

Dynamic Segment-Based Optimization (SBO) for 4D IMRT

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Purpose

Current radiation treatment practice neither detects nor adapts to intra-fraction organ motion beyond gating. We develop a dynamic Segment-Based Optimization (SBO) scheme for 4D IMRT which doesn't rely on gating and simulate its performance.

Introduction

Some aspects of patient geometry change (the location of the tumor and various organs) much during treatment. The lung and stomach are good examples. New techniques are available or are being developed to track or predict patient geometry during dose delivery. These techniques include 4D CT of the lung ahead of treatment to learn the typical motion in the breathing cycle and cone-beam computed tomography (CBCT) during treatment.

While the ability to predict the dynamics of patient geometry during treatment is rapidly improving, current intensity-modulated radiation therapy (IMRT) treatment plans make little use of that ability. Current treatment plans are generally either static (completely ignoring any predictable motion) or use gating to ensure a static plan is applied only when the patient geometry is in the correct position.

Our goal is to develop and tune algorithms for inverse 4D IMRT planning in order to make full use of any predictions of patient geometry dynamics. This research allows us to quantify the improvements 4D IMRT provides compared to static or gated plans in terms of dose distribution, DVH, and reduced margins.

Algorithms

static beamlet planning:

We find the best static plan (a plan that is the same for all phases) under the independent beamlet model.

for every phase $D_i = D$,

$$\text{where } D \in \arg \min_{D \in F_{BM}} \sum_v \alpha(v) \left(\sum_j D(A_j(v)) - D^*(v) \right)^2$$

dynamic beamlet planning:

We use the independent beamlet model to find a different plan for every phase so that the accumulated dose is as close as possible to the prescription.

$$(D_1, \dots, D_N) \in \arg \min_{(D_1 \in F_{BM}, \dots, D_N \in F_{BM})} \sum_v \alpha(v) \left(D^*(v) - \sum_{j=1}^N D_j(A_j(v)) \right)^2$$

dynamic Segment-Based Optimization (SBO):

We do the same as in "dynamic beamlet planning" but now in the segment-based model. In this model we model the leaf positions directly instead of beamlet intensities.

$$(D_1, \dots, D_N) \in \arg \min_{(D_1 \in F_{SBM}, \dots, D_N \in F_{SBM})} \sum_v \alpha(v) \left(D^*(v) - \sum_{j=1}^N D_j(A_j(v)) \right)^2$$

our dynamic SBO uses a stochastic descent algorithm to find the best plan:

1. every step it selects a nearby leaf configuration
2. it optimizes the weights for that configuration
3. if the score of that configuration with optimized weights is better, it moves to that configuration (and goes to step 1)
4. occasionally it may restart at a random leaf configuration

Terminology

$\alpha(v)$	importance factors
N	number of phases
$D^*(v)$	prescription dose for voxel v
$D_i(v)$	dose planned for voxel v in phase i
$A_i(v)$	anticipated location of voxel v in phase i
F_{BM}	set of feasible plans under the independent beamlet model
F_{SBM}	set of feasible plans under the segment-based model (SBM)

The independent beamlet model is simpler than the segment-based model but unrealistically flexible: $F_{SBM} \subset F_{BM}$.

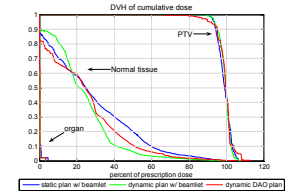
Future Directions

Ways of improving the dynamic SBO,

- add leaf-speed constraints
- use objective functions other than quadratic deviation
- use smarter stochastic search algorithms
- integrate with 4D CT images
- make robust against unpredicted motion

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the geometry

static beamlet planning

dynamic beamlet planning

dynamic SBO

