Recent Progress in Inverse Treatment Planning

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Intensity modulated radiation therapy (IMRT) is being developed into an important modality in radiotherapy. Institutions worldwide are attempting or planning to integrate this new technology into their clinics. Before the IMRT implementation, it is desirable to understand the overall inverse planning process and how the general concept of inverse planning is implemented. This will help in making better decisions regarding which system is best suitable to your clinical environment and thus facilitate the implementation process. In general, there are three integral parts in IMRT: inverse planning [1, 2], dynamic delivery [3], and quality assurance [4-8]. The purpose of this talk is to present an overview of the state-of-the-art inverse planning algorithms as well as our perspectives on several practical issues relevant to the subject. In particular, we will identify the problems in currently available systems and described the techniques that have been or are being developed to overcome the problems.

Radiation treatment planning requires the calculation of a set of parameters for the delivery of a certain radiation dose to the patient. Ideally, radiation dose distribution should be designed to conform perfectly to the entire tumor volume while completely avoiding surrounding normal tissues. Although achievement of this goal is practically impossible, a computer optimization can potentially simplify the tedious planning procedure and yield the best possible plans[1] [2]. Computer optimization becomes necessary for IMRT treatment planning because of the vast search space. The implementation of the general concept of inverse planning differs from system to system. The degree of optimality of the final solution is generally determined by the form of objective function and the methods to search for the minimum (or maximum) of the defined objective functions.

The role of objective function is to establish a link between the output dose distribution and the input beam parameters (beamlet weights or beam profiels). The objective function measures the goodness of a selected plan and its choice is crucial for therapeutic plan optimization. The objective function can be based solely on dose or it can use a radiobiological model. The former is concerned with the interaction between radiation and matter and calls for accurate dose distributions, with the biological aspect being implicitly given in the physician's prescription. The biological model argues that optimization should be based on the biological effects produced by the underlying dose distributions. The treatment objective is usually stated as the maximization of the tumor control probability (TCP) while maintaining the normal tissue complications probability (NTCP) to within acceptable levels. A TCP is related to a dose distribution by the dose response function, which is not sufficiently understood. At this point, the dose-based approach is still widely used in practical optimization whereas biological models are often used conceptually. This is evidenced by the fact that all commercial inverse planning systems use dose-based (with or without dose-volume constraints) objective function.

In IMRT, the objective function is a function of the beamlet weights. The number of beamlet for a given case varies from a few hundreds to several thousands, depending on the tumor size and beamlet size. A given objective function can be optimized using many different optimization algorithms, such as iterative methods [9-11], simulated annealing [12-15], filtered backprojection [15], genetic algorithm [16], maximum likelihood approach[1, 17], linear programming [18], etc. For all their complexity, the algorithms to optimize a multidimensional function are routine mathematical procedures. In general, simulated annealing and genetic algorithms are powerful approaches, but excessive computation time is a drawback to their clinical application. Treatment planning based on filtered backprojection and direct Fourier transformation have difficulty handling the negative fluence problem and are not generally applicable for an arbitrary dose prescription and kernel. An iterative method is a widely used technique to optimize a multidimensional objective function by starting with an initial approximate solution and generating a sequence of solutions that converge to the optimal solution of the system.

Inverse planning is at the foundation of IMRT and its performance critically determines the success of an IMRT treatment. Unfortunately, the currently available inverse planning formalism is deficient and the solutions out of so-called “optimization” systems are often sub-optimal or even not optimal at all from clinical point of view. Considerable effort may be required to compute a clinically acceptable plan and the final results may strongly depend on the planner’s experience and understanding of the planning system. These shortcomings of the existing available systems are familiar to anyone engaged in clinical IMRT treatment planning. A typical inverse planning system is shown in Fig. 1. In addition to the prescription doses, the current planning system requires the user to pre-select the angular variables (gantry, couch, and collimator angles) and the relative importance factors of the involved structures. These variables and parameters constitute an additional multi-dimensional space, which is coupled to the beam profiles in complicated fashion. A survey carried out by us indicates that there are four major problems in current inverse planning systems: (1) No effective mechanism for incorporating prior experience into dose optimization; (2) Lack of direct control over regional dose; (3) No

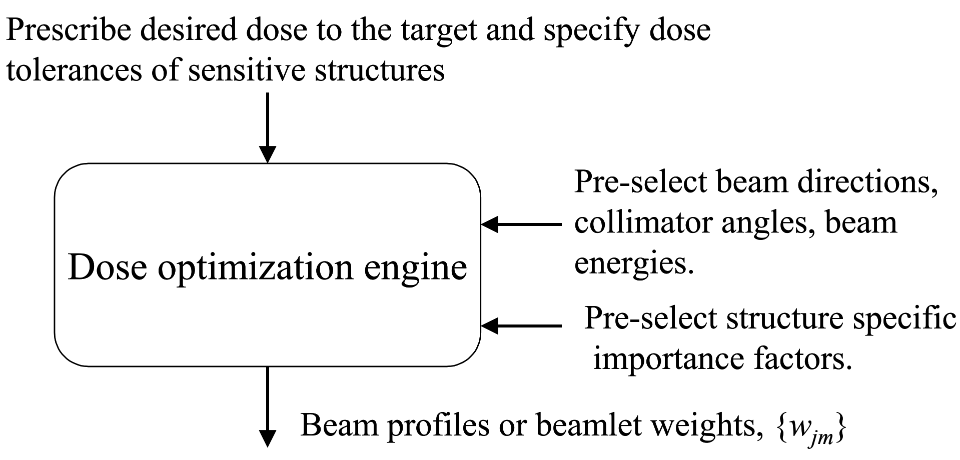

Figure 1 A schematic drawing of currently available inverse planning process. The inverse planning objective function of the system depends on the prescribed target dose and sensitive structure tolerances, beam parameters (beam directions, collimator angles, beam energies), and the structure specific importance factors.

effective tools for aiding beam placement in IMRT planning; and (4) Inefficient interface between planning and delivery systems.

Toward establishment of a clinically efficient and robust inverse planning system, we have attacked the problems mentioned above and developed a series of computational tools, which will be discussed in the presentation. Briefly, we have developed a statistical analysis based inverse planning formalism for incorporating prior knowledge. The approach is based on the concept of preference function [1, 2]. Instead of using rigid dose prescription (with or without DVH constraints), we are able to optimize a system with a range of prescription doses. In addition to make the system less ill-defined, this new scheme allows us to formalize our clinical knowledge (such outcome data and dose-volume-complication [19-21]) and incorporate them into dose optimization.

A voxel-dependent penalty scheme into inverse planning has been introduced to enhance our control over the regional dose. We pointed out that the local dosimetric behavior can be more effectively controlled by this scheme and demonstrated the utility of the approach using a model systemas well as clinical examples. In figure 2 we show an example of 6-field IMRT prostate treatment. To reduce the doses to the two hot spots seen in the conventional plan (left), particularly to the one near the center of the prostate, we graphically identified the hot regions and then assigned a higher importance to the corresponding voxels. The middle panel of Fig. 2 shows the isodose distribution after adjustment. The hot spot near the urethra disappeared and the size of the other hot spot was reduced significantly. This improvement is more evident in the DVH.

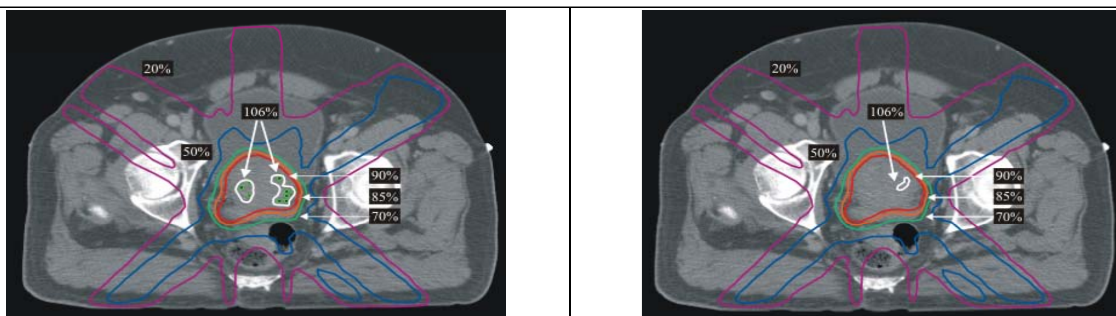

Fig. 2 A conventional IMRT prostate plan (left). Two 106% hot spots are present in the prostate (85% is prescription isodose line). The dose distribution after increasing the local importance factors is shown in the right. The hot spot near the center of the prostate disappeared while the size of the second hot spot is reduced.

Beam configuration may have significant influence on the quality of an IMRT treatment even when a large number of incident beams (e.g., nine beams) is used [14, 22-25]. Clinically, however, beam orientations are still selected based on trial-and-error. To obtain an optimal beam configuration, in principle, one can simply add the degree of freedom of beam angles into the objective function and optimize them together with the beamlet weights. While this does not pose any conceptual challenge, the computational time becomes excessive because of the greatly enlarged search space and the coupling between the beam profiles and the beam configurations. The beam intensity profiles have to be optimized for every trial beam configuration as the influence of a set of gantry angles on the dose distribution is not known until the beam intensity profile optimization is performed. Furthermore, a stochastic optimization algorithm is needed to optimize the gantry and couch angles due to the non-convex structure of the objective function with respect to these variables. A computationally efficient optimization algorithm is necessary to have a clinically practical beam orientation optimization tool. We have developed a beam eye's-view dosemetrics (BEVD) for assisting IMRT beam orientation selection [26, 27]. The basic assumption here is that the merit of a beam direction should be measured by what that beam could achieve dosimetrically without exceeding the dosimetric or dose-volume constraint of the system. The best achievable scenario of a given beam can be determined based on *a priori* dosimetric and geometric information of the given patient. In Fig. 3 we show the BEVD score functions for an IMRT treatment of a para-spinal tumor. Figure 4 shows the DVHs of various structures for plans obtained with and without the BEVD guiding tool. The whole calculation of the BEVD score was less than 3 minutes even for the non-coplanar beam configuration on a SGI O2 R5000 workstation. The BEVD information can also be integrated into beam orientation optimization program to greatly improve the convergence behavior and computing speed of beam orientation optimization calculation. This will be discussed in the presentation.

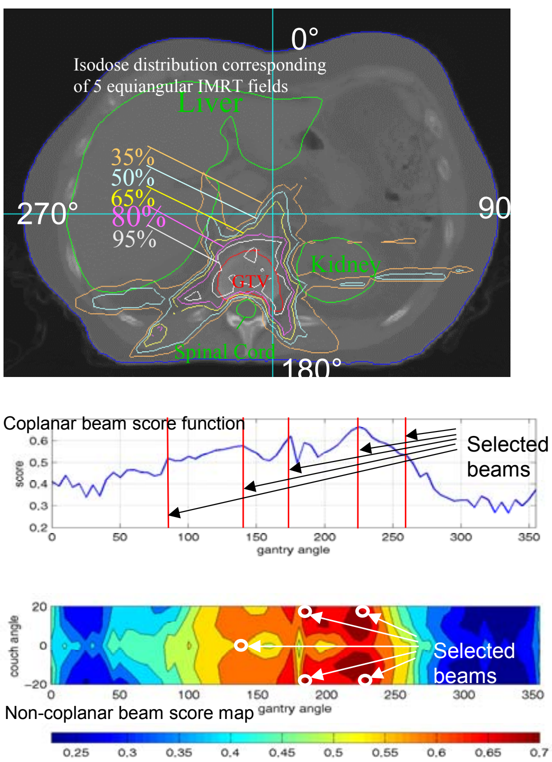

Fig. 3 Isodose distribution of an IMRT treatment with 5 equiangular beams (40°, 110°, 180°, 255°, 325°). The middle and bottom plots show the BEVD score for the patient for coplanar and non-coplanar beam configurations, respectively.

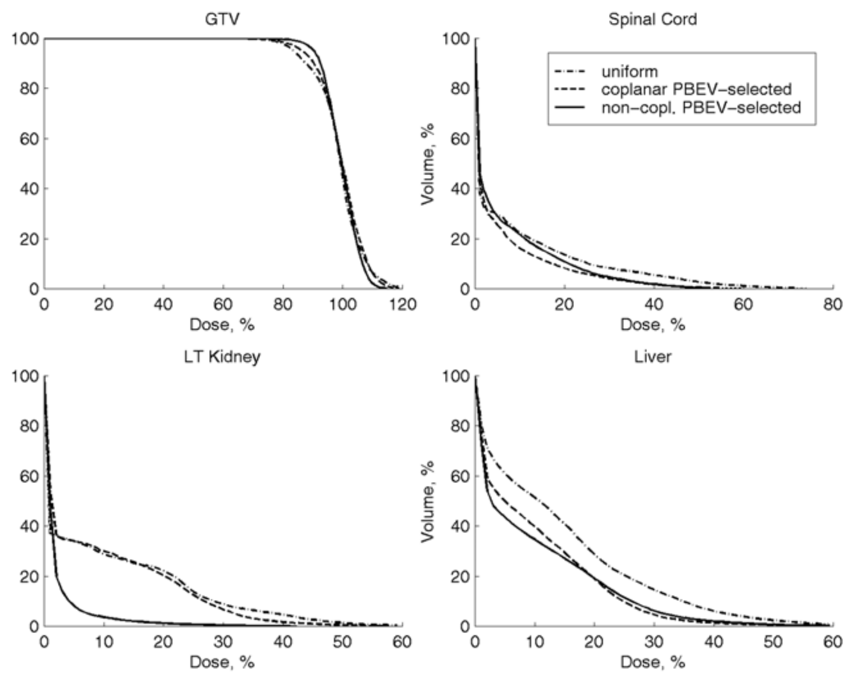

Fig. 4 Comparison of the DVHs of the GTV, cord, kidney, and liver for the treatment plans of paraspinal tumor. DVHs are shown for the plans with following beam configurations: five coplanar equiangular spaced beams (dash-dotted line), five coplanar beams with BEVD-selected orientations (dashed line), and five non-coplanar beams with BEVD-selected orientations (solid line).

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Finally, we mention that it is clinically useful to improve the efficiency of the interface between the inverse planning system and the dynamic MLC delivery system. There are many research activities in this direction, which includes, but not limited to, incorporating machine constraints into dose optimization, aperture-based optimization.

This work was supported in part by Grants from the American Cancer Society, Department of Defense, and the Whitaker Foundation.

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