Deep Learning Based Image Prediction for Abdominal Organ Motion During MR-Guided Radiotherapy

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Introduction: It is challenging to treat cancer in abdomen with precise image guided radiation therapy (IGRT) due to the complicated motion of different organs. For example, the motion of liver is influenced by respiration, and the motion of stomach is influenced by peristalsis. In MR-guided radiotherapy, due to acquisition, processing, and beam delivery, there is latency between the acquired image and actual patient state when beam is delivered. Here we aim to compensate this latency by motion prediction models for abdominal organs. Our final goal is to make dose prediction/correction in advance for 1s to 3s in MR-guided radiotherapy.

Methods: We used a three-layer convLSTM neural network for image prediction. We have focused on liver and stomach motion for our motion analyses. The dataset we used was acquired using Elekta Unity MR-Linac cine-MR image protocol. These cine-MR images were acquired in multi-2D mode using a Philips balanced turbo field echo (bTFE) sequence with a T2/T1 contrast and 200 ms per frame. SSIM (Structural Similarity Index), which ranges from -1 to 1, was used for as the loss and metric in the network training. All images were formatted as six time-ordered input images and 1 output image, which was 1 to 5 frames later (0.6s to 3s) than the last input image. Computations were carried out on 30 core 240 GB memory Virtual Machine running with a single NVIDIA DGX-A100 GPU in the HiPerGator.

Results: From the figures attached, we can observe that the predictions for both liver and stomach showed good agreement with the ground truth images though the predicted images suffered from slight decrease in image quality. For 3s in the future, in the liver prediction model, the average SSIM is respectively 0.67 and 0.65 for the validation and test sets; for the stomach model, the average SSIM is 0.54 for both the validation and test sets.

Conclusion: The convLSTM model is able to make motion predictions for respiration (liver) and peristalsis (stomach) for 3s which can be used to increase the accuracy of IGRT for moving targets, including complex organ motion.

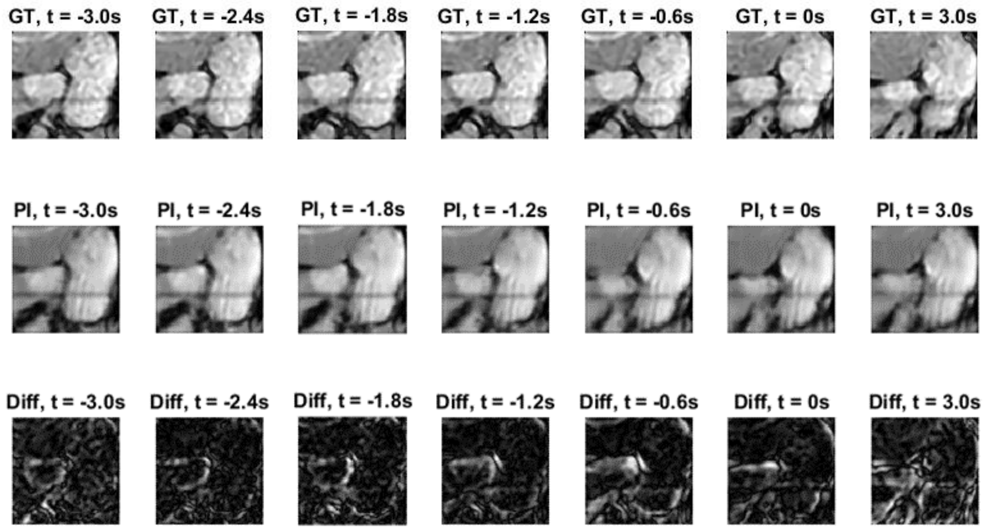

Figure 1. Examples from Stomach Motion Model, GT stands for ground truth, PI stands for predicted image, Diff stands for Pixel Intensity Difference, and t is the time step

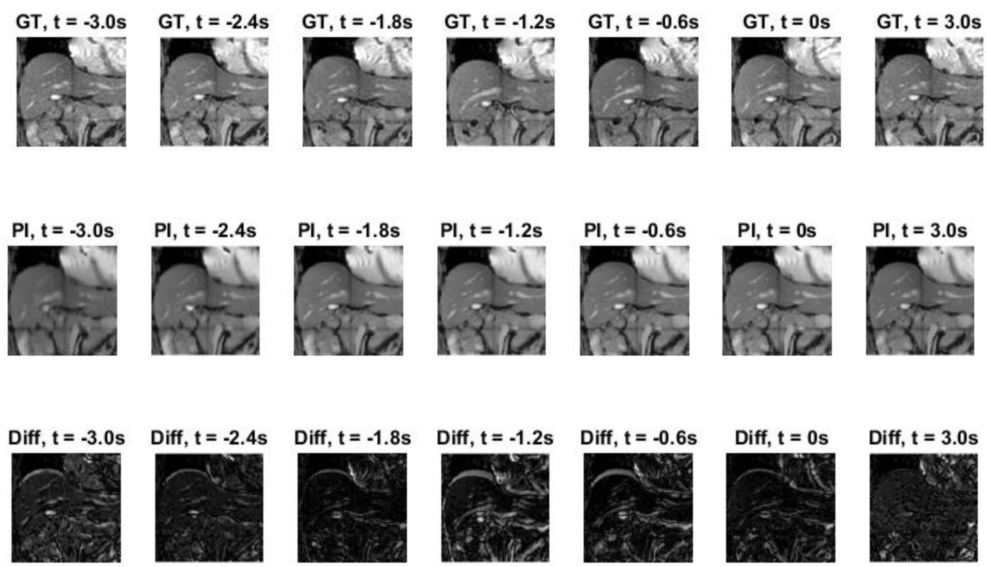

Figure 2. Examples from Liver Motion Model, GT stands for ground truth, PI stands for predicted image, Diff stands for Pixel Intensity Difference, and t is the time step