Deep Learning Augmented Proton Portal Imaging: A Phantom Study

Serdar Charyyev*, Yang Lei*, Joseph Harms*, Bree Eaton*, Mark McDonald*, Walter Curran*, Tian Liu*, Jun Zhou*, Rongxiao Zhang▲ and Xiaofeng Yang*

***Emory University ▲Dartmouth College**

EMORY WINSHIP CANCER INSTITUTE
National Cancer Institute-Designated Comprehensive Cancer Center

Dartmouth-Hitchcock NORRIS COTTON CANCER CENTER

INTRODUCTION

For shoot-through proton treatments, like FLASH radiotherapy, protons exiting the patient can be used for proton portal imaging (PPI), revealing valuable information for the validation of tumor location in the beam's-eye-view (BEV) at native gantry angles. However, PPI has poor inherent contrast and spatial resolution. To deal with this issue, we propose a deep-learning-based method to use kV digitally reconstructed radiographs (DRR) to improve PPI image quality.

METHODS

1) Setup:

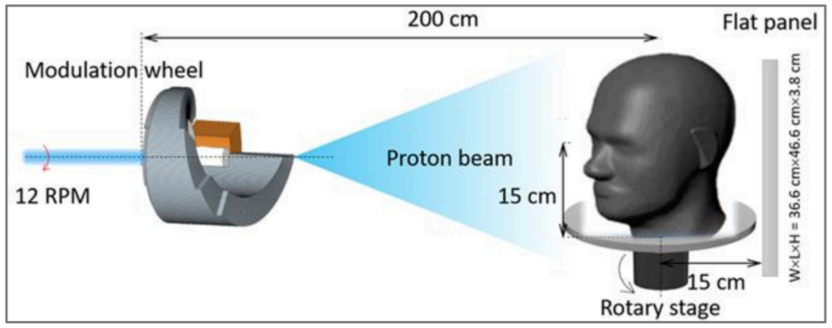

Figure 1. (a) The experimental set-up for proton portal imaging (PPI) with the flat-panel imager. The head phantom was placed on a rotary stage. PPIs were acquired at projection angles from 0 to 358° with an increment of 2° by rotating the phantom.

2) Network structure:

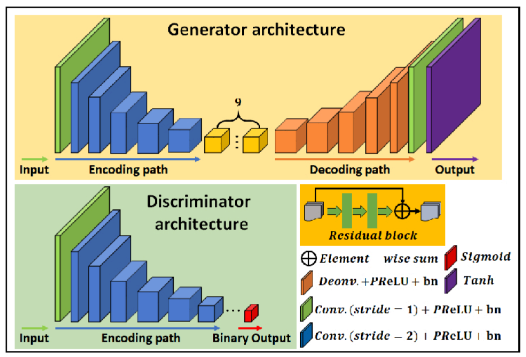

Figure 2. Architecture of the generator and discriminator networks.

PPIs were acquired using a double scattering system (Fig. 1). The DRRs acquired from CT acted as learning targets in the training process and were used to evaluate results from the proposed method using a six-fold cross-validation scheme. We used a residual generative adversarial network (GAN) framework to learn the nonlinear mapping between PPIs and DRRs. Residual blocks were used to force the model to focus on the structural differences between DRR and PPI (Fig. 2). To assess the accuracy of our method, we used 149 images to train the method and 30 images to test the method.

RESULTS

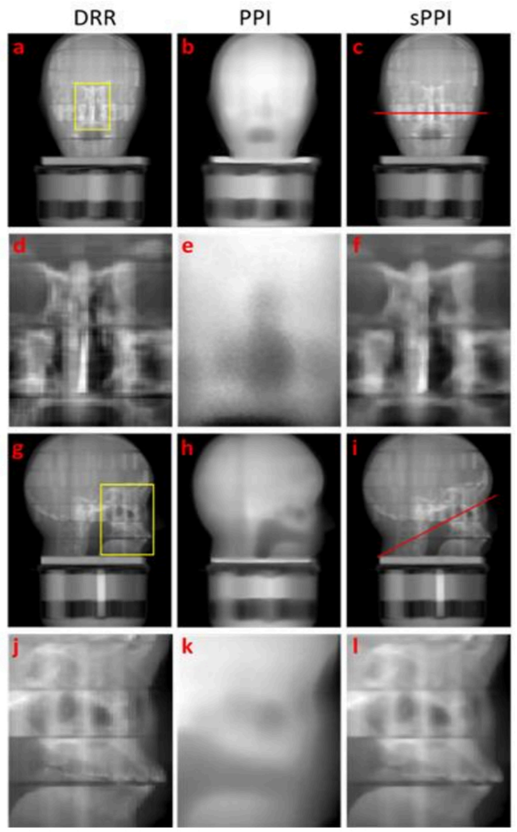

Figure 3. Representative examples of the sPPIs (last column) obtained by our method as compared to ground-truth DRRs (first column) and PPIs (second column) at projection angles 0° and 104°. All images are normalized and shown on the window [0 1]. Rows 2 and 4 are the magnified images of the regions of interest indicated by yellow rectangle selections in (a) and (g) respectively.

Qualitatively, the corrected PPIs showed enhanced spatial resolution, captured fine details present in the DRRs that are missed in the PPIs (Fig. 3). Line profiles (as indicated by the red lines in Fig. 3c and 3i) show the deep learning-based method closely matches the DRR in both shape and pixel value across heterogeneous regions, while the input PPI fails to capture these fine features (Fig. 4). Fig.5 shows that sPPIs can be used for detecting registration errors, identifying mismatches and position verification.

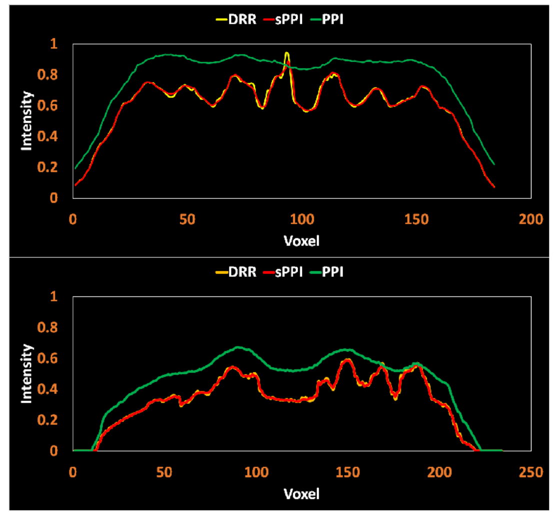

Figure 4. Normalized line profiles of 0° (top) and 104° (bottom) projections, corresponding to the red lines drawn in Fig. 3c and 3i respectively.

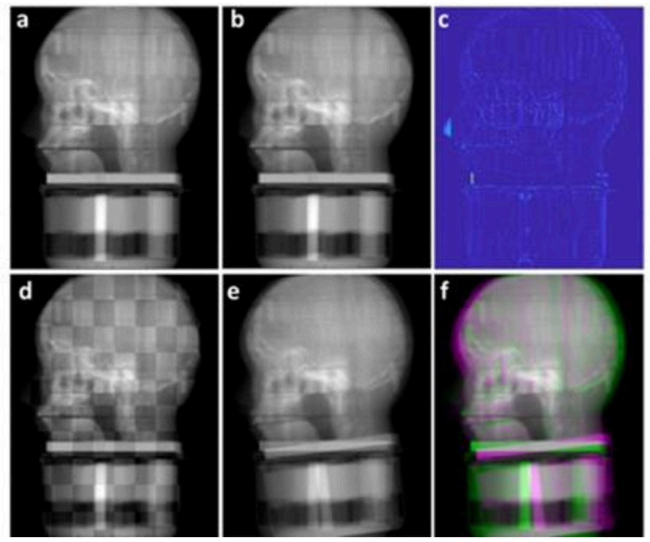

Figure 5. (a) DRR at 270° projection. (b) sPPI at 270° projection. (c) Element-wise subtraction image of (a) and (b). (d) checkerboard overlay of (a) and (b). (e) Blend overlay of (a) and (b) with 7° CCW offset applied to (b). (f) Composite image of (a) and (b) overlaid in different color bands. The DRRs, sPPIs, and the subtraction image are shown on a window of [0 1] normalized DRR pixel value.

SUMMARY AND CONCLUSIONS

We applied a novel deep learning-based approach to integrate dense blocks into a GAN framework to synthesize sPPIs This will allow for BEV imaging with the particle used for treatment, leading to a valuable alternative to orthogonal x-rays or cone-beam CT for patient position verification.