MACHINE LEARNING AUTOMATED TREATMENT PLANNING

Treatment planning is often a time consuming and complex process where sharing of knowledge and expertise between cancer centers is cumbersome and therefore not a reality today. RaySearch already has a strong focus on automation and with machine learning in RayStation, this is taken to a new level.
The machine learning automated treatment planning method learns from historical patient and plan data and infers a 3D spatial dose on a new patient geometry. Together with a powerful mimicking optimization, deliverable treatment plans are generated in minutes. This new approach to planning can improve efficiency, reduce treatment plan variability and facilitate knowledge sharing. University Medical Center Groningen (UMCG) has conducted a clinical study on the method for Head and Neck cancer VMAT cases, showing promising results [1].

MACHINE LEARNING PLANNING IN RAYSTATION

The machine learning treatment planning approach in RayStation utilizes models that have learned the relation between patient geometry, dose shape and tradeoffs from historical treatment plans. A machine learning model is trained by providing treatment plans to the training framework where the model learns to infer dose spatially on a new patient geometry. This can be compared to a dosimetrist learning over time by creating treatment plans for new patient cases. After a trained model has inferred dose to the patient, a dose mimicking optimization is performed to generate an optimized deliverable treatment plan.

The model itself does not contain any personal data and can therefore easily be shared between clinics. In the RayStation 8B* version released in December 2018, the machine learning planning supports VMAT, IMRT, and TomoTherapy treatments. Future releases will support protons and other delivery techniques as well.

The machine learning method for planning [2] has been developed in a collaboration with Princess Margaret Cancer Centre in Toronto, Canada, and is the first machine learning application for treatment planning in a treatment planning system on the radiation oncology market today.

> *"Machine learning is a natural fit for automating the complex treatment-planning process. It will enable us to generate highly personalized radiation treatment plans more efficiently, thereby allowing clinical resources or specialist technical staff to dedicate more time to patient care."*
>
> ***Tom Purdie**, Medical Physicist,*
> *Princess Margaret Cancer Centre, Toronto, Canada*

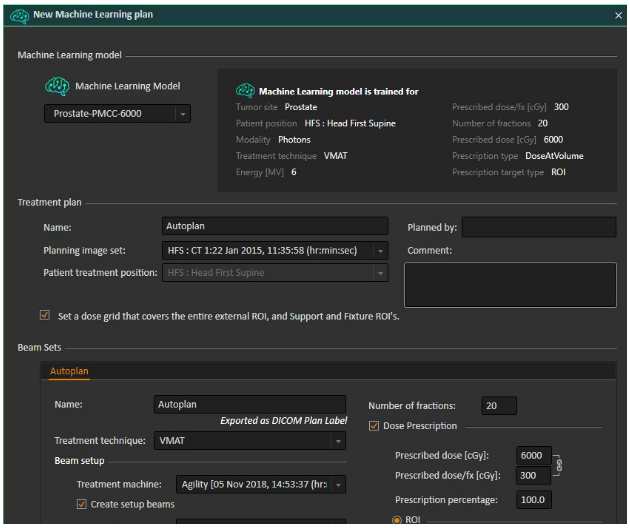


Figure 1. *Dialog box in RayStation for creating a machine learning plan.*

GENERATING MACHINE LEARNING PLANS

With the machine learning planning module in RayStation, it is possible to generate one or multiple deliverable plans in minutes. This is done by applying one or many trained models to the patient, where each model typically is associated with a treatment site, delivery technique and protocol. Each model can produce one or multiple spatial doses for the patient based on learned tradeoffs from the patient anatomy, tumor size and location. The inferred doses are then mimicked in RayStation to retrieve a deliverable plan.

RayStation will come with pre-trained models from leading cancer clinics. Clinics can also train models using their own data. Both model training and treatment plan generation can be accessed via scripting to fully automate the planning process.

MACHINE LEARNING METHOD

Unlike traditional treatment planning methods, where the dose is generated at the end of the workflow, the dose is inferred at the beginning of the workflow as input to the mimicking optimization, see Figure 2.

The mimicking optimization is performed to create a deliverable dose for the selected treatment machine and beam setup. This optimization will also strive to improve the dose when possible; spatially and optionally through clinical goals.

The machine learning framework can also infer multiple doses based on strategies defining tradeoffs and goals for the plan, see Figure 3. This makes it possible to push the machine learning plans to eventually create better plans than the plans used in the training set. The multiple plan option helps to get a better understanding of the tradeoffs for the patient. Any of the generated plans can be selected for delivery or for post-processing.

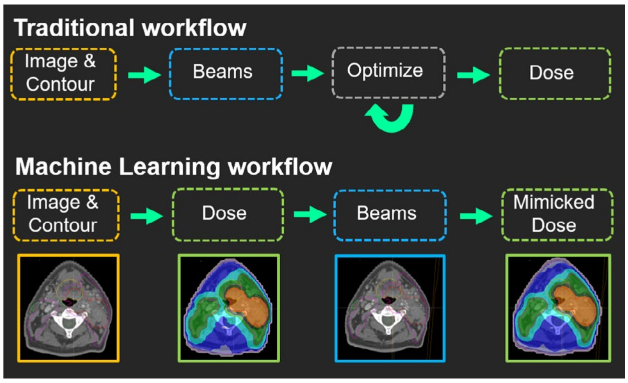
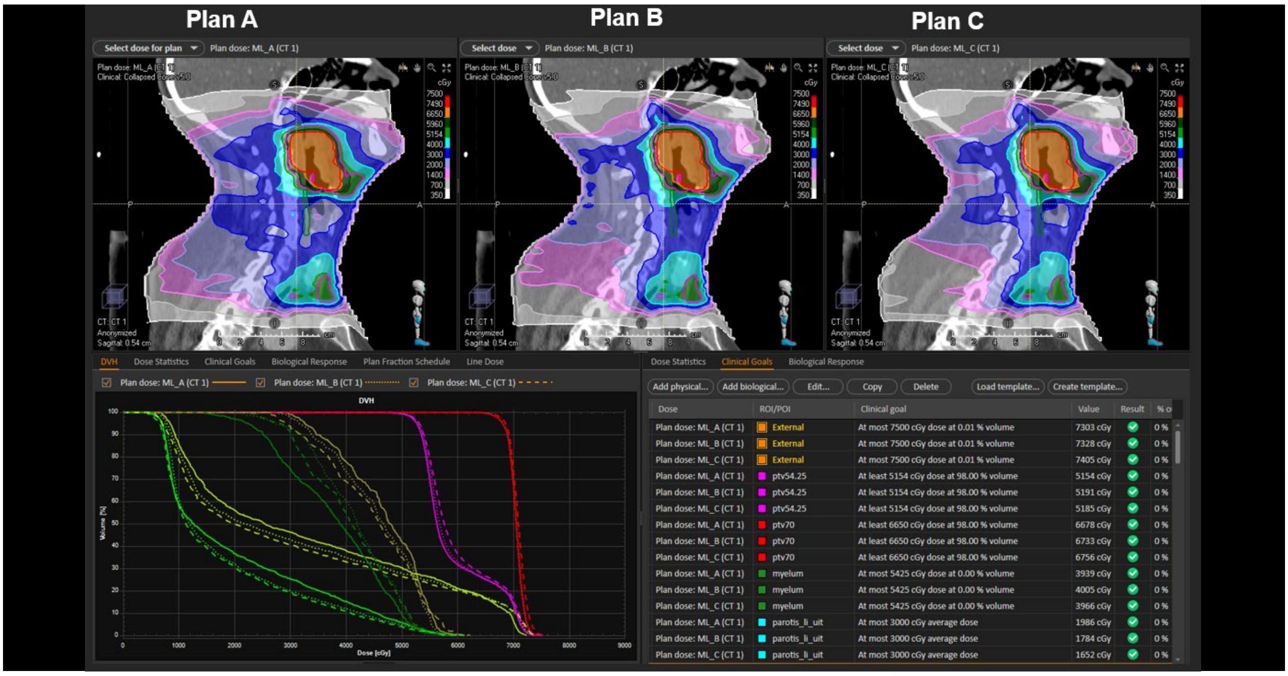


Figure 2. *Schematic overview of the treatment planning process. Top: traditional workflow. Bottom: machine learning workflow.*

Figure 3. *Automatically generated deliverable plans for a Head and Neck cancer case based on three different strategies: Plan A: Standard (solid line), Plan B: Greedy (dashed), Plan C: Avoid Xerostomia (dash-dotted).*



CLINICAL STUDY AT UMCG

CT scans, structures and doses of 71 primary Head and Neck cancer patients from UMCG, treated with dual arc VMAT and two dose levels; 70 Gy and 54.25 Gy delivered in 35 fractions, were collected. Patient selection was restricted to tumors localized in the oropharynx, larynx, oral cavity, nasopharynx and paranasal sinuses. A repeated random subset validation approach was applied where the patient data was split into four sets; using 8 patients for testing and the remaining 63 patients for training in each validation set.

The machine learning method in [2] was used for training. The trained models were used to predict three spatial doses for each patient in the test set, corresponding to three defined strategies: *Standard, Greedy, and Avoid Xerostomia*. In the final step, each predicted dose was input to a mimicking optimization algorithm to generate a deliverable dual arc VMAT plan. The predicted and mimicked doses of the patients in the test set were compared against the dosimetrist-optimized clinical plans, denoted below by reference plans.

Plans were compared in terms of the following dose metrics:

- Targets: D98 > 95%, D2 < 107%;
- OARs: Dmean, Dmax.

One mimicked plan out of the three automatically generated plans per patient was selected based on D98 to both targets and Dmean to OARs. No further post-processing was performed on the mimicked plans.

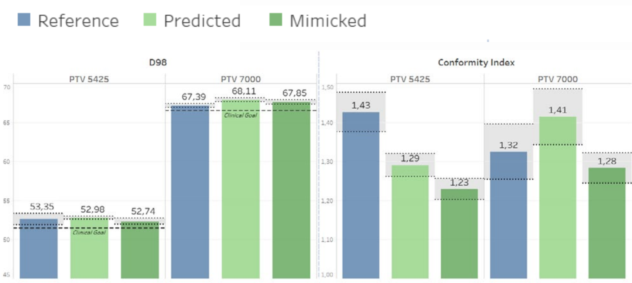


Figure 4. *Dose metric comparison for the two target volumes, D98 (left) and conformity index (right), with grey area showing the 95% confidence interval.*

RESULTS

The machine learning plans were generated automatically via scripting. The average run time per plan was 29 minutes, where the dose prediction took 4 minutes and the mimicking optimization for the dual arc VMAT took 25 minutes on an Intel® i9-7940X CPU.

The predicted dose was in accordance with the reference dose for all plans. The mimicked plans had adequate target coverage for primary and elective target volumes according to clinical goals in 31/32 (97%) of the cases. For reference plans, 30/32 (94%) had adequate target coverage based on the same criteria. Target conformity was better in the mimicked plans compared to the reference plans, see Figure 4.

The maximum dose to brain, brainstem, and spinal cord was lower for the mimicked plans than for the reference plans. Overall, the average dose to parotids, oral cavity, pharynx and supraglottic were similar, see Figure 5.

CONCLUSIONS

The machine learning planning approach is an efficient method to generate high-quality treatment plans automatically. In a retrospective Head and Neck study with UMCG, the machine learning planning approach is capable of generating deliverable dual arc VMAT plans with adequate target coverage in 97% (31/32) of the cases. The dose to the OARs was similar to the dose of the clinical reference plans.

Figure 5. *Dose metric comparison for OARs, max dose (left) and average dose (right), with grey area showing the 95% confidence interval.*

It was great to work together with RaySearch on the forefront of this very promising new technology. Results were good from the start and quality of dose predictions and dose mimicking could be further improved within a short time frame, thanks to the dedicated RaySearch team. It is now ready for prime time to support our efforts to give each patient the best possible treatment."

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[2] McIntosh C, Welch M, McNiven A, Jaffray DA, Purdie TG.
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* Subject to regulatory clearance in some markets.

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