Predicting GI Organ Motion for SBRT Treatments of Pancreatic Cancer Using a Generative Deep Learning Model

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INTRODUCTION

Pancreatic cancer treatments are heading toward ablative regimes such as 5 fraction (Fx) stereotactic body radiation therapy (SBRT). A great challenge in safely delivering these ablative doses is the wide range of motion of the radiosensitive gastrointestinal organs at risk (GI-OARs), that include the stomach, duodenum, colon and small bowel. Therefore, mitigating the motion of these GI-OARs is crucial.

The goal of this work is to introduce an abdominal deep learning motion model that can predict likely patterns of GI-OAR motion based on one input simulation image. By generating several predictions per patient, the most probable range of motion for a specific organ and patient can be measured. This range of motion, relative to the anatomy at simulation, can be used during treatment planning to account for the future variation without needing online adaptive workflows.

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METHODS AND MATERIALS

105 pancreatic cancer patients were treated with MR-guided adaptive radiation therapy (MRgART) to 50 Gy in 5 Fxs.

Data Pre-processing:

- The GI-OARs were fully contoured, and physician validated on one MR-simulation and 5 daily Fx MRIs per patient
- All Fx images were rigidly registered to the MR-simulation, relative to the clinical target volume
- Images were resampled to 1.5 x 1.5 x 1.5 mm^3 resolution in 256 x 256 x 128 voxels

Model Training

- Patients were split into training (80%) and validation sets (20%)
- The model framework[1,2] is seen in Figure 1
- Training parameters:
  - Epochs: 150 , Batch size: 4
  - Learning rate: 1.0e-4
  - Latent dimensions: 64
- Loss parameters and weights:
  - Image loss (Normalized Cross Correlation) $\mathbf{w_{NCC}}$: 6000
  - Contour loss (DICE) $\mathbf{w_{DICE}}$: 3000
  - Regularization loss (penalty for large gradients): $\mathbf{w_{REG}} = 0.0001$
  - Kullback-Leibler Divergence – predicted vs population distribution loss: $\mathbf{w_{KL}} = 1$
  - Center of Mass shift loss: $\mathbf{w_{COM}} = 1$

Loss Equation

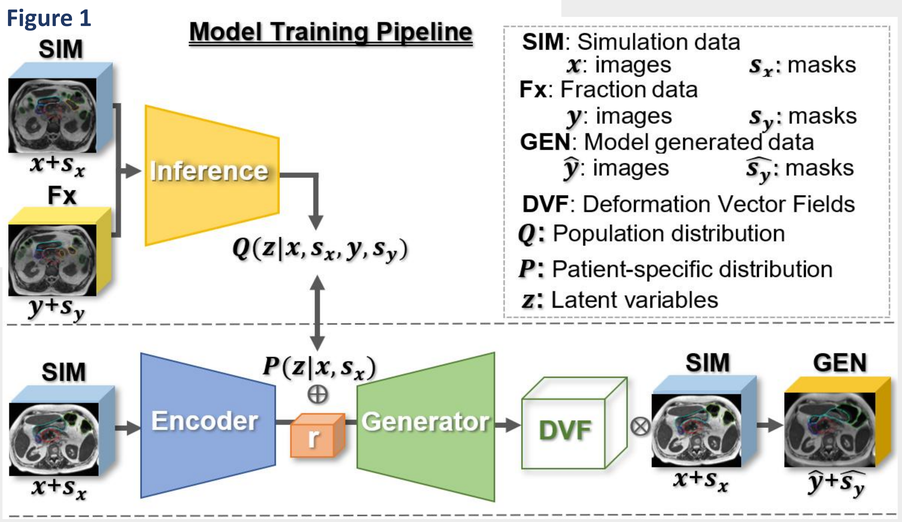
$$Min\big[-w_{NCC}NCC(\hat{y},y) - w_{DICE}DICE(\hat{s_y},s_y) + w_{reg}R(\Phi) + w_{KL}D_{KL}(Q \parallel P) + \boldsymbol{w_{COM}COM_{loss}}\big]$$

*Eq 1: See Figure 1 for variable descriptions

Model Testing

- The Wasserstein distance between the true and generated distributions in volume change (ΔV) and COM shift was calculated, to determine how realistically the model can predict anatomies. The smaller the distance the more similar the distributions.

Figure 1



RESULTS

- The model was successful in generating future abdominal anatomies as seen in Figure 2
- WD results in Table 1 show that model predicted distributions were in range of the population distributions of ΔV and COM. The largest challenge was the COM shift for the colon.
- Figure 3 visually compares the distributions – the model had a smaller range of predicted volume change and on average a smaller COM shift prediction than seen in the population.

Table 1: Wasserstein distance (WD) between the true and model generated distributions, with WD = 0 being identical

	ΔV	COM Shift
Stomach	0.36	0.39
Duodenum	0.12	0.21
Colon	0.31	0.53
Small Bowel	0.25	0.25

Figure 2: The true simulation MRI (Sim) and fraction image (FxN) with three model generated (Gen) future prediction MRIs. The **Stomach**, **Duodenum**, **Colon**, and **Small Bowel** are shown on axial and coronal views for 3 patients.

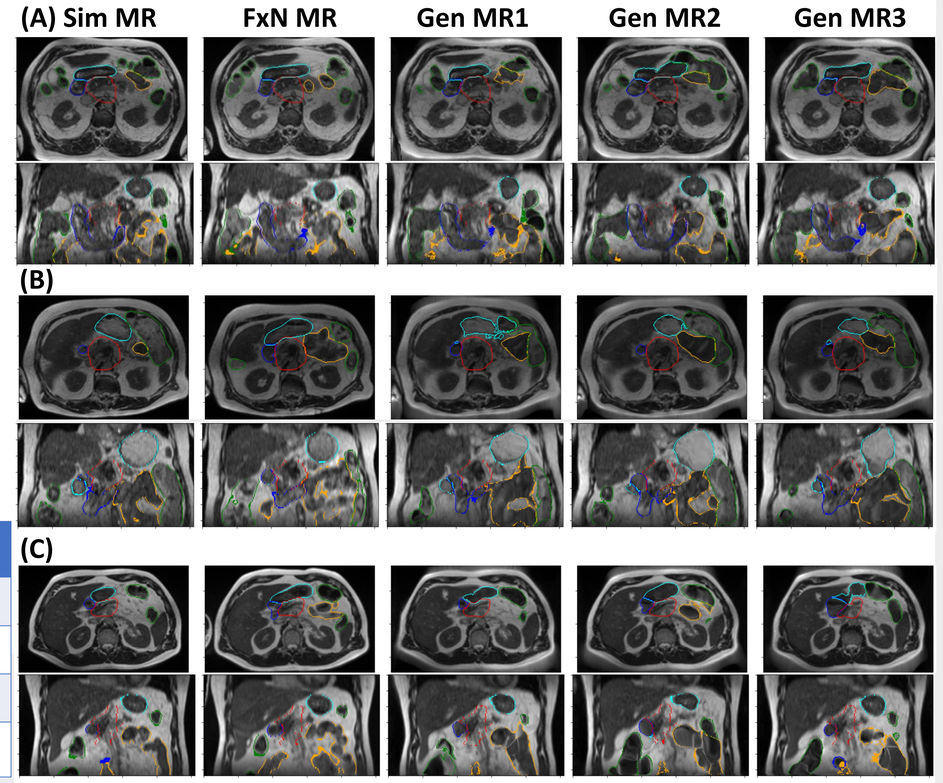
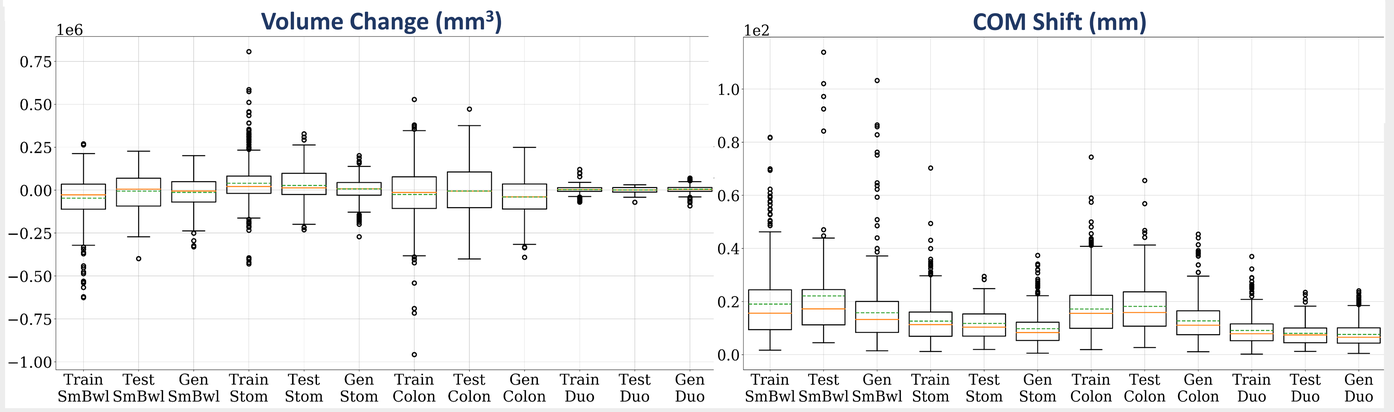


Figure 3: The change in volume and center of mass shift for the training, testing and model generated (Gen) sets. Shown for the small bowel (SmBwl), stomach (Stom), colon, and duodenum (Duo). The distribution mean and median lines are orange and dotted green, respectively. Each box shows the 25th to 75th quartile (Q1, Q3), with whiskers extending ±1.5·(Q3-Q1) beyond Q3/Q1.



DISCUSSION

The abdomen is the most complex site to model due to the large variability of the GI-OARs. This work took advantage of the large dataset available from MRgART with several time points per patient for the model to learn from. It successfully predicts future anatomies that account for the most common range of motion. It struggled to reach the extremes of motion seen in the population, such as predicting the full range of stomach volume or accounting for the larger COM shift seen in the colon. Usage of this model could include calculating patient-specific planning organ at risk volumes (PRVs) as well as a patient selection tool for adaptive vs non-adaptive treatments.

CONCLUSION

A generative deep learning model was successfully developed for abdominal organs at risk surrounding the pancreas over a 5-fraction course of treatment. It can be applied to calculate tailored PRV margins.

REFERENCES

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2. Burlacu T, Hoogeman M, Lathouwers D, Perkó Z. A deep learning model for inter-fraction head and neck anatomical changes in proton therapy. *Phys Med Biol*. 2025;70(6). doi:10.1088/1361-6560/adba39