Advanced IMRT Optimization Strategies

Emilie Soisson, Ph.D.
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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.)
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
PHYSICS CONTRIBUTION

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

THOMAS G. PURDIE, PH.D.,*† ROBERT E. DINNERWELL, M.D.,*† DANIEL LETOURNEAU, PH.D.,*† CHRISTINE HILL, B.Sc.,* AND MICHAEL B. SHARPE, PH.D.*†

*Radiation Medicine Program, Princess Margaret Hospital, University Health Network, Toronto, ON, Canada; and †Department of Radiation Oncology, University of Toronto, Toronto, ON, Canada

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®) 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 inverted 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.
Physics Contribution

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

Thomas G. Purdie, PhD, *, †, ‡ Robert E. Dinniwel, MD, *, †
Anthony Fyles, MD, *, † and Michael B. Sharpe, PhD *, †, ‡

*Radiation Medicine Program, Princess Margaret Cancer Centre, University Health Network, Toronto, Ontario, Canada; †Department of Radiation Oncology, University of Toronto, Toronto, Ontario, Canada; and ‡Techna Institute, University Health Network, Toronto, Ontario, Canada

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## Automatic Beam Placement

### Table 1: Automated planning clinical decision hierarchy

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

* 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 Purdie et al.
Breast Planning in RayStation
Breast Planning in Raystation

From RaySearch Laboratories white paper.
BrainLab Elements

• Multiple brain metastases 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 evaluating target conformity w/ common indices

Automatic Brain Metastases Planning Clinical Whilete 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
Auto-Planning ROIs

Standard ROIs

Body

PTV 63

PTV 70

Expanded OAR1
OAR+3mm

Auto-Planning ROIs

BodyMinusTarget_AP

Resd_OAR2_AP

TargetSurround

PTV 70 AP

PTV 63 AP

Slide courtesy of Francisco Nunez, Philips
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

Slide courtesy of Francisco Nunez, Philips
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)
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 dominated by other so they do lie on the frontier.
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
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.

Department of Radiation Oncology, Massachusetts General Hospital, Harvard Medical School, Boston, MA

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

**Figure 1**
Block diagram for the two treatment planning workflows compared in this study. MCO = multicriteria optimization; DVH = dose–volume histogram; LAPC = locally advanced pancreatic cancer.

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**IMAGE**

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

International Journal of Radiation Oncology, Biology, Physics.

Planning Time Comparison

![Planning Time Comparison](image)

**IMAGE**

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

International Journal of Radiation Oncology, Biology, Physics.

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
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.
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 MBCh, PhD, FRCP (C), Siham Sabri PhD, Bertrand Jean-Claude PhD, Jan Seuntjens PhD
Performance of Knowledge-Based Radiation Therapy Planning for the Glioblastoma Disease Site

International Journal of Radiation Oncology, Biology, Physics.

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

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