# An Approach for Machine Learning-Based Contouring of Daily CBCT with Planning CT as Prior

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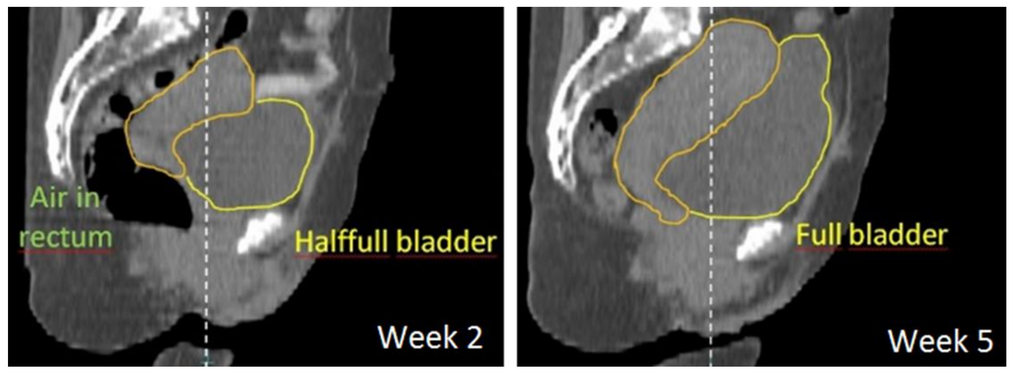
## Motivation

In radiotherapy, sequences of 3D medical images need to be automatically segmented for better treatment follow-up. Classical algorithms rely on the availability of an initial manual (CT) segmentation in order to propagate the contours to a subsequent (CBCT) image. However, such methods fail in case of large changes in the patient's morphology along the treatment. The availability of large inter-patient labelled (CT) datasets raises hope for machine-learning based approaches that will be more robust to such deformations.



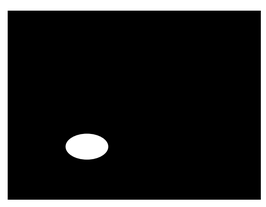

## Our contribution (ongoing work)

| Challenge | Explanation | Proposed solution |
|---|---|---|
| Prior | How to integrate patient-specific prior information in the inter-patient framework? | Three channels as input to the algorithm |
| Modalities | How to learn to segment CBCT images whereas CT images are annotated? | CBCTs are simulated from deformed CTs |
| Contrast | How to separate different regions of interest with comparable appearance on CBCT images? | Deep neural networks |

## Material

For 1000 patients with cancer in the pelvic region, we have the planning CT (CT$i$ for patient $i$) and the corresponding contours (CT$i^c$ for patient $i$) as a binary mask. However, the contoured CBCTs are not available. Hence, they will be simulated on Step 1 below.

CT1



CT1$^c$

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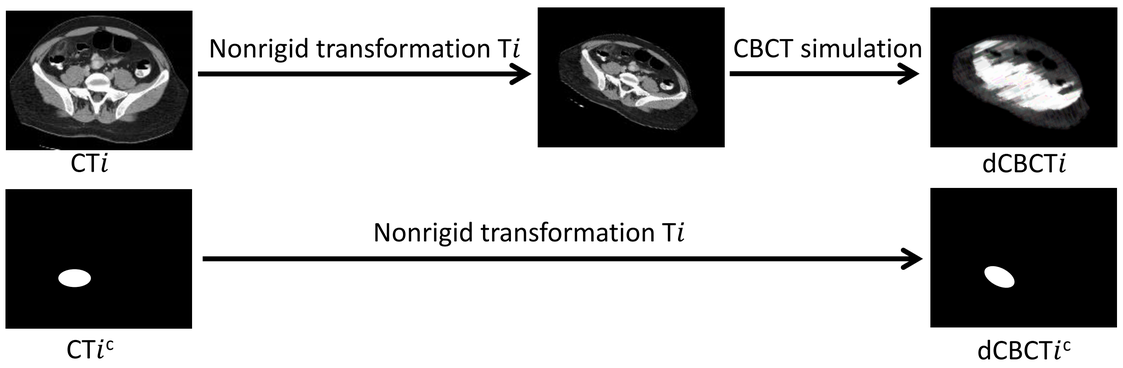
## Methods

### Step 1: Prepare the data

dCT$i$: deformed CT for patient $i$.
dCBCT$i$: simulated CBCT for patient $i$.

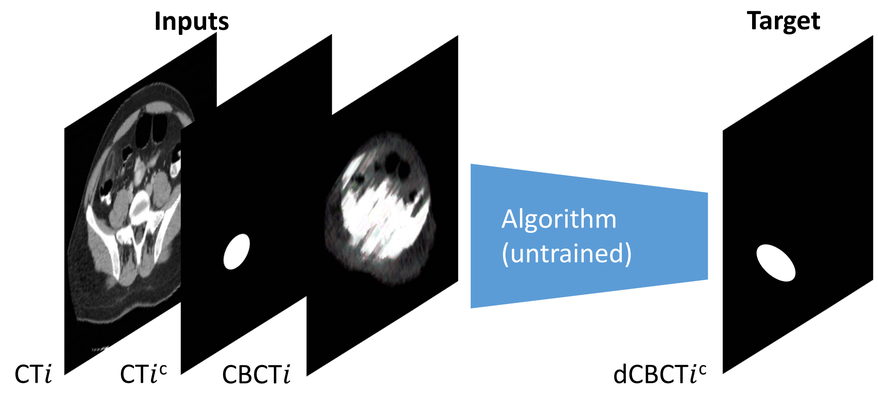
For $i \in$ Training $\cup$ Test:




### Step 2: Train the algorithm

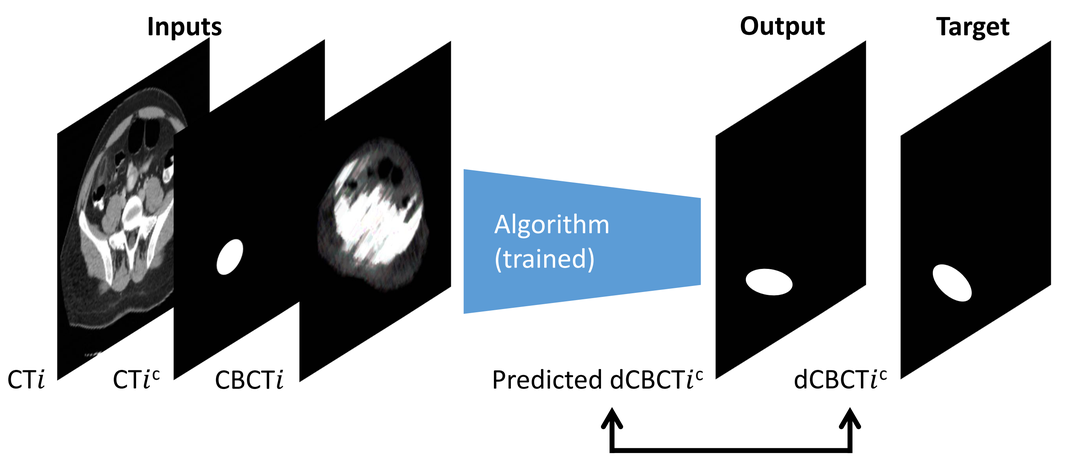
The network that we will use is 3D U-Net [1]. We chose this network because its contracting path can capture context information, while its expanding path enables a precise localization, which is required for segmentation. This ultimately leads to an accurate yet computationally effective segmentation.

For $i \in$ Training:

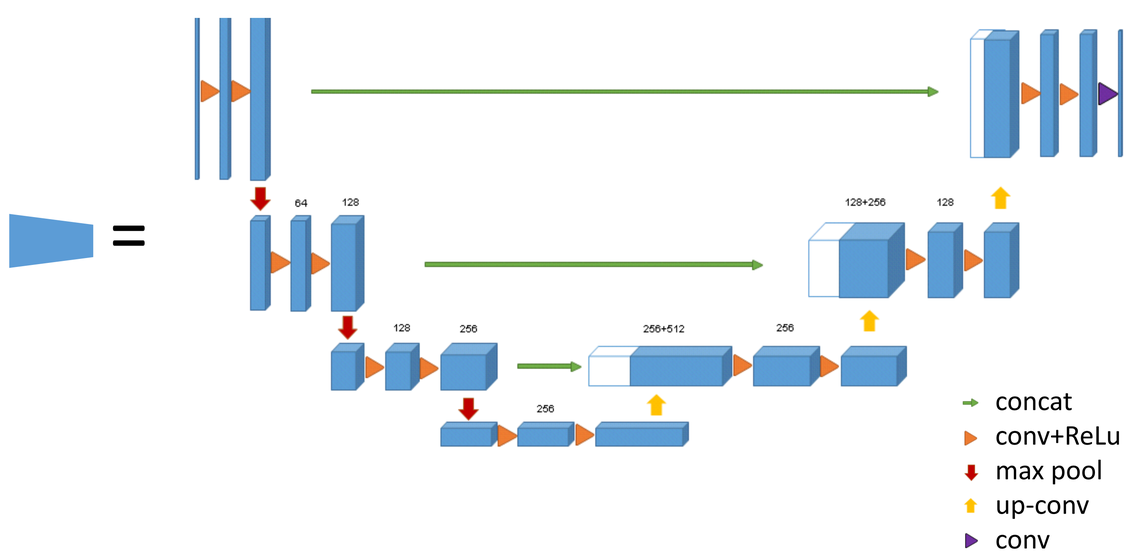



### Step 3: Test the algorithm

For $i \in$ Test:




Finally: assess the pertinence of using the trained algorithm to measure inter-fractional motion in clinical routine.




* Authors contributed equally. † Eliott Brion is supported by FEDER-RW. Source of the image in Section "Motivation": https://www.meduniwien.ac.at/hp/radonc/workpackages/workpackage-2-image-guided-adaptive-radiation-therapy-igart/, Accessed 8/16/2017.
Ref.: [1] Özgün Çiçek, Ahmed Abdulkadir, Soeren S Lienkamp, Thomas Brox, Olaf Ronneberger. (2016), 3d u-net: learning dense volumetric segmentation from sparse annotation. In MICCAI, pp. 424-432. Springer.