SIMPLIFYING THE OPTIMIZATION PROCESS IN INTENSITY-MODULATED RADIOTHERAPY

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ABSTRACT

Intensity-modulated radiation therapy (IMRT) is a state-of-the-art technique for cancer treatment with radiation. Through numerical optimization, IMRT computes suitable radiation intensities that maximize the dose absorbed by a tumor and minimize that absorbed by the surrounding critical organs. However, due to differences in geometry between patients, even expert radiation planners still need to spend a substantial amount of time manually adjusting IMRT optimization parameters such as dose limits and weights in order to obtain a clinically acceptable plan. The bottleneck of current IMRT systems is not optimization, but the trial and error procedure of adjusting optimization parameters. Circumventing or minimizing this procedure would save many person-hours of effort.

In this thesis, we develop a unifying framework to simplify the IMRT optimization process, so that a near-optimal set of parameters or intensities can be reached more efficiently and automatically. The framework consists of three components: machine learning, dimensionality reduction and numerical optimization.

First, we show that in simplified breast IMRT, the optimal intensities are inherently related to the patient's geometry. Given a large number of patients treated effectively under a given protocol, we explore this relationship using machine learning algorithms, including support vector regression. The prediction result for a new patient either leads to a plan that would be instantly approved in the clinic, or serves as a good starting point for subsequent adjustment.

Next, for general IMRT planning where numerical optimization can't be avoided, we present methods to decrease the degrees of freedom for the spaces of both optimization parameters and beamlet intensities. Based on a detailed mathematical analysis of the effects of parameters on IMRT objective functions, we find that typical IMRT planning is over-parameterized. We automatically identify a subset of important parameters using Monte Carlo simulation and sensitivity analysis. We also use Principal Component Analysis to decrease the dimensionality of the intensity space, which would otherwise be prohibitively high for constrained intensity optimization.

Third, after successful dimensionality reduction, different numerical algorithms are

leveraged to obtain suitable values for parameters and intensities. We apply a two-loop optimization scheme to determine the parameters that lead to a plan meeting the clinical requirements. The inner loop is based on traditional unconstrained intensity optimization, and the outer loop leverages a random search algorithm in the reduced parameter space. Since this approach still depends on unintuitive parameters to satisfy certain clinical criteria, we further investigate constrained optimization that eliminates the tunable parameters entirely. To improve the computational efficiency of constrained optimization which remains a major problem in the literature, we identify a low-dimensional subspace that effectively represents the results from unconstrained optimization, and then refine the solutions in the reduced space by constrained programming.

We validate the above methodology in a clinical treatment planning system using dose-volume-based objective functions. Experimental results demonstrate that our framework can effectively reduce the trial-and-error process in IMRT planning. In breast IMRT where the number of trial optimizations ranges between 1 and 9, our machine learning predictions produce acceptable plans in a matter of seconds. In prostate IMRT where manual adjustment takes hours, for 70% of the cases our two-loop optimization can automatically determine a plan in 10 minutes (on the average) that is either clinically acceptable or requires only minor adjustment by the planner. The reduced-order constrained optimization usually takes 15 seconds after 10 minutes of Monte Carlo simulation. In comparison, previous methods reported over 10 hours spent in full-dimensional constrained programming. The methodology developed in this thesis can also be applied to other IMRT planning systems with different types of objective functions.