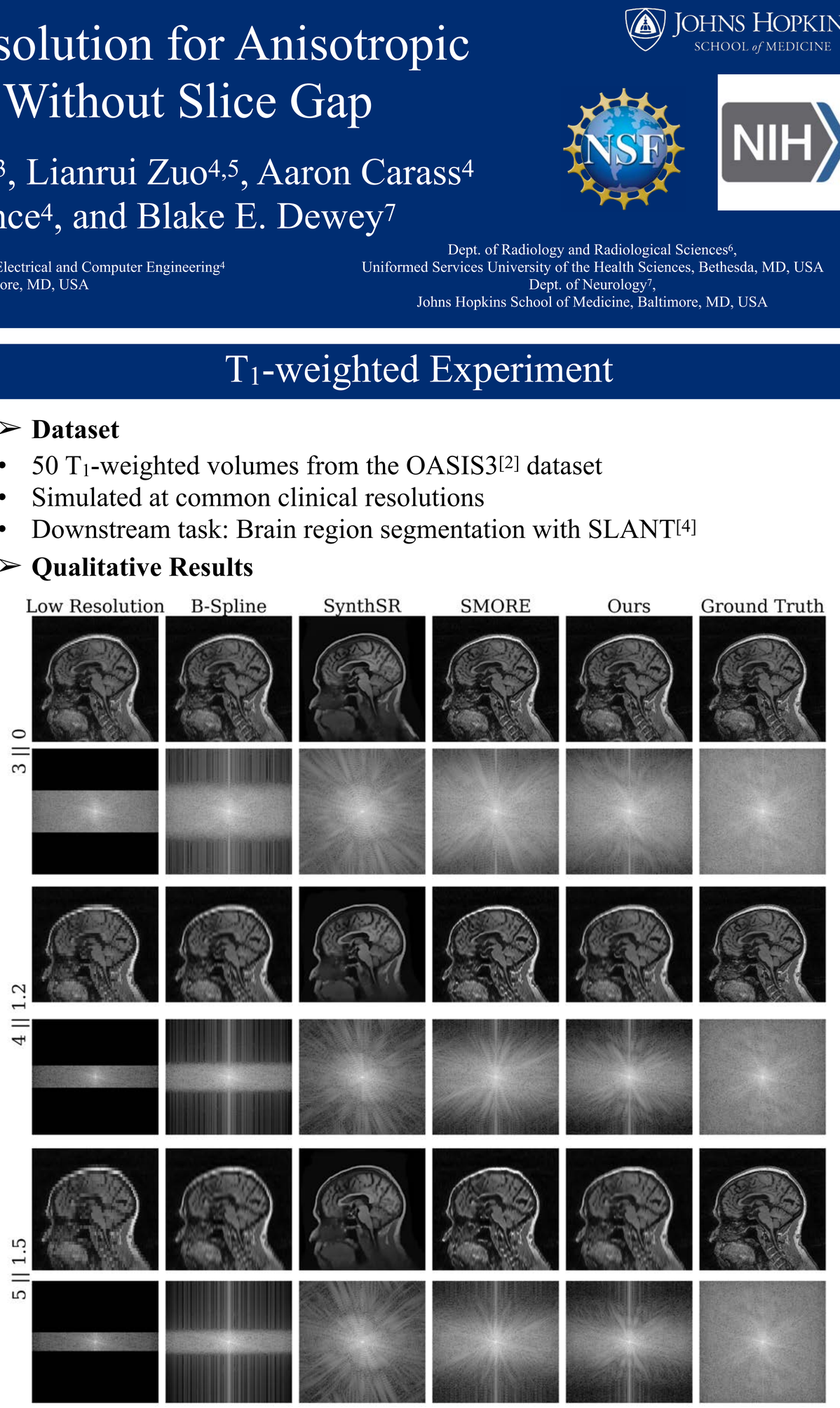


T_1-weighted Experiment

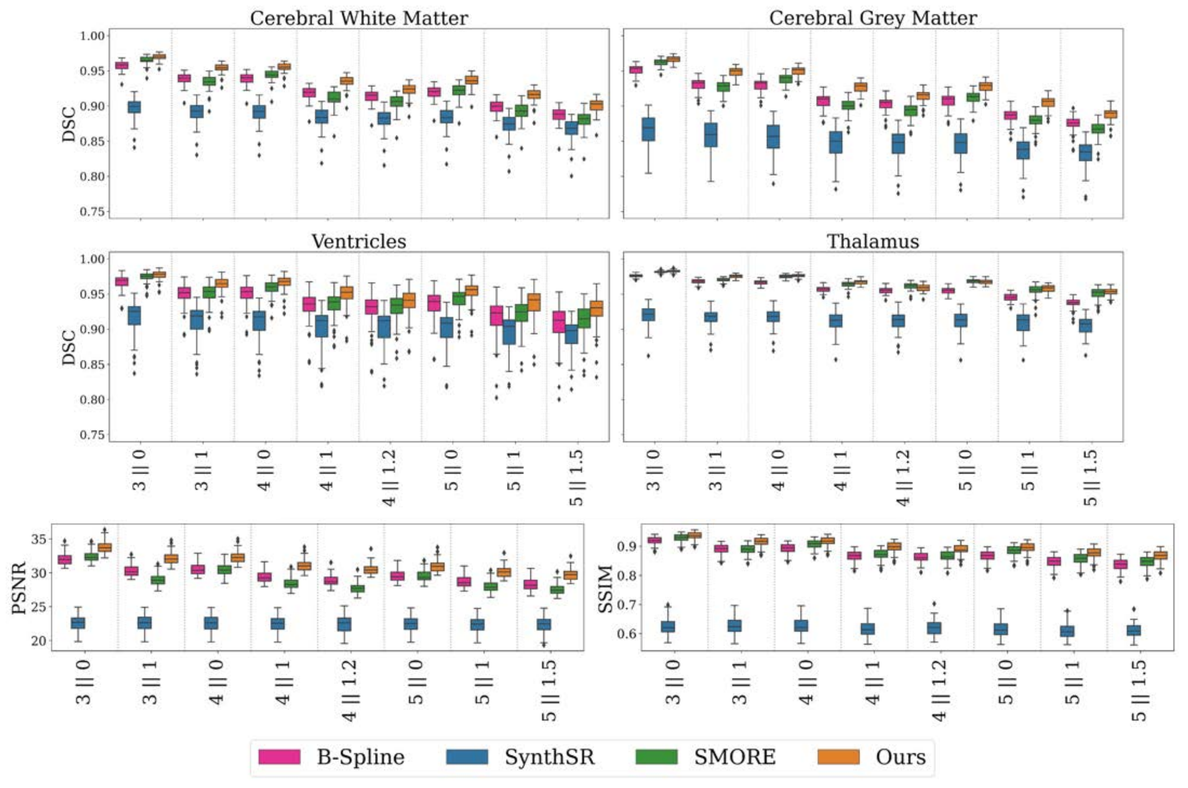
➢ Dataset

- 50 T_1-weighted volumes from the OASIS3[2] dataset
- Simulated at common clinical resolutions
- Downstream task: Brain region segmentation with SLANT[4]

➢ Qualitative Results



➢ Quantitative Results



References

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Conclusion

- Zero-shot self-supervised super-resolution
- Better performance with WDSR, residual connection
- Models scenario where slice thickness is not equal to slice separation
- Strong performance on segmentation downstream task

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samuel.remedios@jhu.edu