JULY 12–16 2020 VIRTUAL JOINT AAPM | COMP MEETING
EASTERN TIME [GMT-4]

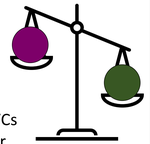
A Flexible Projection-Based Non-Convex Inverse Planning Algorithm for Intensity-Modulated Proton Therapy

M. BROOKE [1], Y. CENSOR [2], A. GIBALI [3], S. PENFOLD [4, 5], R. SCHULTE [6] and F. VAN DEN HEUVEL [1]

[1]CRUK/MRC Oxford Institute for Radiation Oncology, Oxford, United Kingdom [2]Department of Mathematics, University of Haifa, Haifa, Israel
[3]Department of Mathematics, ORT Braude College, Karmiel, Israel [4]Department of Medical Physics, Royal Adelaide Hospital, Adelaide, Australia
[5]Department of Physics, University of Adelaide, Adelaide, Australia [6]Department of Basic Sciences, School of Medicine, Loma Linda University, Loma Linda, USA

OXFORD INSTITUTE FOR RADIATION ONCOLOGY

INTRODUCTION



The incorporation of dose-volume constraints (DVCs) in the inverse optimization of intensity-modulated proton therapy (IMPT) allows for additional control over the physical dose distribution in order to better meet biological objectives. DVCs permit a certain portion (e.g. 5%) of a structure to exceed, or fall short of, the prescribed dose by up to a certain amount (e.g. 3Gy). However, DVCs introduce non-convexity to the inverse problem, so they are often approximated by linear cost functions. Meeting one objective often comes as the expense of another, and so a compromise must be achieved in the final dose solution.

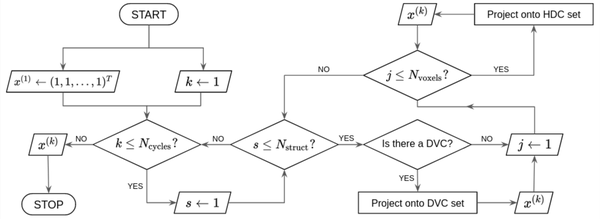
We propose a dynamic string-averaging CQ-method, detailed in [1], to solve the inverse problem, with exact representation of DVCs, using non-convex split feasibility-seeking methods.

AIMS

- **Introduce a novel treatment planning algorithm based on a split-feasibility formulation of the inverse problem for IMPT**
- **Demonstrate its capabilities for handling multiple DVCs**

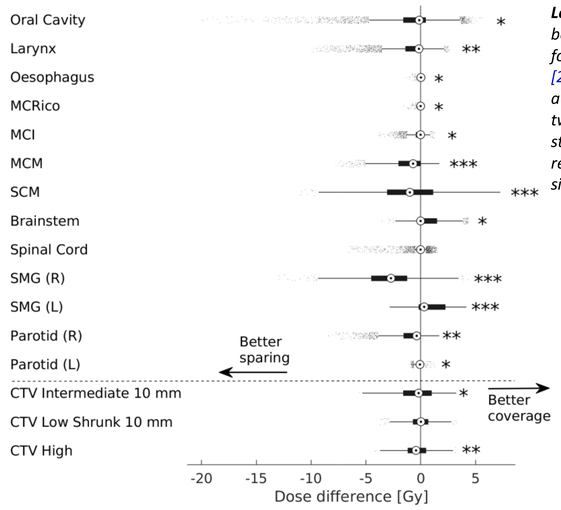
METHODS

- An algorithm [1] was designed to apply successive projections onto both hard dose constraint (HDC) sets (e.g. min/max dose) and DVC sets.
- Each projection updates the vector of relative pencil beam intensities, x.
- The algorithm was implemented in MATLAB for a variety of test cases, including a head-and-neck case containing 23 delineated structures [2].
- An accelerated version was written in Python, using multithreading and just-in-time compilation.

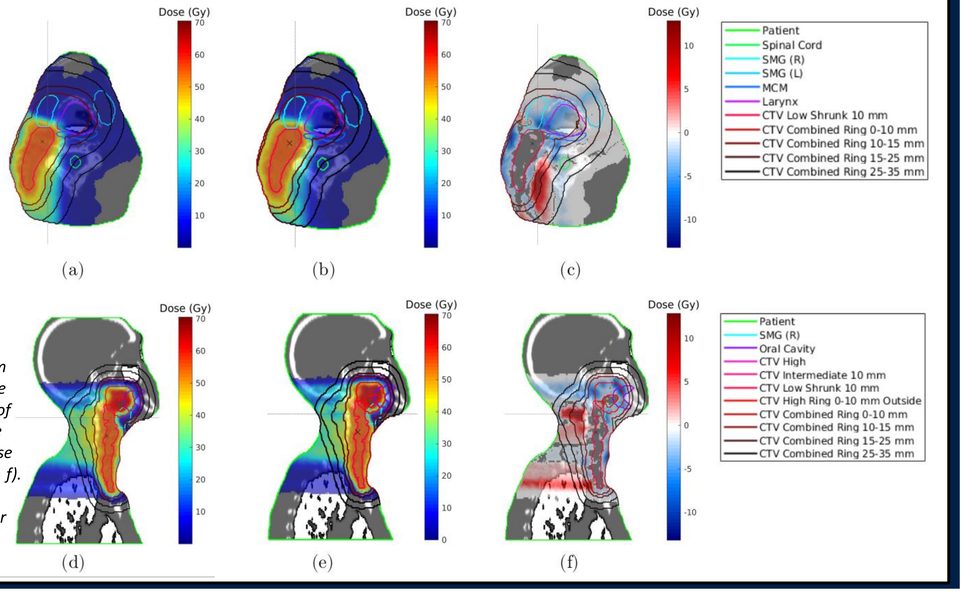


Above: *Flowchart of the algorithm. N_{cycles} is the number of algorithmic iterations, N_{struct} is the number of structures, and N_{voxels} is the number of voxels comprising a structure. Counter increments are implied within each loop.*

RESULTS



Left: *Box plots showing non-zero dose differences between our algorithm and the accepted solution for a head-and-neck case from the TROTS data set [2]. One asterisk beside the data indicates there is a statistically significant difference in the doses; two or three indicate the absolute difference is statistically greater than 0.25 Gy or 0.50 Gy respectively. Significance is defined by a Wilcoxon signed-rank test returning a probability of p<0.05.*



Right: *Transverse (top row) and sagittal (bottom row) CT slices for the TROTS head-and-neck case [2], showing the final dose after 500 iterations of our algorithm using SARP (a, d), the actual dose included with the TROTS data (b, e), and the dose difference between the former and the latter (c, f). Absolute doses above 0.5 Gy or differences less than 2% are not shown. The treatment isocenter is shown by a black cross, and the chosen slices are indicated by dashed gray lines.*

KEY POINTS & CONCLUSIONS

Plan quality

- Achieved target coverage within 0.5 Gy of the accepted clinical dose solution.
- Offered the same or better sparing in 11 out of 13 organs-at-risk.
- Finer spatial considerations (e.g. hot spots) may need judicious correction.

Flexibility

- Algorithm is mathematically robust to the order and weighting of projections.
- Applies in non-convex settings imposed by multiple DVCs.
- Projection parameters may be varied freely within a permitted range, in order to shift attention to meeting constraints that cause the most violations.

Clinical efficiency

- Suitable convergence within 44 seconds using accelerated implementation.
- Optimizing only on linear constraints: less than 20 seconds.

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[2] Breedveld S, Heijmen B. Data for TROTS - The Radiotherapy Optimisation Test Set. *Data Brief*. 2017;12:143–149. Published 2017 Apr 1. doi:10.1016/j.dib.2017.03.037

Further reading:

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CONTACT

Mark Brooke, University of Oxford, mark.brooke@oncology.ox.ac.uk

@markdanbrooke /mdbrooke http://markdbrooke.com