Knowledge Based Treatment Planning

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AAPM 2012

DukeMedicine

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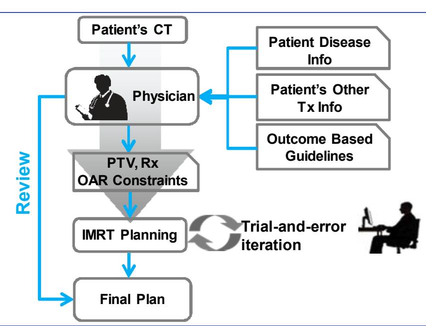
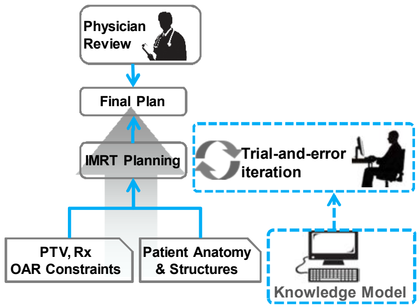
IMRT Planning

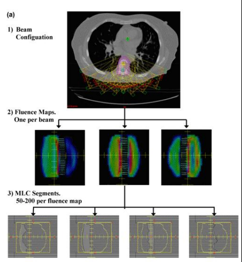


IMRT Planning



IMRT Planning: The Trial-And-Error Process

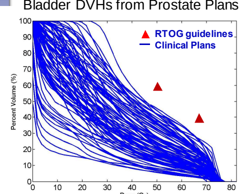
- Define the optimization DVH objectives
- Get the bixel-blocks (segments)
- Calc. the dose distribution
- Review the DVHs & Dose Distributions



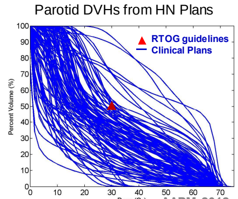
IMRT Planning : The Trial-And-Error Process

- OAR dose sparing is patient specific and often better than the conservative population-based guidelines
- Lack of objective measure to identify patient-specific OAR sparing to guide the trial-and-error process

Bladder DVHs from Prostate Plans



Parotid DVHs from HN Plans



IMRT Planning : The Trial-And-Error Process

- **Experience matters**
  - More experience usually leads to better plan quality and less planning time
- **Planning time matters**
  - Adequate planning time usually leads to better planning quality
  - Complexity of the plan leads to exponential increase of planning time
- **Planning objectives matters**
  - Objectives closer to individual patient goals lead to more efficient planning, sometimes better plan quality
  - Template based objectives leave more room for improvement and more plan quality variations

Knowledge Modeling For IMRT Planning

- **To provide patient specific dose sparing references, based on an array of patient anatomical features, prior planning experience, and outcome-based guidelines**
  - **Understand** the patient's anatomical, physiological and other factors that influence plan design of dose coverage
  - **Quantify** their individual influence via mathematical modeling and machine learning
  - **Codify** treatment planning experience and guidelines using knowledge engineering
  - **Model** these factors to guide treatment planning for new cases

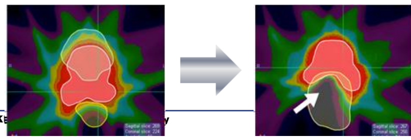
Knowledge of Dose Distribution

Online Re-Optimization of Prostate IMRT Plan for Adaptive Radiation Therapy - A Feasibility Study and Implementation
Danthai Thongphiew, PHD Thesis 2007, Case Western Reserve University

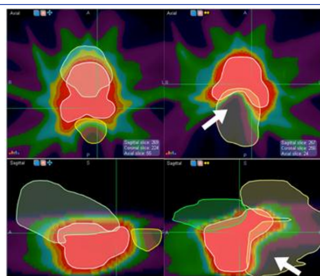
Towards Clinical Implementation Of Online Adaptive Radiation Therapy for Prostate Cancer
Taoran Li, PHD Thesis expected 2013, Duke University

Knowledge of Dose Distribution

- **Experience Learned From Online Adaptive Radiation Therapy (Online ART)**
- **Hypothesis:**
  - Anatomical changes from same patient can be coded through deformable registration
  - Wrapping the dose distribution from original plan to the new anatomy reinforces the dose conformality, and carries the same dose sparing preferences for this patient



Step 1. Deform the Original Dose for New Anatomy



Original Plan In Database

New Plan Dose Distribution Via Deformable Registration

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Step 2. Auto-Optimization With Linear Goal Programming

Target: $D_i - d_i^+ + d_i^- = D_i^p$

OARs: $D_i - d_i^+ \le D_i^p$

Minimize: $\sum_{i \in T} w_{T,i}(d_i^+ + d_i^-) + \sum_{i \in NT} w_{NT,i}(d_i^+)$

Voxel based – flexible control, solved in 1-2 min.
Direct dose based – what's formulated, what's delivered

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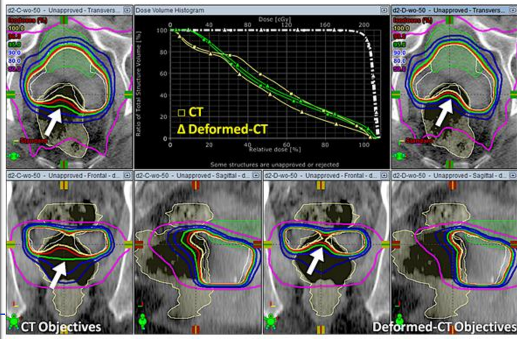
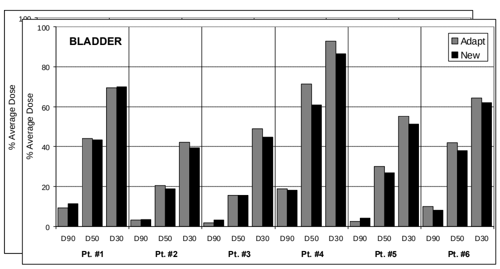
Step 3. Plan Quality Vs. Dose Objectives



Step 3. Plan Quality QA: ART vs. Eclipse



<u>A planning quality evaluation tool for prostate adaptive IMRT based on machine learning</u>
Zhu et al. Med. Phys. 38, 719: 723, 2011.

IMRT Planning For Online Adaptive RT

- Step 1. Deformable registration of CBCT and CT
  Wrap CT dose to CBCT anatomy
  -> <u>known perfect dose</u>
- Step 2. Run auto-optimization to get fluence map
  -> <u>known optimization parameters</u>
- Step 3. Run auto plan quality QA
  -> <u>known plan quality parameters</u>

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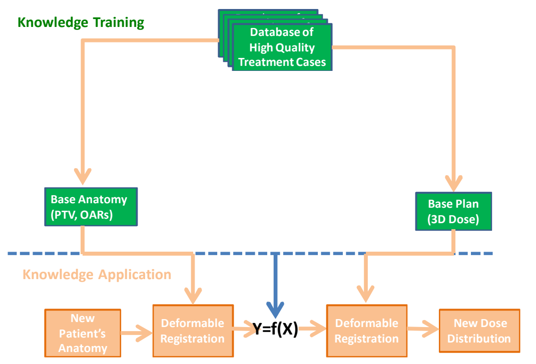
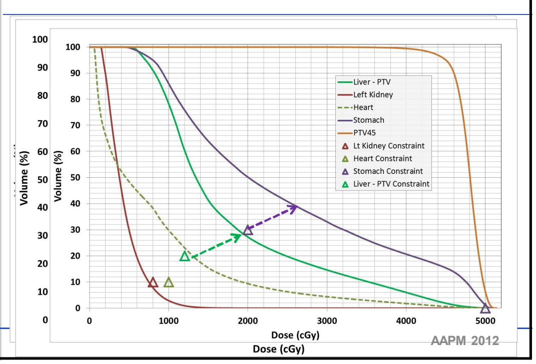
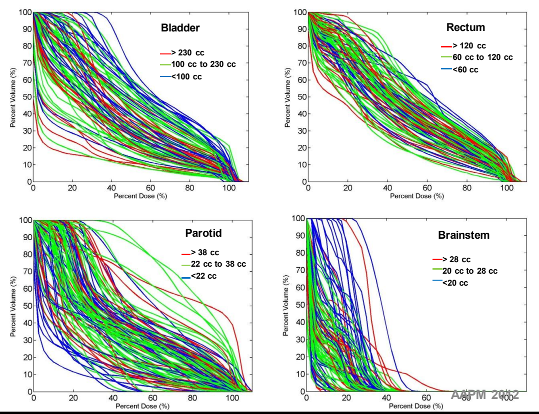


Knowledge of DVH Distribution

Modeling Inter-Patient Variation of Organ-At-Risk Sparing in IMRT Plans: An Evidence-Based Plan Quality Evaluation
Yuan et al
MO-D-BRB-10 Monday 2:00:00 PM - 3:50:00 PM Room: Ballroom B

Knowledge of DVH Distribution





Knowledge of DVH Distribution

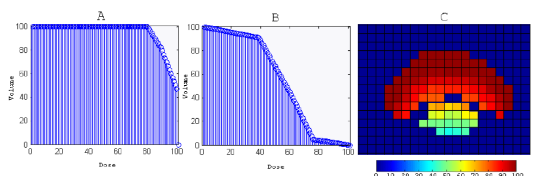
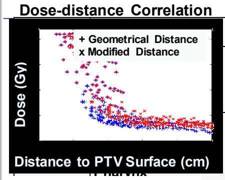


Figure 17 A) A example of a DVH of the target B) An example of DVH of the OAR C) The prescribed dose based on the given DVHs and voxel position

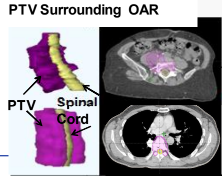
Multiobjective Approach To Morphology-based Radiation Treatment Planning
Boonyanit Mathayomachan, PHD Thesis 2005
Case Western Reserve University

Knowledge of DVH Distribution

Dose-distance Correlation



PTV Surrounding OAR



Anatomical And Dosimetric Features

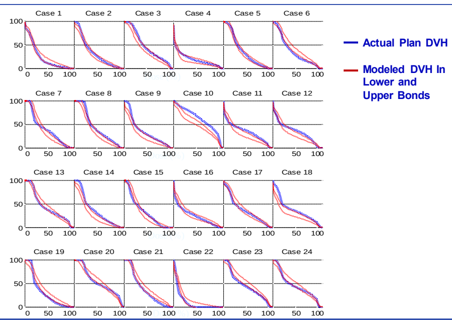
Distance to target histogram (DTH): PCS
Distance to OAR (DOH): PCS

OAR volumes
PTV volume
Fraction of OAR volume overlapping with PTV (overlap volume)
Fraction of OAR volume outside the treatment fields (out-of-field volume)

Tightness of the geometric enclosure of PTV surrounding OAR
Curvature of specific OAR

PTV dose homogeneity
PTV hotspot
OAR DVHs

Example Of Parotid Sparing Modeling



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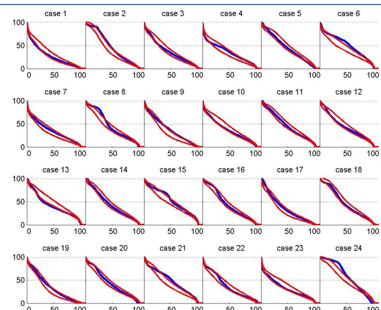
Examples of Rectum DVH Modeling



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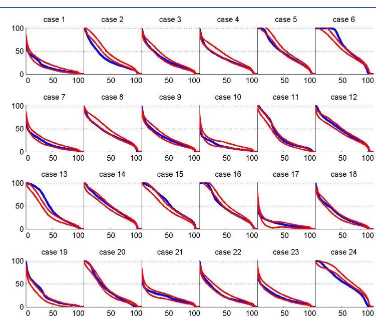
Example of Bladder DVH Modeling



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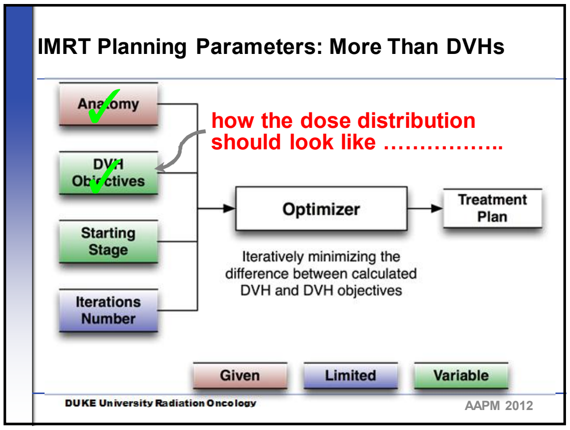
IMRT Planning Parameters: More Than DVHs
Anatomy
DVH Objectives
Starting Stage
Iterations Number
how the dose distribution should look like ……………..
Optimizer
Treatment Plan
Iteratively minimizing the difference between calculated DVH and DVH objectives
Given
Limited
Variable
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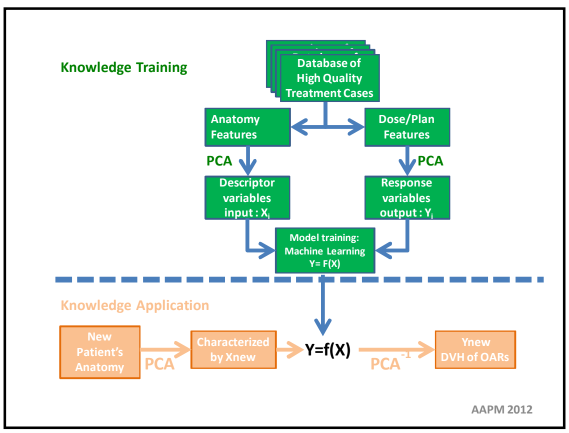
Knowledge Training
Database of High Quality Treatment Cases
Anatomy Features
Dose/Plan Features
PCA
PCA
Descriptor variables input : X_i
Response variables output : Y_i
Model training: Machine Learning Y= F(X)
Knowledge Application
New Patient's Anatomy
PCA
Characterized by Xnew
Y=f(X)
PCA^{-1}
Ynew DVH of OARs
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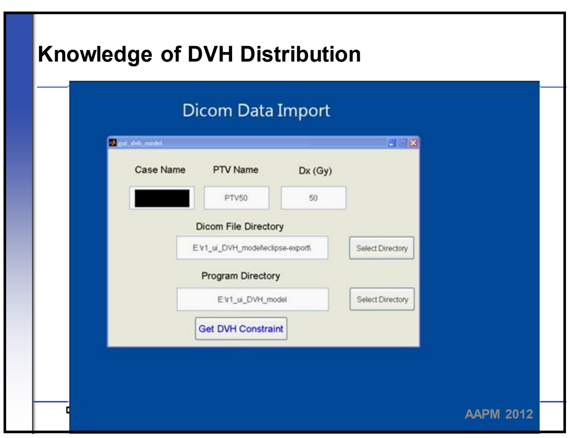
Knowledge of DVH Distribution
Dicom Data Import
Case Name
PTV Name
Dx (Gy)
[redacted]
PTV50
50
Dicom File Directory
Select Directory
Program Directory
Select Directory
Get DVH Constraint
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Knowledge of Patient Specific Trade-offs & Preferences

Individualized Trade-Off of Dose Coverage and Sparing in IMRT Planning
Yuan et al
SU-E-T-626 Sunday 3:00:00 PM - 6:00:00 PM Room: Exhibit Hall

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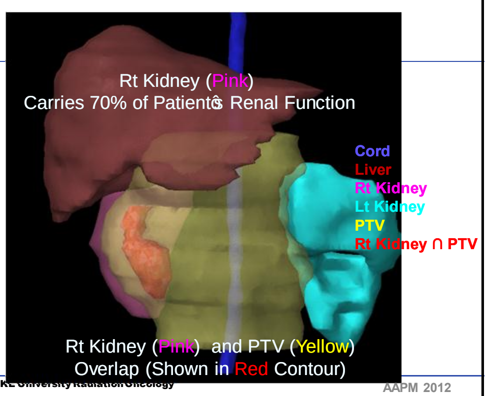

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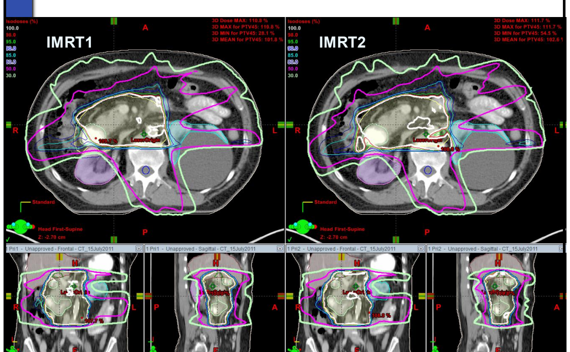

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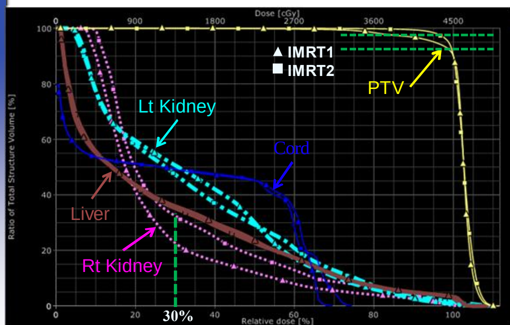

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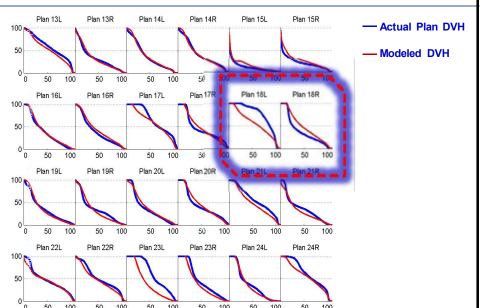
Modeling of Trade-off: Parotid



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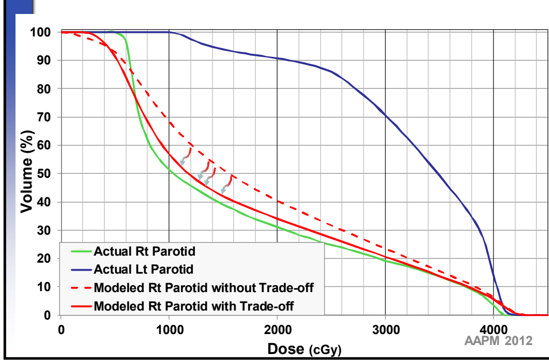

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Knowledge Based IMRT Planning

- Plan quality can rival human expert planner
- Planning time can be fast (minutes)
- Knowledge of IMRT planning can be independent of delivery platforms (e.g. VMAT vs. IMRT)

- Allow more freedom (such as beam angle, beam energy)
- Allow interactive process
- Integrate with all sources of knowledge
- Truly individualized, patient-specific treatment planning

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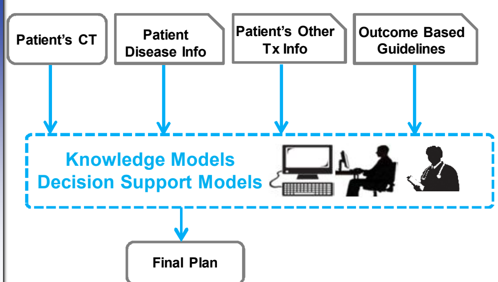
Knowledge-Based IMRT Planning



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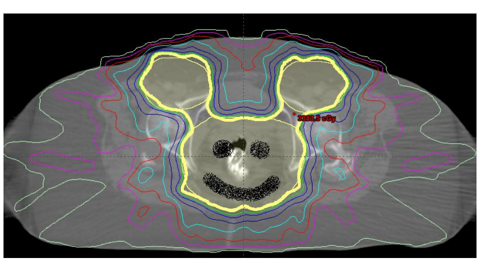
Thank You & Happy Planning With All Types of Knowledge Formats



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