Monte Carlo codes for treatment planning in advanced radiation therapy

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Innovation in radio Particle Therapy

Technology Transfer:

The Past: PlanKIT Project (IBA)

The Future: I-See
THE PHD THESIS GOALS

1) APPLICATIONS OF MONTE CARLO TECHNIQUES TO EXPLORE INNOVATIVE RADIATION THERAPY FEATURES

2) PLANNING AND IMPLEMENTATION OF A INNOVATIVE TPS FOR HADRONS BASED ON AN OPTIMIZED MONTE CARLO ALGORITHM
Radiation Therapy
Dose Delivery: Photons

Linac

Tomotherapy
Dose Delivery: Photons

Range Shifter

Multileaf Collimator

Wedges
Dose Delivery: Photons

range shifter
multileaf collimator
wedges
Dose Delivery: Hadrons
Dose Delivery: Hadrons
**Dose Delivery:** active scanning
Dose Delivery: IMPT
Something more to consider

**Single Strand Break**
recoverable

**Double Strand Break**
may lead to
cell death
The linear-quadratic model

\[ S(D) = S_0 \cdot e^{-\alpha D - \beta D^2} \]

- **S(D)**: Cell population over the delivered dose
- **D**: Physical dose
- **S_0**: Initial cell population
- **\( \alpha \)**: Empirical linear coefficient (cell kill per Gy)
- **\( \beta \)**: Empirical quadratic coefficient (cell kill per Gy²)
TPS: The Treatment Planning System

Computed Tomography
Structure Set
Prescription

Physical Model
Optimization

Biology Model
Dose Matrix

Energies
Fluences
Directions
The General Problem

\[ D_{v}^{ref} = \sum_{b=1}^{N_b} (\phi_b \cdot D_{vb}^{0}) \]

- Fluence of the beam
- Dose per beam on the voxel
- Total dose on the voxel
**Deterministic**

**HOW TO**
- LUT
- Pencil beam
- WEPL

**PROS**
- **very fast (minutes)**

**CONS**
- Approximated calculation problems with non-homogeneous material
- Converting HU → Stopping power for ions
- Information loss on microscopic processes

**Monte Carlo**

**HOW TO**
- Simulation of every particle

**PROS**
- Higher accuracy
- Physical interactions are reproduced
- Takes into account tissues real composition
- Cares about non-homogeneous materials
- Takes into account secondary particles

**CONS**
- HU → To material conversion problem
- **very slow (days on 1 CPU)**
The geometry of the patient must be voxelized.
The morphological information from a Hounsfield unit includes density, density & composition, WEPL, and material.
**Water Equivalent Path Length**

**Approximation:** All the tissues are treated as they were water.
From the HU to the material
The **Photon Source** *(Linac)*

**Varian Clinac 2100**

**6 MV Spectrum**

- **Gamma spectrum**
- Entries: 659073
- Mean: 1.274
- RMS: 1.04
The **Proton Source (Beam)**

**Active Scanning**

**General Particle Source**

*NB: This image is merely illustrative*
Monte Carlo issues: the Time

Monte Carlo efficiency

$$\varepsilon = \frac{1}{\sigma^2 T}$$

Monte Carlo variance

$$\sigma_v^2 = \sum_b \left( \frac{\sigma_{vb}}{\sqrt{N_b}} \phi_b \right)^2$$
Innovations:

- Minimization of computing time (primary particles to simulate) from constraints on the variance

- Iterative MC inverse planning starting from a deterministic TPS intended as the a priori probability of a Bayesian approach to the problem

An abstract has been submitted to PTCOG 2015:

“Bayesian approach for Monte Carlo based treatment planning optimization in ion beam therapy”
The general Problem extended

\[ D_{v}^{\text{ref}} = \sum_{b=1}^{N_{b}} (\phi_{b} \cdot D_{vb}^{0}) \]

\[ \sigma_{v}^{\text{ref}2} = \sum_{b=1}^{N_{b}} \left( \frac{\phi_{b}}{K_{b}} \cdot \sigma_{vb}^{02} \right) \]

\[ K_{b} = \frac{N_{b}^{\text{evt}}}{\phi_{b}} \]
the **Bayesian** approach

\[
P(\phi|D^{ref}) = \frac{P(D^{ref}|\phi) \cdot P(\phi)}{P(D^{ref})}
\]

\[
P(K|\sigma^{ref}) = \frac{P(\sigma^{ref}|K) \cdot P(K)}{P(\sigma^{ref})}
\]
**The Bayesian Approach**

\[
P(\phi | D^{ref}) = \frac{P(D^{ref} | \phi) \cdot P(\phi)}{P(D^{ref})}
\]

\[
P(K | \sigma^{ref}) = \frac{P(\sigma^{ref} | K) \cdot P(K)}{P(\sigma^{ref})}
\]
\[
\max \left[ \ln \left( P(D_{ref} | \phi) \cdot P(\phi) \right) \right] = \min \left[ \sum_v \frac{(D_{ref} - D_v(\phi))^2}{2\sigma_v^2} + \sum_b \frac{(\phi_{0b} - \phi_b)^2}{2\sigma_{\phi_0}^2} \right]
\]

\[
\max \left[ \ln \left( P(\sigma_{ref} | K) \cdot P(K) \right) \right] = \min \left[ \sum_v \frac{(\sigma_{ref} - \sigma_v(K))^2}{2\sigma_v^2} + \sum_b \frac{(K_{0b} - K_b)^2}{2\sigma_{K_0}^2} \right]
\]
From deterministic TPS

\[
\max \left[ \ln \left( P(D^{ref} | \phi) \cdot P(\phi) \right) \right] = \min \left[ \sum_v \frac{(D_v^{ref} - D_v(\phi))^2}{2\sigma_v^2} + \sum_b \frac{(\phi_{0b} - \phi_b)^2}{2\sigma_{\phi_0}^2} \right]
\]

\[
\max \left[ \ln \left( P(\sigma^{ref} | K) \cdot P(K) \right) \right] = \min \left[ \sum_v \frac{(\sigma_v^{ref} - \sigma_v(K))^2}{2\sigma_{\sigma_v^2}^2} + \sum_b \frac{(K_{0b} - K_b)^2}{2\sigma_{K_0}^2} \right]
\]

How much do I trust my a priori assumption?
1)微观信息的使用来评估吸收剂量的增益在黄金纳米粒子的存在。

2) 根据氧气条件评估粒子治疗：低氧 vs 空气。
Innovative radiotherapy with GNP

Radiotherapy (IMRT) with X-rays produced by GNP.

- Au L-line: 9-14 keV
- Attenuation coefficient (cm$^2$/g)

<table>
<thead>
<tr>
<th>Energy (MeV)</th>
<th>Gold</th>
<th>Soft Tissue</th>
</tr>
</thead>
</table>
| X-rays produced by GNP: Au L-line: 9-14 keV
| Radiotherapy (IMRT): 6-15 MV |
Innovative radiotherapy with GNP

Internal total spectrum
Innovative radiotherapy with GNP
Paper in progress and Talk at ESTRO 2015:

“Evaluation of the therapeutic optimality in radiotherapy for breast cancer with targeted gold nano-particles”
Evaluation of the OER in treatment planning for hadrotherapy

**Oxygen enhancement ratio**

\[
OER = \frac{\text{Radiation dose in hypoxia}}{\text{Radiation dose in aerobic conditions}}
\]

**Poster at ESTRO 2015:**

“Tumor control in ion beam radiotherapy with different ions in presence of hypoxia”
EVALUATION OF THE OER IN TREATMENT PLANNING FOR HADROThERAPY
Thank you for your time!
Monte Carlo issues: the materials

“The calibration of CT Hounsfield units for radiotherapy treatment planning”
**Deterministic Issues:**

**non Homogeneous materials**

Deterministic TPS have troubles in case of non homogeneous materials → non suitables in case of artificial plants

Monte Carlo much better
Dose to Volume Histogram
TCP/NTCP

TCP and NTCP (%)

Complication rate-large volume (e.g., 3-D CRT)

Complication rate-small volume (e.g., IMRT or protons)

Tumour dose (Gy)

$D_{pr}$
THE **Linear-Quadratic Model**

$$S(D) = S_0 \cdot e^{-\alpha D - \beta D^2}$$

- $S(D)$: **cell population over the delivered dose**
- $D$: **physical dose**
- $S_0$: **initial cell population**
- $\alpha$: **empirical linear coefficient (cell kill per Gy)**
- $\beta$: **empirical quadratic coefficient (cell kill per Gy^2)**
α and β depend on particle type, LET, and on a set of additional parameters, in agreement to the MKM model (other models could be used e.g. the LEM). These parameters and the particle type being fixed, monoenergetic α and β values vs LET must fit the experimental data (see picture). α and β values must then yield to a linear-quadratic trend.

In the article “Inactivation of Aerobic and Hypoxic Cells from Three Different Cell Lines by accelerated $^3$He-, $^{12}$C- and $^{20}$Ne-Ion Beams”, Furusawa et al. reported the measurements of α and β for different LET values. Such values are used to evaluate the radiobiological response after irradiation.
Various Histograms

Total Dose Deposited

Dose Tot
Entries  7433382
Mean  98.82
RMS  63.33

Gamma spectrum

gamma_spectrum
Entries  659073
Mean  1.274
RMS  1.04