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Accelerating IMRT Optimization by Voxel Sampling

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Abstract

We are developing a new approach to optimize Intensity Modulated Radiation Therapy plans in the presence of uncertainty. We first present a problem formulation to describe the stochastic or semi-robust problem. Unfortunately, this formulation is infeasible to solve in a reasonable time on modern computers. We recognized this and developed a randomized algorithm approach using voxel sampling to solve the problem quickly. This approach turns out to be useful for solving normal IMRT optimization problems as well.

What is IMRT?

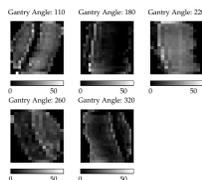
IMRT is a technique for delivering a large dose of radiation to a cancerous tumor. A linear accelerator on a gantry rotates around the patient and delivers high energy photons from 5 to 7 angles. A multi-leaf collimator is used to control the intensity of radiation allowed through each point in the beam. By optimizing the dose to each beamlet, IMRT can maximize the dose to the tumor while minimizing the damage to healthy tissues.



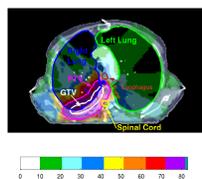
A linear accelerator



A Multi-leaf collimator



Intensity map of each beam



Dose delivered to sample lung case

State of the art

In current clinical practice, uncertainty in patient position is dealt with by adding margins around the target[4] and occasionally around very critical organs[5]. This approach ensures the proper coverage of the tumor in most cases, but it delivers more dose to healthy tissue than is necessary.

Research into uncertainty in IMRT is a very active area and a number of methods have been proposed. These include:

- Optimized Margins - A number of authors including Killoran [6]
- Optimized expected dose - Li [7]
- Incorporating variance into the objective function - Unkelbach [9]
- Replica based optimization - Yang[10], Chu[2]

Comparable research into accelerating IMRT optimization includes voxel clustering work by [8]. Voxel sampling has been used in [3]. Both of these work by solving a reduced subproblem instead of a random algorithms approach.

Challenges and Significance

For handling uncertainty:

- IMRT is able to produce highly conformal dose distributions, but it is limited by the need to add margins around the tumor.
- Margin approaches cannot take advantage of known information about patient motion
- We want to improve tumor control and reduce normal tissue complications

For voxel sampling:

- Planners typically optimize a treatment plan many times with different parameters
- Faster optimization runs allow the planner to experiment more and find a better plan
- A replica based approach is impractical without sampling

Technical Approach

1. Problem Formulation Assume we have a function, $F(h)$ that measures the quality of a dose distribution, h . We wish to find the beamlet intensity vector, x , which produces the optimal dose distribution, given $h = Dx$, where D is the dose-influence matrix. The optimization problem is then

$$\begin{aligned} \min \quad & F(Dx), \\ \text{s.t.} \quad & x \geq 0. \end{aligned}$$

In the uncertain case, D is a random matrix drawn from a set \mathcal{D} with some probability, $Pr\{D = \mathbf{D}\}$. Our basic formulation for this problem is minimizing the expected value of the objective.

$$\begin{aligned} \min \quad & E_{\mathbf{D}}[F(\mathbf{D}x)], \\ \text{s.t.} \quad & x \geq 0. \end{aligned}$$

A more conservative rule would minimize the expected objective for the worst 25% of outcomes.

$$\begin{aligned} \min \quad & E_{\mathbf{D}}[F(\mathbf{D}x) \mid F(\mathbf{D}x) \geq c], \\ \text{s.t.} \quad & Pr\{F(\mathbf{D}x) \geq c\} \leq 0.25, \\ & x \geq 0. \end{aligned}$$

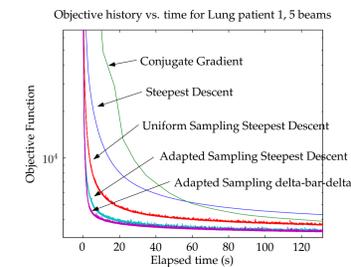
Calculating the dose to each volume element (voxel) inside the patient is quite slow since there are thousands of beamlets, hundreds of thousands of voxels, and tens of millions of nonzero elements in D . Calculating the objective and gradient exactly is hence slow. This problem is greatly magnified in the uncertain case, as even a rough discretization of \mathcal{D} will need many times the memory and computation time of the standard optimization.

2. Voxel Sampling We realized that we could calculate an estimate of the gradient while calculating the dose to a fraction of the voxels in each organ. We re-sample voxels at each step to create an estimate of the gradient. We further developed an algorithm to automatically tune the sampling rate for each organ.

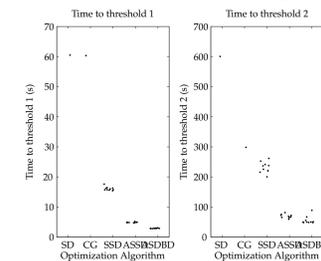
Standard steepest descent works on gradients with errors, but techniques such as conjugate gradient do not. We experimented with the stochastic meta descent and delta-bar-delta algorithms and found that delta-bar-delta works very well.

Results

- 20 times speedup in standard IMRT compared to steepest descent
- Good convergence while only sampling 2% of the voxels



Convergence of various algorithms with 10 runs for the randomized algorithms.



Comparing the performance of various algorithms, with 10 runs for the randomized algorithms.

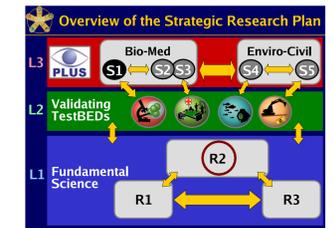
Accomplishments through Current Year

- Implemented probabilistic optimization of simple phantom
- Implemented voxel sampling to accelerate IMRT optimization for standard plan
- Student successfully defended prospectus

Plans

- Publish paper on voxel sampling to accelerate optimization (nearly completely written)
- Implement stochastic optimization using voxel sampling
- Publish paper on voxel sampling for stochastic optimization
- Extensions into Intensity Modulated Proton Therapy range uncertainty in collaboration with Jan Unkelbach
- Student will finish and defend dissertation

Three Level Diagram



Publications Acknowledging NSF Support

- Censor et al.[1].

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