Research Article

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A self-adaptive prescription dose optimization algorithm for radiotherapy

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Abstract

Purpose – The aim of this study is to investigate an implementation method and the results of a voxel-based self-adaptive prescription dose optimization algorithm for intensity-modulated radiotherapy.

Materials and methods – The self-adaptive prescription dose optimization algorithm used a quadratic objective function, and the optimization engine was implemented using the molecular dynamics. In the iterative optimization process, the optimization prescription dose changed with the relationship between the initial prescription dose and the calculated dose. If the calculated dose satisfied the initial prescription dose, the optimization prescription dose was equal to the calculated dose; otherwise, the optimization prescription dose was equal to the initial prescription dose. We assessed the performance of the self-adaptive prescription dose optimization algorithm with two cases: a mock head and neck case and a breast case. Isodose lines, dose–volume histogram, and dosimetric parameters were compared between the conventional molecular dynamics optimization algorithm and the self-adaptive prescription dose optimization algorithm.

Results – The self-adaptive prescription dose optimization algorithm produces the different optimization results compared with the conventional molecular dynamics optimization algorithm. For the mock head and neck case, the planning target volume (PTV) dose uniformity improves, and the dose to organs at risk is reduced, ranging from 1 to 4%. For the breast case, the use of self-adaptive prescription dose optimization algorithm also leads to improvements in the dose distribution, with the dose to organs at risk almost unchanged.

Conclusion – The self-adaptive prescription dose optimization algorithm can generate an ideal clinical plan more effectively, and it could be integrated into a treatment planning system after more cases are studied.

Keywords: intensity-modulated radiotherapy, dose optimization, self-adaptive prescription dose optimization algorithm, molecular dynamics

1 Introduction

Compared with conventional conformal radiotherapy, intensity modulated radiotherapy (IMRT) increases the dose of tumor and decreases the dose of organs by adjusting the intensity distribution of radiation field [1–4]. IMRT is the mainstream of radiotherapy technology at present. Inverse planning is the foundation of IMRT, and its performance determines the success of IMRT [5,6]. There are two kinds of inverse optimization techniques in IMRT: organ-based optimization and voxel-based optimization. In the organ-based optimization, the prescription dose and weight parameters are given to the organ, and all the voxels in an organ are combined and treated equally in the objective function. Because there is no clear relationship between the dose and weight parameters and the final dose distribution, the determination of these parameters is essentially a “guessing game;”
therefore, many trial-and-error are needed, and the plan quality heavily depends on the clinical experience of the planner [7,8]. On the contrary, voxel-based optimization directly adjusts the parameters related to each voxel in the objective function [9–12]. Previous studies showed that compared with organ-based optimization, voxel-based optimization obtained better dose distribution [13–18].

One of the practical difficulties in the voxel-based optimization model is that the number of adjustable parameters increases dramatically, and therefore it is difficult to adjust them manually. In this study, a new algorithm is introduced to automatically adjust the dose prescription of voxels in the optimization process. We call it the voxel-based self-adaptive prescription dose optimization algorithm (SAPDOA). Two cases were used to evaluate the SAPDOA performance.

2 Materials and methods

2.1 Self-adaptive prescription dose optimization algorithm

The optimization engine in this study was molecular dynamics. The implementation detail of conventional molecular dynamics optimization algorithm (CMDOA) has been reported in references, and therefore it is only briefly introduced here [19–21]. The CMDOA used a weighted quadratic objective function defined by

\[
O(I) = \sum_{i} w_i (D_i - D_p)^2,
\]

where \(O\) is the objective function, \(I\) is the beamlet intensity, NO is the total number of organs, \(w_i\) is the penalty weight, \(D_i\) is the calculated dose, and \(D_p\) is the prescribed dose.

The \(D_i\) was calculated through the formula given in equation (2):

\[
D_i = \sum_{j} I_j d_{ij},
\]

where NB is the total number of beamlet, and \(d\) is the dose contribution matrix of one-unit beamlet intensity.

The SAPDOA also used the weighted quadratic objective function, which was the same as the CMDOA we have implemented, but the objective function was redefined as follows:

\[
O(\bar{T}) = \sum_{k} w_k \left( \sum_{j} I_j d_{ij} - D_{m,k} \right)^2,
\]

where NV is the total number of voxels, and \(D_m\) is the self-adaptive prescription dose.

In CMDOA, the \(D_m\) did not change with the number of iterations. However, the \(D_m\) may change at every step of the optimization iteration in SAPDOA. The change of \(D_m\) follows the following rules:

1. For the target volume, if the \(D_c\) was within a certain range (±5%) of the prescription dose \(D_p\), \(D_m = D_c\), else \(D_m = D_p\).
2. For an organ at risk (OAR) volume, if the \(D_c\) was smaller than the prescription dose \(D_p\), \(D_m = D_c\), else \(D_m = D_p\).

Rule 1 allowed us to improve the dose uniformity of the target volume, and rule 2 to avoid the problem of low planning quality caused by excessive prescription dose of OARs.

2.2 Test cases

We evaluated the SAPDOA algorithm with two cases, one of them was from the AAPM TG-119 (mock head and neck) [22], and the other one was a clinical case (breast). We first used the CMDOA to make a reasonable plan (C-plan), and then we used the SAPDOA to get a new plan (S-plan). To make a fair comparison of the two plans, we kept all optimization parameters unchanged except the optimization algorithm. The test process was carried out on the Fonics (Qilin Company, Chengdu, China) treatment planning system (TPS).

For the mock head and neck case, nine 6 MV IMRT beams at 0°, 40°, 80°, 120°, 160°, 200°, 240°, 280°, and 320° were chosen. The dose prescription was PTV \(D_{90\%} = 50\) Gy. The evaluation parameters including \(D_{99\%}\) and \(D_{20\%}\) for PTV and \(D_{90\%}\) for normal structures were used for parotid, and maximum dose was used for cord. In the breast case, a setup with four 6 MV IMRT beams at 122°, 135°, 295°, and 342° was used. The dose prescription was PTV \(D_{97\%} = 50\) Gy. The sensitive structures included lung and heart. We first assessed the plan quality by the dose volume histogram (DVH) for the two cases, and then dosimetric parameters were used to evaluate the difference between the plans using different optimization algorithms. To facilitate the plan comparison, all plans were normalized to the dose prescription.
3 Results and discussion

Figure 1 compares the DVHs for the mock head and neck plan optimized with SAPDOA and CMDOA. The PTV coverage is the same ($D_{90\%} = 50$ Gy), but the sparing of OARs is greatly improved; especially in the high-dose regions, the dose of OARs of S-plan was obviously decreased. Figure 2(a) and (b) shows the isodose curves for the mock head and neck case optimized with SAPDOA and CMDOA, respectively. It is clearly seen that dose uniformity and conformity of PTV are also improved by adjusting the voxel prescription dose in the iterative optimization process. In addition, the over-dose area is obviously decreased in PTV. In particular, the maximum dose to the spinal cord is reduced. Moreover, there is a ~10% reduction in the parotid $D_{50\%}$. The detailed dosimetric parameters are presented in Table 1.

For the breast case, a comparison of DVHs between the C-plan and the S-plan is shown in Figure 3. In this case, the DVH curve of the S-plan is improved. The CMDOA might cause excessive constraints on the target and OARs, which makes it difficult to meet all the optimization objectives. In the SAPDOA proposed in this article, the prescribed dose is automatically adjusted according to the calculated dose in the iteration process of optimization. The SAPDOA balanced the prescribed dose between the target and OARs and avoided the situation of over-constraints on the target and OARs effectively.

Figure 2(c) and (d) shows that the S-plan leads to an increased dose homogeneity and dose conformity within the target, and the over-dose area disappeared compared with the C-plan. The low-dose delivered to the left lung and heart has a tiny difference, ranging from ~2.8 to 1.2%. However, the S-plan has a significant improvement for the OARs at the high-dose region (>45 Gy). The detailed dosimetric parameters are presented in Table 2.

Generally speaking, it is difficult for a treatment plan to meet the dosimetric requirements of target and OARs simultaneously. Therefore, it is usually necessary to adjust the optimization objectives many times to obtain an acceptable compromise solution. At this stage, organ-based inverse optimization is widely used in clinical practice. In organ-based inverse optimization, adding more dose-volume constraints can improve the plan quality, but it cannot change and expand the accessible solution space. Therefore, it is difficult to find a better solution. Different from this is that voxel-based inverse optimization increases

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Plan goal (Gy)</th>
<th>Weight</th>
<th>SAPDOA (Gy)</th>
<th>CMDOA (Gy)</th>
</tr>
</thead>
<tbody>
<tr>
<td>HN PTV $D_{90%}$</td>
<td>&gt;50</td>
<td>10</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>HN PTV $D_{99%}$</td>
<td>&gt;46.5</td>
<td>10</td>
<td>46.9</td>
<td>45.5</td>
</tr>
<tr>
<td>HN PTV $D_{20%}$</td>
<td>&lt;55</td>
<td>10</td>
<td>52.6</td>
<td>54.8</td>
</tr>
<tr>
<td>Cord maximum</td>
<td>&lt;40</td>
<td>20</td>
<td>33.6</td>
<td>35.5</td>
</tr>
<tr>
<td>Left</td>
<td>&lt;20</td>
<td>30</td>
<td>19.4</td>
<td>21.5</td>
</tr>
<tr>
<td>parotid $D_{50%}$</td>
<td>&lt;20</td>
<td>20</td>
<td>18.5</td>
<td>20.6</td>
</tr>
</tbody>
</table>

Table 1: Dosimetric parameters of the mock head and neck case
the accessible solution space [23]. Many study results showed that compared with the organ-based optimization method, the voxel-based inverse optimization method is easier to obtain qualified plans.

In general, there are two ways to adjust the objective function in voxel-based inverse optimization: one is to change the penalty weight of each voxel, and the other is to adjust the prescription dose of each voxel. Zarepisheh et al. [24] proposed a DVH guided intensity-modulated optimization algorithm that automatically adjusted the weight of voxels, and they applied the new algorithm to a head and neck case and a prostate case. The results showed that the voxel-based model is able to improve the plan quality in terms of the DVH at the reasonable price by exploring the parts of the Pareto surface missing in the organ-based models. Li et al. [8] developed an automatic two-loop algorithm to perform re-optimization of a treatment plan on the patient’s new geometry by considering the original DVH as guidance. Automatic voxel weighting factor adjustments avoided tedious trial-and-error schemes, and it is easier to find an acceptable compromise among different structures for re-planning. Lougovski et al. [25] established an inverse planning framework with the voxel-specific penalty. Substantial improvements were achieved in the final dose distribution by adjusting voxel prescriptions iteratively to boost the region where large mismatch between the actual calculated and desired doses occurs. Wu et al. [26] studied the two different modification schemes (weighting factors/dose prescription) based on Rustem’s quadratic programming algorithms. Case studies demonstrated that the two modification schemes had the capability to fine-tune treatment plans.

In this study, our solution is to first determine the organ weight based on clinical experience, and then automatically determine the prescription dose according to the dose calculated in the iterative process. It can be seen from Section 2 that the principle of the SAPDOA algorithm is simple, and it is easily implementable in any existing inverse planning platform. The SAPDOA was tested on a head and neck case and a breast case. As compared with the CMDOA, the PTV experiences improved dose uniformity and the doses to OARs are also reduced. These results show that the SAPDOA provides room for further improvements of currently achievable dose distributions. Our approach could be integrated into a TPS after more case studies.

We acknowledge that the penalty weight of the SAPDOA is determined and adjusted by the planner based on his clinical experience, which limits the algorithm’s ability to find the optimal solution in a larger solution space. The plan optimized by the algorithm finds the solution space corresponding to the set of penalty weight factors, and therefore the optimized plan may not be the global optimal solution. We are introducing an automatic optimization algorithm that combines voxel prescription dose optimization and penalty weight optimization, so as to effectively expand the solution space, navigate in the expanded solution space, and find the global optimal scheme. We hope that the research results could be published in the following years.

### Table 2: Dosimetric parameters of the breast case

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Plan goal</th>
<th>Weight</th>
<th>SAPDOA</th>
<th>CMDOA</th>
</tr>
</thead>
<tbody>
<tr>
<td>PTV $D_{97%}$</td>
<td>&gt;50 Gy</td>
<td>30</td>
<td>50 Gy</td>
<td>50 Gy</td>
</tr>
<tr>
<td>PTV $D_{99%}$</td>
<td>&gt;48.5 Gy</td>
<td>30</td>
<td>48.6 Gy</td>
<td>48.6 Gy</td>
</tr>
<tr>
<td>PTV $D_{95%}$</td>
<td>≤54 Gy</td>
<td>10</td>
<td>53.2 Gy</td>
<td>56.0 Gy</td>
</tr>
<tr>
<td>Left lung $V_{20%}$</td>
<td>&lt;25%</td>
<td>30</td>
<td>24.4%</td>
<td>23.5%</td>
</tr>
<tr>
<td>Left lung $V_{5%}$</td>
<td>&lt;40%</td>
<td>10</td>
<td>33.4%</td>
<td>35.7%</td>
</tr>
<tr>
<td>Right lung $V_{5%}$</td>
<td>&lt;1%</td>
<td>20</td>
<td>0.5%</td>
<td>&lt;0.5%</td>
</tr>
<tr>
<td>Heart $V_{30%}$</td>
<td>&lt;20%</td>
<td>20</td>
<td>18.9%</td>
<td>18.4%</td>
</tr>
<tr>
<td>Heart $V_{5%}$</td>
<td>≤40%</td>
<td>10</td>
<td>37.8%</td>
<td>38.1%</td>
</tr>
</tbody>
</table>

### 4 Conclusion

Although organ-based inverse optimization is widely used in clinical practice at present, the quality of the plan obtained by organ-based optimization heavily depends on the experience of the planner. The continuous
trial-and-error process also leads to the inefficiency of planning. In this study, we investigated a new inverse optimization algorithm, SAPDOA, in IMRT. The results of the two test cases show that this algorithm can more effectively generate an ideal clinical plan. The SAPDOA algorithm is easy to implement on any existing inverse programming platform, and it could be integrated into a 3D TPS after studying more cases.

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References


