A Trajectory-Aware Neural ODE Framework for Multi-Parametric MRI-Based Glioma Segmentation

Hanqing Zhang[1]; Rihui Zhang[2]; Ruihao Li[1]; Ruimeng Zhou[1]; Fang-Fang Yin, PhD[1]; Zhenyu Yang, PhD[1]

[1]Duke Kunshan University, Kunshan, Jiangsu, China, [2]School of Physics and Technology, Wuhan University, Wuhan 430072, China

2026 JULY 19–22 VANCOUVER, BC JOINT AAPM | COMP MEETING

ABSTRACT

Purpose: To develop and evaluate a trajectory-aware segmentation framework that decodes Neural ODE-derived latent feature trajectories for multi-parametric MRI-based glioma sub-region segmentation.

Methods: BraTS2020 multi-parametric MRI data, including T1, T1ce, T2, and FLAIR images, were used for enhancing tumor (ET) and tumor core (TC) segmentation. A Neural ODE trajectory generator was initialized with a pretrained nnU-Net backbone to model latent feature evolution from the initial MRI input. A fourth-order Runge–Kutta solver generated a 10-step latent feature trajectory, which was decoded by a ConvLSTM trajectory reader. The generator and reader were first pretrained separately and then jointly optimized end-to-end using a combined final segmentation loss and auxiliary trajectory loss.

Results: The proposed framework successfully decoded Neural ODE-derived latent feature trajectories for both ET and TC segmentation. After staged pretraining and end-to-end joint optimization, the model achieved strong segmentation performance, with Dice scores of 0.874 for ET and 0.882 for TC. These results support the feasibility of using latent feature trajectories as predictive representations for glioma sub-region segmentation.

Conclusions: The proposed framework demonstrates the feasibility of using Neural ODE-derived latent feature trajectories for glioma sub-region segmentation. By decoding a sequence of latent feature states rather than relying only on a terminal ODE state, the model provides a promising foundation for trajectory-aware segmentation and future trajectory interpretability analysis.

CONTACT

Hanqing Zhang
Duke Kunshan University
hz312@duke.edu

INTRODUCTION

Accurate segmentation of glioma sub-regions is important for treatment planning, response assessment, and quantitative image analysis. Although convolutional segmentation models such as nnU-Net[3] achieve strong performance, they generally produce predictions through a single forward-pass representation and do not explicitly model or exploit the continuous evolution of latent features during segmentation formation.
Neural ordinary differential equations (Neural ODEs)[4] provide a continuous-time formulation in which image or latent feature states evolve from an initial input toward a segmentation-related representation. Our prior Neural ODE work[2] showed that these trajectories can visualize deep feature evolution and quantify channel contribution. However, the trajectory itself has mainly been used for explainability rather than prediction. We hypothesize that intermediate trajectory states contain complementary information that can improve the final segmentation decision.
In this work, we propose a trajectory-aware segmentation framework that combines nnU-Net-guided Neural ODE dynamics with a ConvLSTM trajectory reader. The Neural ODE generator produces latent feature trajectories from multi-parametric MRI inputs, while the ConvLSTM reader decodes the full trajectory to generate the final segmentation. The model is first trained in stages and then jointly optimized end-to-end to align trajectory generation with trajectory-based segmentation.

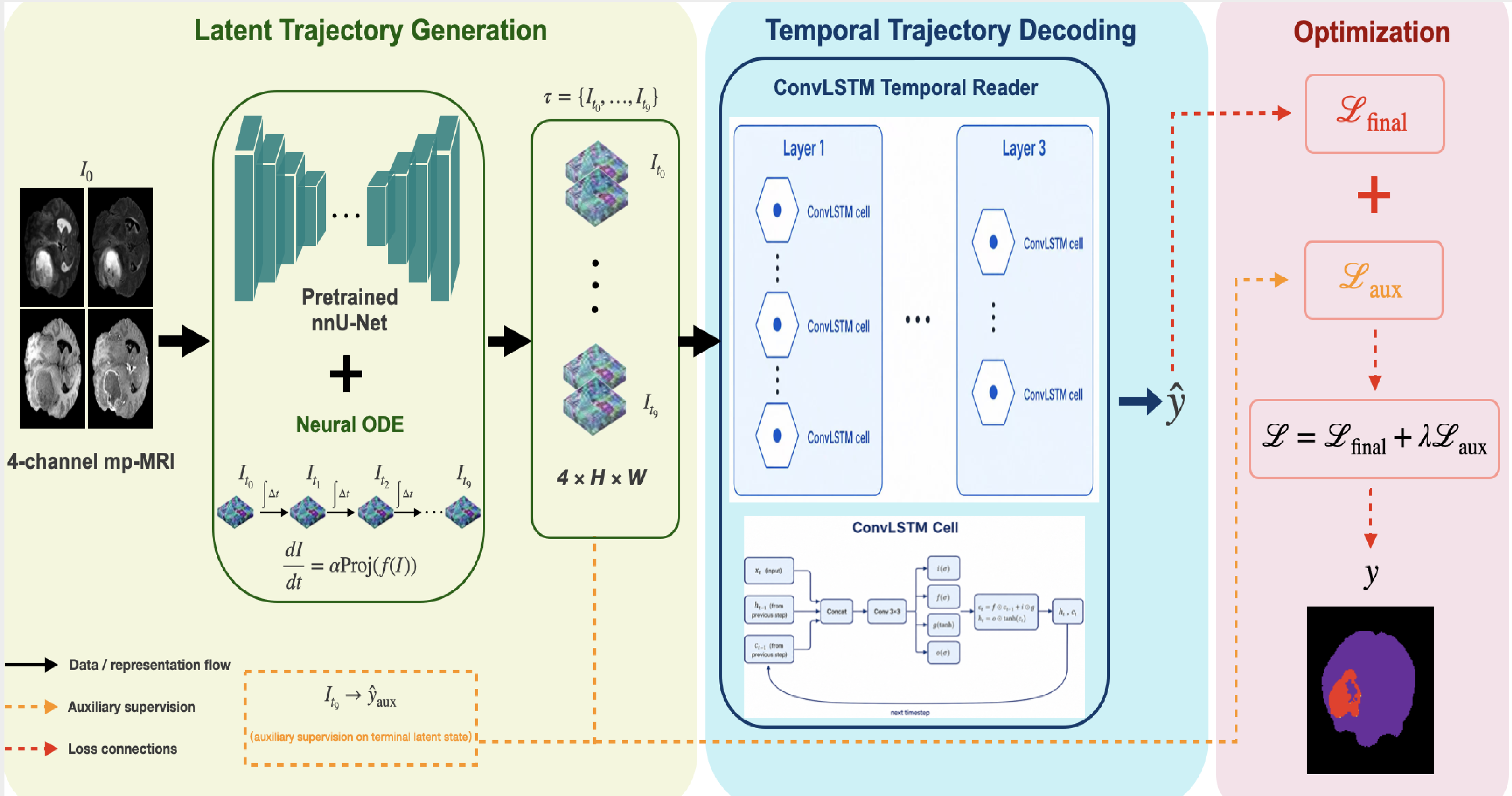

Figure 1: The Overall Framework of the Proposed Dynamic Trajectory Segmentation Model

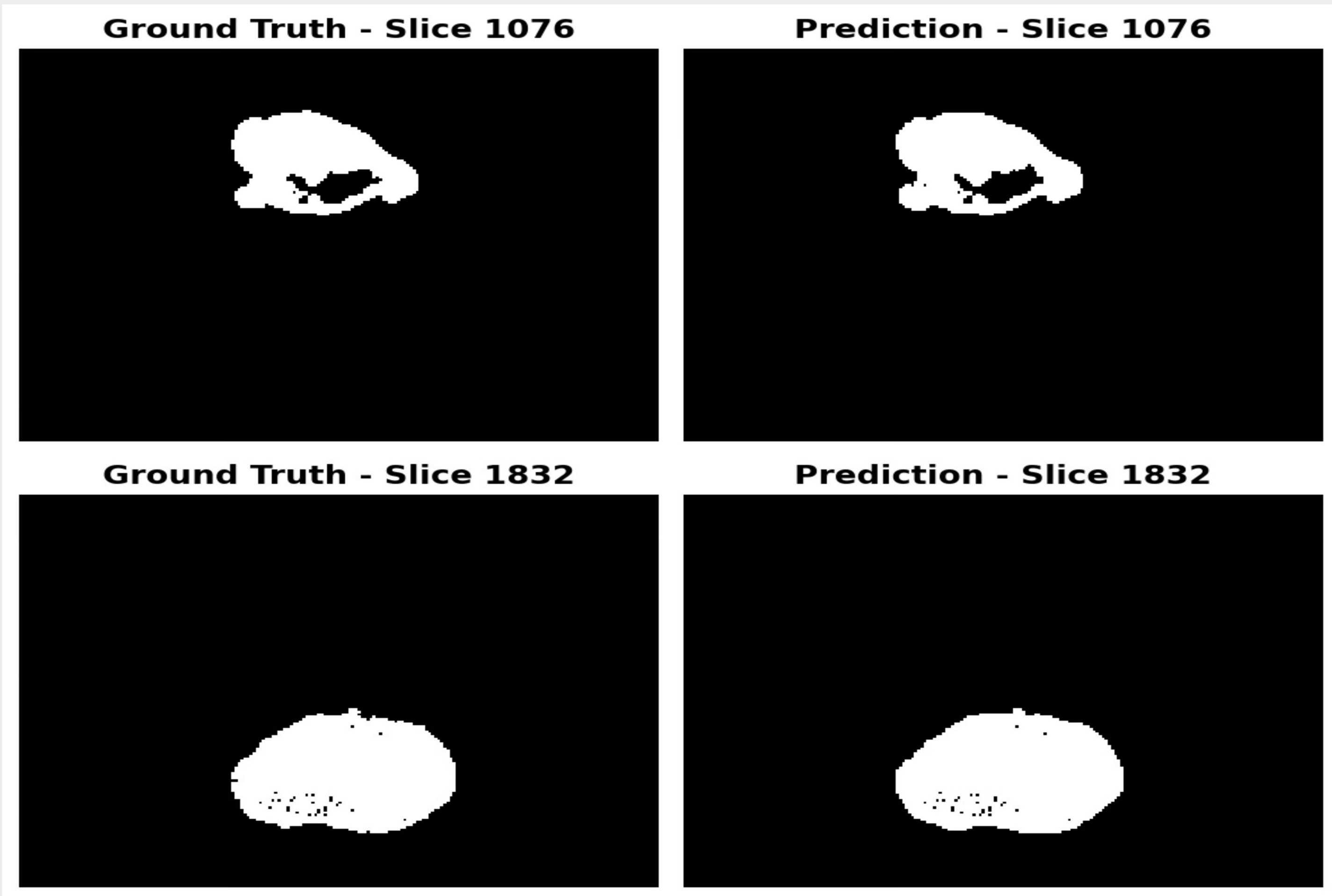

Figure 2 : Representative ET and TC Segmentation Examples

Table 1: Quantitative Results on the ET and TC Test Set

	ET	TC
Dice	0.8736	0.8819
Accuracy (%)	98.92	98.09
Sensitivity	0.8880	0.9027
Specificity	0.9924	0.9933

METHODS AND MATERIALS

The study used BraTS2020 multi-parametric MRI data[1], including T1, T1ce, T2, and FLAIR images with voxel-wise glioma annotations. The segmentation tasks focused on enhancing tumor (ET) and tumor core (TC). MRI volumes were converted into 2D axial slices, and each sample contained four MRI channels, a brain mask, and a task-specific binary segmentation label.
The trajectory generator was built from a Neural ODE initialized with a pretrained nnU-Net[3] backbone. Starting from the initial multi-parametric MRI input I_0, the latent state evolved according to $\frac{dI(t)}{dt} = \alpha \cdot \mathrm{Proj}\left(\mathrm{nnU{-}Net}(I(t))\right)$, where the nnU-Net backbone defined the dynamic feature field, $\mathrm{Proj}(\cdot)$was a 1×1convolution mapping the output to a four-channel latent state space, and α was a learnable scaling factor. The ODE was integrated using a fourth-order Runge–Kutta solver to generate a 10-step latent feature trajectory. The generator was first trained with an auxiliary segmentation loss, L_{aux}, applied to the terminal trajectory state, encouraging the generated trajectory to remain segmentation-aware. A ConvLSTM reader was then pretrained to decode the generated latent trajectory, using the reader's final segmentation loss, L_{final}, defined as a brain-masked BCE-Dice loss. Finally, the pretrained generator and pretrained reader were jointly optimized end-to-end using $L = L_{\mathrm{final}} + \lambda L_{\mathrm{aux}}$, where $\lambda$was gradually reduced during training so that the final trajectory-based segmentation became the dominant optimization target.

RESULTS

The proposed trajectory-aware framework achieved strong brain-masked voxel-level performance for both glioma sub-region tasks. For ET segmentation, the model obtained a Dice score of 0.874, accuracy of 0.989, sensitivity of 0.888, and specificity of 0.992. For TC segmentation, it achieved a Dice score of 0.882, accuracy of 0.981, sensitivity of 0.903, and specificity of 0.993. Representative examples showed good spatial agreement between predicted and reference tumor regions. These preliminary results suggest that Neural ODE-derived latent feature trajectories can be effectively decoded by a ConvLSTM reader for glioma sub-region segmentation.

CONCLUSIONS

We developed a trajectory-aware glioma segmentation framework that integrates a Neural ODE trajectory generator with a ConvLSTM trajectory reader. Preliminary ET and TC results demonstrated strong segmentation performance. Future work will include direct comparisons with terminal-state decoding, temporal ablation studies, and hidden-state visualization to further evaluate the contribution of the learned trajectories.

REFERENCES

1. Bakas S, et al. Advancing TCGA glioma MRI collections with expert labels. Sci Data, 2017.
2. Yang Z, Hu Z, Ji H, et al. A neural ordinary differential equation model for visualizing deep neural network behaviors in multi-parametric MRI-based glioma segmentation. *Med Phys*. 2023;50(8):4825-4838. doi:10.1002/mp.16286.
3. Isensee F, et al. nnU-Net: self-configuring biomedical image segmentation. Nat Methods, 2021.
4. Chen RTQ, et al. Neural ordinary differential equations. NeurIPS, 2018.