Overview and Testing of TPOR 1.0.0

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Outline

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The Optimization Problem

- In computer science, optimization problems belong to a class of problems known as NP-complete (Dasgupta, 2006).
- Typically, the only way to solve an NP-complete problem exactly is an exhaustive search (Dasgupta, 2006).
- Any method to reduce the search space based on some additional info or experience is called a heuristic.
- Heuristics are not guaranteed to find an optimal solution but in some cases, the worst case “distance” from optimal is known (Chvatal, 1979).

The Greedy Heuristic

- The greedy heuristic is a well know heuristic in the computer science community for solving a variety of optimization problems (Chvatal, 1979).
- It simply requires one to make the locally optimal choice, based on some criterion, at each step of solution construction.
- All of the algorithms for interstitial prostate brachytherapy treatment planning optimization that will be discussed are greedy heuristics.
- The decision criterion for each of these algorithms incorporates adjoint dose data related to the patient.

Outline

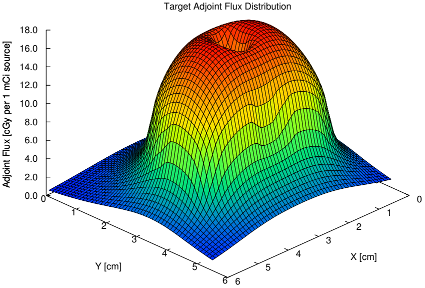
The Basic Position Ranking Metric

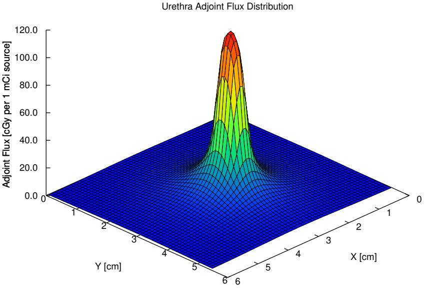
- The most basic quantity used for evaluating the desirability of a brachytherapy seed positions is the adjoint ratio.
- The adjoint ratio essentially indicates the amount of dose delivered to healthy tissue relative to the amount of dose delivered to the target tissue (given weights of unity).
- This quantity is static and can thus be considered a property of a potential seed position.

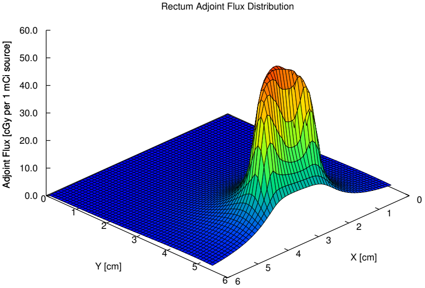
Adjoint Ratio

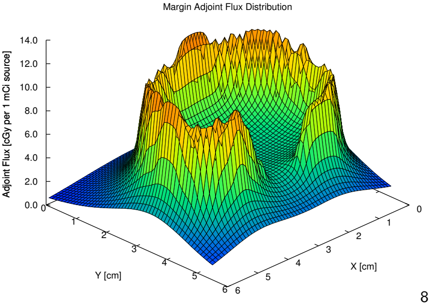
$$C_i = \frac{w_{ur}\phi^{\dagger}_{ur,i} + w_{re}\phi^{\dagger}_{re,i} + w_{ma}\phi^{\dagger}_{ma,i}}{w_{ta}\phi^{\dagger}_{ta,i}}$$

Midplane Adjoint Flux Distributions for Tissue ROIs

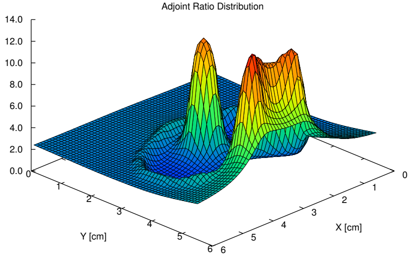


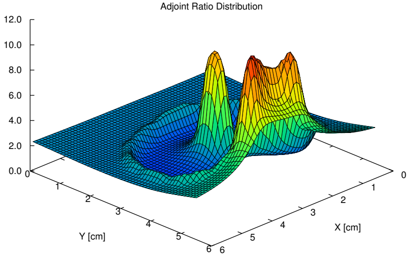


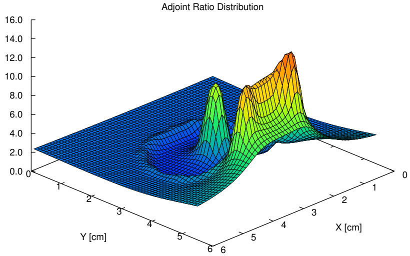


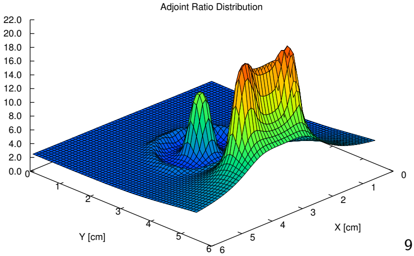


Adjoint Ratios at Z= 1.25, 2.25, 3.25, 4.25 cm

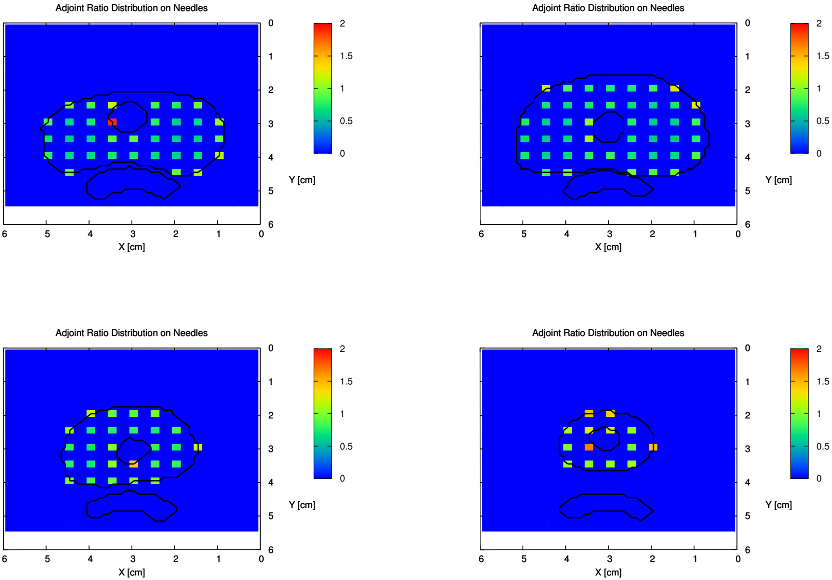






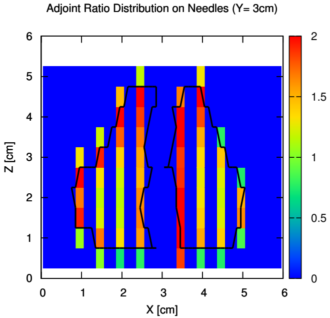


Adjoint Ratios on Needles at Z= 1.25, 2.25, 3.25, 4.25 cm



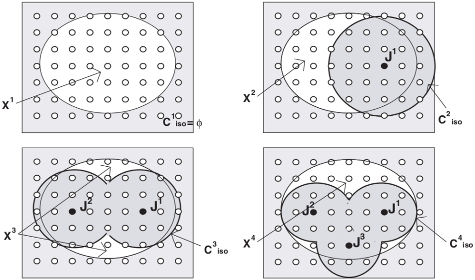
Limitations of the Adjoint Ratio

- Using the adjoint ratio as the sole criterion for choosing a seed position will result in seeds being clustered at low points along a needle.
- A practical criterion needs to include additional information that prevents seeds from clustering.



The Iterative Isodose Exclusion Method[2] (IIEM)

- This method prevents seeds from clustering by imposing an isodose constraint on the seed selection process.
- Even if a seed position has the lowest adjoint ratio, it will not be selected if the dose at that seed position from other selected seeds is greater than the constraint value[1].



[1]Figure courtesy of (Yoo et al., 2003)
[2]This method was developed by Sua Yoo(Yoo et al, 2003).

IIEM Pseudocode

- *Outer Iteration:* Select a needle goal
  - **Inner Iteration A:** Select α for C_{iso}^m
    1. Calculate $C_{iso}^m = \alpha * D_p * (m - 1)$ for this step (starting at m=1)[3]
    2. Selected a seed by finding position with smallest adjoint ratio and current dose less than C_{iso}^m
    3. If needle goal reached, continue to **Inner Iteration B**, else select new α
    4. If maximum α value reached, select new needle goal
  - **Inner Iteration B:** Select β for C_{iso}^m
    1. Calculate $C_{iso}^m = \beta * D_p$ for this step
    2. Select a seed by finding position with smallest adjoint ratio and current dose less than C_{iso}^m
    3. If acceptable treatment plan achieved, end, else select a new β value
    4. If maximum β value reached, return to **Inner Iteration A** and select new α

[3] D_p is the prescribed dose

The Dynamic-Weight Dose Mult. Method (DWDMM)[4]

- This method prevents seeds from clustering by utilizing a dynamic position value (weight).
- After a seed has been selected, the adjoint ratio of all other seed positions is multiplied by the dose at its respective position.
- The closer a seed position is to previously selected seeds, the larger its dynamic weight and the less likely it is to be picked.

[4] This method was developed by Vibha Chaswal (Chaswal et al., 2012)

The Weighted Set Cover Problem

- The set cover method for brachytherapy treatment planning is motivated by the greedy heuristic used to solve (approximately) the weighted set cover problem

Problem Def. (Chvatal, 1979)

There are N sets and M elements. Each set S_i has an associated cost c_i. $I = \cup(S_j : 1 \leq j \leq N)$ contains all M elements, while $J = \{S_1, S_2, ..., S_N\}$ contains all sets. A subset J^* of J is called a cover if $\cup(S_j : j \in J^*) = I$ with corresponding cost $\sum(c_j : j \in J^*)$. **Find a cover of minimum cost.**

Standard Greedy Heuristic (Chvatal, 1979)

1. Set $J^* = \varnothing$
2. If $S_j = \varnothing \; \forall j$ then stop: J^* is a cover. Otherwise find a subscript k minimizing the ratio $\frac{c_j}{|S_j|}$.
3. Add S_k to J^*, replace each S_j by $S_j - S_k$, return to step 2.

Properties of the Set Cover Greedy Heuristic

- The greedy heuristic is a polynomial time algorithm
- The cost of the set cover found with this heuristic is guaranteed to be within $O(log(n)) * C_{opt}$, where n is the number of elements and C_{opt} is the cost of the optimal set cover (Chvatal, 1979).
- No polynomial time algorithm can get you a better approximation (Lund and Yankis, 1994).

Treatment Planning as a Set Covering

- Treatment planning can be recast as a set covering problem:
  - I**:** prostate mesh elements
  - S_j**:** seed position j, *all* prostate mesh elements
  - c_j**:** the adjoint ratio at the seed position.
  - $|S_j|$**:** a new function is needed to evaluate the size of set since all sets contain the same elements (departure from the standard problem).

Set Size Function

$$| S_j | = \sum_i D_{new,i}$$

$$D_{new,i} = \begin{cases} (D_{future,i} - D_{current,i}) & \text{if } D_{future,i} < D_p \\ (D_p - D_{current,i}) & \text{if } D_{future,i} > D_p \text{ and } D_{current,i} < D_p \\ 0 & \text{otherwise} \end{cases}$$

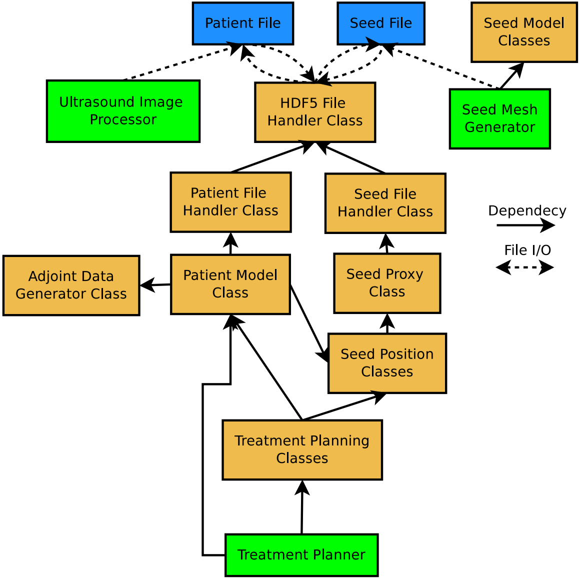
$D_{current,i}$ is the dose at voxel i from all previously placed seeds. $D_{future,i}$ is the dose that will be at voxel i if this seed is placed.

The Set Cover Method (SCM) Pseudocode

1. Set $J^* = \varnothing$
2. If an acceptable treatment plan has been achieved, end. Otherwise find a subscript k minimizing the ratio $\frac{c_j}{|S_j|}$.
3. Add S_k to J^*, return to step 2.

Outline

TPOR Code Flow



The Patient Interface File

- All patient data is stored in a binary (HDF5) file.
- The patient data that can be found in this file are the patient organ masks, the organ volumes (approximate), the needle template, and the adjoint data associated with each seed and each organ.
- One should never interact or manipulate this file directly.
- Only use the *Patient File Handler Class* to access data stored in this file.
- A python script has been written that allows one to create this file for a patient given an ultrasound image file.

The Seed Interface File

- The dose distribution for a seed must be known in order to conduct a treatment planning optimization.
- The seed interface file (usually called *BrachytherapySeeds.h5*) stores the dose distribution of every low dose-rate (LDR) seed currently in production on a predefined mesh.
- One should never interact or manipulate this file directly.
- Only use the *Seed File Handler Class* to access data stored in this file.
- A C++ program has be written that generates this file.

The Brachytherapy Seed Models

- All brachytherapy seeds are modeled using the recommendations from the TG-43 update for a line source approximation.
- The following brachytherapy seeds can be modeled by the TPOR library:
  - Amersham 6711 (I^{125})
  - Amersham 9011 (I^{125})
  - Best 2301 (I^{125})
  - Best 2335 (Pd^{103})
  - Bebig I25.S06 (I^{125})
  - Theragenics 200 (Pd^{103})
  - Theragenics AgX100 (I^{125})
  - IsoAid IAI-125A (I^{125})
  - IsoAid IAPd-103A (Pd^{103})
  - SourceTech STM1251 (I^{125})
  - Nucletron 130.002 (I^{125})

The Seed Proxy Class

- The class was created after profiling the TPOR library.
- One of the original bottlenecks was the seed model class, which has to do many table look-ups and interpolations to get the dose at a point.
- The seed proxy class simply stores the seed dose distribution mesh for a seed and looks up the value at a requested position.
- Its class interface is nearly identical to the seed model class interface.

The Brachytherapy Seed Position Class

- The brachytherapy seed position class only stores the most basic info needed by a treatment planning algorithm, i.e. the adjoint ratio (or weight) of a seed position.
- The class also stores the seed type that would be placed at the position, which facilities multispecies treatment planning.
- When a seed position is chosen, a member function must be called that maps the dose from the seed type to the patient organs.
- Only the IIEM treatment planning class uses this seed position class.
- Several more advanced seed position classes have also been written to provide the information needed by The DWDMM and SCM treatment planning classes.

The Patient Model

- The patient model class stores the patient organ masks, needle template, prescribed dose, dose distribution and treatment plan.
- The class interface allows the treatment planning algorithms to insert seeds into the patient model, determine properties of the patient, and determine properties of the treatment plan.
- Upon completion of the treatment plan, the class can also print the treatment plan and other details that can be used to evaluate the quality of the plan.

The Treatment Planning Optimization Classes

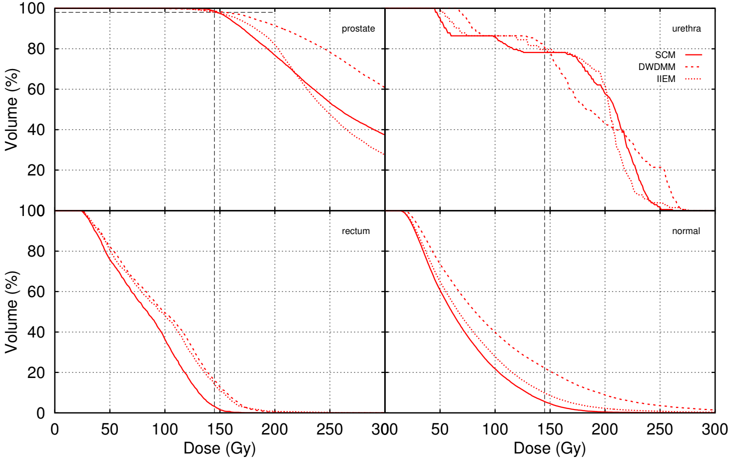
- All classes simply rely on the patient model class and one of the seed position classes.
- As seed positions are selected they are inserted into the patient model.
- Once the patient model indicates that an acceptable treatment plan has been achieved, the class releases the patient model for post processing.

Outline

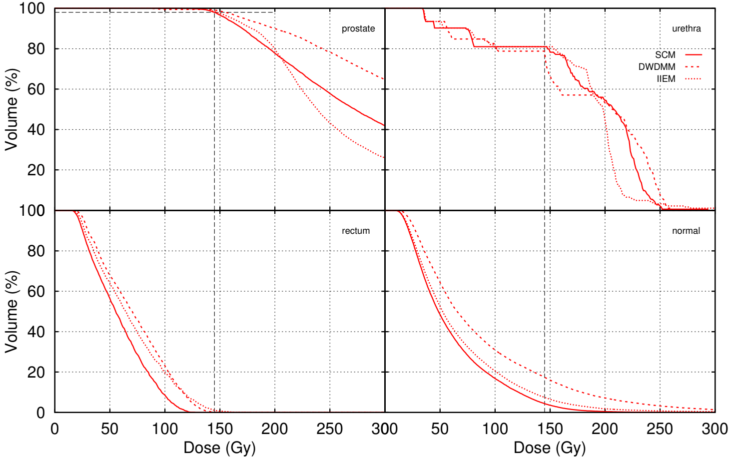
A TPOR Comparison Study

- Treatment plans for 16 patients were calculated using the three treatment planning algorithms currently in TPOR.
- All organ weights were set to one when calculating adjoint ratios.
- The quality of the plans as well as the optimization times were compared to draw conclusions about each of the algorithms.
- Much of the data is still being processed but DVH curves have been created.

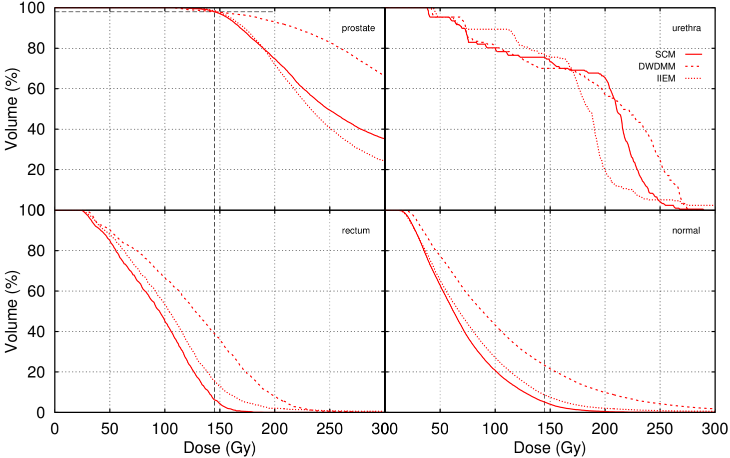
Patient A DVH Curves



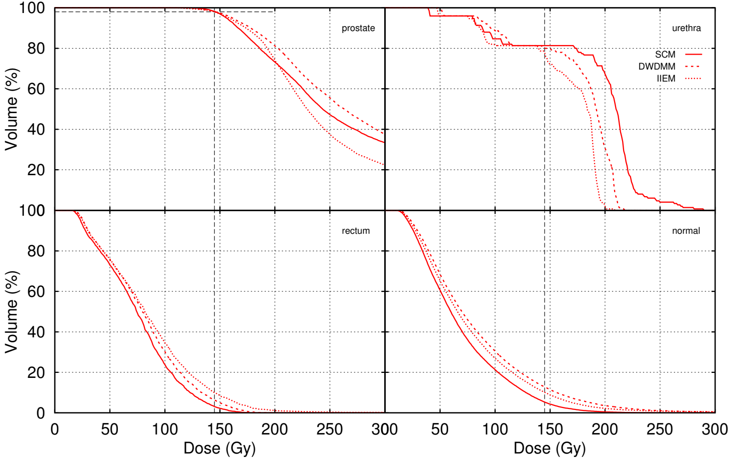
Patient B DVH Curves



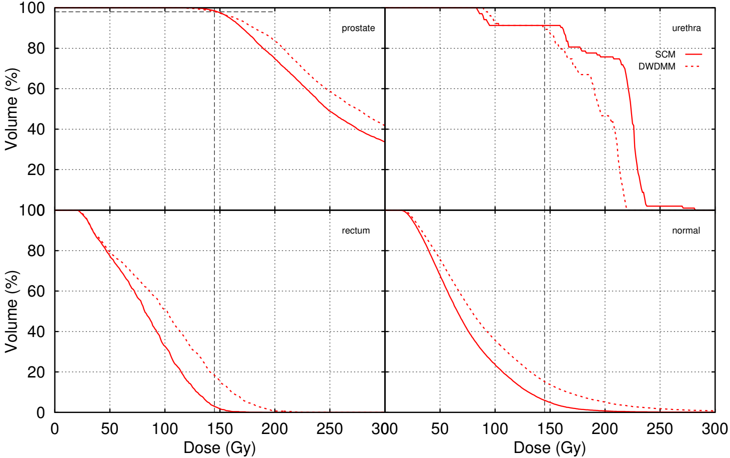
Patient C DVH Curves



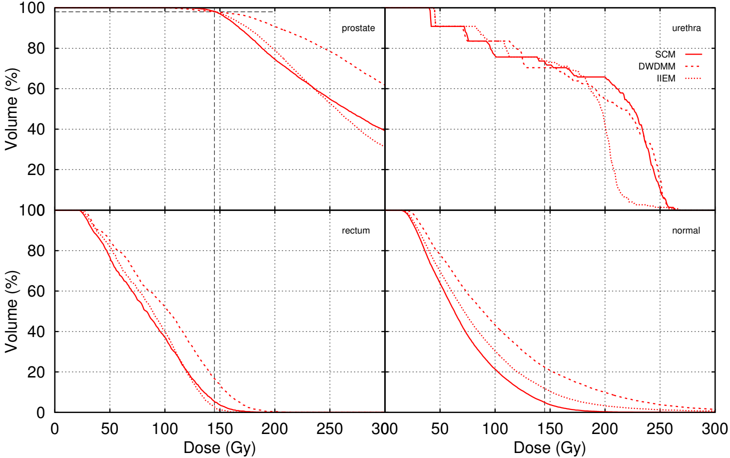
Patient D DVH Curves



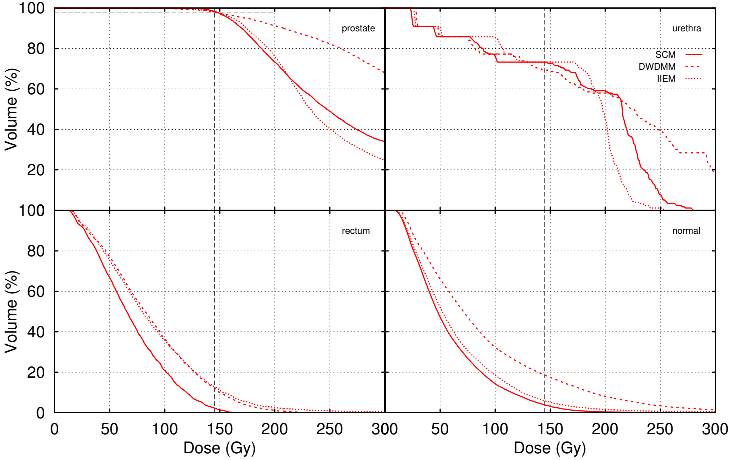
Patient E DVH Curves



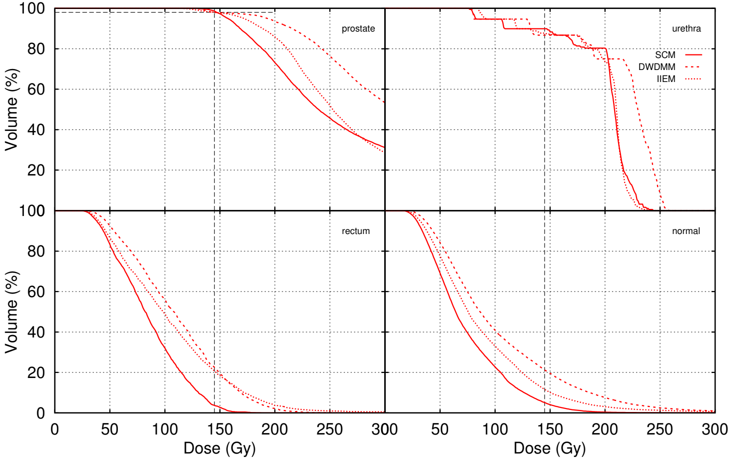
Patient F DVH Curves



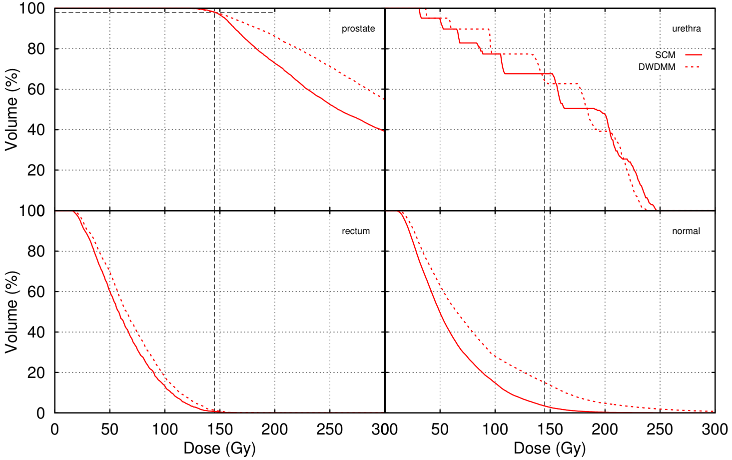
Patient G DVH Curves



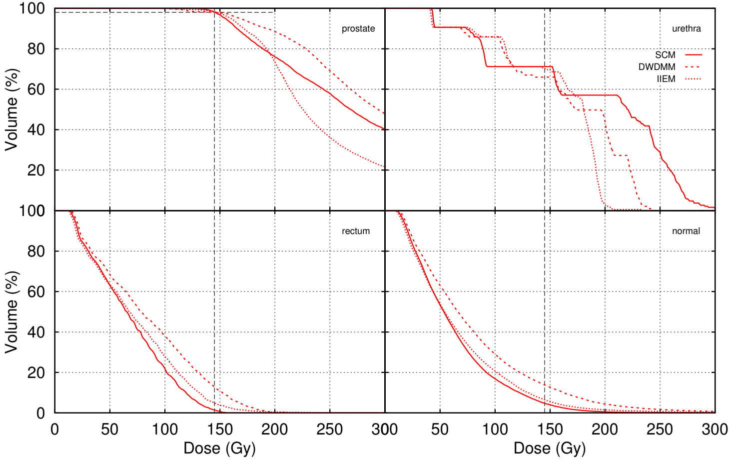
Patient H DVH Curves



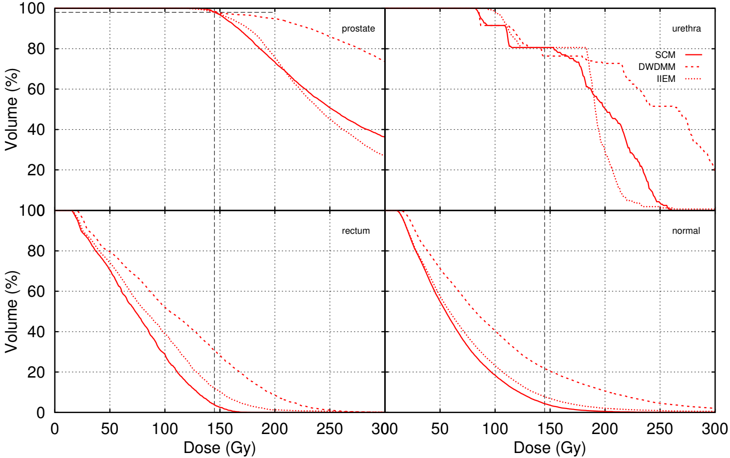
Patient I DVH Curves



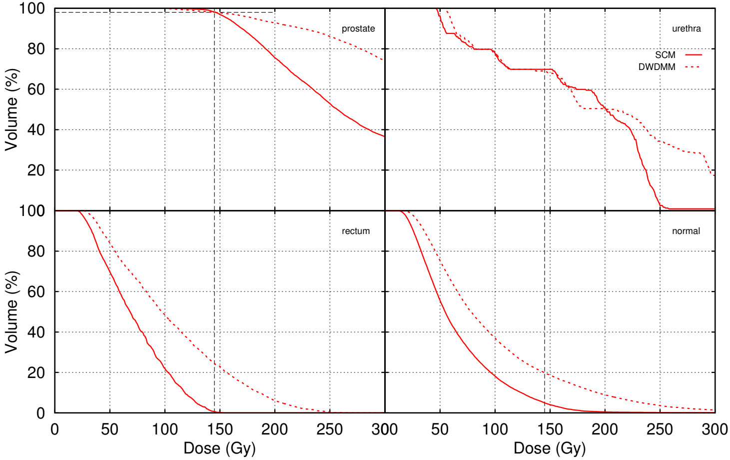
Patient J DVH Curves



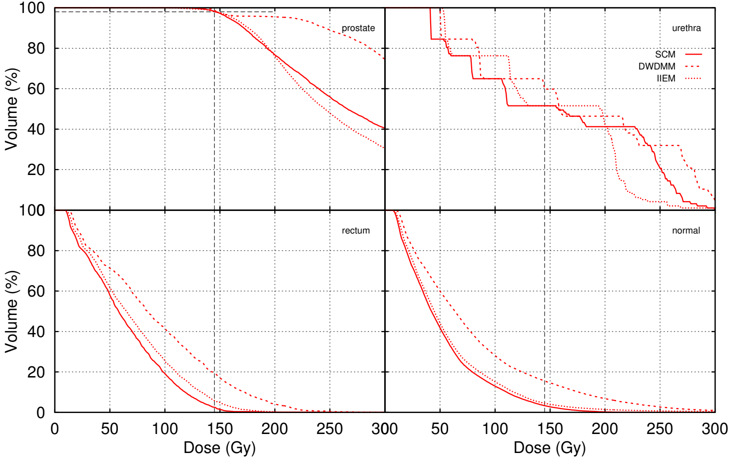
Patient K DVH Curves



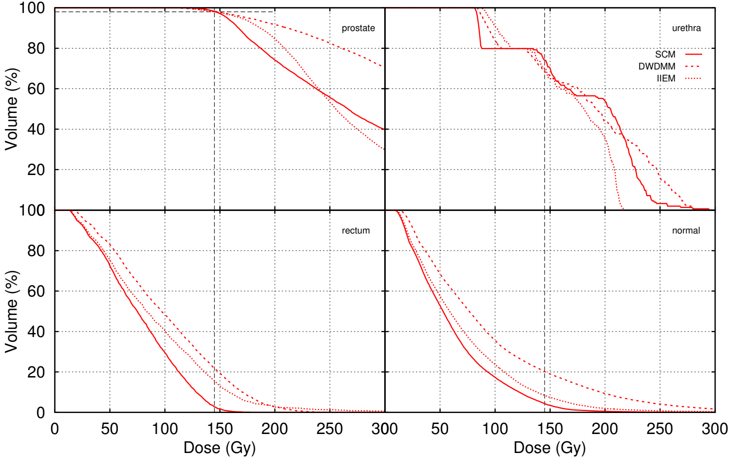
Patient L DVH Curves



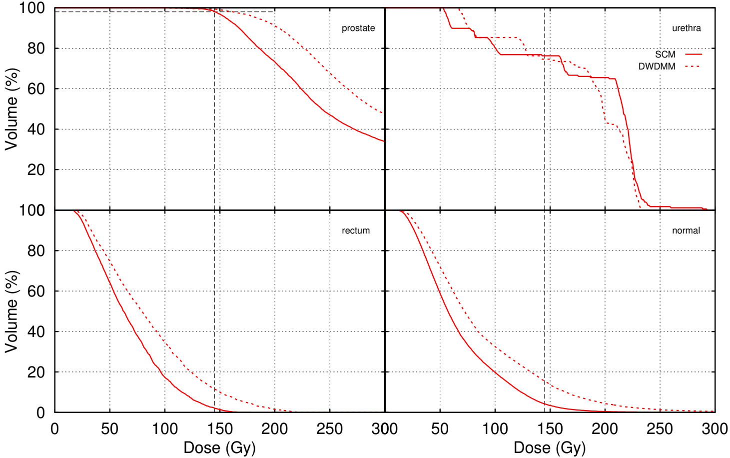
Patient M DVH Curves



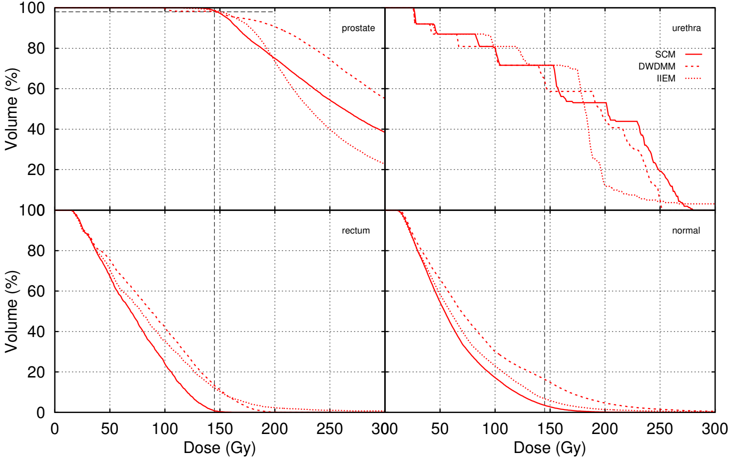
Patient N DVH Curves



Patient O DVH Curves



Patient P DVH Curves



Outline

Pros/Cons of Each Method

- IIEM
  - Pros:
    - Very fast
    - Does a good job of picking a small number of needles and seeds
    - Does a good job of limiting prostate overdosing
  - Cons:
    - Does not always converge (iterative)
- DWDMM
  - Pros:
    - Extremely fast
    - Guaranteed solution (non-iterative).
  - Cons:
    - Tends to select a large amount of seeds
    - Multiplication of the adjoint ratio by the dose does not have a physical motivation

Pros/Cons of Each Method

- SCM
  - Pros:
    - Does a good job of picking a small number of seeds
    - Does a good job of sparing sensitive tissues
    - Motivated by a well established greedy heuristic from computer science
    - Guaranteed solution (non-iterative).
  - Cons:
    - Much slower than the other methods
    - Tends to select a large number of needles

Future Work

- Add support for directional seeds.
- Add support for other types of treatment planning.
- Suggestions?