The Monte Carlo Method: Versatility Unbounded In A Dynamic Computing World
Chattanooga, Tennessee, April 17–21, 2005, on CD-ROM, American Nuclear Society, LaGrange Park, IL (2003)

MODELING OF PTV AND OARS FOR ADJOINT MONTE CARLO TREATMENT PLANNING

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ABSTRACT

The adjoint MC is more efficient than the forward MC for determining the beam weights since the adjoint particles will automatically sample the most important region of the phase space with the highest adjoint fluxes. This paper reports our latest data in applying an AMC based radiation treatment planning system. Simulations were first run with adjoint sources defined inside the PTV and OARs. We implemented a source sampling scheme for different ROIs in a single adjoint Monte Carlo run. The tally results were further extracted for each ROIs and compared with previous results of the same parameters obtained from separate runs. Beam weights were then calculated from the adjoint flux at each possible physical source locations. In a forward MC simulation, the detailed doses at each voxel of the PTV and OARs were calculated with the previously determined beam weights. This study used a 3D standard tomographic patient model called VIP-Man which was developed from the segmented Visible Human images. This study also implements a variation reduction technique for the forward Monte Carlo simulation using the adjoint simulation results.

Key Words: MCNP, adjoint, mesh tally, radiation treatment planning

1 INTRODUCTION

There is a growing interest in applying adjoint method for radiation treatment planning [1, 2, 3]. Adjoint methods have been used in nuclear reactor physics field since the 1960s [4]. Recent studies have shown the usefulness of this method both in brachytherapy and external radiation therapy [3, 5, 6]. The goal of external beam radiation therapy is to deliver a prescribed dose to tumor tissue, while minimizing the doses to the adjacent healthy tissues. Radiation therapy treatment planning is the process of determining the beam positions, directions, energy and intensities that will deliver the distribution of dose as prescribed.

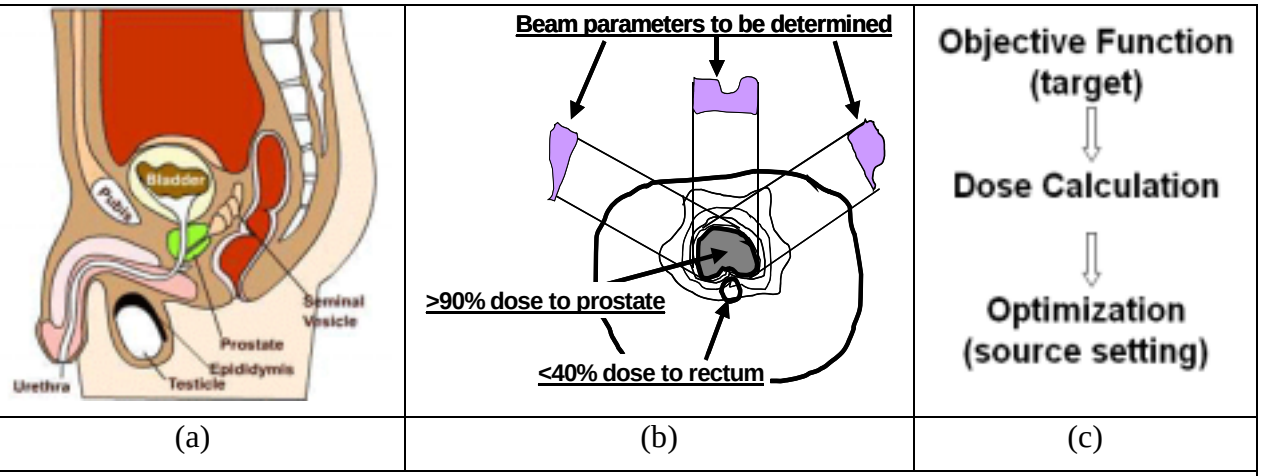
In a previous paper, we have presented a preliminary study on implementing the adjoint Monte Carlo (AMC) method to a real 3D patient model [6]. This paper focuses on the detailed implementation of the AMC method into the Monte Carlo N-Particles (MCNP) code [7]. In particular, we describe a source sampling scheme for multiple Regions of Interest (ROI)s of the patient body in a single adjoint simulation. In addition, we discuss a variation reduction technique for forward Monte Carlo simulation using previous adjoint calculations.

2 METHODS AND MATERIAL

Readers are referred to a previous paper for the detail of implementing the adjoint Monte Carlo method for a realistic 3D patient geometry [6]. In the following sections, we present our new progress on this study and mainly focus on the technical part related to Monte Carlo method. We first introduce the theory of adjoint and forward Monte Carlo transports. It is followed by a method to model the ROIs in the Monte Carlo code of MCNP. Last, we present two methods of improving the forward Monte Carlo efficiency: mesh tally and variation reduction technique.

2.1 Inverse Treatment Planning for Prostate

The general goal of a radiation treatment plan is to deliver a lethal dose to the tumor, while sparing the neighboring healthy organs as much as possible. Radiation treatment of the prostate cancer provides a compelling example of the challenges in radiation treatment planning. Figure 1a shows the anatomy of the prostate, a walnut-shaped gland that is located very closely between the radiosensitive bladder and rectum. Figure 1b illustrates a typical prostate radiation dose distribution map in which a radiation oncologist prescribes the dose levels to the prostate (termed the "planned treatment volume (PTV)") and the rectum/bladder (termed the "organs at risk (OARs)"). It is then the responsibility of a medical physicist to determine the way the x-ray beam is best delivered to achieve the desired dose levels in a patient (including the x-ray source direction, energy, and intensity) [8-13]. Practically, a tradeoff between the doses to PTV and OARs has to be made because the exposure to adjacent healthy tissues cannot be completed avoided. The "inverse" treatment planning procedure, as summarized in Figure 1c, has three major components: 1) the objective function defined for the PTV and OARs, 2) the dose calculation method, and 3) the optimization algorithm. It is desirable that a radiation therapy treatment planning system (TPS) automatically carries out this inverse optimization process.



(a) (b) (c)

Figure 1. (a) The anatomy of the prostate and adjacent organs. (b) A treatment plan (transverse view) showing prescribed high doses to the prostate tumor and low doses to the rectum (bladder not shown). (c) The "inverse" planning from the prescribed doses to the optimal beam setting.

The first component, the “objective function,” is chosen in inverse planning system to rank the candidate treatment plans so that the tumor is controlled by high enough doses and the OARs are kept at low dose to avoid damage [9, 11]. Violation of dose limits penalizes the objective function thereby directing the search process towards solutions that more appropriately satisfy the constraints. The second component, “dose calculation,” determines the quantitative relationship between a photon beam setting and the dose to an anatomical site (i.e., tumor and surrounding tissues). Obviously, the dose calculations should be accurate enough to ensure that the “predicted” dose distribution indeed matches the dose delivered to the patient. The third basic component of the inverse treatment planning is a mathematical “optimization,” which results in a dose distribution that satisfies the constraints (i.e. uniformity of the dose, conformity to the tumor, sparing of the critical tissues). Although treatment planning is an “inverse” process, dose calculation methods available today are essentially a forward process, in which one uses a known radiation source term to verify the dose distributions.

2.2 Adjoint and Forward Monte Carlo Transports

The transport of photons through matter is described by the Boltzman transport equation [14]. In radiation therapy, we solve this equation for transporting emerging photons from the Linac head at certain locations, with certain directions and energies. These photons undergo interactions with electrons on their ways to the patient body, including photoelectric effect, Compton scattering and pair production. The calculated results are the photon fluxes within the voxels of the patient anatomy. When the "forward" fluxes are coupled to the flux-to-dose energy dependent response function, the dose within any voxel of the patient as well as total "volumetric doses" at the ROI may be calculated. The dose *D*, delivered by a source *S* to a specific ROI may be expressed as an inner product, as shown in equation (1).

$$D = \left\langle \phi \cdot S^{+} \right\rangle \tag{1}$$

where ϕ is the is the particle flux and S^{+} is the flux-to-dose response function.

One forward calculation must be performed for each source location, direction and energy. The corresponding adjoint transport equation describes the transport of the adjoint photons starting from a certain ROI with the energy distribution of the response (flux-to-dose) function towards the external photon source [14]. The "adjoint" photons are transported in a similar fashion as the "forward" photons, except that they are moving "backwards" and actually gain energy instead of losing it. The adjoint calculation yields the adjoint flux as a function of position, energy and direction. When this adjoint flux is coupled with the direction and energy distribution of a photon source at each possible location, (e.g. a set of candidate beamlets) the dose at the certain ROI may be calculated. Contrary to the forward MC, the adjoint MC can determine the dose at a specific ROI from every possible source (position, direction and energy) simultaneously. The dose *D* delivered to a specific ROI by a source *S* may be expressed as an inner product of the source distribution *S* and the adjoint flux ϕ^{+} (equation (2)):

$$D = \left\langle \phi^{+} \cdot S \right\rangle \tag{2}$$

The forward and the adjoint MC are related each other through dose as shown in equation (3):

$$D = \left\langle \phi \cdot S^{+} \right\rangle = \left\langle \phi^{+} \cdot S \right\rangle \qquad (3)$$

The adjoint flux at a certain point in the phase space is the contribution to the total dose at the ROI of a photon emerging from this specific point in the phase space. This is the reason that the adjoint flux is called also the "importance function"**.**

2.3 Modeling of the PTV and OARs in MCNP

In the previous simulations, three separate adjoint calculations were performed for the prostate, rectum and bladder. However, clinical applications require these calculations to be integrated and fast. An integrated single adjoint calculation for multiple organs will also allow for automatic AMC-based radiation treatment optimization.

The PTV and OAR's adjoints can be calculated in one adjoint calculation, by defining the adjoint source uniformly at the PTV and OAR's and by using the SCX parameter of the FT card in the MCNP code to identify where the adjoint particle is coming from. Specifically, a source distribution function is entered in the SDEF card by the SIn/SPn card. The SIn card defines the source to be sampled from the three different ROIs. The SPn card then gives the sampling probability for each of the ROIs. The FT card will then be defined as “FT SCX n”. The parameter n corresponds to the name of the source distributions that appears on the SIn card. With this FT card, MCNP outputs additional tally contributions from each source distribution bin.

2.4 Speedup for Monte Carlo Simulations

The main reason for impeding the Monte Carlo method for clinical use is the speed of the simulation. Two methods are used in this study to speedup the Monte Carlo simulations. This includes a mesh tally speedup and a variant reduction technique (VRT) using importance functions from the adjoint Monte Carlo calculations. Even though the current computing time for a typical Monte Carlo run is still not practical for clinical use, these tries will accelerate the research of Monte Carlo speedup. A typical Monte Carlo run currently lasts for several hours in order to obtain satisfying statistical uncertainties.

2.5 Mesh Tally to Improve the Computing Efficiency

Mesh tally is a new capability in MCNP version 5 [15]. It could tremendously speed up the simulation for large lattice structures which are typical case for patient geometry. There are two time-consuming factors for the traditional track-length tally when calculating integral parameters in lattice structure. First, large computing time is needed record particle trajectory crossing lattice boundaries. This is done for the "track length" calculation as usual. Second, MCNP needs to check every lattice element in the geometry in order to look for the next lattice element that the particle enters after leaving the current one. This is where the mesh tally differs from the traditional tally. The implementation of these mesh tally is characterized by a list of the "nearest neighbor elements" instead of the usual list of "all lattice elements". As a result, this stage is much more computing-efficient. A brief comparison shows that it speeds up by a factor of at least several hundred.

2.6 Variation Reduction Technique for Final Monte Carlo Calculations

MC uses a stochastic technique, so there is a variance associated with the dose result at each voxel. Since increasing the precision (and decreasing the variance) requires usually significant additional calculation time, variance reduction is an important topic of current research. It was

observed by Coveyou et al that the source biasing using a reasonable good estimate of the adjoint flux would yield substantial saving in variance or in the computation time [16].

Common Variation Reduction Techniques (VRT), like the Russian Roulette and Splitting, cannot be efficiently used because of the gross segmentation of the human model. A much more detailed segmentation is needed for importance sampling. In other words, each organ should be subdivided into many parts, as well as the tissues in between the organs, and each such part must be given an "importance" of its own.Therefore, we used the prostate adjoint fluxes at the "ring" locations for external source biasing. This is a well known importance sampling procedure, in which a "biased" external source is defined by the equation (1):

$$S^{+}(E) = \frac{S(E) \cdot \phi^{+}}{\int S(E) \cdot \phi^{+} dE} \qquad (1)$$

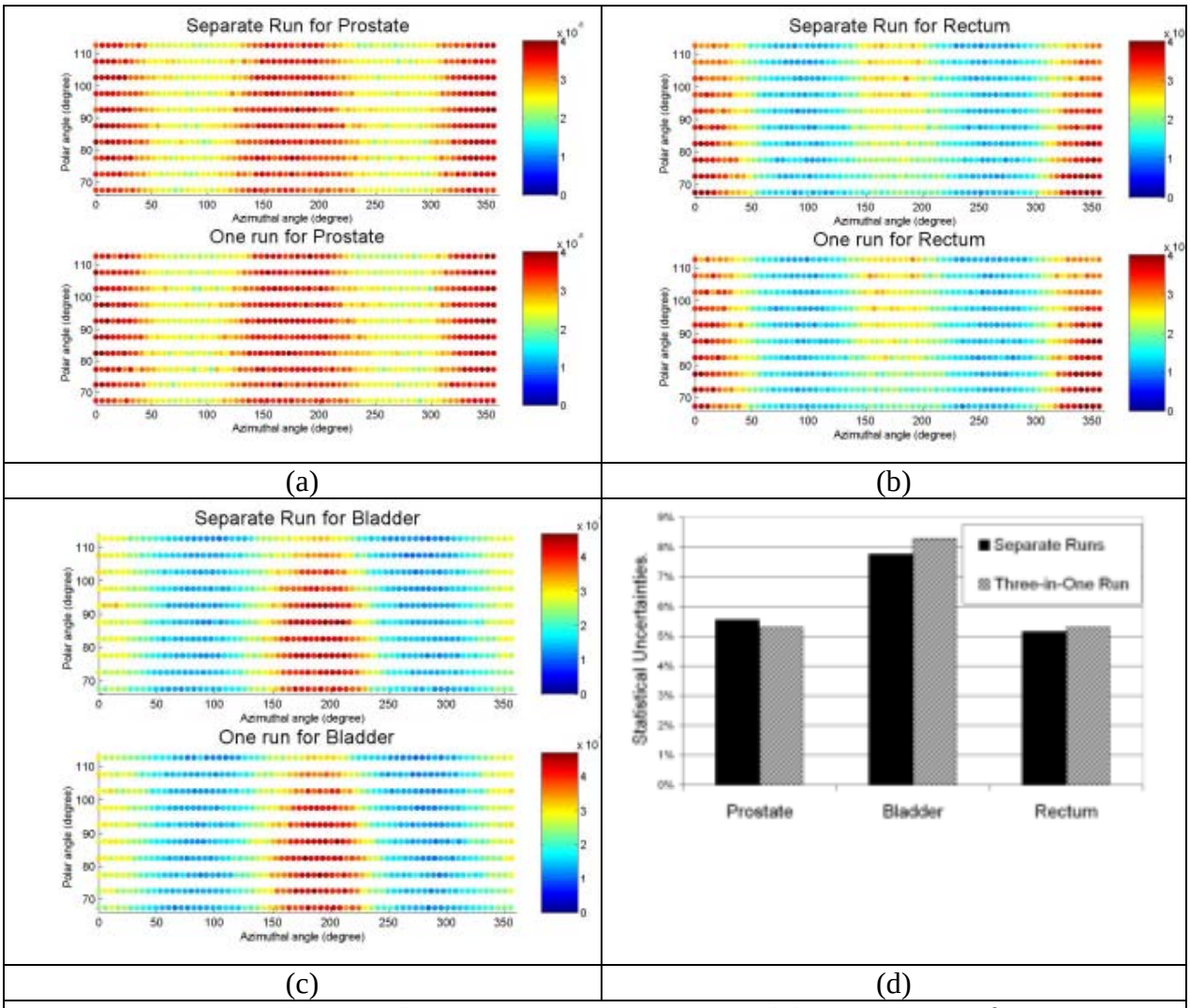
Where $S(E)$ is the "original" source, $S^{+}(E)$ is the "biased" source, ϕ^{+} is the adjoint flux as a function of energy. Finally, the biasing of the external source is "fixed" by multiplying the source photons weights by: $\frac{S(E)}{S^{+}(E)}$.

3 RESULTS AND DISCUSSIONS

In this section, we present our latest results on adjoint source modeling in MCNP and variation reduction technique used in the forward Monte Carlo simulations.

3.1 Adjoint Source Modeling

We implemented a source sampling scheme for different ROIs in a single adjoint Monte Carlo run. The tally results were further extracted for each ROIs and compared with previous results of the same parameters obtained from separate runs. In the separate runs, 4 million histories were simulated for each case: the adjoint source in prostate, bladder and rectum, respectively. The total computing time for all three runs was 1091 minutes using a PC with 1.7 GHz CPU and 512 MB RAM under the Linux operating system. For comparison, 12 million histories were simulated for the single “three-in-one” simulation in this study. Since the adjoint source was equally sampled for the three organs in this three-in-one simulation, the numbers of histories for the ROIs were kept the same as the separate runs. The total computing time for the same PC was 1075 minutes, which is very close to the combined computing time for the three separate runs. This is reasonable since the two computational approaches differ only in additional source sampling subroutine. Figure 2a, 2b and 2c compare the two cases for (a) prostate, (b) rectum, (c) bladder, respectively. Figure 2d summarizes statistical uncertainties at one tally location which typically represents other locations. These data demonstrate that the two sets of results have identical importance distribution patterns for the statistical uncertainties, suggesting that the three-in-one run yielded the same MC results as the separate runs. It should be noted that the original tally results of the three-in-one run need to be multiplied by a constant factor of three in the post-processing algorithm because MCNP normalizes all the tally results to one history. Although integrated adjoint simulations are easy to implement for clinical applications, we can no longer adjust the adjoint simulation for a particular OAR in order to improve the statistics.



(a) (b)

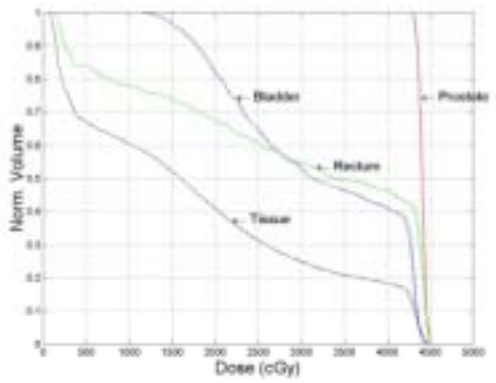
(c) (d)

Figure 2. Comparison between the two cases: separate runs and three-in-one run for (a) prostate, (b) rectum, (c) bladder and (d) statistical uncertainties at one typical tally location

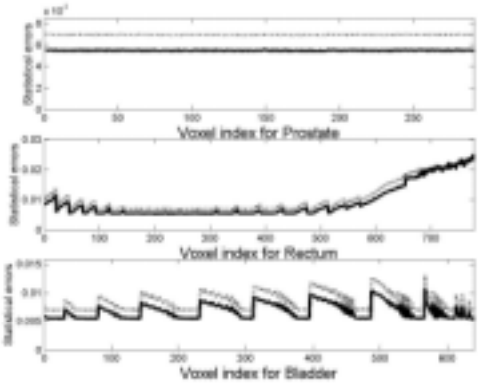
3.2 Variation Reduction Technique for Forward Monte Carlo Calculation

Figure 3a shows that the Dose Volume Histogram (DVH) plots agree closely with each other for two cases with and without source energy biasing. DVH plots are a great tool for evaluating and comparing competing plans. They provide quantitative information with regard to how much dose is absorbed in how much volume. DVH plots also summarize entire dose distribution into a single curve for each anatomic structure of interest which needs to be segmented ahead. Figure 3b compares the statistical errors for two cases with and without source energy biasing. The dotted lines in Figure 3b are for Monte Carlo runs without source energy biasing, while the solid lines with the biasing technique. It is clearly demonstrated that the statistical errors decreased after implementing the variation reduction technique of source energy biasing.

The source energy biasing reduces the computation time by approximately 26.7% (for the same variance) in the case of the prostate dose forward MC calculation. Since the prostate adjoint flux is used for the source energy biasing, the reduction in the computation time for the urinary bladder and the rectum is approximately 24.8% and 13.6% only, while the reduction in the computation time for the healthy tissue in between is approximately 6% only.



(a)



(b)

Figure 3. The (a) DVH plots and (b) statistical errors for the same number of histories for two cases: with (solid lines) and without (dotted lines) source energy biasing.

4 CONCLUSIONS

We have developed an efficient method for modeling the PTV and OARs for adjoint Monte Carlo simulations using the MCNP code and a realistic 3D patient anatomy. The results have demonstrated the efficiency of such a method for treatment planning for prostate cancer. The importance ratios and the weights of the candidate beamlets are first calculated using adjoint MC simulations. The beamlets with their respective weights were subsequently used to calculate the detailed dose distributions at each ROI, during a forward MC simulation. By exploring a tally feature (FT card) of MCNP, we successfully implemented a source sampling scheme for different ROIs in only one simulation. This facilitates future implementation of an automatic AMC-based radiation treatment planning system. The tally results were further extracted for each ROIs and compared with those from the previous separate simulations. It was shown that the total computing time is very close for the three-in-one run and the previous separate runs. The tally results agree with each other within statistical uncertainties. We also presented two methods to improve the forward Monte Carlo efficiency: mesh tally and variation reduction technique. This study also identified a number of issues that need to be addressed in the near future including the implementation of an optimization algorithm to solve the problem of voxel-like prescribed constraints.

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