Synthetic CT generation using generative adversarial networks for MR-only radiotherapy

Using artificial intelligence to improve patient care and simplify radiotherapy workflows.

Background and Goal

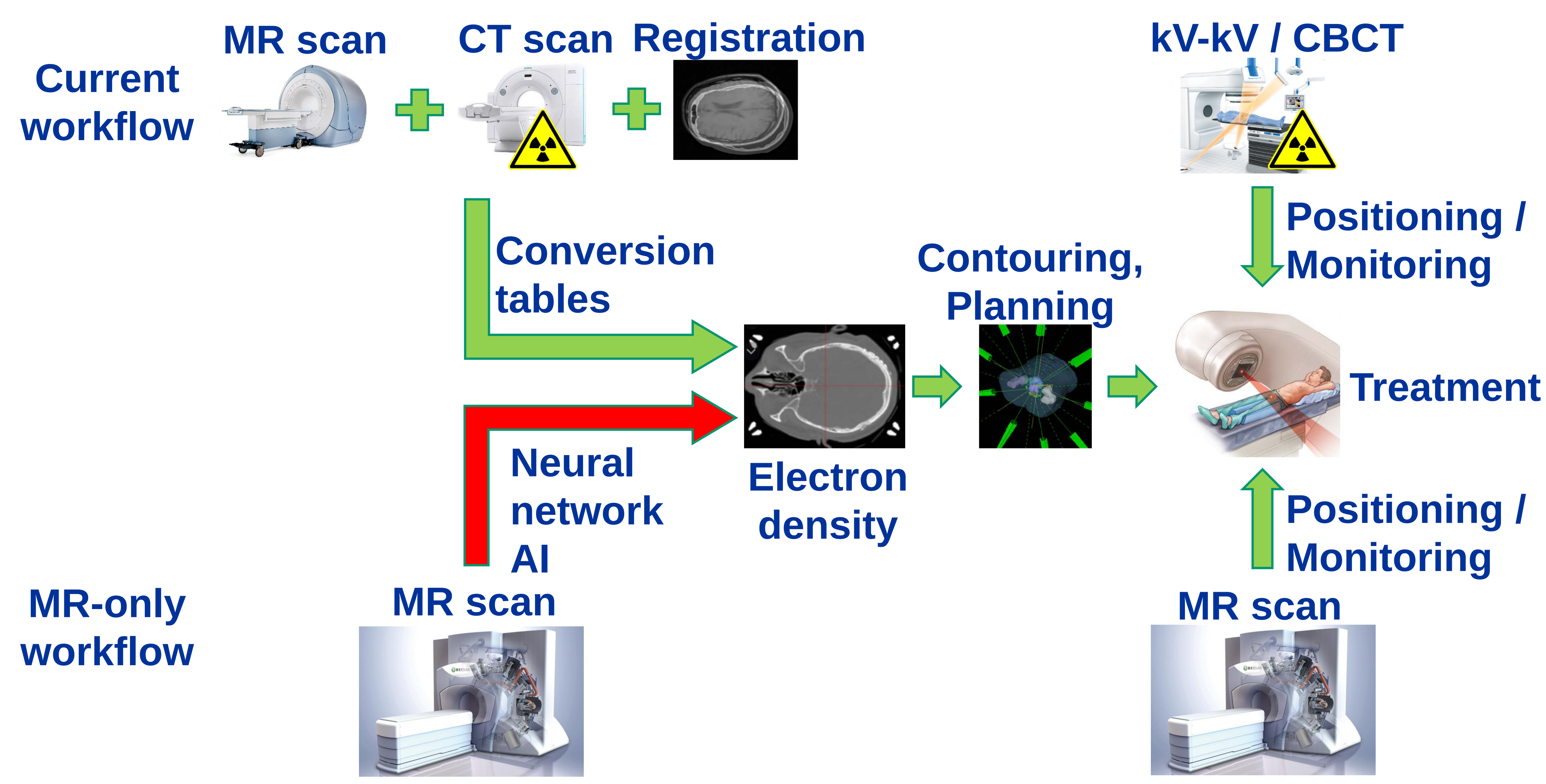

Figure 1. Visualization of the currently viable radiotherapy workflow (green arrows) and the envisioned MR-only workflow with the neural network presented here as a key player (red arrow).

Many forms of cancer can be treated with modern radiation therapy techniques. University Hospital Zurich operates an **MR-Linac**, which is a hybrid device containing a magnetic resonance imaging device and a linear accelerator (Linac) to deliver **image-guided radiotherapy**. That way, the treatment can be adapted to the specific anatomical situation on each treatment session (fraction) and even motion of the patient during treatment (such as breathing) can be compensated.

The **acquisition of a computed tomography** (CT) image using x-rays before the beginning of the treatment is still **required for radiation dose calculation in the current workflow**. However, this imaging exposes the patient to additional radiation dose and the anatomical features in the image (such as the filling level of the bowel or the location of air pockets) may not be identical for a given fraction to their status at the time of CT acquisition.

The goal in this work was to use **artificial intelligence to synthetically create CT images** based on the MR images acquired at each fraction. The ultimate goal is to **remove the need for CT imaging** for patients treated at the MR-Linac, and instead rely on the MR images, which should be a better representation of the current anatomy at any fraction and do not expose the patient to additional ionizing radiation. This would allow for a faster, simpler radiotherapy planning workflow on the MR-Linac.

Methods and Results

MR images acquired on the MR-Linac at the first fraction served as the input data. Additionally, the original CT was adjusted to the anatomy of the first fraction using deformable image registration. The resulting **deformed CT served as the target during training of the AI** and as a comparison during testing and validation (figure 2).

Synthetic CT images were generated using **generative adversarial networks** (GAN). The specific method used was cycleGAN (figure 3). The resulting images (shown for one case in figure 2) were compared to the deformed CTs using image similarity metrics and on the basis of the effect on the radiation dose distribution in radiotherapy planning.

The synthetic CTs were found to be of good similarity to the deformed CT and the resulting radiation dose distribution (precision <2%, accuracy <0.5% for dose volume histogram objectives compared to deformed CT) was on a **clinically acceptable level** for all investigated cases.

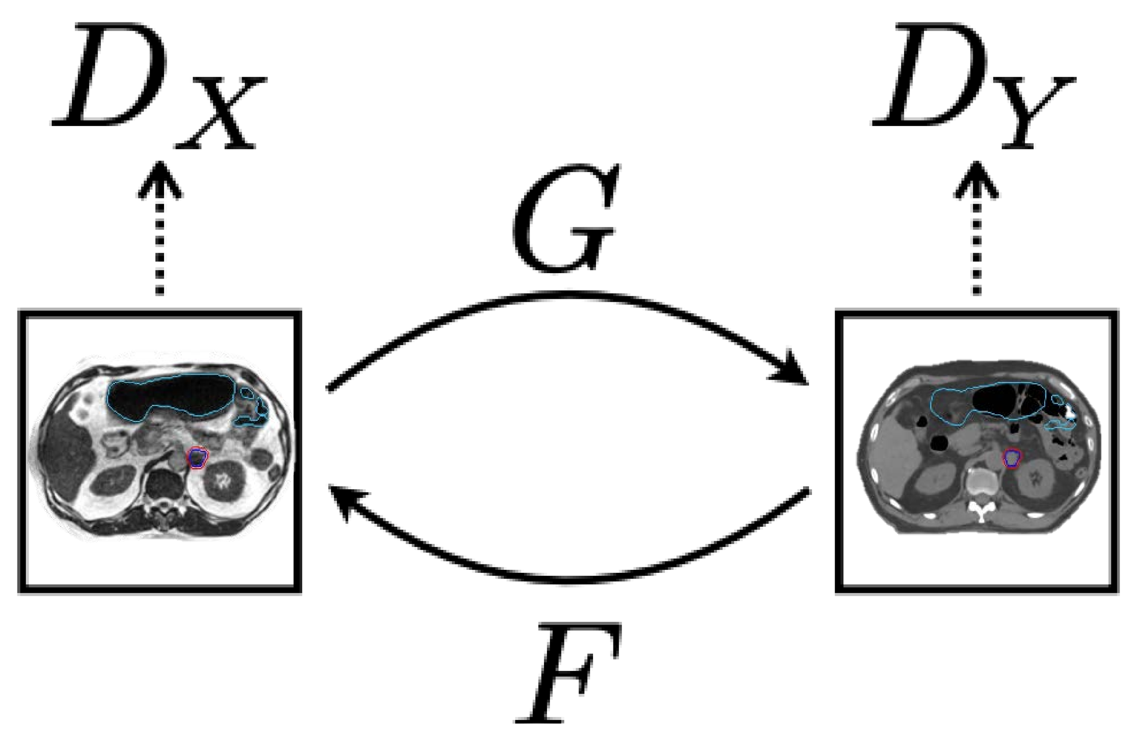

Figure 3. Visualization of the cycleGAN approach of synthetic CT generation.

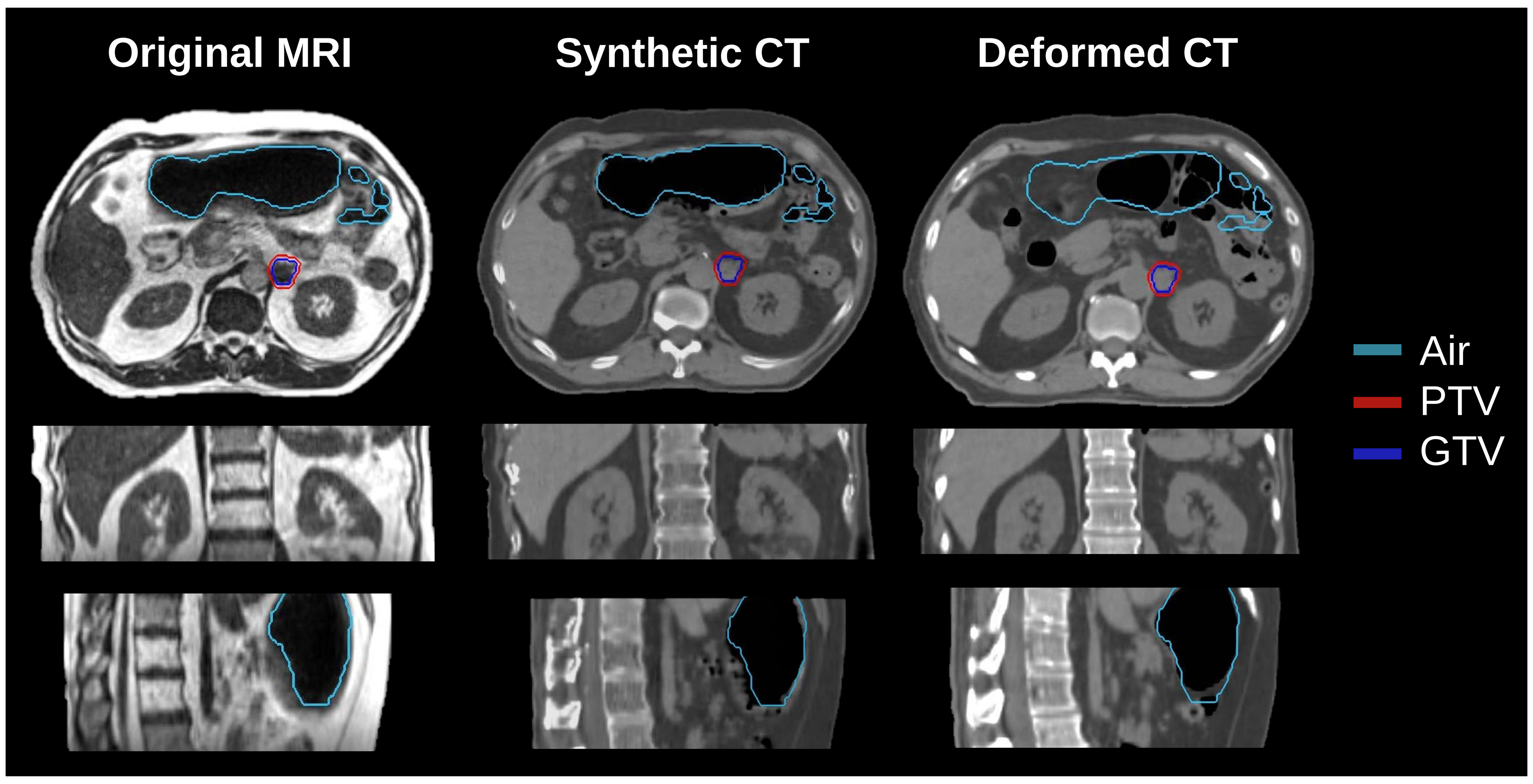

Figure 2. Comparing images for one example patient. Original MRI on the left, the synthetic CTs produced with CycleGAN in the middle and the deformed original CTs on the right.

Conclusion

Synthetic CT image generation from abdominal MR images using neural networks shows **promising results**. With further development, it could enable an MR-only workflow for radiation therapy at the MR-Linac. Certain challenges remain, such as the handling of image artifacts or a systematic procedure for quality assurance of the synthetic CT images.

This project is demonstrative of the **interdisciplinary nature of medical physics**. Physics-based images of biological tissue are complemented with modern computer science techniques to improve the clinical treatment of patients.

This work was primarily conducted by ***Mariia Lapaeva*** *as a master thesis.*

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