Knowledge Based Treatment Planning – Clinical Background and Application

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Overview

- How We Started?
- The Initial Framework
- Going Back to Clinic
- What’s next?
Building Planning Knowledge Models

- How We Started?
  - Learning Curve, Quality, Consistency
  - Standardization, Automation, Integration

- The Initial Framework

- Going Back to Clinic

- What’s next?
Basics Of Knowledge-Based Planning (KBP)
Basics Of Knowledge-Based Planning (KBP)
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Basics Of Knowledge-Based Planning (KBP)

Duke University Medical Center – Radiation Oncology

**IMRT Constraints**

<table>
<thead>
<tr>
<th>Patient Name</th>
<th>Patient ID</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Treatment site</th>
<th>Imaging sets</th>
<th>Fusion (Y/N)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rt pelvis</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Prescription**

<table>
<thead>
<tr>
<th>Target</th>
<th>Margin</th>
<th>Prescription</th>
</tr>
</thead>
<tbody>
<tr>
<td>PTV1</td>
<td></td>
<td>1.8 to 54Gy</td>
</tr>
</tbody>
</table>

**Constraints**

<table>
<thead>
<tr>
<th>OARs</th>
<th>Dose</th>
<th>Volume (absolute or %)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALARA for all</td>
<td></td>
<td></td>
</tr>
<tr>
<td>No hot spots in bladder, rectum, small bowel</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Don't push as much on femur, prefer to meet bowel/bladder</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Building Planning Knowledge Models

- How We Started?

- The Initial Framework
  - Portable: Cases/Plans => Features
  - Systematic: Knowledge => Machine Learning

- Going Back to Clinic

- What’s next?
Building Knowledge

- Platform Design
- Knowledge Base
- Training

Knowledge Base Application

New Patient \( \rightarrow \) Feature Characterization \( \overset{X_{\text{new}}}{\rightarrow} \) Dose Parameter \( Y_{\text{new}} \)

\[ Y = f(X) \]
Building Knowledge Models

- Platform Design

Knowledge Base Application

New Patient ➔ Feature Characterization $X_{new}$ ➔ $Y = f(X)$ ➔ Dose Parameter Features $Y_{new}$
Building Knowledge Models

- Feature Organization

Database of Expert Knowledge & Treatment Cases

- Distance-Based
- Volume-Based
- Dose-Based

Feature Extraction

- High Order
- Institutional

Building Planning Knowledge Models

- Systematic Modeling of Knowledge
  - Machine learning, Descriptive statistics, Pattern classification

Diagram:
- Database of Expert Knowledge & Treatment Cases
  - Feature Extraction
  - Model Training
    - Multi-regression
    - Support Vector Regression
    - Neural Network
    - Descriptive statistics
Example of Bladder DVH Modeling

Building Planning Knowledge Models

- How We Started?
- The Initial Framework
- Going Back to Clinic
  - Knowledge Model Guided Treatment Planning
- What’s next?
1. Generate a new model

- Generate a new model in “Model Configuration”
2. Add plans to the model

- Extract high quality plans into the model in “External Beam Planning”
3. Model training

• In “Model Configuration”, select the plan to include in the training and then click “Train”.

![Image of software interface with selected plan for training]
4. DVH Estimation

- In “Optimization” panel, “DVH Estimation” can be invoked to generate DVH estimates.

Dose Volume constraints and priorities can be customized.

Fixed for PTV

Predicted by model
Knowledge Model-based HN Planning
Using IMRT Knowledge Model For VMAT
Clinical Application of Knowledge Models - Integration

- Cross-institution Knowledge
  - If you believe best planning knowledge is shared among all planners
  - LUNG IMRT Pilot Study By RTOG/NRG
    - 71 Cases
    - 3 Institutions
### Clinical Application of Knowledge Models - Integration

<table>
<thead>
<tr>
<th></th>
<th>Institution 1</th>
<th>Institution 2</th>
<th>Institution 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prescriptions (Gy)</td>
<td>Mean</td>
<td>Median</td>
<td>Min</td>
</tr>
<tr>
<td></td>
<td>67</td>
<td>64</td>
<td>40</td>
</tr>
<tr>
<td>Volume (cm$^3$)</td>
<td>mean</td>
<td>421</td>
<td>595</td>
</tr>
<tr>
<td></td>
<td>median</td>
<td>343</td>
<td>519</td>
</tr>
<tr>
<td></td>
<td>min, max</td>
<td>62, 1132</td>
<td>76, 1132</td>
</tr>
<tr>
<td>Location (side)</td>
<td>Total</td>
<td>45</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>Left/Left-Medial</td>
<td>18</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>Right/Right-Medial</td>
<td>21</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>Medial</td>
<td>6</td>
<td>0</td>
</tr>
</tbody>
</table>
Clinical Application of Knowledge Models - Integration

Circle: Training Plan  Cross: Validation Plan

Not contributing to model
Clinical Application of Knowledge Models - Integration

Institution 2  Not contributing to model

Institution 3  Contributing to model
Cross-Modality Knowledge Base

- Cross-Modality Knowledge
  - If you believe best planning knowledge is independent of treatment modality

<table>
<thead>
<tr>
<th>Institution A</th>
<th>Institution B</th>
</tr>
</thead>
<tbody>
<tr>
<td>7-8 min delivery time</td>
<td>7-8 min delivery time</td>
</tr>
<tr>
<td>Delivery system: Varian IMRT</td>
<td>Delivery system: Tomotherapy</td>
</tr>
<tr>
<td>Planning system: Eclipse</td>
<td>Planning system: Tomotherapy</td>
</tr>
<tr>
<td>Sequential Boost</td>
<td>SIB</td>
</tr>
<tr>
<td>- Multiple plans (one plan for 1 PTV)</td>
<td>- 1 plan (one plan cover all PTVs with diff. daily doses)</td>
</tr>
<tr>
<td>- 40-50 Gy and 60-70 Gy</td>
<td>- 54.25 Gy and 70 Gy</td>
</tr>
<tr>
<td>~60 head-and-neck cases</td>
<td>~60 head-and-neck cases</td>
</tr>
</tbody>
</table>

Tomotherapy Model vs. IMRT Model vs. Actual Plan DVH
Other Knowledge Models: Dose Models

- In Spine SBRT, dose distributions in cord are highly correlated with tumor contour shapes.

Other Knowledge Models: Dose Models

- Compute correlation between tumor contour shapes and cord dose distributions
- Use learned correlations to predict voxel-level dose distributions

Other Knowledge Models: Dose Models

- **Active Shape Model**
  - Align the reference tumor contours and all other contours using the iterative closest point (ICP) algorithm

Other Knowledge Models: Dose Models

- Active shape models
  - PCA analysis of a set of aligned tumor contours

Other Knowledge Models: Dose Models

- Optical Flow Dose Distribution Model
  - measures dose variance between a reference image and any other images within the training dataset

\[ E(u_x, u_y) = \int\int \Psi((I(x + u_x, y + u_y, t + 1) - I(x, y, t))^2 + \beta \Psi(\nabla u_x^2 + \nabla u_y^2) + \alpha (\nabla I(x + u_x, y + u_y, t + 1) - \nabla I(x, y, t))^2 \, dx \, dy \]
Other Knowledge Models: Dose Models

- Active optical flow dose distribution model
  - PCA analysis of a sequence of optical flow fields

Other Knowledge Models: Dose Models

- Machine Learning
  - PTV contour space
  - cord dose space

Other Knowledge Models: Dose Models

- Modeled vs clinical plan DVH
Clinical Application of Knowledge Models - Integration

- Rapid Learning Framework
- Multiple Knowledge Resources

![Diagram](image.png)
Clinical Application of Knowledge Models - Integration

- **Lung IMRT Model as A Rapid-learning Show Case**
  - DVH Model + Beam Angle Model
    - 100 Lung Cases
    - All co-planar beams (best clinical knowledge)
    - Ignore non-planar plans (clinical knowledge sparse)
Phase 1: Class Solution

- Step 1: Define distance between two beam bouquets
- Step 2: Classify beam configuration using clustering analysis
- Step 3: Extract standard bouquets
Phase 1: Class Solution - Beam Bouquet Atlas
Clinical plan: solid

Beam Bouquet plan: dashed
Phase 1: Class Solution
Plans Using Beam Bouquets VS. Clinical Plans for 20 Validation cases

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**Dose (Gy)**

**Volume (%)**

- Lung and PTV
- Esophagus
- Heart
- Spinal Cord

Clinical plans: solid
Plans using templates: dashed
Phase 2: From Class Solution to Patient Specific Solution

- Anatomy variation always happens in clinical treatment planning
- Reflects clinical application of knowledge
- Natural progression of knowledge application
Clinical Application of Knowledge Models - Integration

- Correlation between the anatomical features and beam angle configurations learned by supervised classification method

Anatomical Features and Beam Configuration Correlation
Clinical Application of Knowledge Models - Integration

- **Lung IMRT Model as A Rapid-learning Show Case**
  - DVH Model + Beam Angle Model
    - 100 Lung Cases
    - All co-planar beams (best clinical knowledge)
    - Ignore non-planar plans (clinical knowledge sparse)
  - Extend Knowledge Models to Other Thorax Cases (large esophageal case)
Phase 2: From Class Solution to Patient Specific Solution

- Example case: esophagus tumor extending from neck to abdomen
- Separate fields, even isocenters, may be needed to treat different parts of the tumor in superior-inferior direction
- Multiple beam configurations in one plan
Phase 2: From Class Solution to Patient Specific Solution
Axial CT Slices

Z=-21

Z=-16

Z=-13

Z=-10

Z=-7

Z=-4

Z=-1

Z=2

Z=5

Z=8

Z=11

Z=13
Phase 2: From Class Solution to Patient Specific Solution

Clinical Plan

Model Plan
Phase 2: From Class Solution to Patient Specific Solution

Clinical Plan

Model Plan
Phase 2: From Class Solution to Patient Specific Solution

Liver
Clinical
Auto

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Clinical Application of Knowledge Models - Integration

- **Lung IMRT Model as A Rapid-learning Show Case**
  - DVH Model + Beam Angle Model
    - 100 Lung Cases
    - All co-planar beams (best clinical knowledge)
    - Ignore non-planar plans (clinical knowledge sparse)
  - Extend Knowledge Models to Other Thorax Cases
  - Extend Knowledge Models to Non-coplanar Cases
    - Clinical knowledge about non-coplanar beam angles is sparse, immature
    - Extend the knowledge learned from co-planar beam to non-coplanar beam
Phase 3: Progressive Modeling - From Coplanar to Non-coplanar Beams

Out-of-plane Angle

In-plane Angle

Inferior

Superior

black circle: clinical angles
white diamond: knowledge driven angles
Phase 3: Progressive Modeling
- From Coplanar to Non-coplanar Beams

Clinical Plan

Model Plan
Phase 3: Progressive Modeling
- From Coplanar to Non-coplanar Beams

Clinical Plan

Model Plan
Summary

- **Benefits of Knowledge Modeling: Clinical**
  - Learning Curve, Quality, Consistency
  - Standardization, Automation, Integration

- **Benefits of Knowledge Modeling: Institutional**
  - Systematic, Objective
  - Integrated Refinement and Evolution

- **Benefits of Knowledge Modeling: Future**
  - Feature Based Knowledge for Big Data Research
  - Standardization (Evidence-based) and Optimization (Personalized)
SAM Questions

Treatment planning knowledge models are:

3%  a. Confined to a single institution

90%  b. Applicable to multiple modalities

6%  c. Useful for only IMRT

1%  d. Physician Specific

0%  e. Useable only with Monte Carlo-based dose calculation algorithms
SAM Questions

1. Treatment planning knowledge models are:
   a. Confined to a single institution
   b. Applicable to multiple modalities
   c. Useful for only IMRT
   d. Physician Specific
   e. Useable only with Monte Carlo-based dose calculation algorithms

Answer: b

Reference:
- Lian et al, Modeling the dosimetry of organ-at-risk in head and neck IMRT planning: An inter-technique and inter-institutional study, Medical Physics 2013, 40(12)
SAM Questions

The treatment planning knowledge that we can model include:

- 0% a. incident beam angle selection
- 1% b. multiple OAR structures
- 0% c. multiple PTV prescriptions
- 1% d. DVHs of OARs
- 97% e. All the above
2. The treatment planning knowledge that we can model include
   a. incident beam angle selection
   b. multiple OAR structures
   c. multiple PTV prescriptions
   d. DVHs of OARs
   e. All the above

Answer: e

Reference:
SAM Questions

The organ sparing capability predicted by the knowledge model is

13%  a. The average value of the sparing in the database

15%  b. Interpolated among a few similar cases

6%   c. Independent of prescription dose

1%   d. Only valid for maximum dose

65%  e. Patient specific, based his/her anatomy and physician’s prescription
SAM Questions

3. The organ sparing capability predicted by the knowledge model is

a. The average value of the sparing in the database
b. Interpolated among a few similar cases
c. Independent of prescription dose
d. Only valid for maximum dose
e. Patient specific, based his/her anatomy and physician’s prescription

Answer: e

Reference:

Thank you