

Fiducial-free real-time image-guided robotic radiosurgery for tumors of the spine

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INTRODUCTION

Image-guided radiosurgery (IGRS) is a safe and attractive treatment option for many sites, such as brain, spine and lung, and especially for lesions that are surgically inaccessible. Current IGRS is mostly fiducial-free and often relies on the use of image registration for patient setup and intra-fractional tracking. In our current clinical practice, the intensity-based image registration method is inadequate in a few cases, especially when the target involves multiple vertebral bodies.

AIM

Accordingly, we aim to develop a novel fiducial-free targeting strategy using deep learning approach to interpret routine live kV X-ray images for spinal radiosurgery. Due to the limited access to the training data, we are also developing a realistic training data generation scheme for the deep learning model.

CT simulation 1 CT simulation 2 DRR 1 gtvDRR 1 DRR 2 Patient-specific deep learning model X-ray image with target location

The above (*Figure 1*) shows the workflow of the proposed deep learning-based IGRS method. The first step is to incorporate the motion model to the planning computed tomography (CT) images. Second, the deformed and translated CT simulations were projected in the geometry of the live imaging system to generate digitally reconstructed radiographs (DRRs). Finally, the DRRs together with their corresponding gross target volume annotations were used to train a patient-specific model to localize target position on the real-time live images.

RESULTS

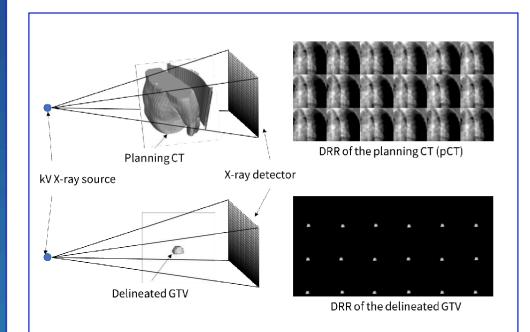
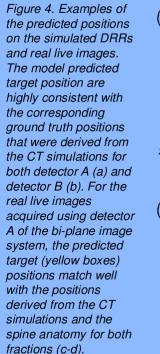


Figure 2. Generation of the simulated kV live images using motion incorporated planning CT images with geometry consistent with the in-room orthogonal bi-plane X-ray imaging system. For this purpose, we placed patient planning CT images in the live image geometry, and then introduced a series of changes (translations/rotations/deformations) in planning CT images to mimic different clinical scenarios. For each of the changes, we generated two DRRs which are consistent with the live images acquired using the bi-plane imager. Meanwhile, the DRRs of the delineated GTV were also generated for each of the changes.



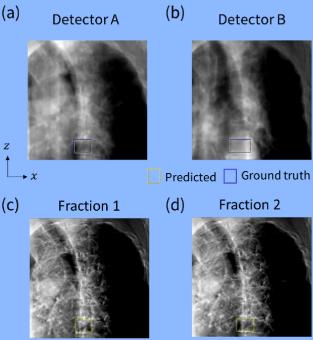


Table 1. Quantitative evaluation of the predicted results on simulated live images.

	Plane A		Plane B	
	Δx (mm)	Δz (mm)	Δx (mm)	Δz (mm)
Case 1	0.35	0.36	0.30	0.58
Case 2	0.53	0.40	0.48	1.17
Case 3	0.73	0.58	0.51	0.31
Case 4	0.77	0.74	0.38	0.58
Case 5	0.50	0.40	0.51	0.66
Case 6	1.38	1.21	1.08	1.47
Mean <u>+</u> std	0.71 <u>±</u> 0.36	0.61 <u>±</u> 0.32	0.54 <u>+</u> 0.27	0.79 <u>+</u> 0.43

CONCLUSIONS

The deep learning model required approximately one hour of training for each view angle of the two orthogonally mounted X-ray systems. Following training, the model identified the spinal tumor on the testing DRR or a live image within 200 ms. The deviations between the target position obtained by deep learning model and the testing DRRs range from -2.25 mm to 1.48 mm and from -1.10 mm to 1.23 mm for the two X-ray systems. The overall mean absolute targeting error for the two X-ray systems are 0.66 mm. Target positioning provided by the trained deep learning model for tracking periodic live images is consistent with the derived positions from the couch correction.

This study demonstrated that fiducial-free spinal tumor targeting for radiosurgery is achievable with high accuracy by using a deep learning approach. The proposed method may be useful for pre-treatment patient setup and real-time target tracking during treatment delivery. It provides a clinically valuable solution for routine spinal radiosurgery and could be adapted to other challenging treatment sites.

ACKNOWLEDGEMENTS

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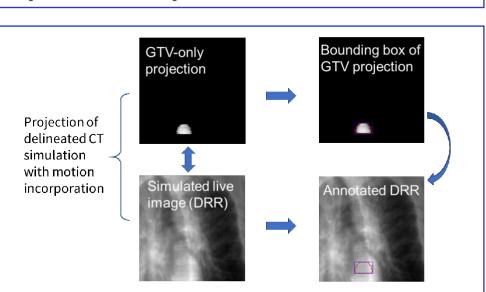


Figure 3. Generation of the annotated DRRs for model training. For each of the simulated live image and its corresponding GTV-only DRR, we first find the contour and bounding box of the target in the GTV-only DRR and then attach them to the simulated live image to obtain an annotated sample.