

Evaluation of Three-Dimensional Fiducial Marker Position Fidelity in FBPCConvNet-Based Sparse-View Reconstruction Using Treatment kV Images for Prostate SBRT

Hyesun Yang, PhD student^{1,2}; Dae Yup Han, PhD²; Duhee Jeon, PhD¹; Jiwon Park, PhD student¹; Hyosung Cho, PhD¹
¹Yonsei University, department of radiation engineering, ²Yale University school of medicine



PURPOSE

This study aims to quantitatively evaluate the three-dimensional **positional fidelity of implanted fiducial markers** in **deep learning-based sparse-view reconstruction** from **on-treatment kV images** acquired during **prostate stereotactic body radiotherapy (SBRT)**.

IMPACT

By enabling three-dimensional positional evaluation from routinely acquired on-treatment kV images, **this work supports post-treatment intrafraction motion assessment** without additional imaging system. This study is also expected to providing valuable information for treatment assessment, patient outcome prediction, and toxicity analysis.

INTRODUCTION

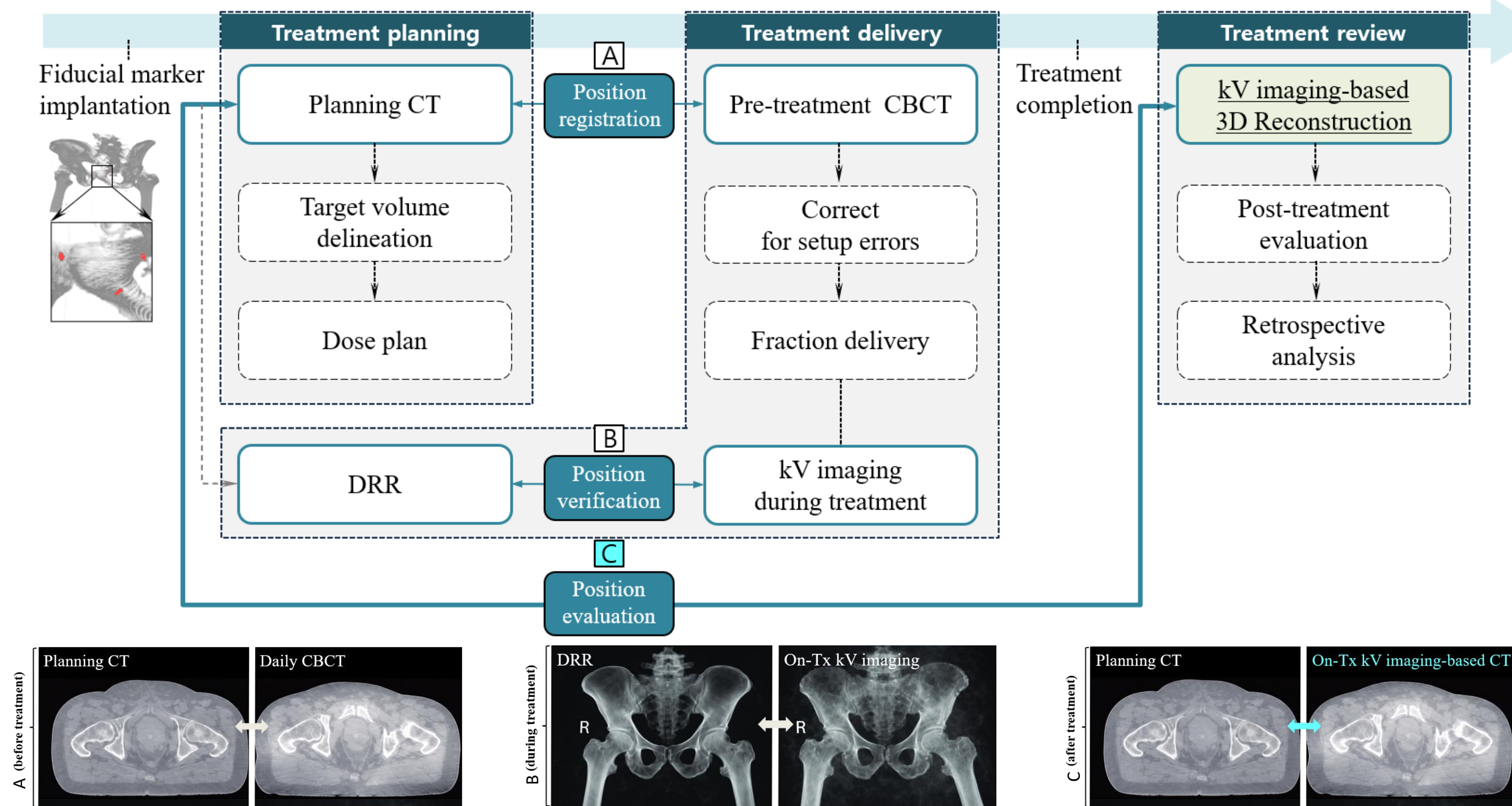


Figure 1. Fiducial marker-based image-guided radiotherapy (IGRT) workflow for patient positioning in prostate stereotactic body radiotherapy (SBRT), including pre-treatment registration, intrafraction verification, and post-treatment evaluation: (A) pre-treatment position registration using cone-beam computed tomography (CBCT) aligned to the planning computed tomography (CT) for initial patient setup. (B) Intrafraction position verification using 2D on-treatment kilovoltage (kV) images compared with planning CT-derived digitally reconstructed radiographs (DRRs). (C) 3D intrafraction position evaluation based on on-treatment kV imaging, performed retrospectively after treatment completion for post-treatment assessment.

In most prostate cancer patients, fiducial markers are implanted at the time of biopsy and are widely used for target localization [1]. For prostate SBRT, accurate target positioning is critical given the high fractional dose and steep dose gradients [2,3]. Consequently, image-guided techniques are used (A) before, (B) during, and after treatment for patient positioning and treatment verification. During treatment, the prostate may move due to internal organ motion. However, intrafraction motion is still assessed using 2D kV images. In this study, we investigate a deep learning approach for 3D marker position fidelity for post-evaluation using routinely acquired treatment kV images.

MATERIALS AND METHODS

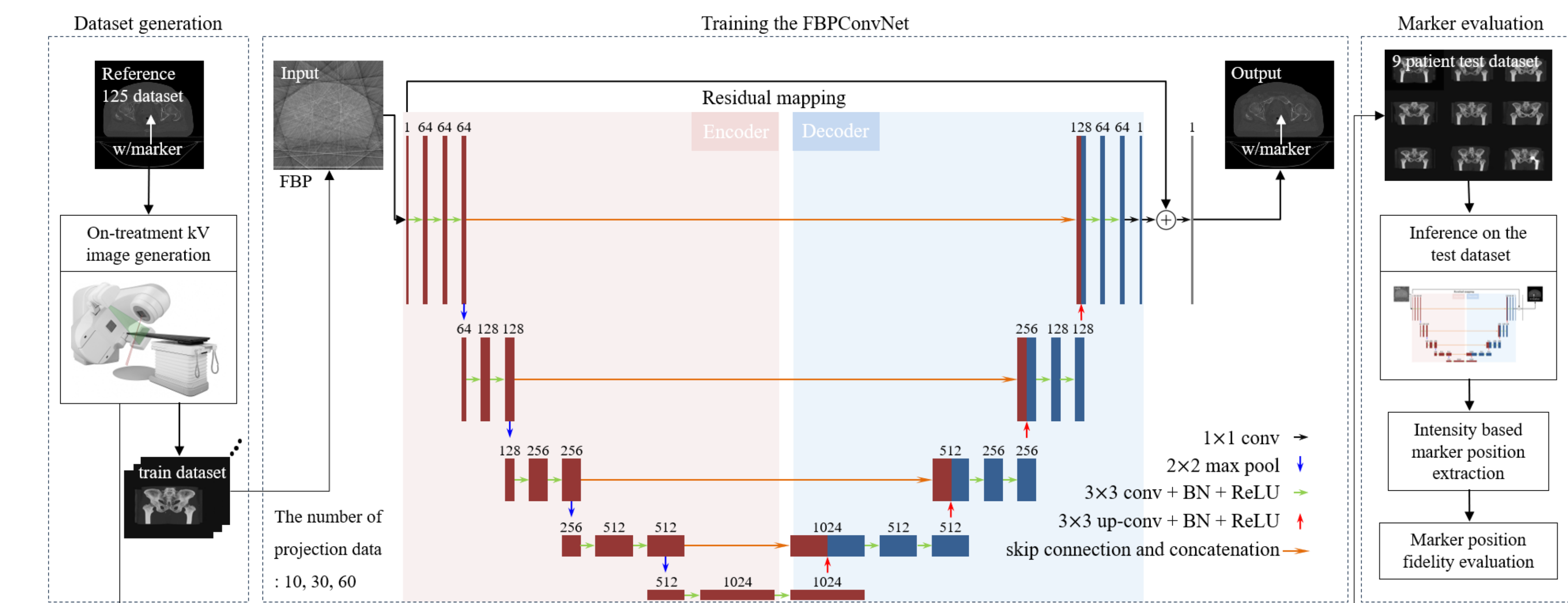


Figure 2. Overview of the FBPCConvNet-based residual learning framework for dataset generation, training, and evaluation. Reference volumes were first used to simulate on-treatment kilovoltage (kV) projection images, which were reconstructed using filtered backprojection (FBP) to generate the network input images. The FBPCConvNet was trained in a residual learning framework, where the network predicts the residual between sparse-view FBP reconstructions and the corresponding reference images using an encoder-decoder architecture with skip connections. During inference, the predicted residuals were added to the FBP reconstructions to produce artifact-suppressed volumetric images. The trained model was then applied to an independent test dataset, followed by intensity-based fiducial marker position extraction and quantitative evaluation of marker position fidelity.

Sparse-view kV projection data with 10, 30, and 60 views were simulated by forward projection of CT images under clinical acquisition geometry and reconstructed using FBP to generate the initial 3D reconstructed images. The images were processed using an FBPCConvNet-based convolutional neural network (CNN). The network learns a residual mapping between artifact-corrupted FBP images and artifact-reduced reconstructions, thereby combining physics-based reconstruction with data-driven refinement. Localization accuracy of resulting reconstructions was evaluated for nine test patients using multiple quantitative metrics.

RESULTS

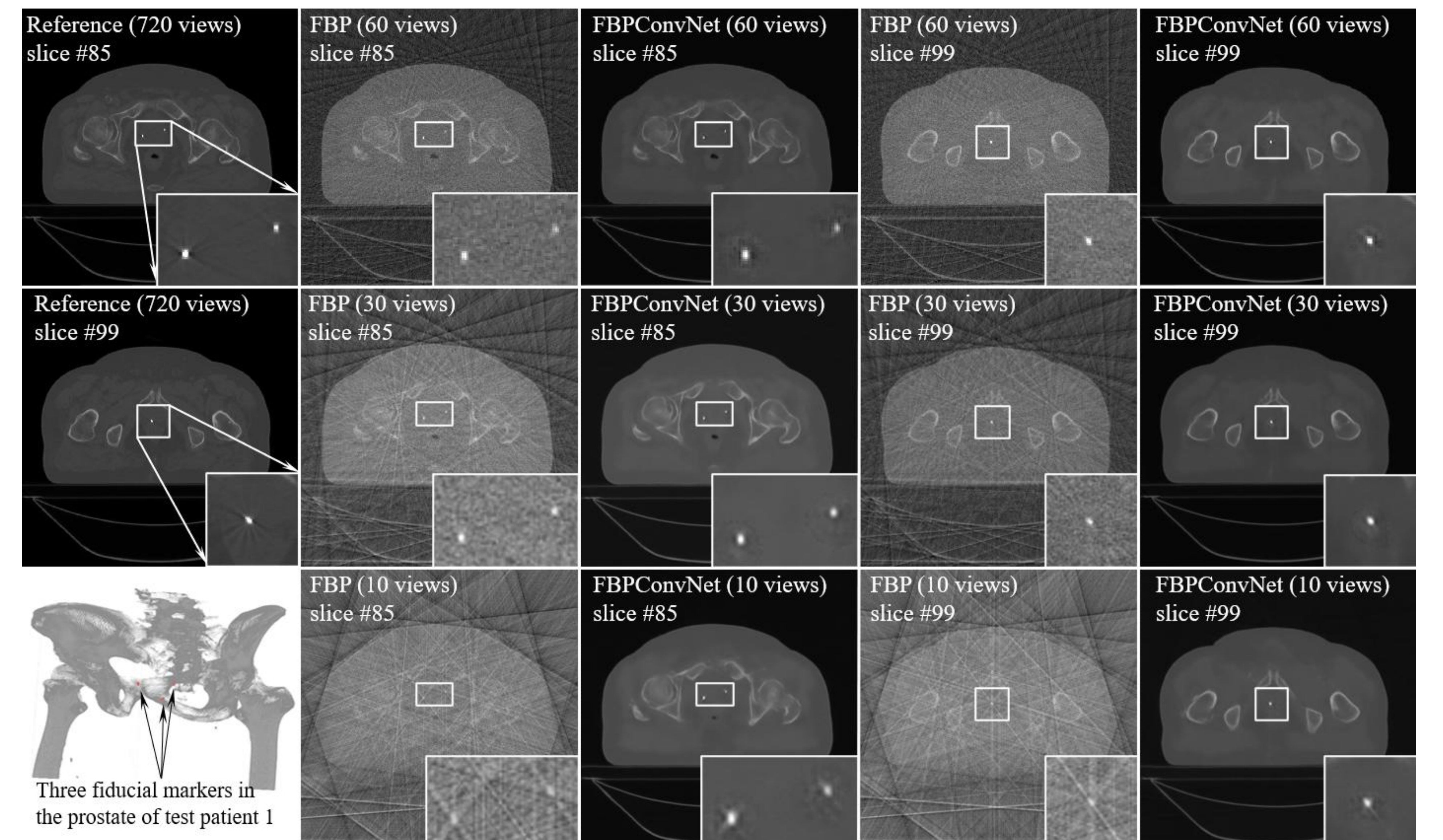


Figure 3. Qualitative comparison of reconstructed axial cone-beam computed tomography (CBCT) images for a representative test patient (patient 1). Reference images reconstructed from 720 projection views are shown for slices #85 and #99, followed by sparse-view reconstructions obtained using conventional filtered backprojection (FBP) and deep learning-based FBPCConvNet with 60, 30, and 10 projection views. White boxes indicate regions of interest containing implanted fiducial markers, which were enlarged for visualization. The bottom-left panel illustrates the anatomical locations of the three fiducial markers implanted in the prostate of patient 1.

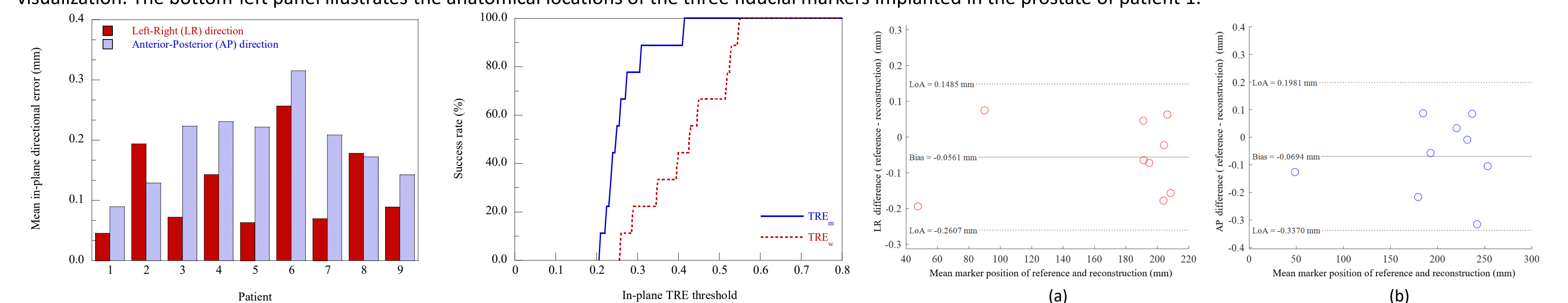


Figure 4. Mean positional errors of fiducial markers in the left-right (LR) and anterior-posterior (AP) directions for nine test patients. The blue and red curves correspond to the case-level mean and worst-case, respectively. The success rate represents the percentage of cases with TRE below a specified tolerance threshold. A success rate exceeding 95% is achieved at an error threshold of 0.41 mm for mean case and approximately 0.54 mm for worst case, indicating consistently low localization error across patients.

Figure 5. Cumulative success rate curves of target registration errors (TRE) for the nine test patients. The blue and red curves correspond to the case-level mean and worst-case, respectively. The success rate represents the percentage of cases with TRE below a specified tolerance threshold. A success rate exceeding 95% is achieved at an error threshold of 0.41 mm for mean case and approximately 0.54 mm for worst case, indicating consistently low localization error across patients.

Figure 6. Bland-Altman analysis of agreement between fiducial marker positions derived from FBPCConvNet reconstructions and the corresponding 720-view reference images in the (a) left-right (LR) and (b) anterior-posterior (AP) directions. Each data point represents the patient-level mean of slice-wise signed positional differences between reconstructed and reference marker positions. Solid lines indicate the mean bias, and dashed lines denote the limits of agreement (LoA). In the LR direction, the mean bias was -0.056 mm, with LoA ranging from -0.261 to 0.149 mm (LoA width: 0.41 mm). In the AP direction, a similarly small bias of -0.069 mm was observed, with LoA varying from -0.337 to 0.198 mm (LoA width: 0.54 mm).

Qualitative results showed that fiducial markers remained clearly identifiable in FBPCConvNet reconstructions across all sparse-view conditions. Quantitative analysis demonstrated that mean TRE values remained at the submillimeter level for all patients, while worst-case TRE values remained below approximately 0.6 mm. Bland-Altman analysis revealed minimal bias and no systematic directional trends in the left-right and anterior-posterior directions. In both directions, the mean bias remains close to zero, and most differences fall within the limits of agreement (LoA).

CONCLUSION

These results demonstrate that CNN-based sparse-view reconstruction can preserve fiducial marker positional fidelity with submillimeter accuracy under sparse-view acquisition. By quantitatively validating marker localization performance, this study supports the feasibility of using deep learning-reconstructed kV images for post-treatment intrafraction motion assessment and suggests a pathway toward future real-time motion monitoring in radiotherapy workflow.

REFERENCE

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CONTACT

Author name: Hyesun Yang
Department: Radiation Engineering
Email: tjs798@yonsei.ac.kr



Linked in



Google scholar