Prior-guided automatic segmentation of brain tumor targets for adaptive radiation therapy on MR-LINACs

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ABSTRACT

Purpose: T1-weighted (T1w) and T2-weighted (T2w) FLAIR MRI provide complementary image contrast for delineating gross tumor volume (GTV) and clinical target volume (CTV) in brain tumor radiotherapy (RT) planning during both MRI simulation (MR-Sim) and MRI-guided RT (MRIgRT). However, manual re-contouring across multiple MRI sequences is time-consuming for clinicians (typically 20-30 minutes), substantially prolonging treatment procedure sessions on MR-LINACs compared with conventional workflows. In this study, we propose an automatic tumor segmentation approach that integrates multiple-sequence MRI with prior information from MR-Sim and previous treatment fractions to enable efficient and consistent target delineation for adaptive MRIgRT.

Methods: We retrospectively collected MR-LINAC-based ART data from 75 brain tumor patients. Each patient underwent 3-6 treatment fractions, with most fraction including T1w and T2w-FLAIR MRI and multiple target contours. We developed a prior-guided, multi-modality LSTM-UNet model that use imaging information from multiple MRI sequences and ground-truth target contours drawn in previous fractions.

Results: We evaluated the proposed multi-modality LSTM-UNet against a baseline UNet and a traditional image-registration-based method. The multi-modality LSTM-UNet achieved the highest segmentation performance, with an average Dice similarity score of 84.5%, compared with 82.2% for the image-registration method and 83.0% for the baseline UNet.

Conclusion: By integrating multi-sequence MRI and prior knowledge from previous treatment fractions, the proposed method improves segmentation accuracy for brain tumor targets in MRI-guided ART on the MR-LINACs.

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INTRODUCTION

The integration of MR imaging into radiotherapy has introduced a new paradigm of MR-guided radiotherapy (MRgRT), which reduces or eliminates the dependence on CT images. MR-Linac systems typically acquire multiple MR sequences to highlight different anatomical characteristics. For example, T1-weighted imaging provides clear structural information, while T2-weighted fluid-attenuated inversion recovery (T2-FLAIR) imaging improves the visualization of edema and tumor-related abnormalities. By combining information from multiple sequences, clinicians can more accurately delineate radiotherapy targets, including the Gross Tumor Volume (GTV), Clinical Target Volume (CTV), and Planning Target Volume (PTV). Accurate delineation of these target volumes is critical for maximizing tumor control while minimizing radiation exposure to surrounding healthy tissues. However, target delineation remains one of the major bottlenecks in MR-based adaptive radiotherapy. While current methods demonstrate strong performance in many applications, they often struggle in adaptive radiotherapy scenarios where temporal changes between fractions must be considered. Therefore, there is a strong need for robust and accurate automatic segmentation methods that can delineate radiotherapy targets from multi-sequence MR images in adaptive treatment settings. [1, 2]

To address these challenges, we propose a novel multi-modal and multi-fraction segmentation framework for MR-guided adaptive radiotherapy.

METHODS AND MATERIALS

A total of 75 patients with various brain malignancies treated on a 1.5T MR-LINAC (Elekta Unity) were retrospectively analyzed for this study. The cohort exhibited a diverse range of diagnoses, primarily consisting of malignant neoplasms of the temporal lobe and overlapping brain sites, as well as secondary metastatic lesions. The demographic and clinical characteristics are summarized in Table 1. The median age of the population was 60 years, with a distribution of 40 male and 35 female patients. Treatment intent varied across the cohort, including definitive, adjuvant, and palliative cases. To facilitate the prior-guided segmentation approach, we collected the planning MRI and subsequent daily fractional MRIs. After cleaning we have 292 individual image sets in total, and most image sets have a T1 image, a T2 FLAIR images and at least one target contour. Most patients received a hypo-fractionated regimen (5 fractions) with a median prescription dose of 30 Gy. Surgical intervention prior to radiation was documented in 48/75 of the cases, providing a robust dataset of both intact tumors and post-operative cavities.

METHODS AND MATERIALS

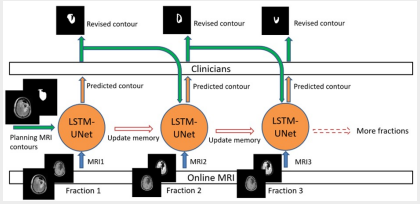

Figure 1. The proposed progressive segmentation workflow for MRI-based adaptive radiation therapy.

We developed a multi-fraction and multi-modality architecture. For each fraction, the model has three channels of input and one channels of output. As shown in Figure 1, given a planning MR image and its target contour, the model combines the contour registered to the first fraction and T1 and T2 FLAIR image from the first fraction as the first input. The model predicts the target contour for the first fraction and receive a physician-approved target contour as feedback. The feedback contour of the first fraction is registered to the second fraction as part of the input again.

The LSTM-UNet model is based on a 3D U-Net with five 3D LSTM units between the encoder and decoder. Those LSTM units together form a multi-level perception and memory about the historical inputs. The detailed architecture of LSTM-UNet is shown in Figure 2.

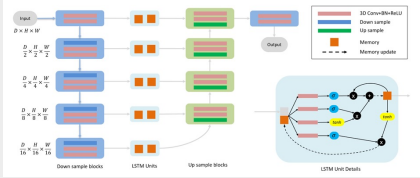

Figure 2. The architecture of LSTM-UNet with memory modules.

A significant challenge of prior-guided segmentation is that prior information from earlier fractions may dominate the prediction, leading to a "copy-paste" effect in which the model reproduces previous contours rather than adapting to newly observed anatomical changes. Therefore, we introduce a residual learning strategy that encourages the model to focus on anatomical changes between fractions, thereby mitigating the tendency to directly replicate prior contours.

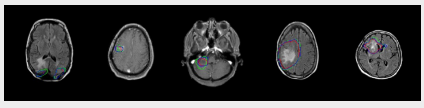

Figure 3. Sample images from LSTM-UNet prediction (Blue), rigid registration (Red) and ground truth (Green).

RESULTS

The performance of the four models is summarized in Table 1. The "Registration" baseline was obtained via rigid registration using the most recent available fraction; specifically, a translation matrix was calculated to map the previously segmented MRI onto the current daily MRI. This translated target serves as the rigid registration result and was utilized as an input feature—referred to as the "prior contour" for the subsequent deep-learning architectures. While the UNet and LSTM-UNet models were implemented based on established literature, the UNet-Res and LSTM-UNet-Res variants incorporate the residual learning components shown in our proposed framework. Sample images are shown in Figure 3.

Model/Metric	Dice(%)	HD95(mm)	ASD(mm)
Registration	82.2±10.5	3.22±2.23	1.11±0.66
UNet	83.0±9.7	3.16±2.16	1.12±0.62
LSTM-UNet	84.2±9.2	3.83±3.21	1.30±1.04
UNet-Res	83.8±9.5	3.16±2.28	1.07±0.69
LSTM-Unet-Res	84.7±8.9	3.11±2.06	1.04±0.58

Table 1. Results of different models. Registration: Rigid registration from the most recent physician-approved ground truth. UNet/LSTM-UNet: The published 3D UNet and LSTM-UNet prediction. UNet-Res/LSTM-UNet-Res: The prediction of the published 3D UNet and LSTM-UNet with residual learning.

DISCUSSION

While traditional rigid registration provided a reasonable baseline (Dice = 82.2%), it inherently lacks the flexibility to account for complex physiological changes or tumor deformation among fractions.

The transition from a standard UNet to an LSTM-UNet architecture resulted in a noticeable improvement in the Dice Similarity Coefficient, allowing for more consistent delineations across the treatment course.

CONCLUSIONS

In this work, we developed and validated a novel multi-modal and multi-fraction deep learning framework for MRI target segmentation in adaptive radiotherapy. By incorporating LSTM modules to capture temporal dependencies and a residual learning strategy to focus on inter-fractional changes, we addressed the common pitfalls of "copy-paste" errors in longitudinal image sets.

REFERENCES

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