Closed-Loop Control Algorithms for Planning Adaptive Radiation Therapy

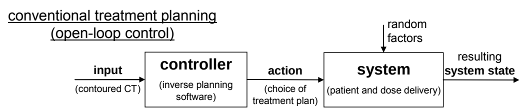
Adam de la Zerda, Benjamin Armbruster, Lei Xing

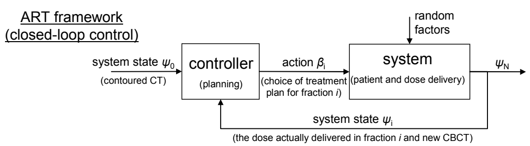
STANFORD SCHOOL OF MEDICINE
Stanford University Medical Center

Abstract

Current radiation therapy (RT) does not adapt to inter-fraction organ movement and dosimetric errors caused by inaccurate setup or organ deformation during a course of treatment. The emergence of on-board cone beam CT (CBCT) affords an effective means to obtain the patient's geometric model just before treatment and recompute on a routine basis the dose to be delivered or actually delivered to the patient. This makes it possible to adaptively correct for dosimetric errors in the previous fractions by modifying the treatment plan. However, before this new scheme of RT can happen clinically, an inverse planning algorithm capable of taking into account the dose delivery history and the patient's geometric model must be in place. In this paper we devise dynamic closed-loop control algorithms for adaptive therapy (ART) and demonstrate their utility with data from phantom and clinical cases. To meet the need of different clinical applications, we study two classes of algorithms: those *Adapting to Changing Geometry* and those *Adapting to Geometry and Delivered Dose*. The former class takes into account organ deformations found just before treatment. The latter class optimizes the dose distribution accumulated over the entire course treatment by adapting at each fraction not only to the information just before treatment about organ deformations but also to the previous dose delivery history. We showcase two algorithms in the class of those *Adapting to Geometry and Delivered Dose*. We study the feasibility and utility of the algorithms using phantom and clinical cases. A comparison with conventional approaches indicates that ART optimization may significantly improve the current practice.

Introduction – IMRT in Control Theory





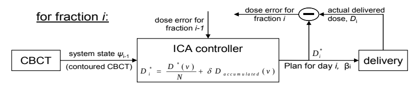
Closed-Loop Control	Radiation Therapy
time period (i)	fraction
input (ψ_0)	contoured CBCT images
action (β_i)	treatment plan (D_i^*)
system state (ψ_i)	contoured CBCT images and actually delivered dose (D_i)
controller	RT inverse planning software
system	patient geometry and treatment delivery

Methods and materials

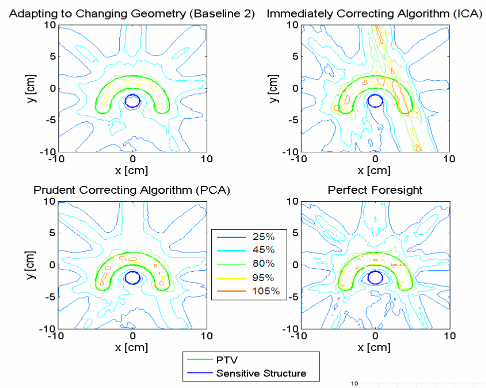
Algorithm		Objective functions for different schemes of dose optimization
Perfect Foresight (The theoretical upper limit of any RT algorithm)		$\left(\beta_1,\dots\beta_N\right)=\arg\min\sum_v \alpha(v)\left(D^*(v)-\sum_i^N D_i(v)\right)^2$ Minimize the difference between the prescription and the delivered dose accumulated over all treatment fractions.
Baseline 1: Population-Based Margins		$\beta_1=\dots=\beta_N=\arg\min\sum_v \alpha(v)\left(\frac{\bar{D}^*(v)}{N}-D_0^*(v)\right)^2$ Add margins to the prescription ($\bar{D}^*$) and then minimize the difference between the prescription and the daily planned dose (D_0^*)
Baseline 2: Adapting to Changing Geometry		$\beta_i=\arg\min\sum_v \alpha(v)\left(\frac{D^*(v)}{N}-D^*_i(v)\right)^2$ Update the patient's geometric model every fraction using CBCT and plan a dose for that geometry that minimizes the difference to the daily prescription.
Adapting to Geometry and Delivered Dose	Immediately Correcting Algorithm (ICA)	$\beta_i=\arg\min\sum_v \alpha(v)\left(\frac{D^*(v)}{N}+\delta D(v)-D^*_i(v)\right)^2$ Update the patient's geometric model every fraction using CBCT and plan a dose for that geometry that minimizes the difference to the prescribed dose plus the accumulated error.
	Prudent Correcting Algorithm (PCA)	$\left(\beta_i,\dots\beta_{i+d}\right)=\arg\min\sum_v \alpha(v)\begin{pmatrix} D^*(v)\frac{i+d}{N}-D_1(v)-\dots-D_{i-1}(v) \\ -D_i^*(v)-\dots-D_{i+d}^*(v)\end{pmatrix}^2$ Update the patient's geometric model every fraction using CBCT and using that geometry plan a dose for remaining (d+1) fractions that minimizes the difference to the prescribed dose plus the accumulated error.

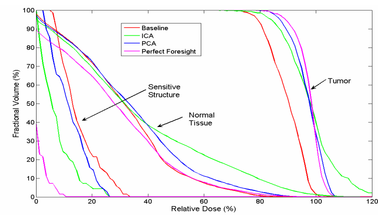
Terminology

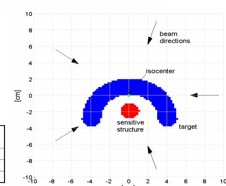
α(v)	Importance factors
β_i	Beam modulation for fraction *i*
N	Number of fractions
D*(v)	Prescription dose for voxel *v*
$D_i(v,\beta)$	Actual delivered dose to voxel *v* under modulation β in fraction *i*
$D_i^*(v,\beta)$	Planned dose to voxel *v* under modulation β in fraction *I*
δD(v)	Accumulated dose error for voxel *v*



Results - Phantom

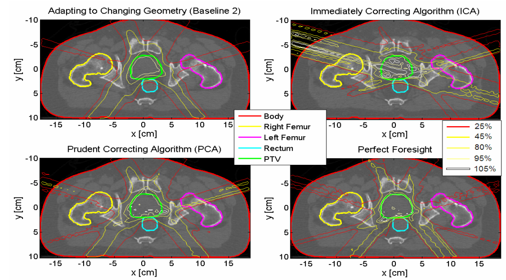




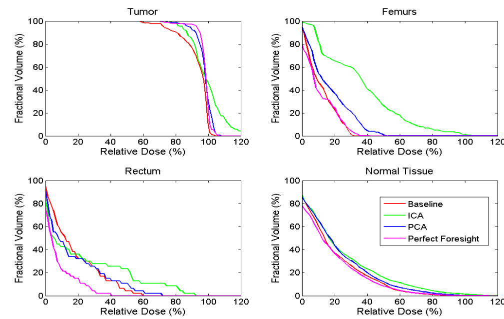


Algorithm	Tumor Avg. Dose	Tumor 1σ	Sensitive Structure Avg. Dose	Sensitive Structure 1σ	Normal Tissue Avg. Dose	Normal Tissue 1σ
ICA	+9%	+48%	-48%	-12%	+18%	+47%
PCA	+8%	-13%	-18%	-9%	+7%	+14%
Perfect Foresight	+9%	-30%	-89%	-65%	-8%	+13%

Results - Prostate Case



Algorithm	Tumor Avg. Dose	Tumor 1σ	Femurs Avg. Dose	Femurs 1σ	Rectum Avg. Dose	Rectum 1σ	Normal Tissue Avg. Dose	Normal Tissue 1σ
ICA	+6%	+14%	+196%	+165%	+21%	+73%	+24%	+28%
PCA	+5%	-44%	+40%	+45%	-5%	+18%	+13%	+11%
Perfect Foresight	+5%	-49%	-8%	+12%	-54%	-40%	-7%	+2%



Discussion

Analysis of ICA & PCA Results

- Errors do not accumulate (see phantom's sensitive structure)
- Dose escalation to the tumor while keeping the sensitive structure close to 25%
- Steeper gradients around the tumor
- ICA performs much worse than PCA (As it tries to fully compensate for previous dose daily)

Future Directions

- use better objective functions (not just quadratic deviation)
- apply optimal stochastic control / Dynamic Programming

Acknowledgements

We wish to thank Dr. J. O. Deasy for his generous help with CERR and Drs. Y. Yang and B. Widrow for useful discussions. This work was supported in part by grants from the Department of Defense (PC040282), the National Cancer Institute (1R01 CA104205), the American Cancer Society (RSG-01-022-01-CCE), and a Graduate Research Fellowship from the National Science Foundation.