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Dose painting by means of Monte Carlo treatment planning at the voxel level

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ABSTRACT

Purpose: To develop a new optimization algorithm to carry out true dose painting by numbers (DPBN) planning based on full Monte Carlo (MC) calculation.
Methods: Four configurations with different clustering of the voxel values from PET data were proposed. An optimization method at the voxel level under Lineal Programming (LP) formulation was used for an inverse planning and implemented in CARMEN, an in-house Monte Carlo treatment planning system.
Results: Beamlet solutions fulfilled the objectives and did not show significant differences between the different configurations. More differences were observed between the segment solutions. The plan for the dose prescription map without clustering was the better solution.
Conclusions: LP optimization at voxel level without dose-volume restrictions can carry out true DPBN planning with the MC accuracy.

1. Introduction

Nowadays, tumor heterogeneity is one important factor to be considered in radiation therapy. Functional information, as positron emission tomography (PET) or functional magnetic resonance imaging (fMRI), provides us image data associated to tumor progression and potential recurrence after therapy. Moreover, recent studies are based on the hypothesis that boosting volumes with high standard uptake value (SUV) on the pre-treatment ^{18}F-fluoro-deoxyglucose (FDG)-PET scan potentially increases local control while maintaining acceptable toxicity levels [1–4].

The strategy for delivering a non-uniform dose distribution with a prescription based on functional information from medical images is called dose painting (DP) [5,6]. There are two approaches to carry out the DP strategy: threshold-based dose painting by contours (DPBC) [7] and voxel-based dose painting by numbers (DPBN) [8]. In DPBC, sub-volumes within the tumor are differentiated in the functional images in order to be treated with an escalated dose level. In DPBN, an individual dose prescription is assigned to each voxel within the tumor, varying according to the voxel value in the functional image. These individual doses are usually represented in a dose prescription map.

Tumour sub-volumes can be implemented in commercial treatment planning systems (TPS) to calculate a planning treatment with an escalated dose. Simultaneous integrated boost (SIB) is usually the used technique to achieve this dose. However, as far as we know, planning of DPBN at voxel level is not supported by any commercial TPS [9]. Some DPBN approximations have been made, by introducing sub-volumes as targets [10] or dose maps with prescription to the voxel as objective function [9], but always by using dose-volume based optimization algorithms.

The purpose of this work is to present a new optimization algorithm based on LP to carry out true DPBN planning. This algorithm is able to implement directly constraints to voxels instead of volumes. Furthermore, we propose full Monte Carlo (fMC) calculation in our model as the adequate tool for planning so demanding dose prescription maps as those involved in DPBN.

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2. Material and methods

2.1. Imaging protocol and image analysis

Images were acquired with a Siemens Biograph mCT 64 PET/CT scanner. FDG-PET images were reconstructed with OSEM3D (Ordered Subset Expectation Maximization in three dimensions) algorithm, with 2 iterations and 8 subsets. A post-reconstruction 2 mm Gaussian filter was used for dataset smoothing. A 200×200 image-matrix with a pixel size of 4 mm and a slice thickness of 3 mm was obtained. CT-based attenuation correction method was applied.

A case of non-small cell lung cancer was selected to study our optimization approach for DPBN planning. Breathing movements associated to this disease site were not taken into account in order to achieve solutions only dependent on the prescription dose scheme proposed as input data for our model. The case was selected due to the current consensual use of FDG-PET for the characterization and staging of non–small cell lung carcinoma (NSCLC). Also, the patient presented two spatially separated adenopathies, being a complex scenario to evaluate the behavior of the new optimization algorithm.

DICOM data were imported in CARMEN TPS [11,12], an in-house fMC treatment planning system controlled through a MATLAB platform. This software was specifically developed to allow previous image analysis to the optimization process. A primary tumor volume was located in the CT images. Co-registered PET/CT images were also evaluated by using the platform in order to determine the extension of the disease. Another adenopathy was then included together with the PET corrected primary tumor in the planning target volume (PTV). In addition, the organs at risk (OARs) were defined. PET and CT data were interpolated to a grid with 256 x 256 pixels per slice, with a $1.9 \times 1.9 \times 3$ mm voxel size.

In order to make an evaluation consistent with previous published works based on commercial planning systems [10,13], SUV data from PET images were semi-automatically segmented for clustering. Regarding considerations about essential robust optimization in the case of DPBN related to noise in PET [14,15], for this study, a specific algorithm based on Affine Propagation (AP) was implemented in CARMEN platform by utilizing a novel intensity affinity metric within the affinity propagation clustering framework [16]. For thresholding purpose, Kernel density estimation (KDE) uses Gaussian kernel but it lacks local adaptation in the PET images histogram. To improve local adaptation, an adaptive KDE is considered by means of the smoothing properties of linear diffusion processes. Also, due to the flexibility of the AP method, the implemented algorithm generates a novel affinity function that best suited PET image segmentation effectively, where the radiotracer uptake regions is distributed widespread over the region. In this way, this algorithm is able to reflect the diffuse and multifocal nature of the uptake regions, due to uncertainties in object boundaries, low resolution and the inherent noise in PET images. Thus, random errors due to the PET images registration process is reduced, making our approach a robust optimization process regarding this kind of uncertainties. Different combinations of parameters were selected to obtain several levels of clustering. The maximum number of different levels distinguished by this algorithm was 7 (DPBN7 in Fig. 1). In addition, 5 and 3 clustering levels of the SUVs were generated (DPBN5 and DPBN3 in Fig. 1, respectively). The average SUV of each level was assigned to every voxel of this level. Unlike other works [10], the clusters of voxels were not considered as structures or subvolumes within the target, since each voxel was treated as an independent entity during the planning process for all configurations. Furthermore, in order to put into value our model, it was also proposed the true option without clustering for planning study exclusively at the voxel level (TOTAL-DPBN in Fig. 1).

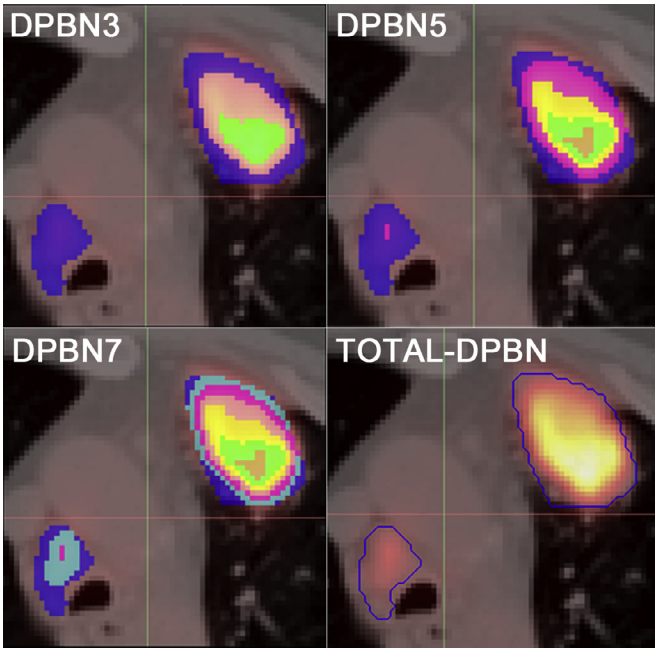

Fig. 1. PET/CT fused images at the isocenter slice with the different clustering levels (DPBN3, DPBN5 and DPBN7) and the voxel distribution without clustering (TOTAL-DPBN) generated to establish the dose prescription maps for planning.

2.2. DPBN prescription maps

The dose prescription maps were generated with the same size of the PET/CT calculation grid, assigning zero values to those voxels located out of the PTV. For the voxels within the PTV, it was applied a linear relationship between the prescribed dose and SUV, based on previous work [17]. In this way, the dose value assigned to each voxel is linearly escalated from the minimum to the maximum prescription dose values.

A minimum dose value of 68 Gy, to be delivered in 41 fractions, was assigned, in order to maintain a standard prescribed dose to the conventional target defined only by means of the use of CT images. The maximum prescribed dose was 82 Gy.

2.3. Optimization procedure for Monte Carlo planning

Intensity modulated radiation therapy (IMRT) based on an inverse planning was carried out. A novel algorithm based on previous work by our group [11] has been developed, including an optimization method at the voxel level under Lineal Programming (LP) formulation (1), since the usual restriction of dose to volumes makes no sense for DPBN. The optimization consists of minimizing an objective function (min o.f.), in order to fulfill a set of constraints.

$$
\begin{aligned}
&\min o.f. \equiv P_T^{max}\sum_{i=1}^{N_T} x_i + P_T^{min}\sum_{i=1}^{N_T} y_i + P_{OAR}^{max}\sum_{i=N_T+1}^{N} x_i \\
&\text{subject to} \\
&\sum_{j=1}^{M}\omega_j d_{ij} - x_i \leqslant D_i^{max} \quad i = 1,\ldots,N_T \\
&\sum_{j=1}^{M}\omega_j d_{ij} + y_i \geqslant D_i^{min} \quad i = 1,\ldots,N_T \\
&\sum_{j=1}^{M}\omega_j d_{ij} - x_i \leqslant D_{OAR}^{max} \quad i = N_T+1,\ldots,N \\
&x_i, y_i, \omega_j \geqslant 0 \ \ \forall i,j
\end{aligned}
\tag{1}
$$

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