Advanced IMRT Optimization Strategies

Emilie Soisson, Ph.D.

ICTP 2019

Learning Objective

To understand new tools to improve standardization and efficiency in IMRT planning

Acknowledgements

I am not a user of any of the products in this talk. I would like to thank the following vendors for supplying this information.

Philips

RaySearch Laboratories

Varian Medical System

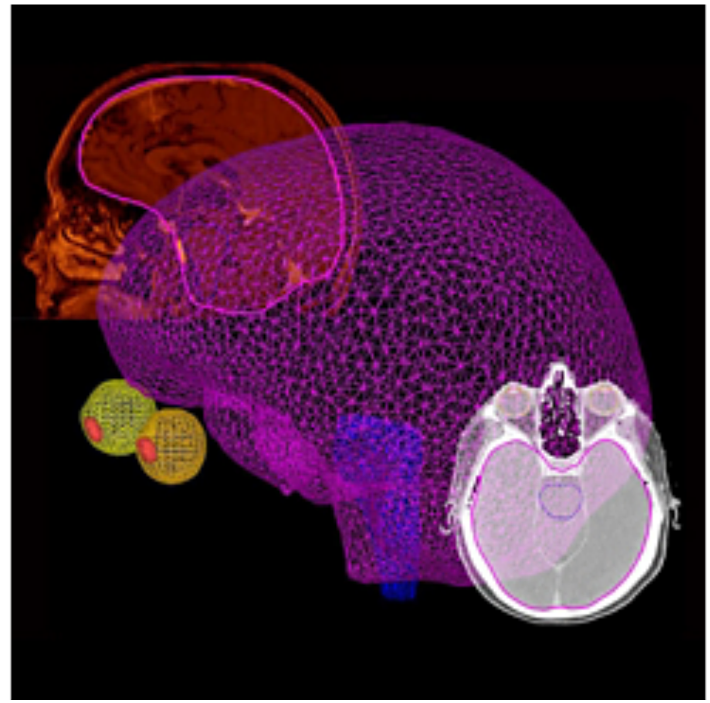
BrainLab

Why Automate Planning?

- Efficient
- Standardization
- Consistent plan quality and evaluation

Automatic Segmentation

- Model Based Segmentation (Pinnacle)
  - Triangular mesh adapted to points identified as boundaries between one organ and the next
- Atlas based segmentation (Brainlab, MIM, etc.)
  - More standard deformable registration used to propagate contours from one image to the next
- Many TPS have tools to autosegment particular areas (ie. Bone, brain, lung, eyes, etc.)



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Automatic Beam Definition

- Use of scripting to automatically position and shape beams
- TPS may have an algorithm to determine beam angles
- Tools generally exist to shape blocks, jaws, etc. to the field

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PHYSICS CONTRIBUTION

AUTOMATED PLANNING OF TANGENTIAL BREAST INTENSITY-MODULATED RADIOTHERAPY USING HEURISTIC OPTIMIZATION

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Purpose: To present an automated technique for two-field tangential breast intensity-modulated radiotherapy (IMRT) treatment planning.
Method and Materials: A total of 158 planned patients with Stage 0, I, and II breast cancer treated using whole-breast IMRT were retrospectively replanned using automated treatment planning tools. The tools developed are integrated into the existing clinical treatment planning system (Pinnacle[3]) and are designed to perform the manual volume delineation, beam placement, and IMRT treatment planning steps carried out by the treatment planning radiation therapist. The automated algorithm, using only the radio-opaque markers placed at CT simulation as inputs, optimizes the tangential beam parameters to geometrically minimize the amount of lung and heart treated while covering the whole-breast volume. The IMRT parameters are optimized according to the automatically delineated whole-breast volume.
Results: The mean time to generate a complete treatment plan was 6 min, 50 s ± 1 min 12 s. For the automated plans, 157 of 158 plans (99%) were deemed clinically acceptable, and 138 of 158 plans (87%) were deemed clinically improved or equal to the corresponding clinical plan when reviewed in a randomized, double-blinded study by one experienced breast radiation oncologist. In addition, overall the automated plans were dosimetrically equivalent to the clinical plans when scored for target coverage and lung and heart doses.
Conclusion: We have developed robust and efficient automated tools for fully inversed planned tangential breast IMRT planning that can be readily integrated into clinical practice. The tools produce clinically acceptable plans using only the common anatomic landmarks from the CT simulation process as an input. We anticipate the tools will improve patient access to high-quality IMRT treatment by simplifying the planning process and will reduce the effort and cost of incorporating more advanced planning into clinical practice. © 2011 Elsevier Inc.

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Physics Contribution

Automation and Intensity Modulated Radiation Therapy for Individualized High-Quality Tangent Breast Treatment Plans

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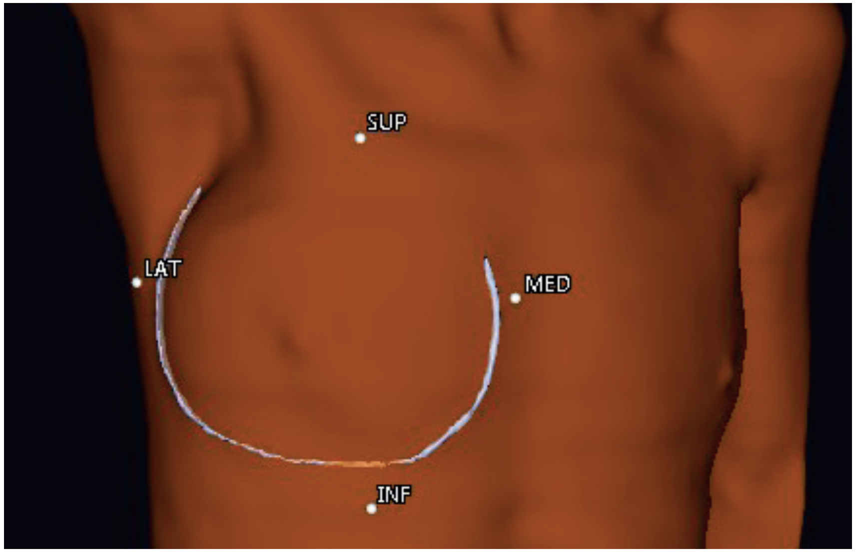
Automatic Beam Placement

Table 1 Automated planning clinical decision hierarchy

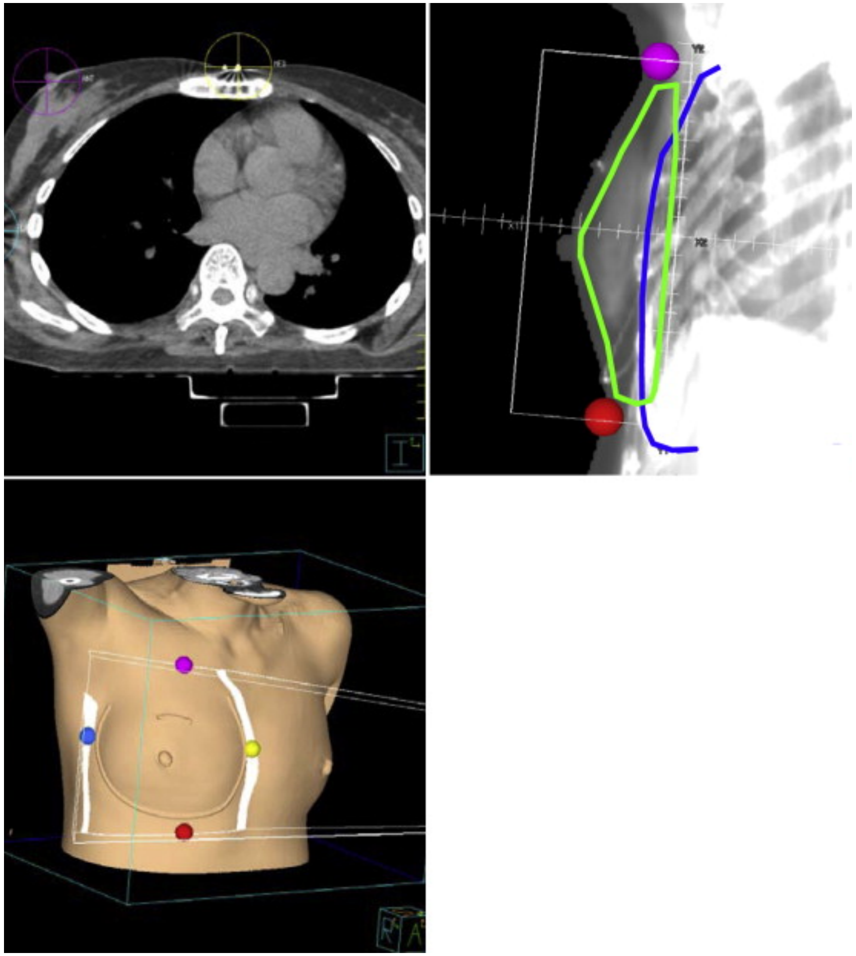
Constraint no.	Clinical constraint*	Description	Default setting	Default value
1	Anatomical constraints	To direct placement of the treatment beams based on patient anatomy	Medial and lateral beams avoid contralateral breast	Contralateral breast sparing is on
2	Breast wire to beam	To direct placement of beam relative to the breast wire (if placed at simulation)	Breast wire exposed with a margin	1 mm
3	Seroma cavity to beam	To direct placement of beam relative to the delineated seroma cavity	Seroma cavity exposed with a margin	10 mm
4	Cavity proximity	To direct beam placement incorporating the proximity of the cavity within the breast volume	Medial cavities will force beam placement for additional medial coverage	Cavity proximity correction is on
5	Lung volume exposed	To direct placement of the beams based on the lung volume exposed	The target mean and/or maximum lung distance is set by the algorithm. The distance(s) can be adjusted to incorporate a priori patient information such as previous treatment or use of breath-hold imaging	The lung distance is a function of a number of anatomical factors and is calculated for each patient
6	Breast volume	To direct placement of the beams based on the volume of exposed breast tissue	The breast volume is set by the algorithm	Breast size correction calculates the breast tissue in the field. Breast size correction is turned on
7	Shielding	To place shielding for the heart, liver, spleen and humeral head following beam placement optimization	Shielding is set according to either a negative or positive margin	Heart, 10-mm margin; liver/spleen, 8-mm margin; humeral head, off

* The clinical constraints follow the order shown in the default case. The user can reorder the priority of the clinical constraints or remove clinical constraints by using the user interface in order to generate an automated plan. Each clinical constraint encodes a prescribed rule, that is, constraints 1, 2, 3, 4, and 7, or is learned based on previous (10) planning data, that is, constraints 5 and 6.

Automatic Beam Placement

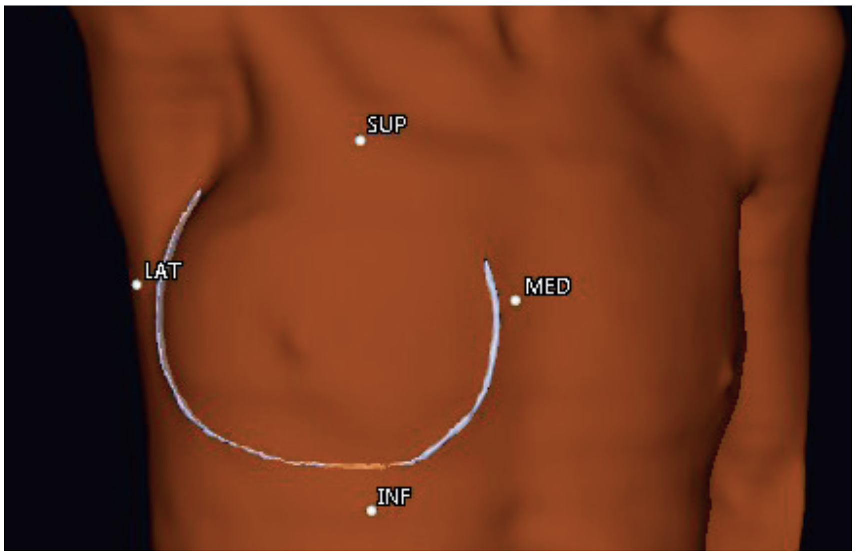


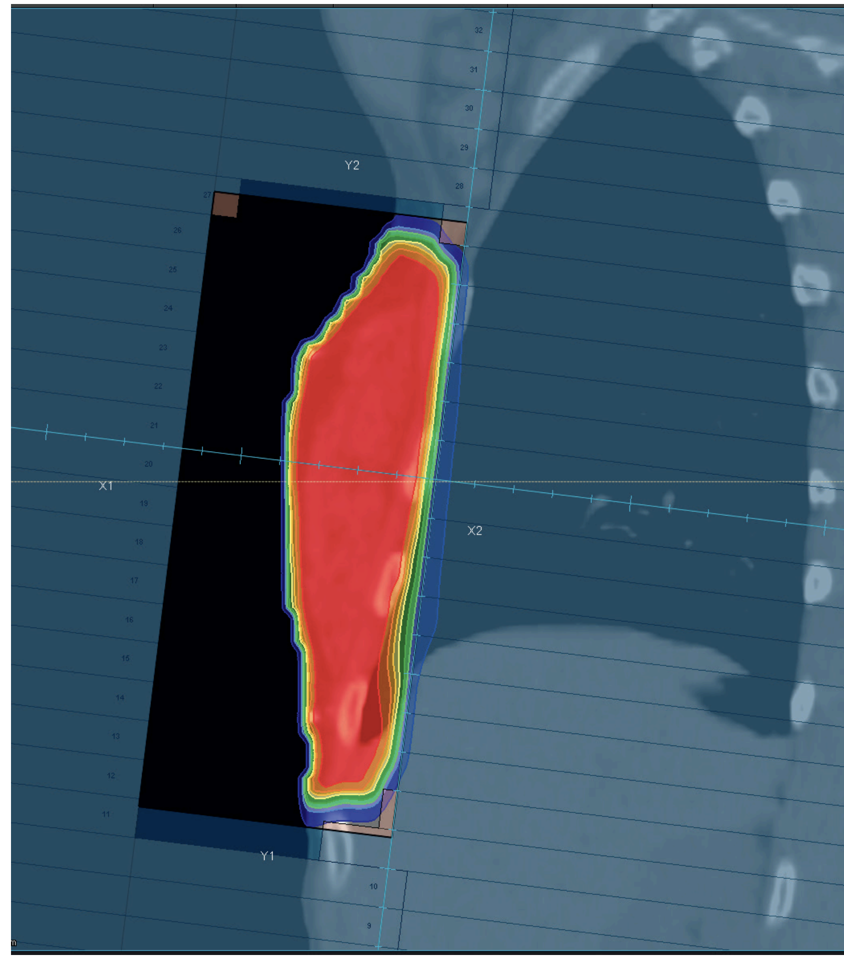
From www,raysearchlabs.com.



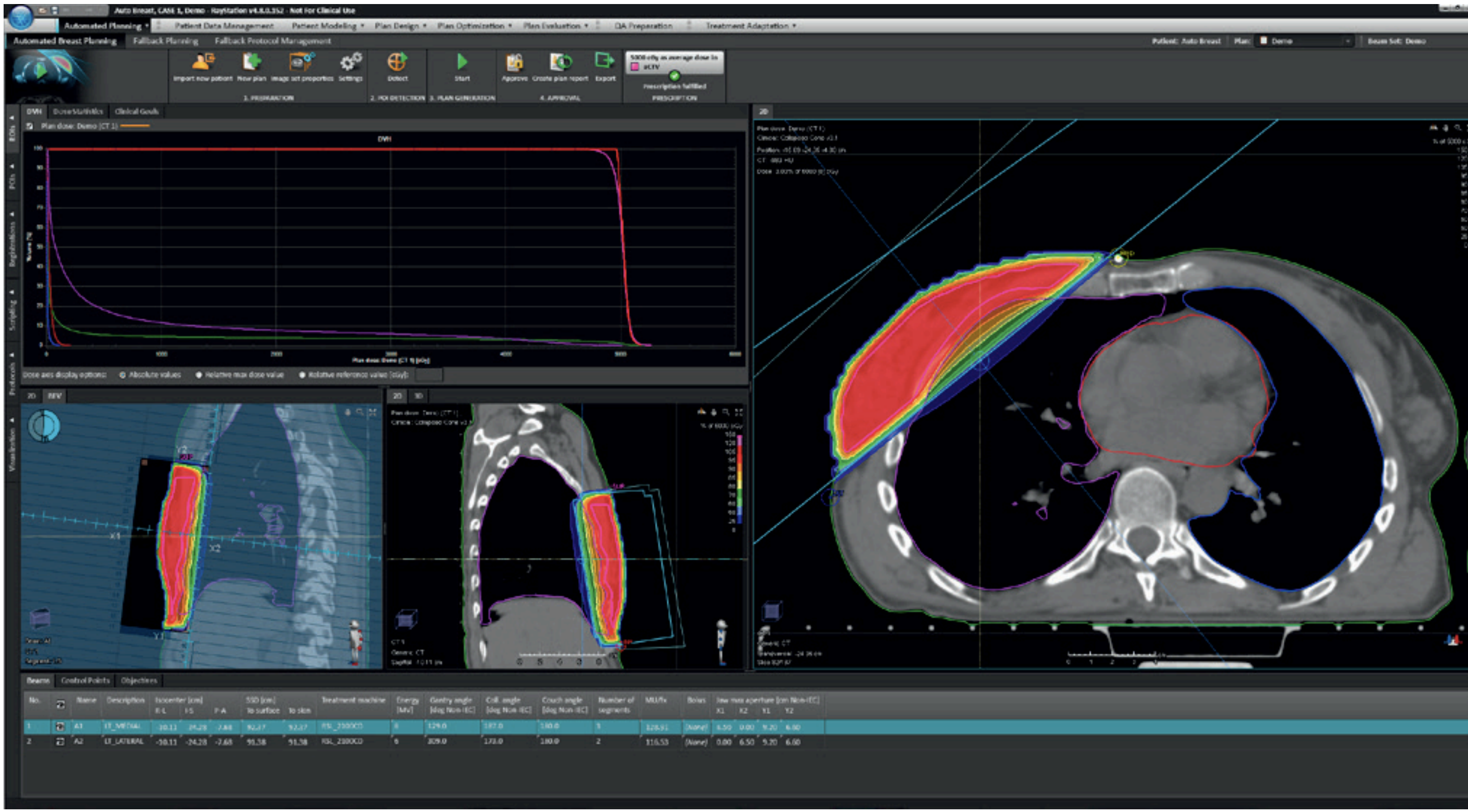
From Purdie et al.

Breast Planning in RayStation





Breast Planning in Raystation



From RaySerach Laboratories white paper.

BrainLab Elements

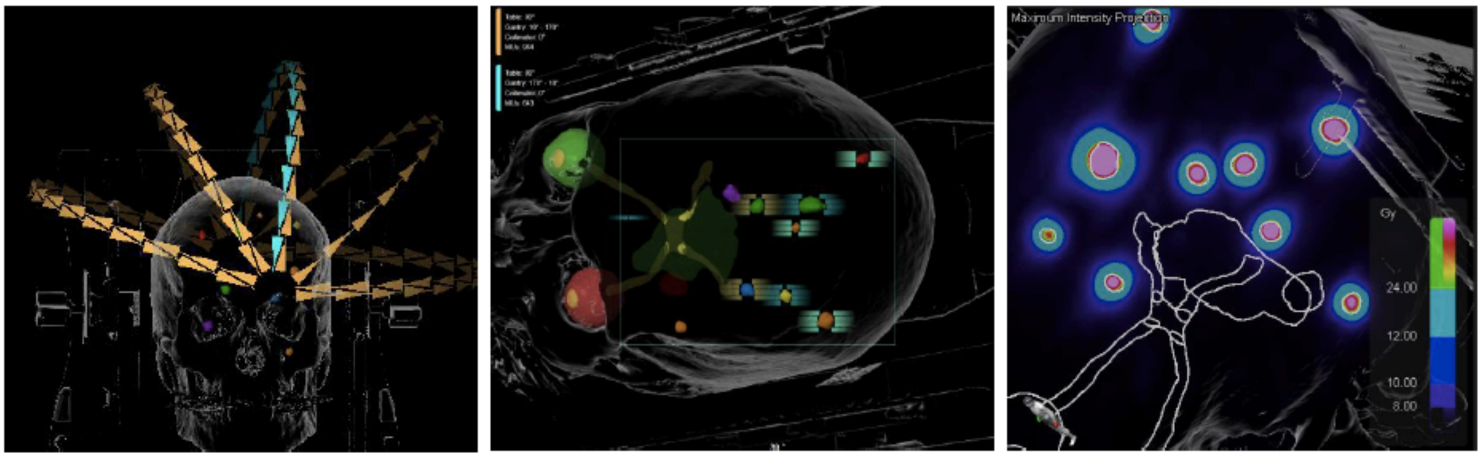


Figure 1: Automatic Brain Metastases Planning details for Patient 4 with 9 lesions.

- Multiple brain metastese plans
- Automated: critical organ segmentation (atlas based), margins, prescription, isocenter, places 2 arcs per predetermined table angle, arc stop and stop angles, MLC leaf pattern
- Each leaf pair can only expose one target at a time, collimator minimizes interleaf leakage
- Weights, angles and margin adjusted after evaluting target conformity w/ common indices

Automatic Brain Metastases Planning Clinical Whilte Paper available from BrainLab

IMRT Optimization

Was not supposed to be so difficult……

Automatic IMRT Optimization

- Pinnacle Autoplanning
- Raysearch Multicriteria Optimization
- Varian Knowledge based planning
- Most of these solutions aim to avoid the trial and error process of manually changing objectives and searching for the “best” plan

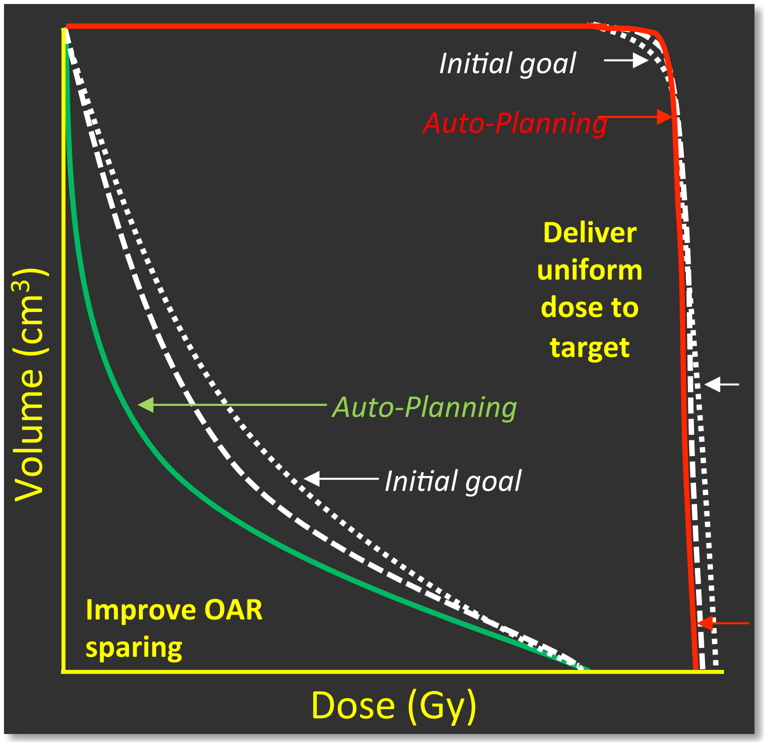
Pinnacle Autoplanning

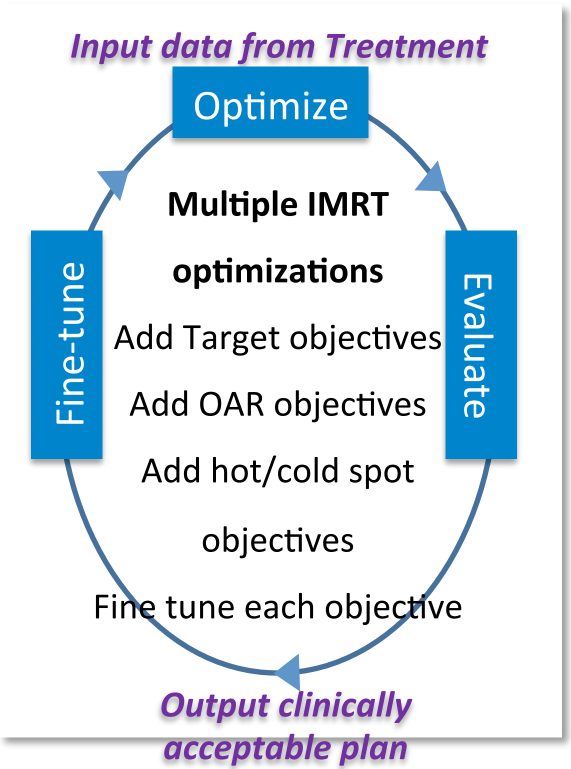
- Mimics the planning process of an experienced user
- Creates residual structures (rings, etc.)
- Adjust optimization goals based on overlap
- Progressive tuning (based on match to training plans)
- Hot and cold spot reduction

Progressive optimization algorithm

Drives target coverage and sparing to the limits

Auto-Planning achieves these results… by mimicking the experienced planner





Slide courtesy of Francisco Nunez, Philips

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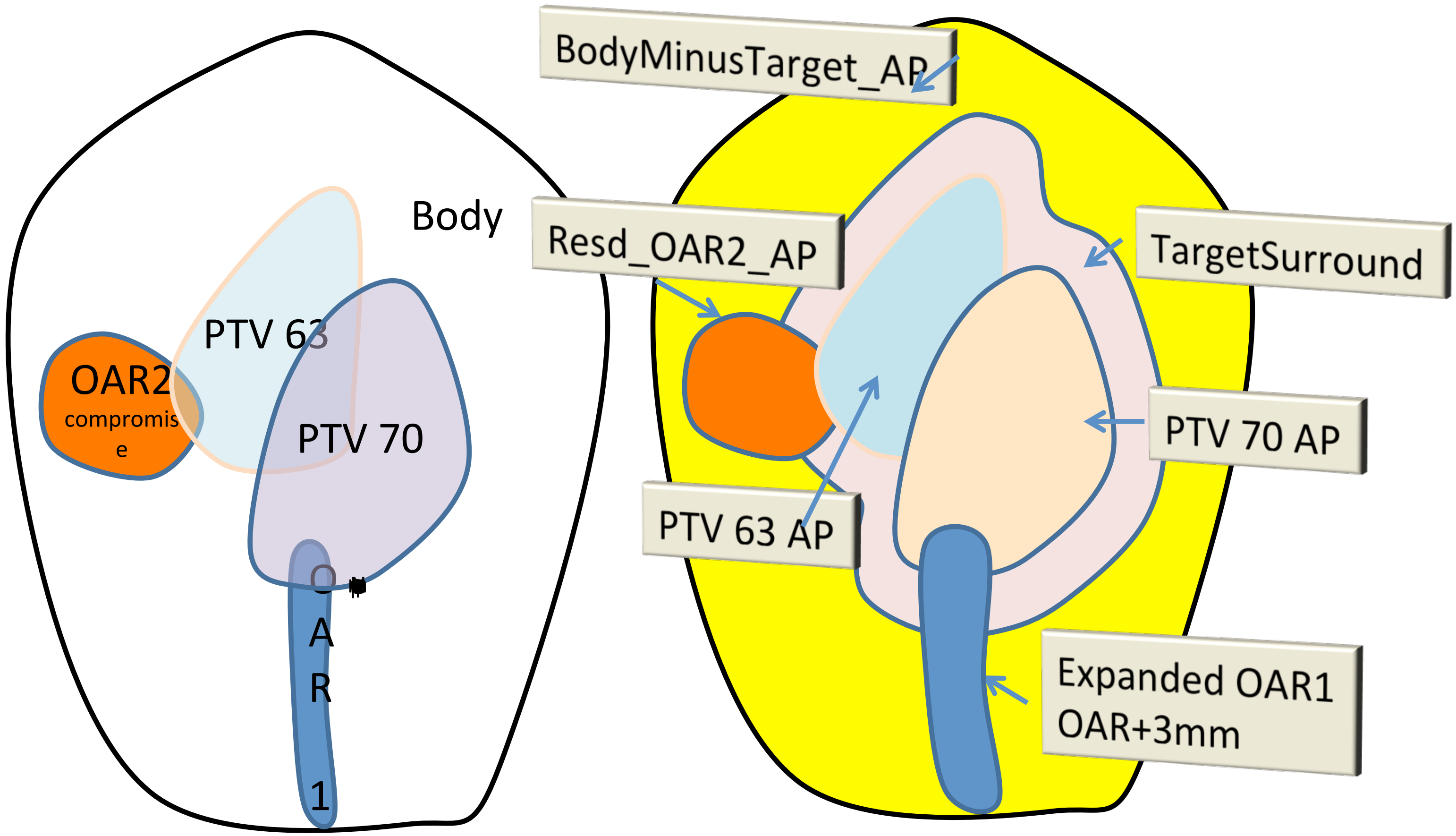
Auto-Planning ROIs

Standard ROIs **Auto-Planning ROIs**



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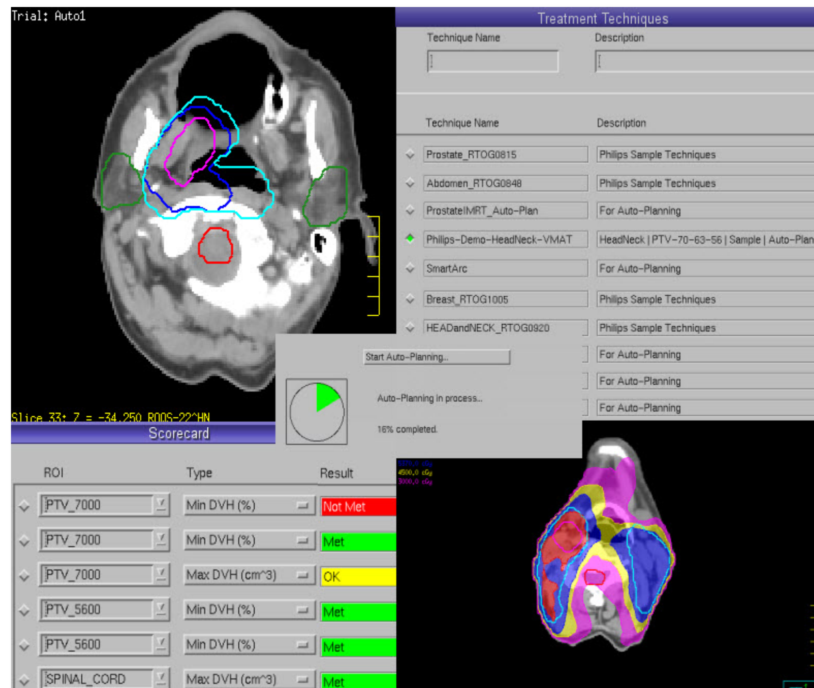
Pinnacle³ Auto-Planning

Accelerating IMRT & VMAT planning

- Reduces the total time required to create an IMRT or SmartArc plan
  Simplified 3-step process reduces time & effort to create a plan
- Replaces exhaustive manual data entry to just a few clicks
  Treatment Techniques created at setup are used repeatedly for each plan
- Enhances plan quality and consistency
  The Auto-Planning Engine generates high quality plans at the 1st pass
- Simplifies and standardizes the plan approval process
  Scorecards reduce the need for multiple plan reviews



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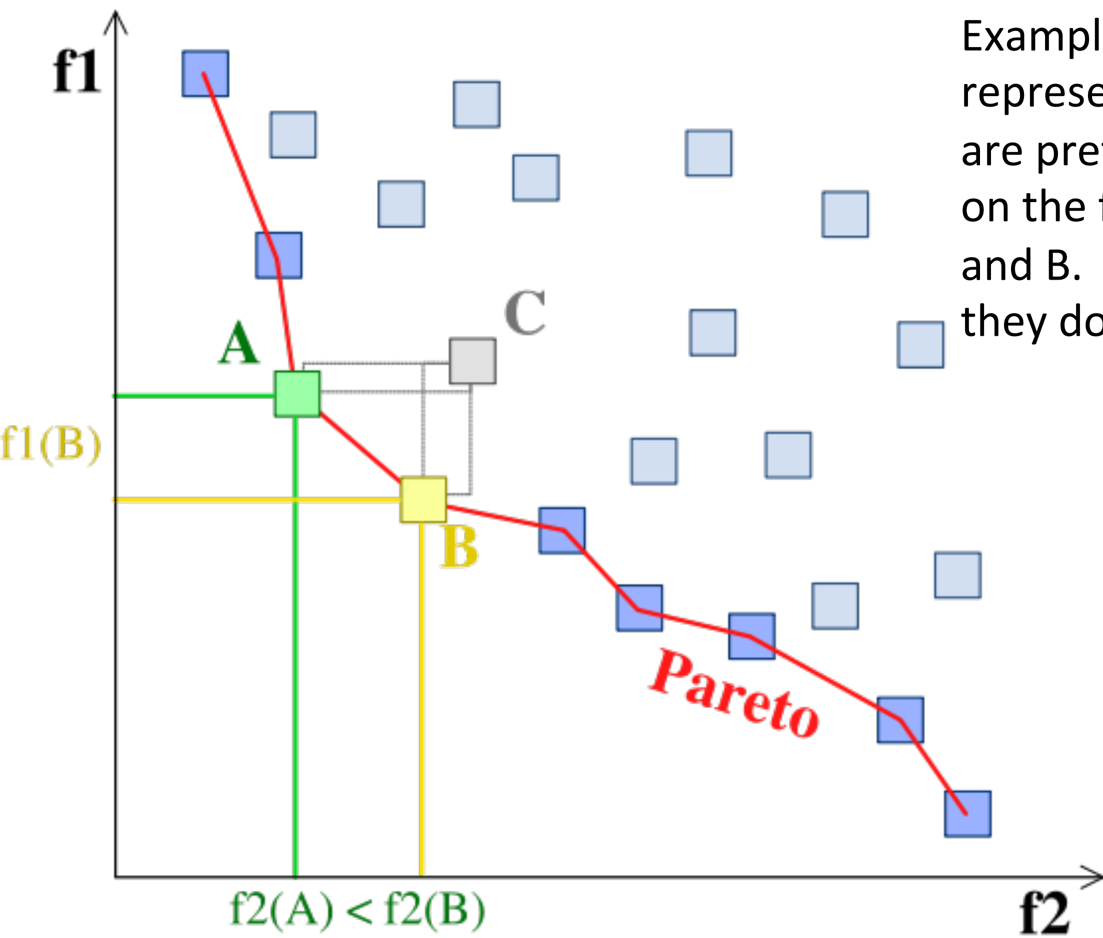
Multi-Criteria Optimization

- Optimization technique that tries to allow planners to more effectively explore trade-offs in IMRT planning
- In IMRT you never know you have the best plan of all the possible solutions and it would be prohibitively time consume to evaluate all possibilities
- Allows for interactive exploration of the solution space
- Commercialized by RayStation

Multi-Criteria Optimization

- MCO optimization avoid explicit weights
- MCO identifies "pareto optimal" plans with respect to user specified objectives
- Pareto optimal plans are feasible with respect to all constraints and no objective can be improved without impairing at least one other
- An infinite number of possible plans is represented by a discrete number of plans that emphasize different objectives
- Dose in each structure is characterized using the EUD (Equivalent Uniform Dose − Uniform dose that leads to the same biological effect as the nonuniform dose in the organ)

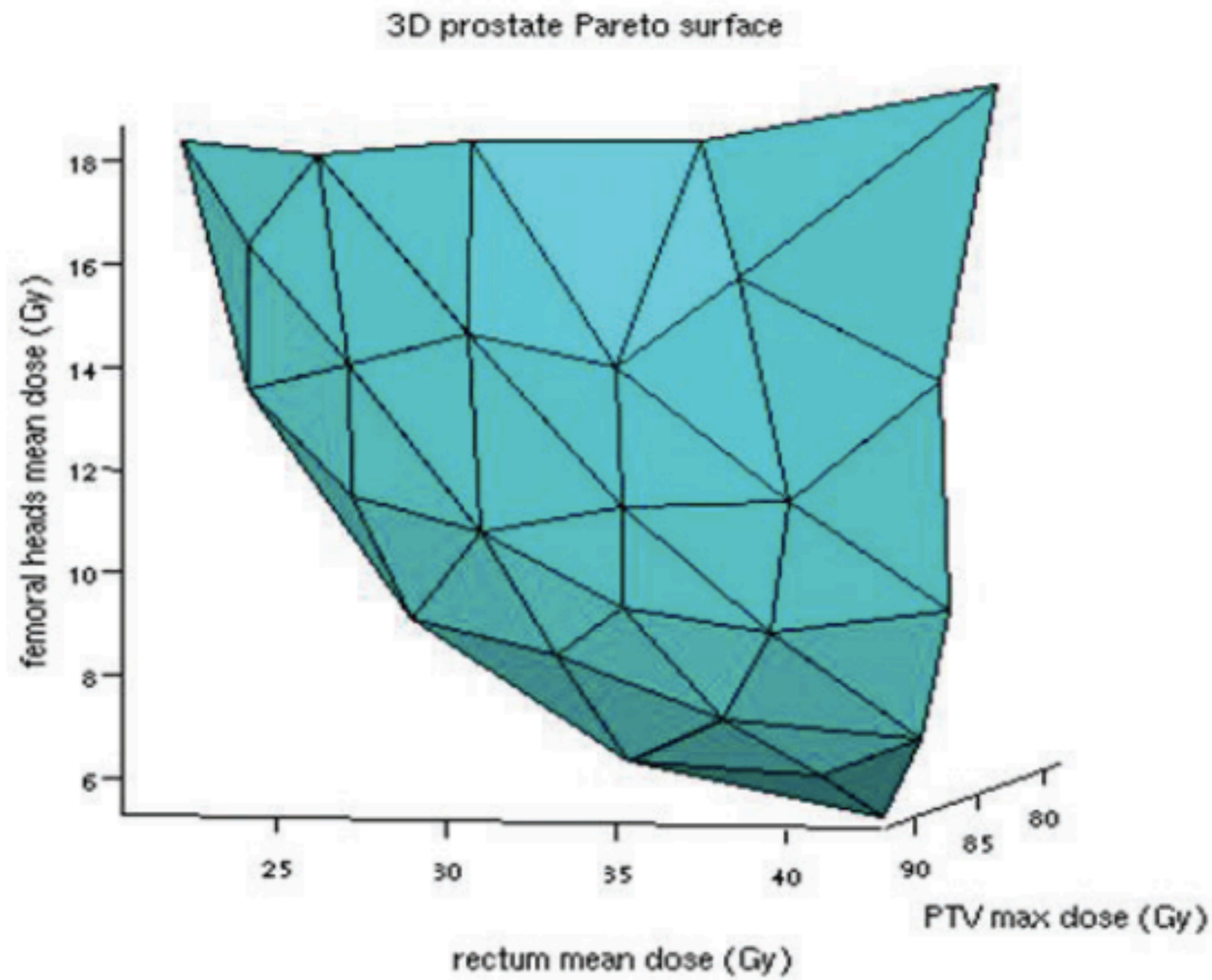
Pareto Frontier



Example of Pareto Frontier. The boxed points represent feasible choices and smaller values are preferred to larger values. Point C is not on the frontier because it is dominated by A and B. A and B are not domiated by other so they do lie on the frontier.

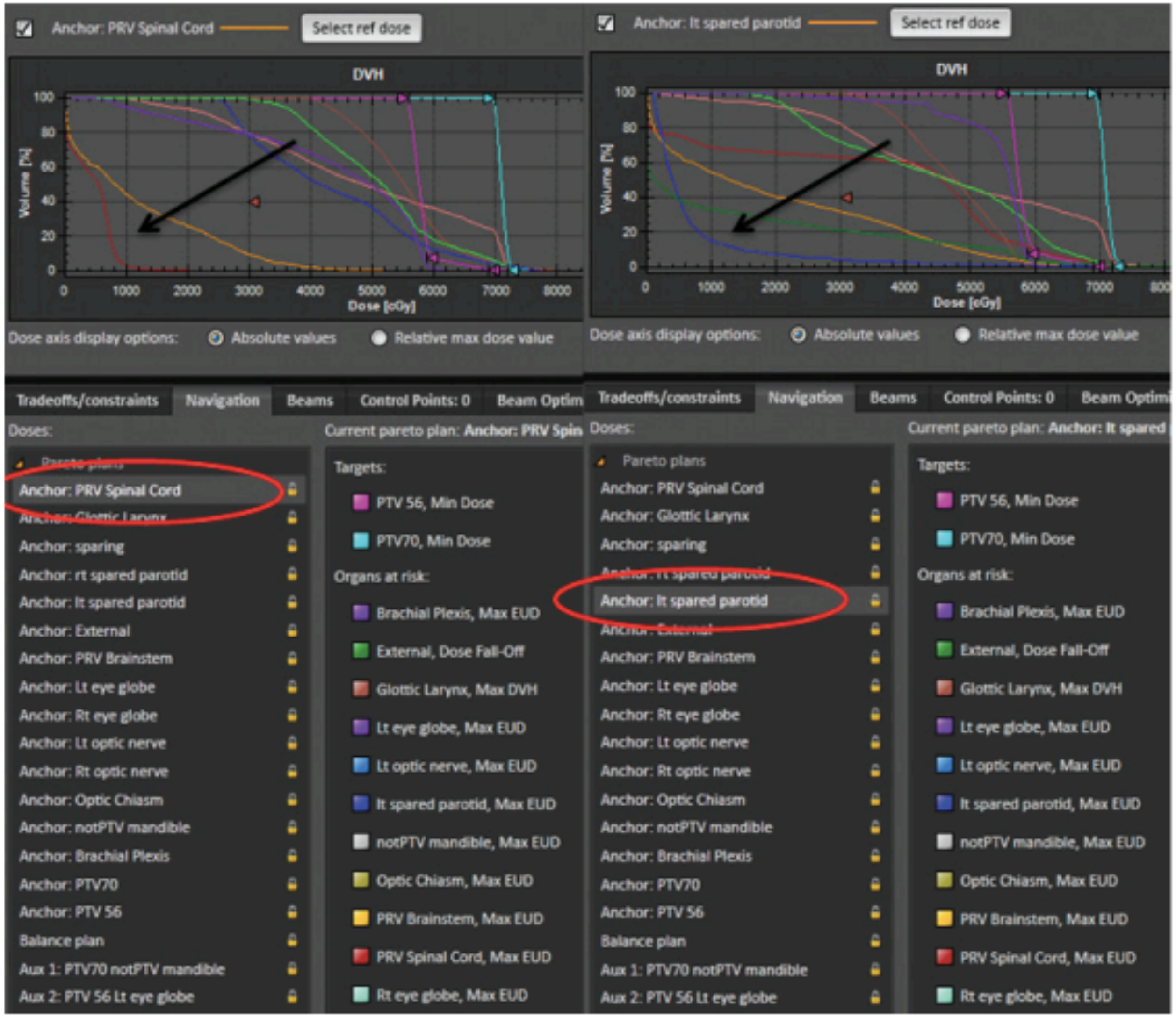
From Wikipedia

3D pareto surface for a prostate case



From RaySearch White Paper

Anchor Plans

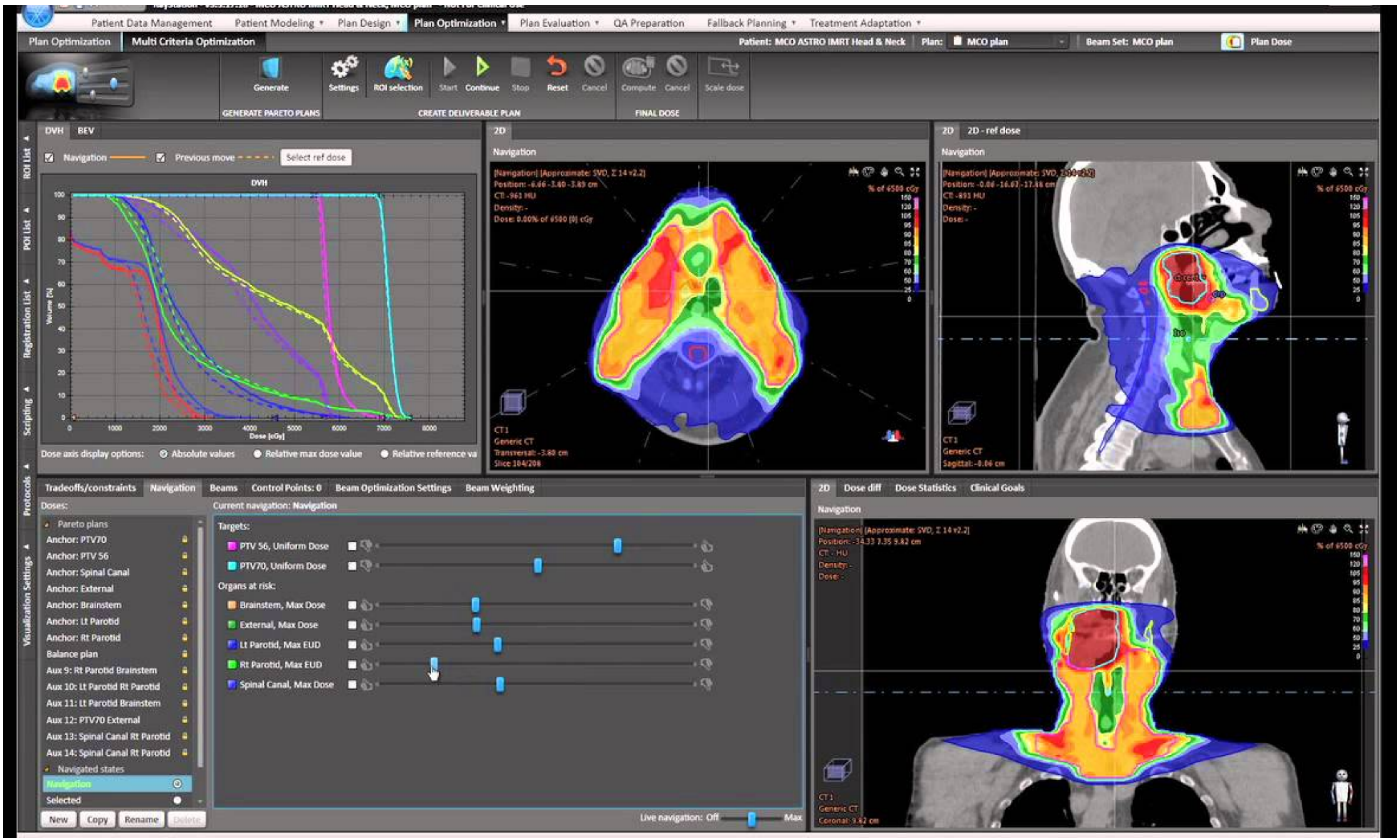


From RaySearch White Paper

MCO Algorithm

- Optimizations performed using beamlet intensities
- N plans generated where N=number of objectives (anchor plans)
- N+1 places equal emphasis on all objective (balance plan)
- Beyond N+1 (auxiliary plans) improve the Pareto surface representation
  - Generated by giving emphasis to pairs of objectives

Raystation Interface



Navigation Algorithm

- Uses linear programming to translate input from slider bars adjust by the user to movement along the Pareto surface
- Algorithm looks for the best point that meets the user specified trade off
- Dose is updated in real time by interpolation between the Pareto optimal plans

Dose "Mimicking" Algorithm

- Use of direct machine parameter optimization (DMPO) reduces the error between the navigated solution and the deliverable plan
- The solution space is searched in dose which minimizes error between the optimized and delivered dose

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CLINICAL INVESTIGATION **Physics**

IMPROVED PLANNING TIME AND PLAN QUALITY THROUGH MULTICRITERIA OPTIMIZATION FOR INTENSITY-MODULATED RADIOTHERAPY

David L. Craft, Ph.D., Theodore S. Hong, M.D., Helen A. Shih, M.D., and Thomas R. Bortfeld, Ph.D.

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Purpose: To test whether multicriteria optimization (MCO) can reduce treatment planning time and improve plan quality in intensity-modulated radiotherapy (IMRT).

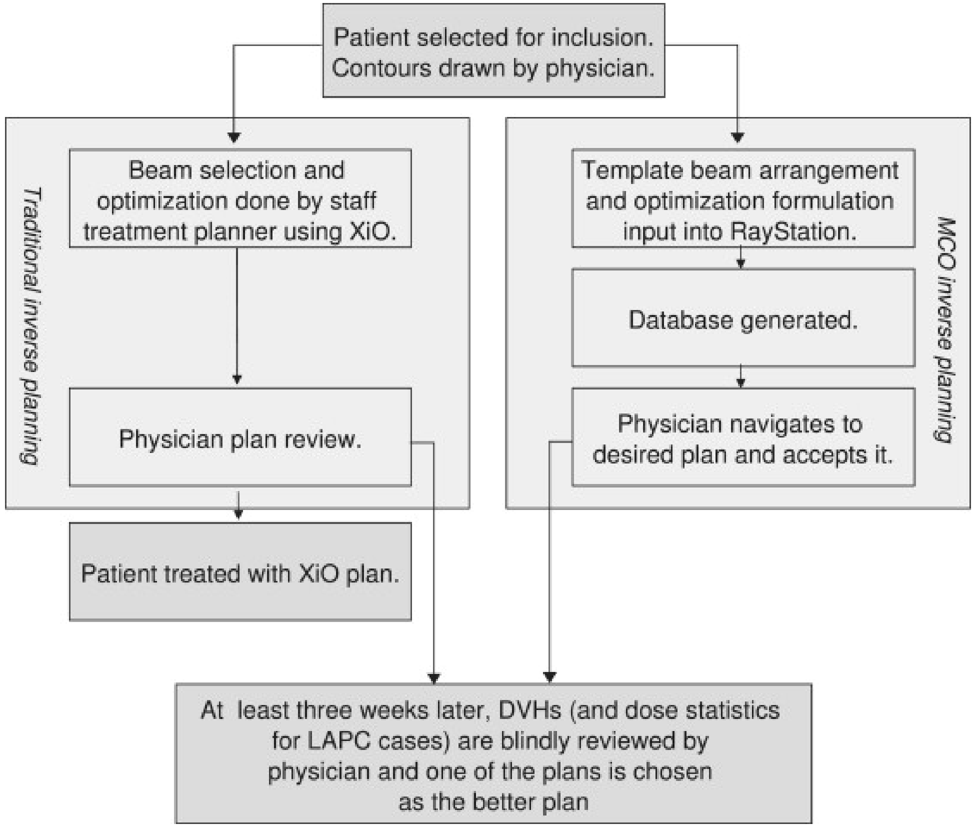
Conclusions

This provides the first concrete evidence that MCO-based planning is superior in terms of both planning efficiency and dose distribution quality compared with the current trial and error–based IMRT planning approach.

Conclusions: This provides the first concrete evidence that MCO-based planning is superior in terms of both planning efficiency and dose distribution quality compared with the current trial and error–based IMRT planning approach. © 2012 Elsevier Inc.

Multiobjective, Inverse planning, Pareto optimization, Multicriteria.

Comparison to Conventional Optimization



IMAGE

Improved Planning Time and Plan Quality Through Multicriteria Optimization for Intensity-Modulated Radiotherapy

International Journal of Radiation Oncology, Biology, Physics.

Craft, David L., Ph.D.; Hong, Theodore S., M.D.… Show all. Published December 31, 2011. Volume 82, Issue 1. Pages e83-e90.

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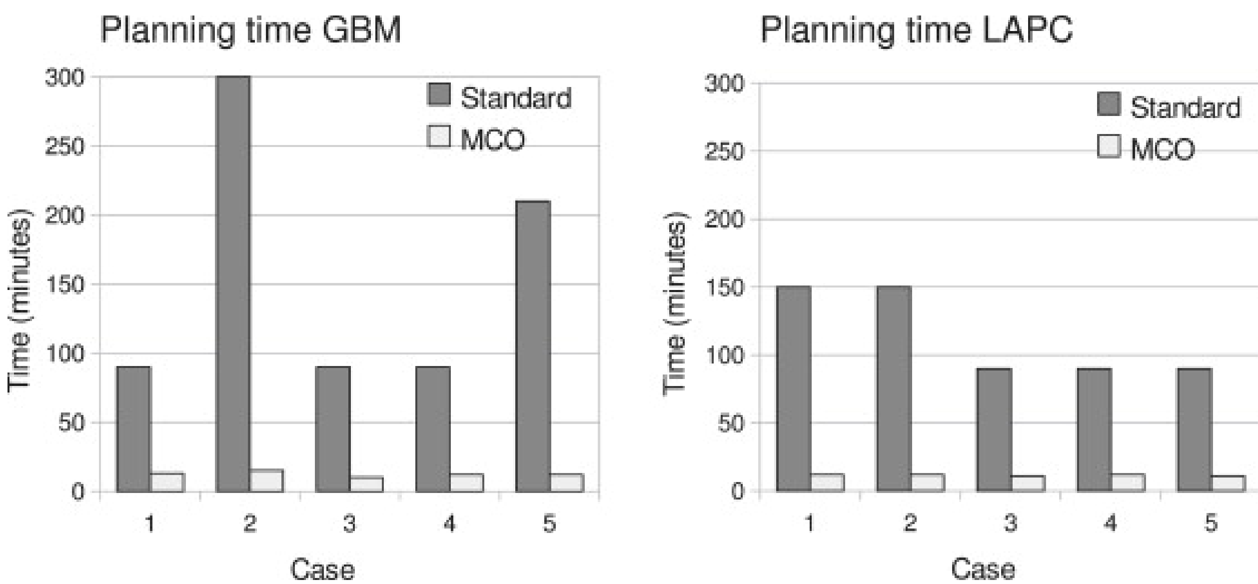
Planning Time Comparison



IMAGE

Improved Planning Time and Plan Quality Through Multicriteria Optimization for Intensity-Modulated Radiotherapy

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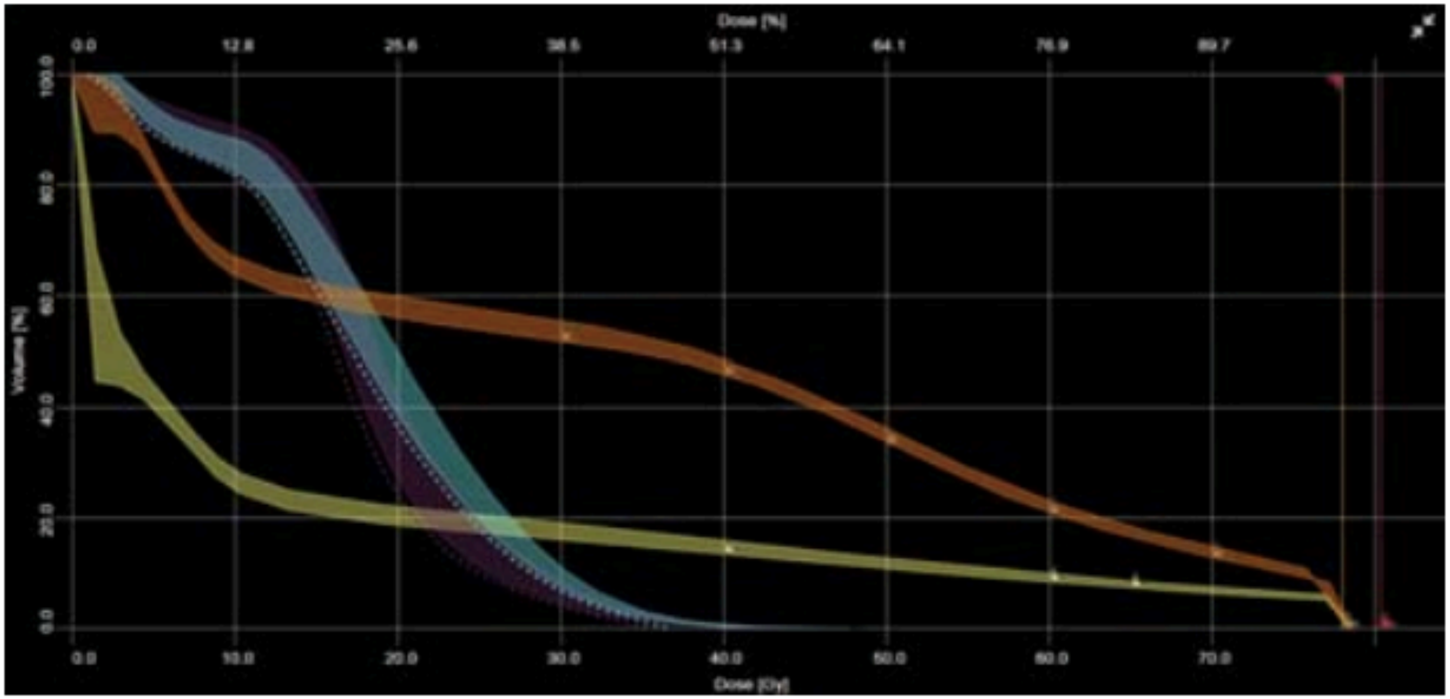
Knowledge Based Planning

- Aim is consistency between plans
- Planning should be efficient and produce plans of high quality
- Uses shared clinical knowledge and supplied treatment plan models or create their own
- RP provides estimated DVHs as a starting point for IMRT
- Dose and patient anatomy information from existing plans used to estimate dose in new patient based on patient anatomy
- Marketed first by Varian Medical Systems

Dose Spread Known From Prior Plans



Using a knowledge base of prior treatment plans, RapidPlan may improve efficiency. The DVH chart above displays an estimated dose spread (shaded colors) for a prostate case.

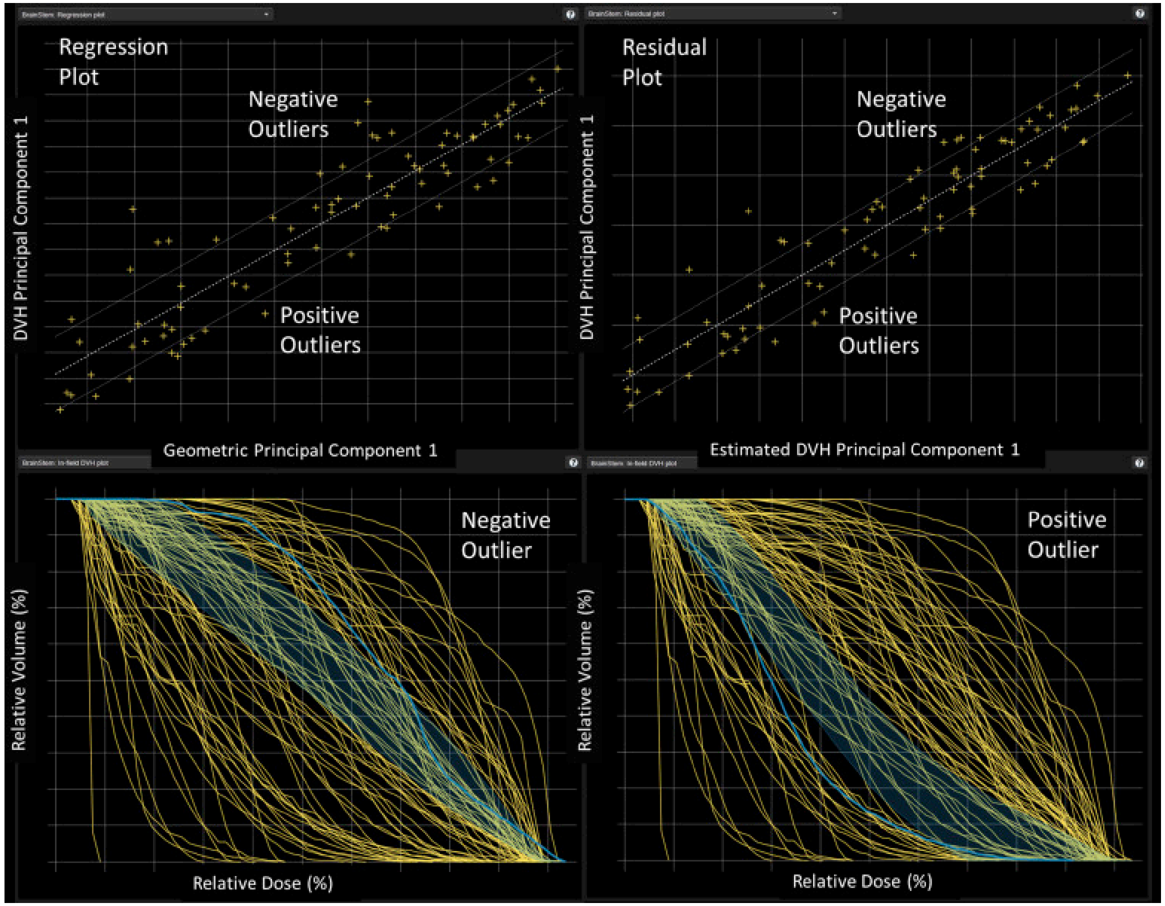
International Journal of Radiation Oncology*Biology*Physics

Volume 99, Issue 4, 15 November 2017, Pages 1021-1028

Physics Contribution

Performance of Knowledge-Based Radiation Therapy Planning for the Glioblastoma Disease Site

Avishek Chatterjee PhD, Monica Serban MSc, Bassam Abdulkarim MD, PhD, Valerie Panet-Raymond MD, Luis Souhami MD, FASTRO, George Shenouda MBBCh, PhD, FRCP (C), Siham Sabri PhD, Bertrand Jean-Claude PhD, Jan Seuntjens PhD



IMAGE

Performance of Knowledge-Based Radiation Therapy Planning for the Glioblastoma Disease Site

International Journal of Radiation Oncology, Biology, Physics.

Chatterjee, Avishek, PhD; Serban, Monica, MSc… Show all. Published November 14, 2017. Volume 99, Issue 4. Pages 1021-1028. © 2017.

McGill Study Summary

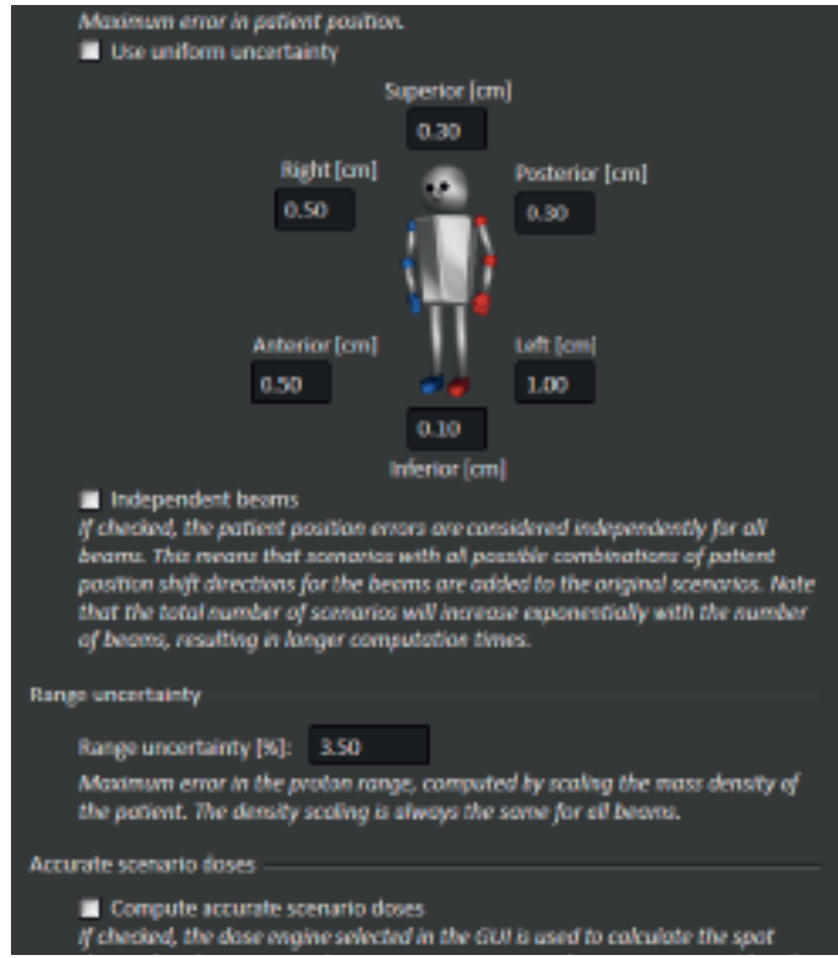
- A knowledge based RT plan was created
- 82 GBM patient plans were used to train the model
- Model was validated on 45 patients
- KB plans had superior PTV dose metrics and better optic apparatus sparing than manual plans
- KB planning time 7 mins versus 4 hours average time for manual planning

Comparison

Knowledge-based	Multi-criteria optimization	Autoplanning
• Dependent on a knowledge base • Not flexible to inter-physician variability • Only as good as the knowledge • Does not address new knowledge on toxicity endpoints • No direct way to manage trade off	• Trade offs easily managed • Multiple solutions can be compared very quickly • Requires most physician time • Does not lend to Standardization	• Mimics actions of trained planner • Still hard to determine plan quality • Data required for modeling from institution • Can build separate models for physician preferences

Robust Planning

- Errors occur in delivery due to patient positioning errors, anatomical changes, etc.
- Robust planning allows for improved delivery accuracy (Robustness) for certain defined weaknesses
- More relevant for proton therapy where the PTV concept breaks down



Robust Optimization white paper by RaySearch

Biological Optimization

- Feed dose volume histogram data into biological models for plan evaluation of the impact of the dose distribution on biology
  - NTC - Normal Tissue complication probability
  - TCP – Tumor control probability

Summary

- There are several automated planning tools available.
- These tools can be used to provide standardized treatment plans
- These tools will make planning more efficient.