Deep Learning Based Cine-MR Image Prediction and Analysis for Abdominal Motion

Jingxi Weng[1], Sri Hrushikesh Varma Bhupathiraju[2], Thomas Samant[3], Alex Dresner[4], Jian Wu[1], Sanjiv S. Samant[1]

1. Department of Radiation Oncology, University of Florida, Gainesville, FL
2. Department of Computer and Information Science and Engineering, University of Florida, Gainesville, FL
3. UF Research Computing, University of Florida, Gainesville, FL
4. Philips Healthcare

Introduction

IGRT in abdomen can be challenging in the presence of organ motion, ranging from the mostly respiratory motion of dome of liver to more complex peristalsis and respiratory motions of stomach region. MR-linacs offer real-time internal anatomy based gating but there is latency between acquired images of patient states before and during beam delivery. Here we compensate for this latency by presenting a deep learning model for organ motion prediction.

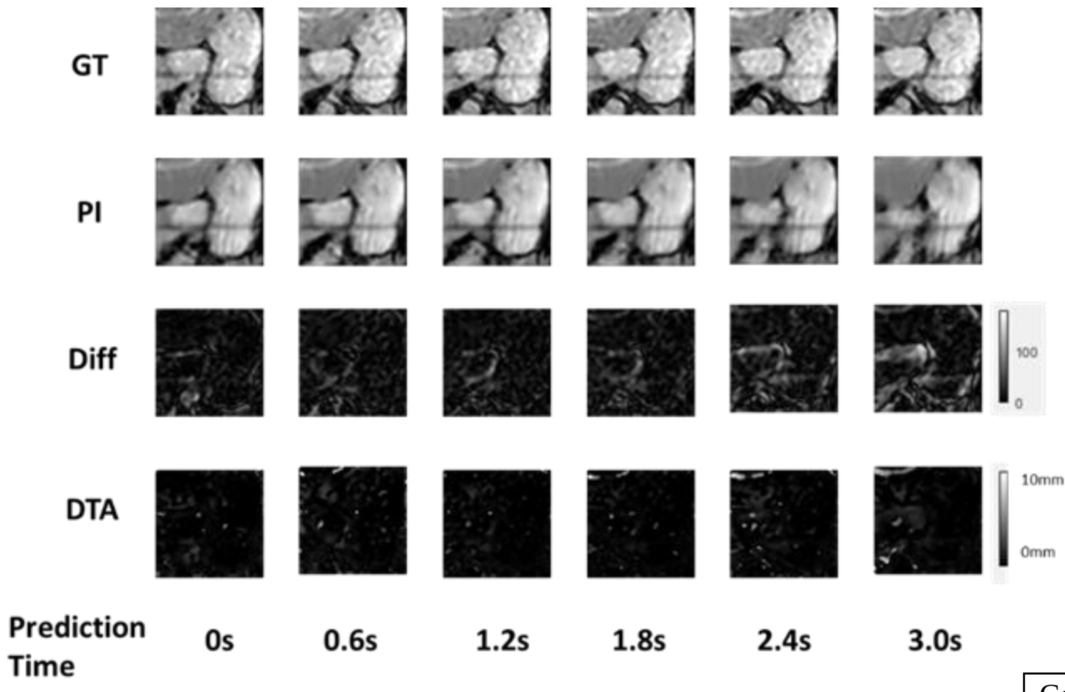

Figure 1. Examples from Stomach Motion Model for 3 Second Prediction with SSIM as Loss Function (GT: Ground Truth, PI: Predicted Image, Diff: Pixel Intensity Difference, DTA: Distance to Agreement)

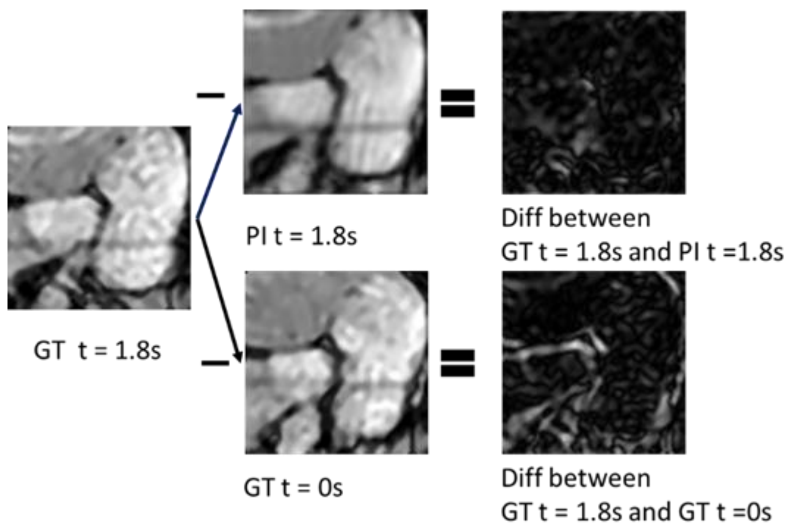

Figure 2. Difference between GT Image in 3 seconds and Difference between PI and GT Image at 3.0s

Method

Multiplanar cine-MRI was acquired every 600ms on 10 volunteers on Philips Ingenia MRsim, which is equivalent to the MR module on Elekta Unity MR-linac. A T2/T1 balanced turbo field echo (bTFE) sequence was used. A deep learning model, using 6 input images to predict future image(s), was generated with convLSTM neural network using SSIM (Structural Similarity Index) and MSE as loss functions. SSIM, MSE, NMI(normalized mutual information) and DTA(distance to agreement) were used to evaluate performance.

Results

Planar cine-MRI prediction was successful for time frames of 0.6s-3.0s. The performance of the model remained stable over the 2min of test data with variations in SSIM and MSE within 2std. Due to noise in the cine-MRI from fast acquisition, DTA here is defined that values within 10% are considered the same. For stomach, using a patient specific model, DTA of 3.8mm over 100% ROI volume and 1.8mm for 90% ROI volume were achieved. For liver, using nonpatient specific global model, DTA of 4.3mm over 100% ROI volume and 2.3mm for 90% ROI volume were achieved.

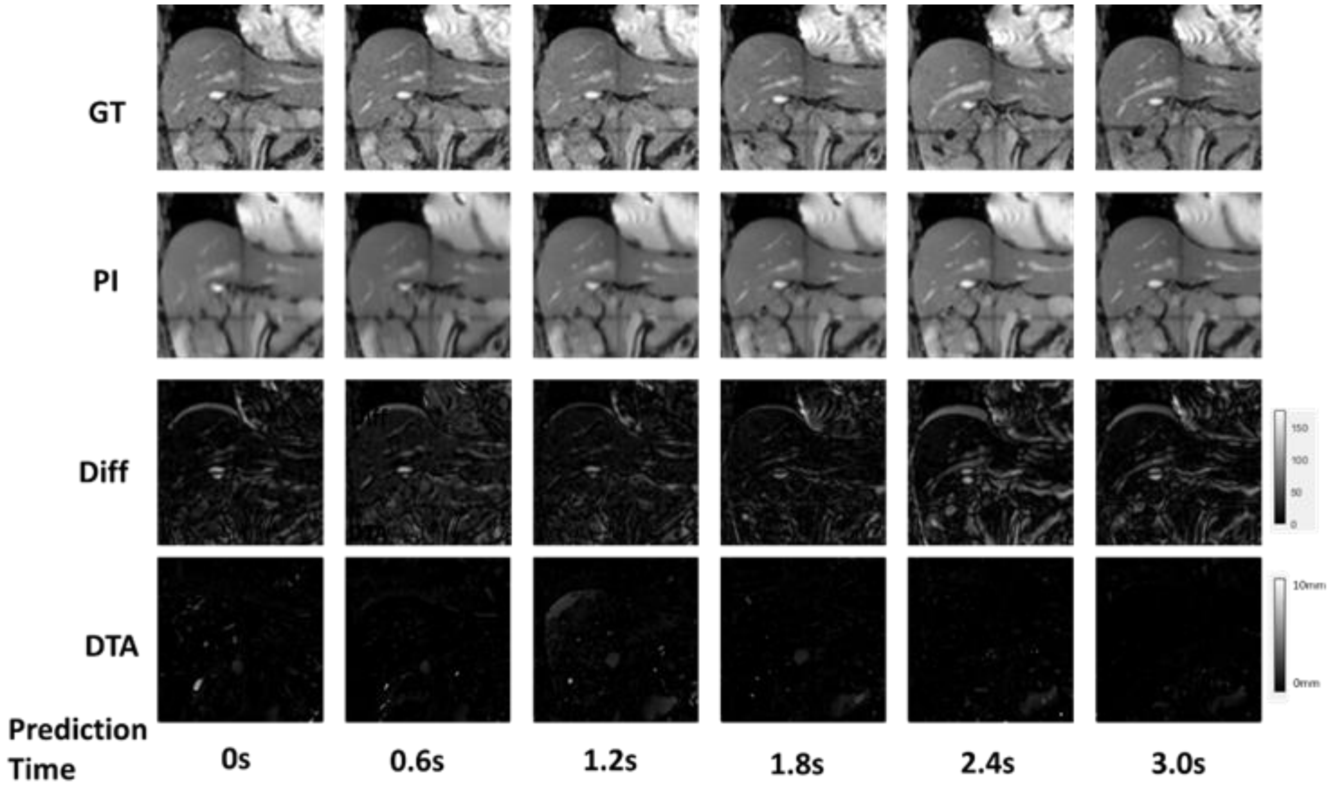

Figure 3. Difference between GT Image in 3 seconds and Difference between PI and GT Image at 3.0s

Table 1. Comparison of Different Metrics for Stomach Test Set

Cost Function	Predicted Time (sec)	SSIM (Range: 0-1)	MSE	NMI	DTA 100% (mm)	DTA 99% (mm)	DTA 95% (mm)	DTA 90% (mm)
SSIM	0.6	0.5371	676.9	0.4288	3.1547	2.3837	1.6664	1.3322
SSIM	1.2	0.4578	1000.6	0.4203	4.1040	3.1661	2.1320	1.7136
SSIM	1.8	0.4306	1117.2	0.4204	3.7792	3.0659	2.1917	1.7541
SSIM	2.4	0.4311	1178.4	0.4193	4.2650	3.3549	2.3181	1.8662
SSIM	3.0	0.4246	1331.0	0.4206	3.8322	3.3141	2.5930	2.1405
SSIM	3.6	0.4214	1241.0	0.4191	4.1662	3.3718	2.4616	1.9870

Table 2. Comparison of Different Metrics for Liver Test Set

Cost Function	Predicted Time (sec)	SSIM (Range: 0-1)	MSE	NMI	DTA 100% (mm)	DTA 99% (mm)	DTA 95% (mm)	DTA 90% (mm)
SSIM	0.6	0.4620	468.5774	0.3196	3.1258	2.6397	2.0438	1.6475
SSIM	1.2	0.3808	607.3737	0.2994	3.6384	3.0126	2.2925	1.8406
SSIM	1.8	0.3502	717.9855	0.2961	4.2766	3.6854	2.8590	2.3152
SSIM	2.4	0.3698	668.9250	0.2984	3.7507	3.1798	2.4200	1.9494
SSIM	3.0	0.3693	704.0209	0.2968	4.0830	3.4499	2.6491	2.1432
SSIM	3.6	0.3761	713.4961	0.3001	4.3768	3.7250	2.8344	2.2851

Conclusion

Deep learning models were constructed to successfully predict motions from 0.6s to 3.0s for peristalsis of the stomach (patient specific model) and for respiratory motion of liver (nonpatient specific global model). In both cases, cine images predicted for 1.8s had negligible difference from the ground truth, and 90% DTA was <2.5mm for both stomach and liver motions.

References

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