A Lightweight Optimization Framework for Estimating 3D Brain Tumor Infiltration

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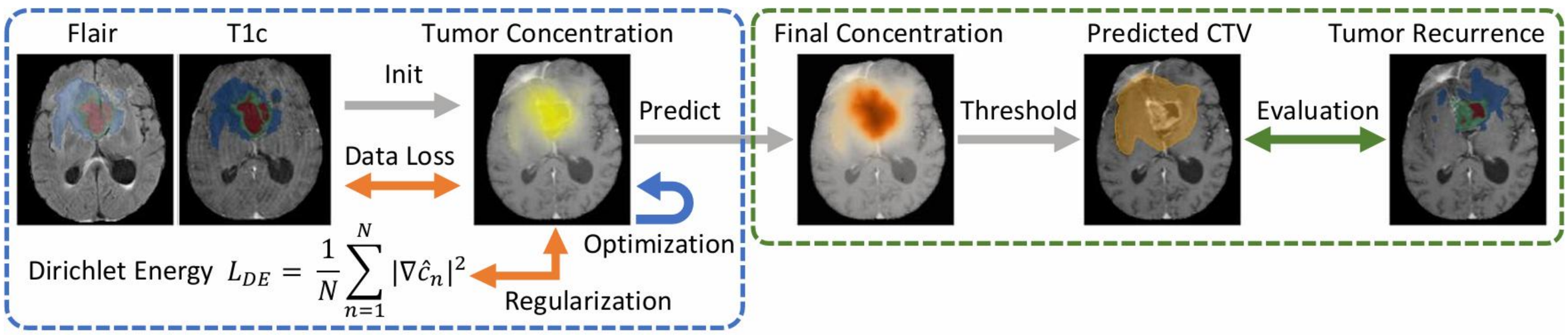
1 Motivation

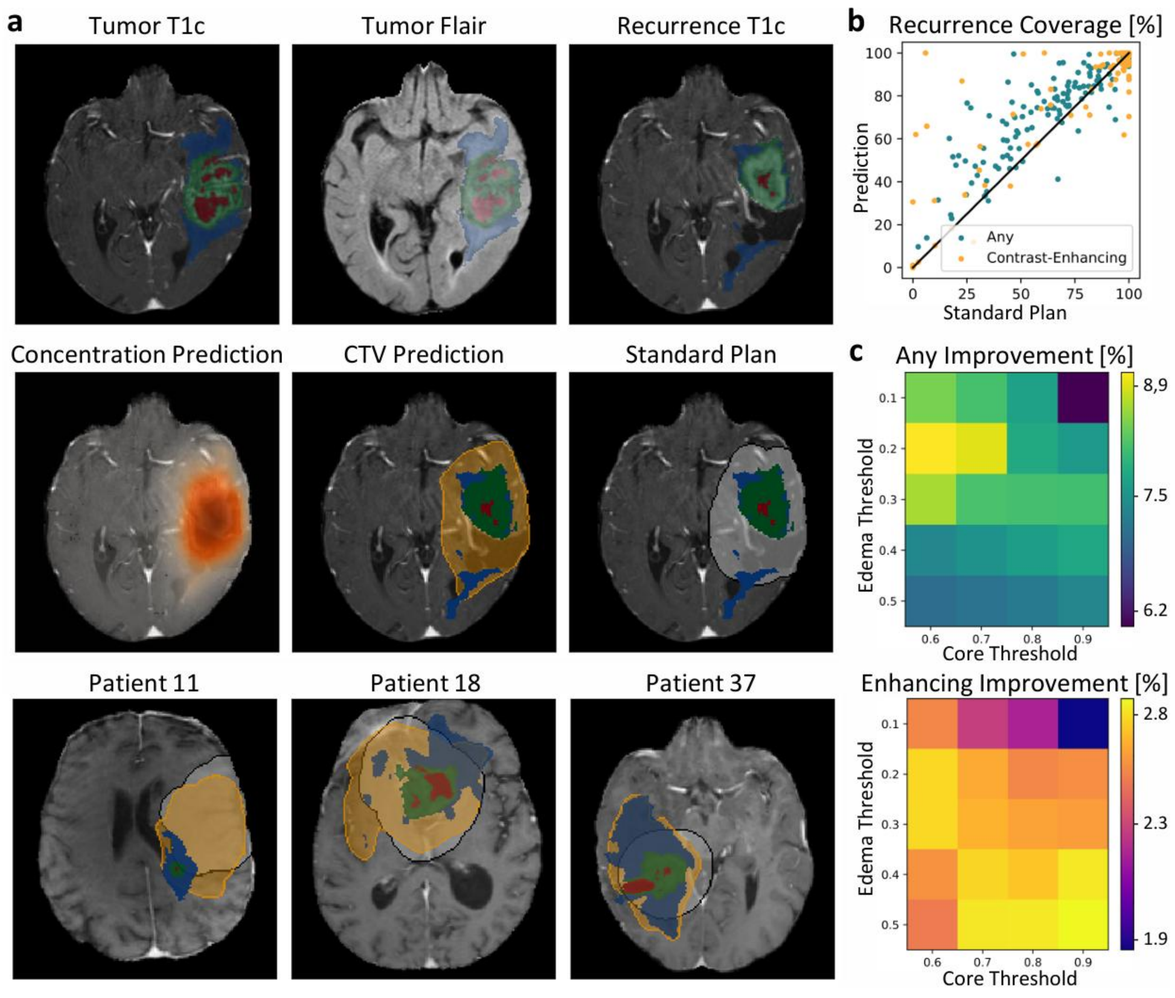
Glioblastoma is the most aggressive primary brain tumor, with poor survival rates. A major challenge is that tumor cells infiltrate far beyond what is visible on standard MRI. Current radiotherapy planning applies a uniform 15 mm margin, which ignores patient-specific infiltration patterns. More advanced biophysical and learning-based models exist, but they are either **too slow or lack robustness for clinical use**. There is a strong need for a fast, reliable, and adaptable method that can estimate hidden tumor spread and improve individualized treatment planning.

2 Method



We optimize (blue) a 3D scalar tumor concentration estimation (yellow) by simultaneously fitting the data while ensuring a smooth concentration landscape by minimizing the Dirichlet energy. Using this predicted tumor concentration (orange), we propose a radiotherapy plan (Clinical Target Volume (CTV), orange). We evaluate (green) our method's ability to capture areas of subsequent tumor recurrence.

3 Qualitative Results



a.) Demonstration of our method on example patients. In the first row, we show the two input MR images with the tumor and the recurrence that should be covered. Edema is shown in blue, enhancing tumor in green, and necrotic in red. Our method predicts a continuous estimation of tumor cells, as shown in the second row. This continuous concentration is thresholded to have the same volume as the standard plan (grey) to create the CTV (orange). In the last row, we compare our method to the standard plan for different RHUH patients. b.) The recurrence coverage is shown for the GliODIL Dataset with 152 patients. The individual results for each patient are shown compared to the standard plan. A clear improvement is visible for many patients, while also a lot of patients result in 0% or 100% coverage. c.) We are comparing any recurrence (green) and contrast-enhancing recurrence (orange) coverage improvement over the standard plan for different core and edema visibility threshold parameters τ.

4 Quantitative Results

Recurrence Coverage - GliODIL	Any [%]	Enhancing Core [%]	Runtime
NN (Unconstrained) [3]	65.38 ± 2.05	69.02 ± 2.79	< 1 min
NN (Physics-Constrained) [7]	62.06 ± 2.11	75.25 ± 2.84	< 1 min
Numerical Physics Simulations [16]	61.16 ± 2.12	75.34 ± 2.87	2 h
Static Grid Discretization [3]	67.80 ± 2.09	84.42 ± 2.40	30 min
Standard Plan	63.59 ± 2.26	82.42 ± 2.60	< 1 min
Ours Worst Thresholds	$69.72 \pm 2.07^{\ddagger **}$	$84.34 \pm 2.38^{**}$	1 min
Ours Median Thresholds	$70.93 \pm 1.99^{\ddagger **}$	85.02 ± 2.31	1 min
Ours Best Thresholds	$\mathbf{72.48} \pm 1.99^{\ddagger **}$	$\mathbf{85.19} \pm 2.28$	1 min

Comparison of recurrence segmentation coverage given equal radiation volume, tested for different edema and core thresholds (Figure 2) on the GliODIL dataset with 152 patients. Our method outperforms all others with short runtime.

5 Physical Constraints

Including physical constraints improves robustness by enforcing a wave-like solution derived from the Fisher-Kolmogorov model of tumor growth. Adding this constraint increased recurrence prediction for **any recurrence from 70.9% to 71.8%** and for the **enhancing core from 85.0% to 85.5%**, while also reducing sensitivity to threshold parameters.

6 Conclusion

- **Fast and robust**: Estimates 3D tumor concentration in under one minute, enabling clinical applicability.
- **Improved accuracy**: Outperforms the current standard plan and state-of-the-art methods in predicting tumor recurrence.
- **Flexible framework**: Easily integrates additional imaging modalities and physical constraints for personalized radiotherapy.