Taking automated radiotherapy planning to the next level: automated batch planning via scripting

[1]Kirby J, [1]West N, [2]Wheeler P
[1]Northern Centre for Cancer Care, The Newcastle upon Tyne Hospitals NHS FT, UK.
[2]Velindre Cancer Centre, Velindre University NHS Trust, Wales.

Background.

The manual creation of radiotherapy treatment plans is a time-consuming process where variation in plan quality across a cohort of dose planning staff can be expected.[1] There are now a variety of techniques utilised for the automated planning of individual patients.[2] One such method devised by Wheeler et al[3] is 'EdgeVcc' which uses a protocol based automatic iterative optimisation algorithm that incorporates clinician preferences relating to the trade-offs of clinical objectives. The use of such an algorithm requires no human interaction during the optimisation phase of treatment planning. This opens the door for more efficient work practices where the optimisation of many patient plans can be batched together in the background. Here we discuss the design and implementation of a system that is able to continuously batch plan patients using the underlying EdgeVcc automated planning algorithm.

Methods.

Python scripts were created for use with the RayStation (v9B) treatment planning system (TPS). After the required OARs and PTVs have been created for the patient, a script is used to add the patient to a batch queue (stored in an SQLite database). A graphical user interface (GUI) is shown to the user to allow them to view the queue and to make simple interactions such as removing a patient from the queue or to change the order. In the background, on one of the TPS servers, a separate script runs continuously that creates a plan and optimises for any patients that are added to the queue. Within normal working hours a single license is used to plan patients but outside of working hours the batch planning script is allowed to plan patients simultaneously limited by the number of available licenses. Once planning is complete, the log file is available to view by planners and any errors are shown within the batch queue GUI.

Results & Discussion.

A batch planning process has been designed that is capable of automated planning using EdgeVcc and RayStation for any calibrated (via the EdgeVcc calibration process) treatment protocol. The system is currently calibrated for prostate and seminal vesicles with 60Gy/20# and it is expected to add additional protocols in the near future. Maximum capacity on a single server (with potential to expand to additional servers) with this protocol (~20 minutes per patient) is approximately 30 patients during working hours and ~200 patients outside of working hours. This leads to a change in the working practices of dose planners whereby they no longer need to be present during the optimisation and dose calculation phases of dose planning, giving them time to focus on other tasks. When combined with automated contouring, there is potential to streamline the planning process and minimise the time between planning scan and treatment. This batch planning concept would also work with other automated planning solutions and is a more efficient use of time whilst maximising plan quality across the patient cohort.

Conclusion.

We have demonstrated that the automated batch planning of patients is possible and has the potential to improve workflows, shorten care paths and reduce pressure on busy dose planning departments.

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Creation of a Deep Learning treatment planning model based on CHHiP trial

Timothy Atkins, Simon Whittle, Rasmus Helander, Fredrik Löfman

Background. Machine Learning (ML) based treatment planning is a technique for automating the generation of deliverable treatment plans. This work investigates the process of developing and evaluating a deep learning (DL) based approach to plan generation following the hypofractionated arm of the CHHiP trial for prostate treatments [1].

Methods. 100 patient datasets were selected from patients previously treated at the RUH Bath. Each of these datasets were assessed to ensure that they delivered dose distributions that were acceptable according to the CHHiP trial criteria. These datasets were used to train (90 datasets) and validate (10) a UNet convolutional neural network (CNN) to predict a dose distribution based on 3D binary representations of the bladder, rectum and target volumes. The UNet dose distribution was then utilised in a dose mimicking/optimisation pipeline to generate deliverable plans. The settings for post-processing and dose mimicking were configured using feedback from comparison of the resultant plans with the clinical plans on an independent set of 10 cases. The dose distributions created by the final model were compared using a Wilcoxon signed-rank test.

Results. All dose constraints defined in the CHHiP trial for the bladder, rectum and PTVs were satisfied for all test patients. However, two issues were found with the spatial properties of the first iteration of the model upon slice-by-slice inspection of the dose distribution. These two issues were remedied in a second and third iteration of the configuration, see Figure 1. For the third version, statistically significant ($p < 0.05$) improvements compared to the clinical plan was observed for most of the dose constraints considered, see Table 1.

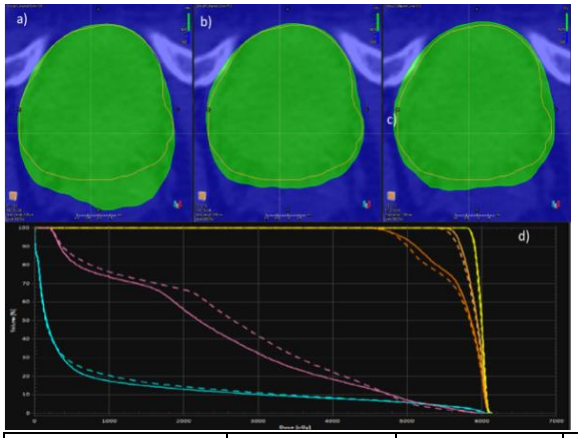

Figure 1 a)-c). Isodose cloud for 45.7Gy together with PTV_5760 (orange) for the first, second and third versions of the post-processing and dose mimicking settings respectively. a) the isodose area extends too far past the PTV posteriorly, which the anterior margin to the structure is too small. b) the posterior extension is solved but the anterior margin is still too small. c) the anterior margin is sufficient. d) DVHs for bladder (blue), rectum (pink), PTV_4800 (orange), PTV_5760 (beige) and PTV_6000 (yellow) for the clinical plan (dashed) and the ML plan (solid) generated by the third version of the settings.

Goal	CHHiP dose Constraint	CP	DLP	p
PTV_6000: D99%	>57.0	58.49 (0.12)	58.49 (0.07)	0.922
PTV_5760: D99%	>54.7	55.44 (0.31)	56.05 (0.10)	0.002
PTV_4800: D99%	>45.6	47.70 (0.40)	47.11 (0.40)	0.002
Rectum: D3%	<60.0	56.09 (1.96)	56.73 (1.94)	0.02
Rectum: D15%	<57.0	47.44 (4.10)	46.96 (5.01)	0.275
Rectum: D30%	<52.8	38.17 (5.52)	36.43 (6.40)	0.004
Rectum: D50%	<48.6	27.95 (4.71)	25.81 (5.77)	0.014
Rectum: D60%	<40.8	23.79 (3.46)	21.51 (4.65)	0.014
Bladder: D5%	<60.0	55.68 (3.07)	55.91 (3.62)	0.084
Bladder: D25%	<48.6	24.35 (8.91)	21.34 (5.97)	0.002
Bladder: D50%	<45.6	11.23 (7.20)	8.80 (5.97)	0.004

Table 1 Dosimetric evaluation of mean doses across 10 DL-generated plans (DLP) as compared to clinical plan (CP). DLP were generated with the third version of postprocessing and dose mimicking settings. Green cells indicate statistically significant differences in favour of the DLP. Red cells indicate statistically significant differences in favour of the CP. Dose constraints are from the CHHiP trial for the ROIs relevant to the study. Dose values are in Gy. Values in brackets indicate 1 standard deviation.

Discussion. This work has outlined the process of developing and testing a DL model intended for implementation in the clinical workflow. In terms of OAR sparing the model outperforms the benchmark data while achieving clinically acceptable target coverage. The development of the model stresses the importance of configuring settings for a specific clinical use case, while highlighting that retraining of a neural network is not mandatory to improve results. The first patient planned using this model was treated at the RUH in January 2023.

Conclusion. A clinically acceptable DL based planning technique for prostate was developed and tested during a collaboration between RaySearch Laboratories and Royal United Hospitals, Bath.

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Knowledge-based planning site by site implementation process

Miranda Frizzelle

Background.

With the introduction of 17-day pathways for multiple new sites in radiotherapy [1], knowledge-based planning has become increasingly important in helping to reduce the planning workload for departments [2-5]. A standardised approach to allocating appropriate sites, testing and clinically trialling models has been implemented with strategies in place to feedback and adjust models to achieve optimum results.

Methods.

The implementation process involves an initial patient audit stage, creating generalised Rapidplan models which apply to a wider range of prescriptions, and a testing phase with structured dose objective reporting allowing clear comparisons between techniques. The method was fine-tuned and optimised during a project to validate a Rapidplan 'super-model', created by combining data libraries from three centres within the UK Rapidplan Consortium [2]. This utilised the expertise and knowledge of multiple centres to maximise the robustness and clinical success of the final model.

Discussion and Results.

Rapidplan has been in use at UCLH since 2019 following the successful implementation of a lower head and neck model which reduced planning and optimisation times from ~2.5 hours to ~15 minutes. Since then, four more site models have been commissioned for use, and a further three are in progress. Overall, the process has streamlined the introduction of new models, allowing faster relief of the planning workload and increased automation within the planning pathway.

Conclusion.

We propose a clear process which enhances the applicability of knowledge-based models, improves the efficiency of implementation and allows easy collaboration between colleagues to share the workload in creating models whilst ensuring safe operation. The aim is to share the step-by-step process with the aim of improving knowledge-based planning model implementation nationally.

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An assessment of the accuracy of the organ at risk contours for five commercial AI contouring solutions

P. Doolan[1*], S. Charalambous[1], Y Roussakis[1], A Leczyski[1], K Ferentinos[1,2], I Strouthos[1], C Zamboglou[1], E Karagiannis[1,2]
(1) German Oncology Center, (2) European University Cyprus
*Corresponding author: paul.doolan@goc.com.cy

Background. Auto-segmentation with artificial intelligence (AI) can remove inter- and intra-observer variability in contouring, improve the quality of contours and also reduce the time taken to conduct this manual task. In this work we assess the AI auto-segmentation contours produced by five commercial vendors against a common dataset..

Methods. Organ at risk (OAR) contours generated by five commercial AI auto-segmentation solutions (Mirada (Mir), MVision (MV), Radformation (Rad), RayStation (Ray) and TheraPanacea (Ther)) were compared to expert contours from 20 breast, 20 head and neck, 20 lung and 20 prostate patients. The expert contours were drawn by a Radiation Oncologist following RTOG atlas, Brouwer *et al* (1), Scoccianti (2) or Gay (3) guidelines. Comparisons were made using geometric similarity metrics including volumetric and surface Dice similarity coefficient (vDSC and sDSC), Hausdorff distance (HD) and Added Path Length (APL). The time taken to manually draw the expert contours and the time to correct the AI contours were recorded.

Results. Each AI auto-segmentation solution offered different numbers of contours at the time of the study (Mir 99; MV 142; Rad 83; Ray 67; Ther 86). Averaged across all structures, the median vDSCs were good for all systems: Mir 0.80; MV 0.85; Rad 0.83; Ray 0.85; Ther 0.87 (see example for prostate in Fig. 1). All systems offer substantial time savings, ranging between: Breast 14.2-20.6 mins; head and neck 80.7-104.6 mins; lung 20.0-25.6 mins; prostate 33.9-41.1 mins. The time saved, averaged across all sites, was similar for all systems: Mir 42.2 mins; MV 46.0 mins; Rad 38.0 min; Ray 46.0 mins; Ther 47.8 mins.

Conclusion. All five commercial AI auto-segmentation solutions evaluated in this work produce high quality, consistent, contours while simultaneously offering significant time-saving. Compared to manual contouring they could be used to make the radiotherapy workflow more efficient and standardized.

Key words. 1. Artificial intelligence, 2. Contouring, 3 Geometric similarity.

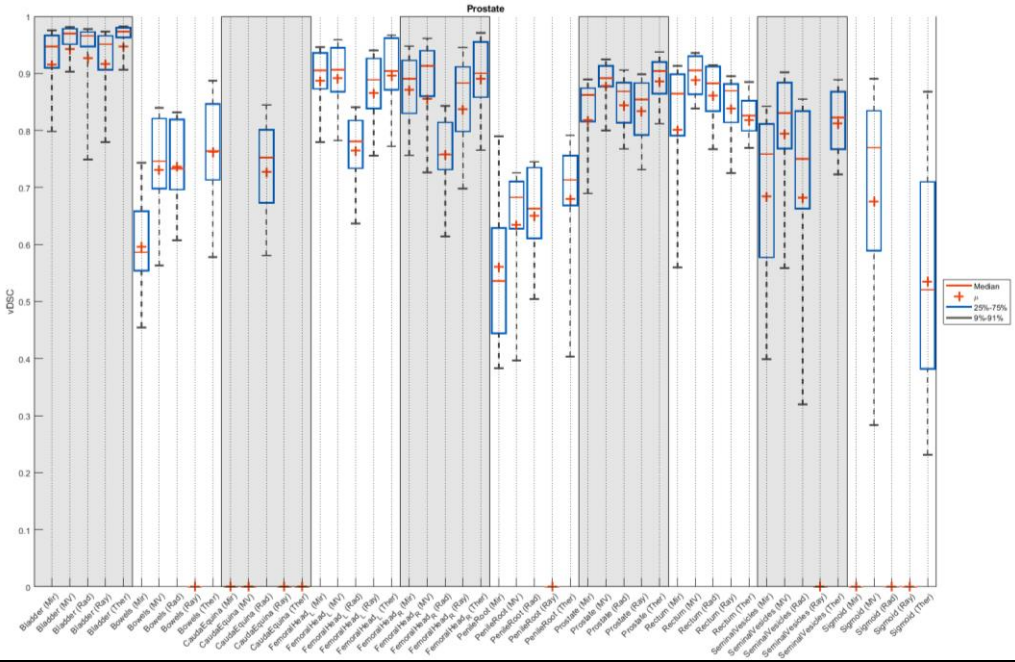

Figure 1: Volumetric dice similarity (vDSC) coefficients for twenty prostate cases, compared to expert manually-drawn contours, for each commercial AI contouring solution. Mir = Mirada; MVis = MVision; Rad = Radformation; Ray = RayStation; Ther = Therapanacea.

Title of Study: Evaluating the Safety and Utility of Auto-Segmentation Software using ProKnow

Submitters details: Alexandra Constantinou (CUH), Andrew Hoole (CUH), Raj Jena, Andrew Robinson, Liam Stubbington

Background. Automation in Radiotherapy is desirable but it is imperative that it is rigorously evaluated and implemented safely.[1] CUH are currently developing an in-house auto-segmentation software for organ at risk (OAR) contouring in radiotherapy treatment planning, OSAIRIS, with funding from an NHSx AI Award. Part of the development of a medical device involves carrying out a clinical evaluation to demonstrate its benefits, compare its performance to other devices, and evaluate its safety. To this end, our first aim was to set up a 'Turing test' to determine the clinicians' subjective assessments of the contour quality of OSAIRIS compared to clinician gold-standard contours and those from two other auto-segmentation software.[2] Here, we would obscure the origin of a structure-set, and ask clinicians to review them and rate each contour's clinical acceptability. The second aim was to set up a 'mystery shopping' exercise, in which we would introduce discrepancies into the OSAIRIS output contours, and ask clinicians to edit them until they are clinically acceptable, to see if they are able to pick up any serious errors, were any to be made by OSAIRIS.[3] For this exercise, it was imperative that we use a platform that is not used for treatment planning, so we could separate this pilot study from the clinical workflow. We therefore decided to use ProKnow to host both of these evaluations.[4]

Methods. To set-up the evaluations, we made use of ProKnow's various features such as its API functionality, collections and custom metrics, which we used to record the clinicians' contour acceptability ratings. We generated scripts to automate as much of this process as possible.

Firstly, for the utility evaluations, there was one gold standard clinician structure set, and 3 auto-segmentation structure sets per patient scan for clinicians to review. Using ProKnow's API, we wrote scripts to create a separate collection for each clinician, with separate patients with a consistent naming system, and upload the scans and structure sets in batch. Custom metrics were created in ProKnow for each OAR so that clinicians could rate them and these were ascribed to each structure set using the API. We wrote scripts to ensure the naming and colour conventions used for the structure sets were consistent, so that clinicians would not know their origin. These custom metrics were then exported using another script and were subsequently analysed.

Secondly, for the 'mystery shopping' exercise, we had one OSAIRIS-generated structure set for each of the five patient scans used, and we had introduced discrepancies into them. In a similar fashion to the previous evaluation, collections and patients were created for each clinician using a script, and the scans and structure sets were subsequently uploaded using another script. The edited contours were then exported using a script.

Results. We were able to set up the two evaluations as described. We have had good clinician engagement so far, with three clinicians completing both evaluations for the Prostate, and two for the Head and Neck.

Discussion. This result is significant, as it paves the way for ProKnow to be used in future evaluations of automation techniques and new technologies. ProKnow is currently available to all NHS Radiotherapy departments, and enables safe data sharing between them, with built-in anonymisation. This opens the door to larger-scale evaluations involving multiple trusts.

Conclusion. We have shown that it is possible to use ProKnow to set up an evaluation for auto-segmentation software with good clinician engagement. This paves the way for future large-scale evaluations of automation devices in radiotherapy.

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The evolution of the clinical treatment planning system scripting service over 7 years at the NCCC

[1]Kirby J, [1]Dixon B
[1]Northern Centre for Cancer Care, The Newcastle upon Tyne Hospitals NHS FT, UK.

Many commercial radiotherapy treatment planning systems (TPS) include scripting functionality allowing users to optimise the planning workflow and enabling interactions beyond the use of the standard interface. This functionality can lead to improved efficiency as time-consuming repetitive steps are completed without requiring user interaction, allowing staff to spend their time where they add more value. Safety is improved with reduced likelihood of transcription errors, greater consistency in approach and a reduction in small errors that are inevitable when a human completes a repetitive task[1]. Scripting also makes it easier to work with the vast quantity of data available in the TPS and other clinical systems, maximising process efficiency and unlocking the potential for data mining and analysis[2].

Since commissioning the RayStation (RaySearch Laboratories)TPS in 2016 at the NCCC, the clinical scripting service within radiotherapy physics has evolved from one or two users using the built-in script recording functionality for very simple tasks to having a team of scientists developing a range of more complex scripts that share a suite of in-house developed modules. Currently, there are 31 clinical scripts in use or in development covering areas such as ROI creation, automated planning, secondary dose calculation for an independent TPS, plan checking, CBCT dose evaluation and quality assurance processes. Scripting therefore plays a large role at all stages within the planning process and complements other automation tools such as AI contour segmentation to optimise the pathway.

The management of the scripting service has necessarily developed over this time as the quantity and complexity of the scripts have grown. A new software lifecycle has been introduced with version control and each stage of the software lifecycle tracked using Git (open source) and Azure DevOps (Microsoft Corporation), providing an audit trail. The quantity and quality of documentation has increased to be compliant with current and future legislation (as described in IPEM guidance[3]), with additional workload minimised by the use of an automated document creator and management within the quality management system, Q-Pulse (Ideagen Products Ltd.).

Current process developments include the logging of script uses and code exceptions in an SQLite database to demonstrate the value of specific scripts, enhance identification of bugs and facilitate future audit.

From small beginnings, the scripting group and associated processes have necessarily expanded to keep up with demand and to aim for best practice. The value of the group has been recognised by the department with investment in external training and the creation of a new lead clinical scientist role for clinical and scientific computing in radiotherapy. It is expected that the team will continue to evolve for the benefit of both patients and staff as new technologies, techniques and workflows are developed.

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Scripting with Varian's ESAPI: The Beginner's Experience

Glenn Whitten, Denise Irvine
Radiotherapy Physics, Northern Ireland Cancer Centre, Belfast.

Background.

Many processes within the radiotherapy and treatment planning workflow involve repetitive and time consuming tasks[1]. With complexity of planning techniques and pressures on the workforce increasing, being able to harness the power of automation and scripting can prove to be a valuable tool in improving efficiency, safety and quality[2, 3]. Often the idea of scripting can be daunting however with some basic training and understanding of the resources available scripts can be created and put to use in both a safe and efficient way which will bring benefits to your department.

Methods.

Varian's Eclipse scripting application programming interface (ESAPI) became available in v11 and we have been using it since 2019 in v15.6 and v16.1. ESAPI allows the user to create scripts that leverage the functionality of Eclipse and can retrieve plan, image, dose, structure and DVH information. With automation it is possible to create and modify structure and plan data and execute dose calculation and optimization algorithms. A learning experience was developed to gain familiarity with ESAPI which included acquiring the correct tools to script, using online resources and attending the Varian ESAPI Basics course. Within the NICC treatment planning department, areas where scripting could be of benefit to improve the workflow were identified and scripts were created and put in to use. This presentation aims to give an overview of what is being used at the NICC showing our scripting journey from novice to clinically useful scripts developed by a non-expert.

Results.

Within the treatment planning database there is a wealth of information about treatment plans. This information can be harnessed through data mining of DVHs for a cohort of patients to inform service development and local quality improvement. Plan checking is a task which requires the user to click through multiple windows within the treatment planning system retrieving often the same information for every patient. A script was developed to assist in the checking of plans which automatically populates a checklist that the checker is required to retrieve and evaluate, reducing the amount of 'clicks' and time required to view the information. A script was also created to compare the plan parameters set by a Clinician at VSim to the final plan issued for treatment to identify if any inadvertent changes have been made. Shift directions and magnitude from tattoos to isocentre for multiple coordinate systems can easily be scripted to give the correct information, removing the operator error and ensuring the instructions are correct each time. Site specific automatic plan generation scripts have been created to assist planners in performing repetitive tasks such as the generation of planning structures, placing beams, adding optimisation parameters, optimising and calculating plans enabling a VMAT plan to be generated with only one click in a few minutes.

Discussion.

Scripting with ESAPI reduces the time taken to perform repetitive tasks allowing staff more time to focus on the complex cases or devote further time to specific details. Scripting can reduce the chance of human errors and allows staff to harness the vast wealth of information stored within the Varian database. There are hurdles to overcome and it is important to operate within a quality framework but there are still many areas to further develop.

Conclusion.

ESAPI is a powerful tool which can be used by Varian users. This can be utilised by a computer programming beginner with a good understanding of Eclipse to create useful and valuable scripts which will help the department save time and reduce errors.

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Automation within the Prostate Brachytherapy Workflow

George Kirby, Gerry Lowe, Victoria Newton – Mount Vernon Cancer Centre

Background: Throughout the prostate brachytherapy workflow, time is an important constraint because of the potential movement of internally placed catheters as peri-prostatic oedema forms, causing caudal displacement, and leading to a geographic miss if uncorrected. 'Corrective Action' CT images are often obtained after the physics planning is completed to make these adjustments. Utilising automation techniques and automatic optimisation has the potential to reduce the time spent planning treatments, while producing clinically ready plans, thereby reducing the magnitude of oedema during the planning process.

Method: Following from the clinician contouring the OARs (Urethra and Rectum) and CTV, an Eclipse Scripting API (ESAPI) script has been written generate a set of optimisation structures for prostate planning: a contracted, inner urethra structure; an extended PTV structure; and a ring structure around the prostate. Legal dwell positions for the optimiser are set to be within the extended PTV structure, which allows the use of needles that are close to but not intersecting the PTV itself.

The Varian VEGO TG-43 optimiser is weighted heavily to reduce urethral dose, with the Inner Urethra structure being highly restrictive. There is also heavy weighting on maximum rectal dose, with a lower weighting on ring structure dose. This optimiser, new to us in the current Eclipse version, is a significant improvement over previously available optimisers.

Following the planning process, an ESAPI checking script is run to check for technical problems within the plan. This script will check: dwell times are within the correct range; plan data are correct, including course name, plan name and prescribed dose; needle lengths are standard and matching; reference points are placed and named. The plan is then ready to be checked and reviewed by the clinician and by a second, independent, physicist as usual.

Results/Discussion: For most whole-prostate treatments, a clinical plan that was within OAR thresholds was created quickly and automatically. In a retrospective sample of 8 patients, in every case a higher PTV coverage was achieved, and in 7 out of 8 cases the OARs remained below tolerance. Plans that were not clinically ready (such as the one case from the sample) were found to require minimal adjustment from a planner. The physics optimisation time was reduced from an average of 37 minutes (retrospective sample of 81 patients) to an average of 7.5 minutes (most recent 4 patients in series). For focal salvage cases, the results of optimisation heavily depended on the needle placement; these cases required manual planning.

By using the developed techniques, time can be saved in the planning phase, which would potentially remove the need for a 'corrective action' CT scan. The additional time could also allow for more efficiency within a department in the context of a large patient load. The checking script allows efficient detection of issues.

Conclusion: The results show that implementation of automation and scripting in HDR prostate planning has led to a large decrease in physics planning time. The plans produced have a good distribution, OAR doses within tolerance and a high coverage to the PTV. The results are based on whole prostate treatments and do not include focal treatments.

Key Words: *Brachytherapy, Automation, HDR, Prostate, Scripting, Optimisation*

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Development, evaluation and widespread implementation of Pareto navigation guided automated planning in the clinic

Wheeler P.A.[1], Berenato S.[1], Millin A.E.[1]

[1]Velindre Cancer Centre, Radiotherapy Physics Department, Cardiff, Wales, United Kingdom.

Background.

Current automated planning solutions are calibrated using trial and error or machine learning on historical datasets. Neither method allows for the intuitive exploration of differing trade-off options during calibration, which may aid in ensuring alignment with clinical preference. Pareto navigation provides this functionality and offers a calibration alternative. This work presents our experience in developing, evaluating and clinically implementing a fully automated radiotherapy planning solution which incorporates a novel multi-dimensional Pareto navigation calibration interface.

Methods.

The implemented 'Pareto Guided Automated Planning' (PGAP) methodology was developed in RayStation using scripting and consisted of a Pareto navigation calibration interface built upon a 'Protocol Based Automatic Iterative Optimisation' planning framework. Robust single institution evaluations against manually generated plans (MP) were performed for prostate (PSV, n=20), prostate and pelvic nodes (PPN, n=20), Extreme hypo-fractionated prostate (EHRT, n=22), head and neck (HnN, n=35) and two-phase PET adapted HnN (HnN_{PET}, n=9). In addition, a two centre multi-institutional study was performed for PSV ($PSV_{External}$, n=40). Validation for all sites included quantitative comparison across clinical dose metrics and blind qualitative review by a clinical oncologist. For PSV and PPN timing data was collected to estimate efficiency savings. Based on validation results and additional small scale implementation studies, fully automated PGAP was clinically implemented for PSV, EHRT, HnN_{PET}, anus, oesophagus, rectum and lung treatments, which represent ~ 30% of all radical indications. HnN implementation is due in the coming months. Our methodology has been adopted by an external institution, with implementation due Q3 2023.

Results.

Upon blind review 95%, 100%, 91%, 80%,100%, and 93% automated plans were considered clinically equivalent or superior to MP for PSV, PPN, EHRT, HnN, HnN_{PET} and $PSV_{External}$ respectively, with 92/134 AP plans considered clinically superior. For PSV and PPN hands on planning time was reduced by 94% and 79% respectively. A summary of the quantitative DVH comparison for key metrics is presented in Table 1. In general, automation led to statistically significant ($p<0.05$) reductions in mean dose for high priority OARs (e.g. rectum and parotid), but increases for low priority OARs (e.g. bladder). PTV coverage and conformality were nominally equivalent. Results for all small-scale implementation studies were also supportive of AP, leading to clinical rollout.

Table 1: Summary of validation studies, bold represents $p<0.05$.

Site	ROI	Metric	$VMAT_{Auto}$	$VMAT_{Manual}$
PSV (n=20)	PTV60	D98% (Gy)	57.90 ± 0.10	57.80 ± 0.20
		D2% (Gy)	**61.60 ± 0.10**	**61.70 ± 0.20**
		CI	**0.86 ± 0.01**	**0.84 ± 0.03**
	Rectum	Dmean (Gy)	**22.70 ± 3.90**	**25.10 ± 3.50**
	Bladder	Dmean (Gy)	**23.00 ± 9.10**	**22.20 ± 8.60**
	Bowel	Dmean (Gy)	8.60 ± 4.70	8.40 ± 4.70
PPN (n=20)	PTV60	D98% (Gy)	**57.80 ± 0.10**	**58.00 ± 0.10**
		D2% (Gy)	**61.70 ± 0.10**	**61.90 ± 0.20**
		CI	**0.82 ± 0.02**	**0.81 ± 0.03**
	Rectum	Dmean (Gy)	**29.50 ± 2.70**	**30.40 ± 2.60**
	Bladder	Dmean (Gy)	**33.00 ± 3.90**	**31.30 ± 3.50**
	Bowel	Dmean (Gy)	**18.70 ± 2.60**	**19.60 ± 2.60**
EHRT (n=22)	PTV36.25	D98% (Gy)	**35.40 ± 0.60**	**35.60 ± 0.70**
		D2% (Gy)	42.50 ± 0.20	42.50 ± 0.10
		Dmax (Gy)	43.00 ± 0.10	43.00 ± 0.20
	Rectum	V18.1Gy (%)	**16.90 ± 5.50**	**20.10 ± 5.90**
	Bladder	V18.1Gy (%)	18.60 ± 6.00	18.40 ± 6.20
	Bowel	V18.1Gy (cc)	**0.70 ± 1.50**	**0.30 ± 0.70**
HnN (n=35)	PTV66	D98% (Gy)	**63.50 ± 0.10**	**62.60 ± 1.10**
		D2% (Gy)	68.50 ± 0.10	68.50 ± 0.30
		CI	**0.80 ± 0.04**	**0.78 ± 0.06**
	Parotid_CL	Dmean (Gy)	**21.50 ± 7.10**	**24.70 ± 8.30**
	SpinalCord_5mm	Dmean (Gy)	**44.30 ± 3.20**	**46.90 ± 1.50**
	BrainStem_5mm	Dmean (Gy)	**41.00 ± 7.00**	**43.90 ± 7.00**

Discussion.

PGAP consistently yielded high quality plans that prioritised high priority over low priority objectives. Results of the blind reviews suggest this prioritisation was more congruent with clinical preference than MP and supported the use of Pareto Navigation as a calibration tool. In terms of clinical implementation, software development under a quality management system and calibration of automated solutions was time consuming, but once released for clinical use implementation was highly successful.

Conclusion. PGAP is a highly effective automated planning methodology, which is suitable for broad scope implementation and yields marked improvements plan quality and efficiency.