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NOTE

Improved lung tumor autocontouring algorithm for intrafractional tumor tracking using 0.5 T linac-MR

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Abstract

To add an intelligent parameter optimization capability to our autocontouring algorithm, and evaluate its performance using in-vivo data. Methods An autocontouring algorithm for intrafractional lung-tumor tracking using linac-MR was previously developed based on pulse-coupled neural networks. The algorithm’s contouring performance is dependent on eight parameters (including four integer parameters). Previously, the parameters were optimized using a time-consuming, exhaustive method. To avoid this inefficiency, adaptive particle swarm optimization (APSO) was adopted in this study, which is a stochastic, non-gradient based optimization algorithm that can handle integer variables. For this study, six non-small cell lung cancer patients were imaged with 3T MRI at ∼4 frames per second (2D sagittal plane, free breathing). For each patient, an expert delineated a gold standard contour (ROIstd) of the lung tumor in 130 consecutive images. The first 30 ROIstd were used for parameter optimization, and the rest 100 ROIstd were used to validate autocontours (ROIauto). In each image, Dice similarity index, Hausdorff distance, and centroid position difference (Δdcentroid) were calculated between ROIstd and ROIauto to measure their similarity. Results & Conclusion An efficient, fully automatic parameter optimization was added to our autocontouring algorithm. Using the six patients data, approximately 1/24 time reduction was achieved in parameter optimization (63–125 hrs to 2–4 hrs per patient), while maintaining the same or slightly improved performance.

1. Introduction

Intrafractional tumor tracking is of considerable interest as a method of minimizing normal tissue irradiation in treating mobile tumors. A hybrid radiotherapy-MR system known as linac-MR at the Cross Cancer Institute has potential to achieve intrafractional tracking via intrafractional MR imaging of a tumor (Fallone et al 2009). Using our 0.2 T linac-MR prototype, we developed a direct, non-surrogate based intrafractional tumor tracking system and physically demonstrated its feasibility by delivering highly conformal dose to a moving target with simulated lung tumor motions (Yun et al 2013). Currently, our 2nd generation linac-MR is equipped with 6 MV linac, whole-body 0.5 T MRI, and fully rotational gantry.

The first step of tracking using linac-MR is to detect the shape and position of the tumor in each intrafractional MR image. An autocontouring algorithm for intrafractional lung-tumor tracking was previously developed based on pulse-coupled neural networks (Yun et al 2015). While this algorithm’s performance was satisfying, it required time consuming parameter optimization process for each patient. To improve inefficiency, we studied an intelligent parameter optimization scheme applicable to our autocontouring algorithm, and evaluated its performance using in vivo data.
2. Methods and materials

The aforementioned algorithm’s contouring performance is dependent on eight parameters (including four integer parameters). It is important to note that, once these parameters are set, less than 20 ms is required for our algorithm to autocontour the tumor in each dynamic image. Previously, these parameters were optimized using an exhaustive searching method, by trying every possible combination of parameters from the user defined ranges and increments (~74 h required for each patient). To improve inefficiency, the adaptive particle swarm optimization (APSO) was adopted in this study (Zhan et al 2009).

APSO is a stochastic, non-gradient based optimization algorithm that can handle integer variables. APSO begins by generating many candidate solutions that are spread over an $n$-dimensional solution space. These solutions ‘fly’ through the solution space under APSO rules to find a specific location, where the solution at that location produces the optimum result with regard to a user defined fitness function.

For this study, six non-small cell lung cancer patients were imaged (head first supine position) in a 3 T MRI (Achieva 3 T, Philips Medical Systems, Andover, MA) with a torso coil (Philips Medical Systems, 6 channel array coil, bandwidth = 1553.5 Hz/voxel, slice thickness = 20 mm). We used a dynamic balanced steady state free precession (bSSFP) sequence (sagittal slice, FOV = 40 $\times$ 40 cm$^2$, voxel size = 3.1 $\times$ 3.1 $\times$ 20 mm$^3$, TE = 1.1 ms, TR = 2.2 ms, dynamic scan time = 275 ms) under free breathing. For each patient, the lung tumor in 130 consecutive images was delineated by an expert and used as a gold standard contour (ROIstd). The first 30 ROIstd were used for parameter optimization, and the rest 100 ROIstd were used for autocontouring validation.

ROIstd was delineated on 3 T images. However, to evaluate the autocontouring performance in our linac-MR environment (0.5 T MRI), the 3 T-acquired images were degraded to reflect the image quality characteristic of lung tumor at 0.5 T (Yun et al 2012). These pseudo-0.5 T images were used for parameter optimization as the following:

Step 1. APSO was initiated with 100 solutions. Each solution was composed of the 8 parameters, randomly chosen from the user defined range.

Step 2. Using each solution, lung tumor in each of the 30 pseudo-0.5 T images was autocontoured, referred as ROIauto.

Step 3. The similarity between ROIstd and ROIauto was calculated using dice similarity index (DSI). The average DSI ($DSI_{avg}$) from the 30 images defines our fitness function. Based on $DSI_{avg}$ each solution was updated by APSO rules (Zhan et al 2009).

Step 4. Steps 1–3 iterate until user defined criteria is satisfied. In this study, 80 iterations was set to be the stopping point, which provided the best balance between performance and time duration.

Since APSO is initiated with randomly chosen solutions, the quality of initial solutions may affect the final algorithm performance. Thus, to evaluate the importance of initial solution selection in step 1, we repeated the optimization 10 times with different sets of initial solutions.

The APSO-optimized parameters were used to autocontour the rest 100 pseudo-0.5 T images. In each image, DSI, Hausdorff distance (HD), and centroid position difference ($\Delta d_{centroid}$) were calculated between ROIstd and ROIauto to measure their similarity. Additionally, the contouring performance was compared using 10 different sets of initial solutions.

3. Results and discussions

Each patient’s sample image is shown in figure 1. Here, ROIstd and ROIauto is overlapped and visually compared. Table 1 summarizes the DSI, HD, and $\Delta d_{centroid}$ from the 100 images. The optimization time requirements between the previous and current optimization methods are compared, as well as the performance comparison from the 10 APSO repetitions.

In all 6 patient cases, autocontouring performance using the APSO-optimized parameters is either identical or slightly improved compared to the previous exhaustive method; DSI increased up to 3%, HD decreased up to 1.9 mm, and $\Delta d_{centroid}$ decreased up to 0.5 mm. Concurrently, the optimization time requirement was largely reduced from 47–125 h to 1.9–4.1 h. Comparing the first APSO run to the 10 APSO repetitions, the initial solution selection made minimal influence on autocontouring performance; DSI decreased up to 2%, HD increased up to 0.5 mm, and $\Delta d_{centroid}$ increased up to 0.5 mm. Patient 5 showed relatively low agreement between ROIstd and ROIauto. This was mainly due to the severe tumor shape variations during imaging. In figure 1 (row 5, column 2), the small regions of low pixel intensities can be seen just outside of the contoured region along its longitudinal axis (tip and tail). These regions intermittently disappeared or became blurred from the image due to the breathing motions.

If all possible ranges of solutions in our multi-dimensional solution space can be assessed via the exhaustive searching method, a more optimized solution may be generated. However, this is not practical, which was the motivation of this study. Initially, the comparable/improved performance of the APSO in our application was not taken for granted due to (1) the stochastic nature of the APSO, and (2) the number
Figure 1. Sample images of the six patients. Column (a): pseudo-0.5 T images. Column (b) and (c): ROI_{std} and ROI_{auto}. Column (d): comparison between ROI_{std} and ROI_{auto} (overlapping region is shown in white pixels, whereas any deviation is indicated by gray pixels). Each example image (from top to bottom) showed DSI of 0.97, 0.95, 0.97, 0.98, 0.94, and 0.96, respectively.
Table 1. Summary of contour shape fidelity and centroid position accuracy (DSI: dice similarity index, HD: Hausdorff distance, Δd centroid: centroid position difference, SD: standard deviation).

<table>
<thead>
<tr>
<th>Optimization method</th>
<th>Contour similarity measures</th>
<th>P1</th>
<th>P2</th>
<th>P3</th>
<th>P4</th>
<th>P5</th>
<th>P6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Previous (Exhaustive)</td>
<td>DSI Mean/SD</td>
<td>0.91/0.03</td>
<td>0.90/0.03</td>
<td>0.87/0.07</td>
<td>0.90/0.04</td>
<td>0.79/0.06</td>
<td>0.90/0.03</td>
</tr>
<tr>
<td>HD (mm)</td>
<td>Max/Min/Median</td>
<td>0.97/0.85/0.92</td>
<td>0.95/0.81/0.90</td>
<td>0.98/0.46/0.89</td>
<td>0.97/0.80/0.90</td>
<td>0.94/0.66/0.79</td>
<td>0.96/0.82/0.90</td>
</tr>
<tr>
<td>Δd centroid (mm)</td>
<td>Mean/SD</td>
<td>2.96/0.90</td>
<td>4.03/1.17</td>
<td>2.57/1.07</td>
<td>5.68/2.98</td>
<td>12.15/3.69</td>
<td>4.62/1.69</td>
</tr>
<tr>
<td></td>
<td>Max/Min/Median</td>
<td>5.63/1.56/3.13</td>
<td>7.81/1.56/3.49</td>
<td>6.44/1.56/2.21</td>
<td>10.48/1.56/6.44</td>
<td>18.82/2.21/12.20</td>
<td>10.48/2.21/4.42</td>
</tr>
<tr>
<td>Optimization time (hr)</td>
<td></td>
<td>63</td>
<td>64</td>
<td>47</td>
<td>74</td>
<td>125</td>
<td>73</td>
</tr>
<tr>
<td>Current (APSO)</td>
<td>DSI Mean/SD</td>
<td>0.91/0.03</td>
<td>0.90/0.03</td>
<td>0.88/0.05</td>
<td>0.93/0.03</td>
<td>0.82/0.05</td>
<td>0.91/0.03</td>
</tr>
<tr>
<td>HD (mm)</td>
<td>Max/Min/Median</td>
<td>0.97/0.84/0.91</td>
<td>0.95/0.82/0.91</td>
<td>0.97/0.68/0.89</td>
<td>0.97/0.84/0.93</td>
<td>0.94/0.68/0.82</td>
<td>0.96/0.82/0.91</td>
</tr>
<tr>
<td>Δd centroid (mm)</td>
<td>Mean/SD</td>
<td>3.02/0.85</td>
<td>3.89/1.19</td>
<td>2.55/1.08</td>
<td>3.79/1.86</td>
<td>10.65/3.82</td>
<td>4.19/1.28</td>
</tr>
<tr>
<td></td>
<td>Max/Min/Median</td>
<td>5.63/1.56/3.13</td>
<td>9.38/1.56/3.49</td>
<td>6.25/1.56/2.21</td>
<td>7.97/1.56/3.13</td>
<td>17.68/2.21/10.53</td>
<td>9.50/2.21/4.42</td>
</tr>
<tr>
<td>Optimization time (hr)</td>
<td></td>
<td>2.3</td>
<td>2.5</td>
<td>1.9</td>
<td>4.1</td>
<td>4.1</td>
<td>3.7</td>
</tr>
<tr>
<td>Average from 10 APSO repetition</td>
<td>DSI Mean/SD</td>
<td>0.91/0.03</td>
<td>0.90/0.03</td>
<td>0.88/0.05</td>
<td>0.92/0.03</td>
<td>0.80/0.06</td>
<td>0.90/0.03</td>
</tr>
<tr>
<td>HD (mm)</td>
<td>Mean/SD</td>
<td>3.04/0.87</td>
<td>3.93/1.15</td>
<td>2.51/1.02</td>
<td>3.92/1.87</td>
<td>11.18/3.89</td>
<td>4.27/1.33</td>
</tr>
<tr>
<td>Δd centroid (mm)</td>
<td>Mean/SD</td>
<td>1.01/0.50</td>
<td>1.25/0.69</td>
<td>0.96/0.56</td>
<td>1.19/0.69</td>
<td>3.49/1.44</td>
<td>1.39/0.81</td>
</tr>
</tbody>
</table>
of parameters involved in the optimization. From the 6 patient cases, however, we have established an optimization scheme (100 initial solutions, 80 iterations, $10 \times$ APSO repetition) that can find reasonable solutions navigating through the multidimensional integer/non-integer solution space. Based on this initial study, providing better understanding of the eight parameters (e.g. performance sensitivity vs. each parameter change) will be the next step in future studies.

Our autocontouring algorithm was developed assuming the following scenario in a clinical environment: (1) A pretreatment MR scan is performed with the treatment unit (e.g. linac-MR) using the same MR sequence, patient setup, and imaging plane orientation intended to be used during the treatment. 30 images acquired from this scan are manually contoured, on which the parameter optimization is performed as discussed in this study. (2) During treatment, the linac-MR provides intrafractional, dynamic MR imaging of a lung tumor within the same plane. Each intrafractional image is autocontoured in less than 20 ms (Yun et al 2015), which is the first step of the intrafractional tumor tracking. Ideally, the time interval between the pretreatment scan and the actual treatment should be kept as short as possible. In reality, however, this will depend a lot on many practical factors in the clinic.

It is important to clarify that in radiation therapy, a target volume and its extent (e.g. tumor) must be defined by a responsible expert (e.g. radiation oncologist), typically in a pretreatment MR scan. This process cannot be replaced by an automatic algorithm. Accordingly, our algorithm is equipped with a training session, so that the expert’s intent can be fully reflected in the patient treatment.

The algorithm was coded in LabVIEW 2011 (National Instruments, Austin, TX) and tested on 32 bit computer system (Windows7, Intel i7-2600k, 4 GB RAM). We expect significant increase in optimization speed with higher end hardware and more optimized coding technique to make our method clinically feasible. Also, validation of our algorithm in a real 0.5 T Linac-MR environment will be conducted using our second generation Linac-MR system in our institution.

4. Conclusions

An efficient, fully automatic parameter optimization was added to our autocontouring algorithm, and we evaluated its performance using in vivo MR images. Approximately 1/4 time reduction was achieved in parameter optimization (6 patients average) while maintaining the same or slightly improved performance.

Acknowledgments

The authors disclose a conflict of interest; BG Fallone is co-founder and CEO of MagnetX Oncology Solutions, Edmonton, Canada.

References


