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Leveraging Machine Learning to Reduce Simulation to Treatment Time: Single-Isocenter Multi-Lesion Brain Stereotactic Radiosurgery

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Abstract
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Abstract

Objectives:

Stereotactic radiosurgery and radiotherapy (SRS/SRT) of metastatic brain lesions with a single-isocenter multi-lesion (SIML) approach has become a standard of care in the realm of radiation treatment due to its prevalence in patients and its urgent necessity for immediate action. Unfortunately, current clinical workflow often facilitates a 1 to 2-week gap from patient CT simulation to first treatment. Numerous studies have shown this time delay is detrimental to the accuracy and effectiveness of the planned SRS/SRT treatment. Due to the incessantly growing tumor in a nutrient-rich brain ecosystem, the tumor volume planned for, is not the tumor volume being treated 1-2 weeks later. To address this issue, we set out with the objective of optimizing the current clinical workflow through leveraging an in-house Eclipse RapidPlan model trained on, and used with, fully-automated, highly non-coplanar HyperArc plans to quickly generate high-quality SRS/SRT plans that could help reduce the delay in simulation to treatment time.

Methods:

At our institution, a HyperArc-based RapidPlan model was developed for a TrueBeam LINAC using 81 high quality, previously treated HyperArc SRS/SRT plans. These plans had prescriptions of 18-24 Gy in 1 fraction, 24-27 Gy in 3 fractions, and 25-40 Gy in 5 fractions depending on tumor size, location, and proximity to critical organs. The training set initially consisted of 68 plans, including SIML plans, however after the iterative process of training the model and removing geometric and dosimetric outliers, the resulting training set consisted of 60 plans. The training set had 2.3 lesions on average, ranging from 1 to 9. Training plans consisted of 7 single-fraction, 25 three-fractions, and 28 patients five-fractions treatments. The testing set had 13 plans with 1.7 lesions on average, ranging from 1 to 4. Testing plans consisted of 2 single-fraction, 6 three-fractions, and 5 five-fractions treatments. Training of the model was done using Varian's DVH Estimation Model Configuration. Training plans were added and recursively assessed for geometric and dosimetric outliers. After the model was trained, structure objectives were established and the model was used to re-plan the testing plans. The resulting plans were assessed and used to tweak the structure objectives until the best performing model was determined at the trainer's discretion. Plans were calculated using Acuros External Beam, optimized with Photon Optimizer, and DVH estimation generated with DVH Estimation Algorithm (all version 15.6). All plans were optimized with intermediate dose calculation turned on with restart set to MR3, SRS Auto Normal Tissue Objective was used, all plans used the HyperArc module and maintained their fully-automated delivery capabilities. Plans were evaluated for the BED10 (α/β=10 Gy) of target coverage (PTV D95% and GTV D0.03cc), dose to normal brain (V12Gy, V19.6Gy, V24.4Gy for 1, 3, and 5 fraction schemes, respectively) and doses to optic pathway and brainstem. Additionally, the total number of monitor units (MUs) and optimization times were recorded.

Results:

For single fraction treatments, the clinically-delivered plans provided an average PTV D95% of 64.6 ± 6.3 Gy BED10 and a GTV D0.03cc of 82.9 ± 4.4 Gy BED10. Compared to the model generated plans achieving 66.4 ± 6.5 Gy BED10 and 82.9 ± 7.8 Gy BED10, respectively. The normal brain V12Gy was 8.3 ± 5.1 cc and 8.2 ± 5.2 cc for clinical and model plans, respectively. For three fractions scheme, the clinically-delivered plans provided an average PTV D95% of 52.1 ± 0.8 Gy BED10 and a GTV D0.03cc of 67.0 ± 6.0 Gy BED10. Compared to the model generated plans achieving 52.6 ± 0.5 Gy BED10 and 64.7 ± 0.6 Gy BED10, respectively. The normal brain V19.6Gy was 6.6 ± 2.6 cc and 6.0 ± 2.8 cc for clinical and model plans, respectively. For five fraction treatments, the clinically-delivered plans provided an average PTV D95% of 47.0 ± 1.9 Gy BED10 and a GTV D0.03cc of 58.0 ± 1.9 Gy BED10. Compared to the model plans achieving 47.8 ± 1.6 Gy BED10 and 59.7 ± 1.4 Gy BED10. The normal brain V24.4Gy was 13.1 ± 8.2 cc and 13.2 ± 8.6 cc for clinical and model plans, respectively. For all fractionation schemes, doses to optic pathway and brainstem were within agreement

with the criteria outlined in Alliance A071801 brain SRS/SRT trial and AAPM TG-101 report. The clinical plans averaged 2895 ± 1131 MUs compared to the model generated plans with 3027 ± 1845 MUs, with similar beam modulation factors. The HyperArc-based model plans were generated in approximately 50 minutes (2.5-minute DVH estimation, 45-minute dose optimization, and 2.5-minute dose calculation) compared to 2-6 hours of manual planning times for expert HyperArc planners.

Conclusion(s):

The HyperArc-based RapidPlan model developed throughout this research clearly demonstrates the role machine learning can have in patient care for LINAC-based brain radiosurgery treatment. On case-by-case basis, this comprehensive model can handle 3 different fractionation schemes while achieving equivalent or reduced normal brain toxicity. We are able to significantly reduce the planning time required to have a high-quality treatment plan ready that is dosimetrically equivalent, if not better, than the clinically-delivered plans generated by expert HyperArc planners at our institution, indicating a potential use for “same-day” SIML brain SRS/SRT treatment in the future. Additionally, by employing machine learning we fundamentally improve the consistency of plan quality by removing inter-planner variability. We strongly recommend other clinics pursue developing and validating HyperArc-based RapidPlan models for their brain SRS/SRT treatments to standardize patient care and optimize their clinical workflow.