Real-time tumor-contouring by patient-specific deep learning: Evaluation using a respiratory moving phantom

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1. Introduction

Our research group has developed a principle of a real-time tumor-contouring method by patient-specific deep learning (DL) and has preliminarily reported the feasibility of the method using some clinical X-ray fluoroscopic images [1-5]. However, accurate evaluation of the method is difficult in clinical X-ray fluoroscopic images because no one can identify the ground truth of target contour precisely due to the daily anatomical difference between CT imaging and X-ray fluoroscopic imaging. The purpose of this study is to examine the accuracy of the tumor contouring using a respiratory moving phantom which reproduces the same condition in CT imaging and fluoroscopic imaging.

2. Materials and Methods

Fig.1 shows the respiratory moving phantom consisting of a rib-bone phantom (in-house) and a moving rod with plastic cores (1-3 cm in diameter) of dynamic thorax phantom (Model 008A, CIRS, CO, USA). Fig.2 shows the experimental setup in CT imaging (Optima 580w, GE healthcare) and X-ray fluoroscopy (DAR-3000(I.I.), Shimadzu) which installed on proton therapy system (PROBEAT, Hitachi).

Digitally reconstructed radiographs (DRRs) with 0.3 mm image resolution, which is equal to the fluoroscopic resolution, were generated by projecting CT data with 2.5 mm slice thickness. Image contrast of DRR was improved by the simulation including the beam hardening effect and the scatter effect [4]. The plastic cores were defined as gross target volumes (GTVs) and then volumes with 5 mm margin on GTV were defined as clinical target volumes (CTVs). The projected-CTV images as supervised images were generated under the same geometric condition as DRR. The method of creating massive training images and processing by a convolutional neural network (CNN) was followed by our previous reports [1-5].

In the inference stage, the fluoroscopic images were processed by the trained-CNN, then the inferred projected-CTV images were generated.

3. Results and Discussion

The tracking error in SI direction calculated from the centroid of segmentation between the inferred images and the ground truths was 0.1 ± 0.3 mm for 3 cm target. The similarity between the inferred tumor contours and the ground truths was 0.95 ± 0.02 in the Jaccard index.

This satisfactory result shows that the tracking accuracy is enough despite the difference in image quality between the fluoroscopic image and the DRR projected from coarse CT slicing.

4. Conclusion

We confirmed the robustness of patient-specific deep learning using the respiratory moving phantom.

References

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3) Terunuma et al. “Patient-optimized deep learning for robust tumor tracking”. 2nd ECMP 2018
4) Tomoda et al. “Markerless tumor tracking by patient-specific deep learning (1) Improvement of DRR quality for training”. 116th JSMP 2018
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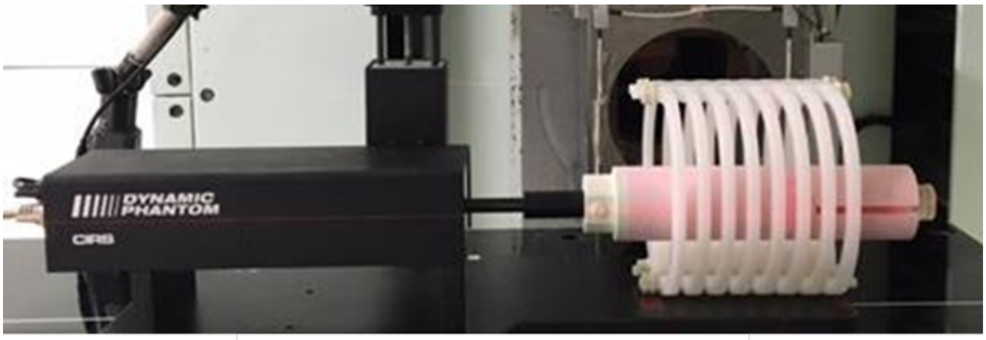

CIRS + Plastic(rib&spine)

Fig.1 Respiratory moving phantom

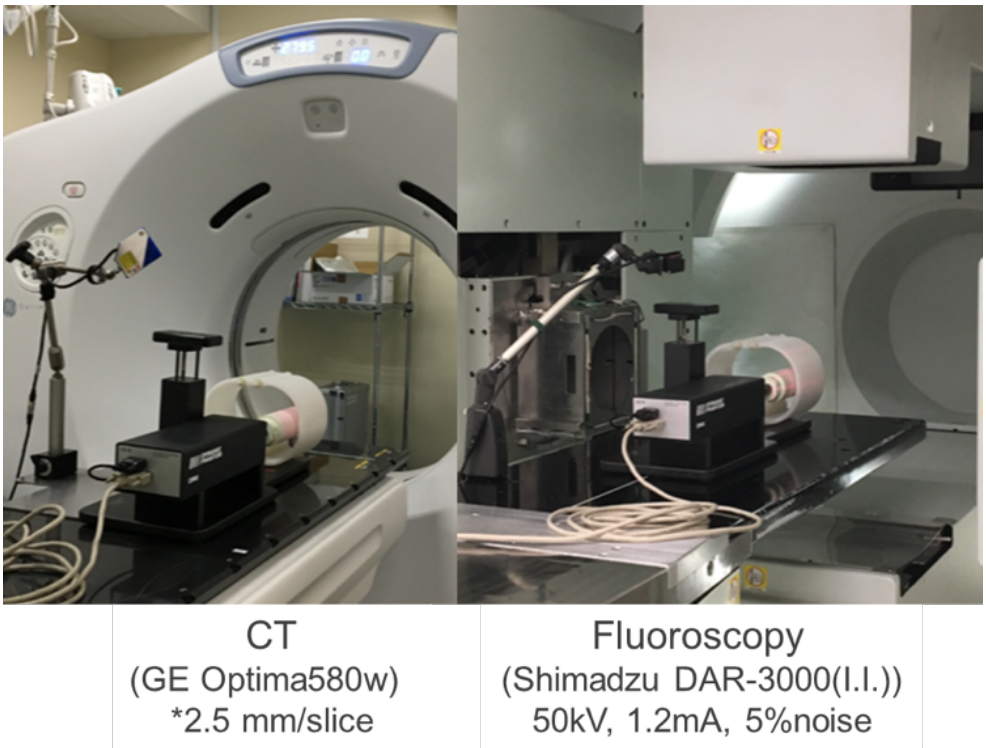

Fig.2 The experimental setup in CT imaging and Fluoroscopy

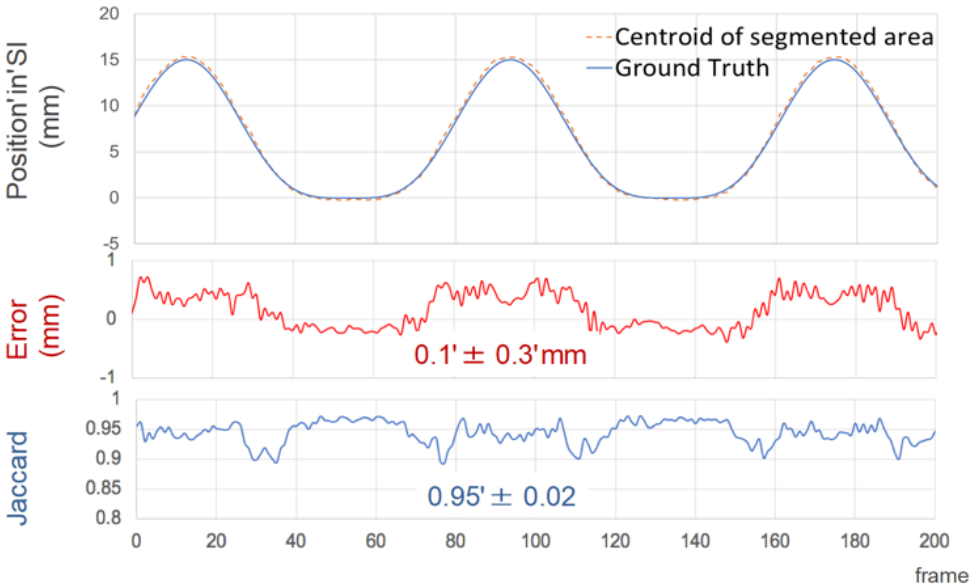

Fig.3 The result of tumor tracking