



3DCT reconstruction from single X-ray projection



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Background

The treatment of abdominal or thorax tumor is challenging in particle therapy because the respiratory motion induces a movement of the tumor. One current option to follow the breathing motion is to regularly acquire one (or two) X-ray projection(s) during the treatment, which does not give the full 3D anatomy [1]. The purpose of this work is then to reconstruct a 3DCT image based on a single X-ray projection using a neural network.

Materials and Methods

1. Three patients are considered in this study. The deep learning training uses patient-specific CT data to refer to individual features. For each patient, the learning dataset contains 260 3DCT images created by oversampling with random deformations of a planning 4DCT. Digitally reconstructed radiographs (DRRs) are generated from the input 3DCTs.

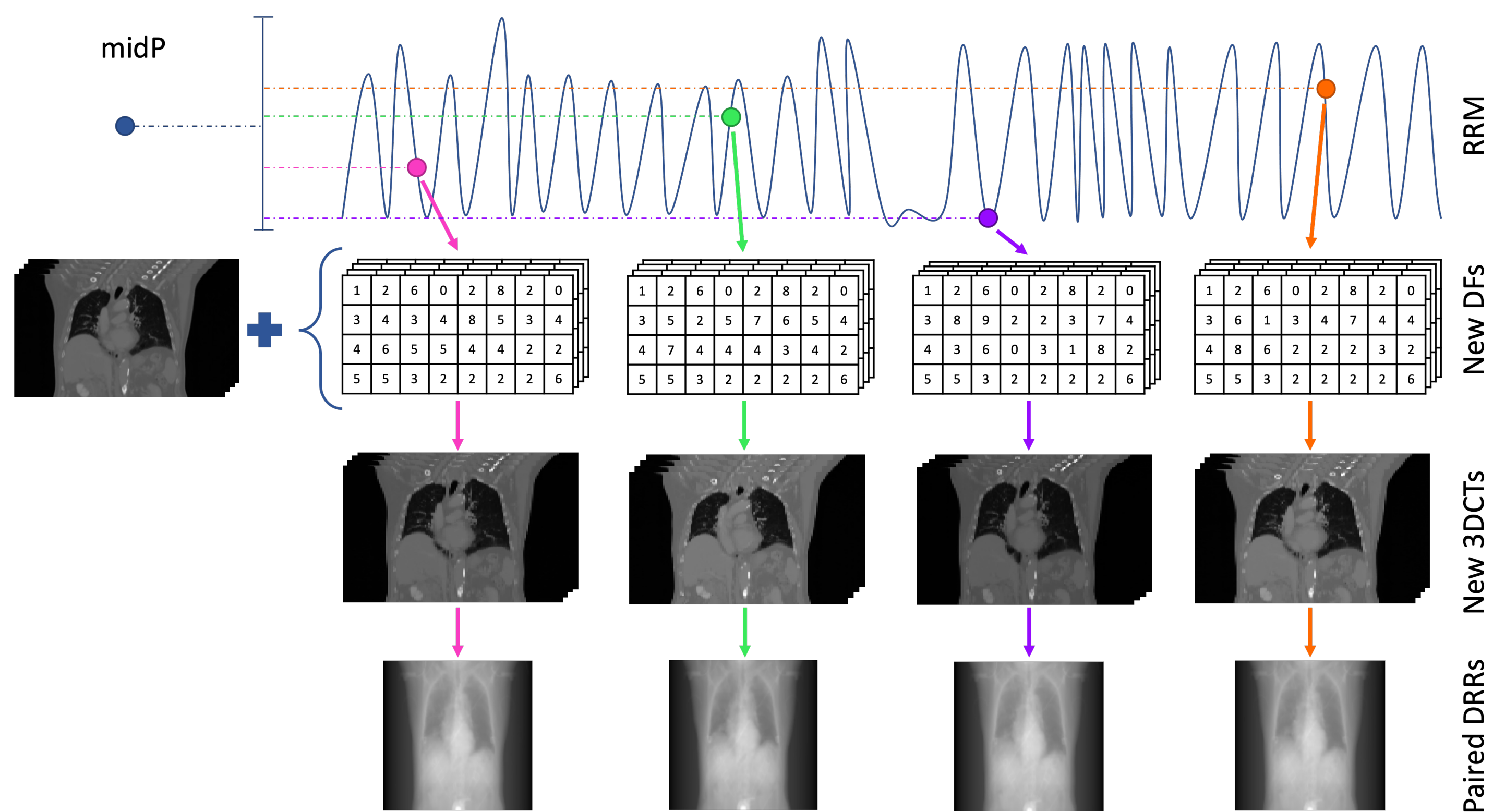


Figure 1: Creation of the dataset using a random respiratory motion (RRM), the corresponding new deformation fields and the midP of the patient to obtain new 3DCTs and paired DRRs.

2. A neural network is used to learn the mapping between the 3DCTs and the paired DRRs. This network, proposed by Henzler et al. in [2], consists of a deep CNN (dCNN) architecture composed of an encoder-decoder structure with skip connections.

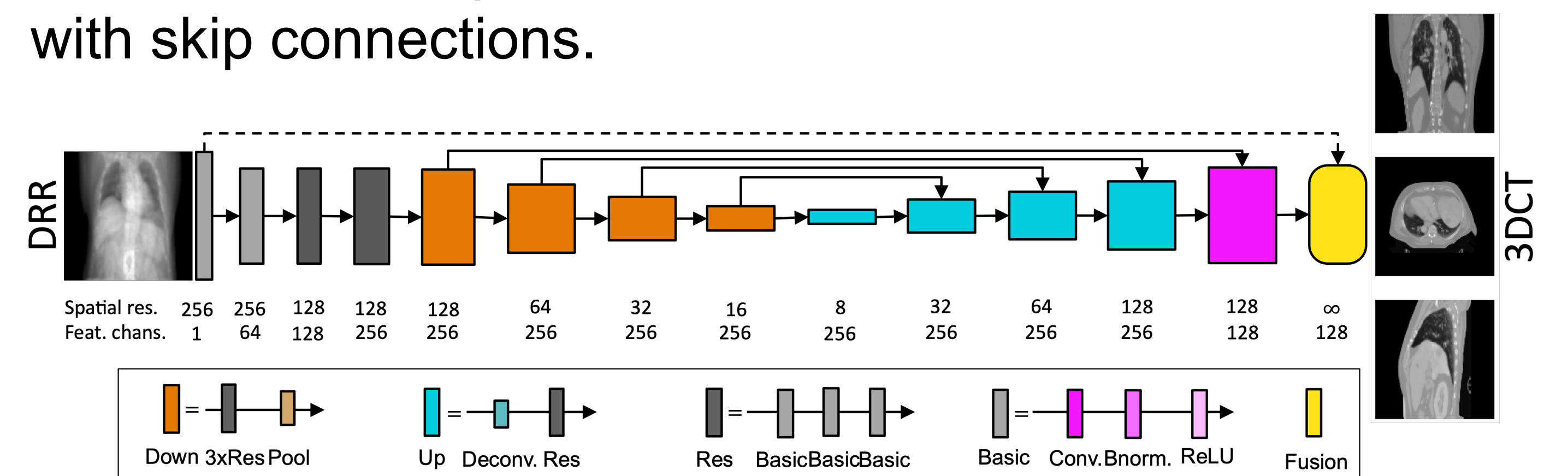


Figure 2: Architecture of the network proposed in [2]. Input is a DRR, and output is a 3DCT.

3. An additional test set consisting of 11 specific images is also generated to better quantify the results. These 11 3DCTs are created at regular intervals between two breathing phases N and $N+1$ (e.g., phases $N.1$, $N.2$, $N.3$, ...) for which the deformation relatively to the reference phase N is known in mm. The NRMSE can then be computed for each of the intermediate image with the reference phase N .

Results

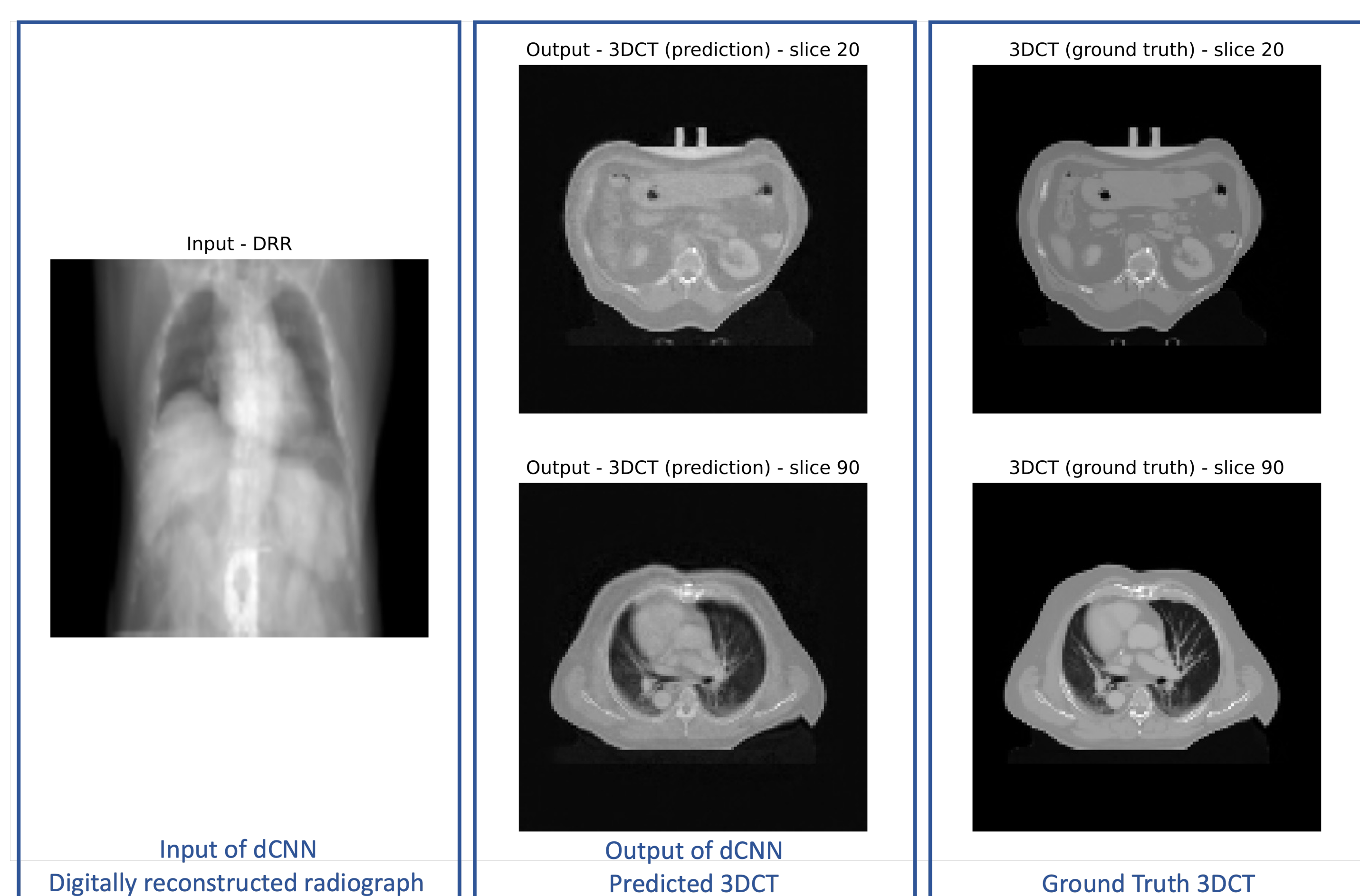


Figure 3: Example of resulting 3DCT created by the dCNN. On the left, the input DRR image, on the center two slices from one predicted 3DCT and on the right the two corresponding slices of the ground truth 3DCT.

Applying the trained dCNN to one DRR of the test set takes less than a second. Figure 3 represents one DRR from the test set (Input of dCNN), two slices of the predicted 3DCT (Output of dCNN) compared with both ground truth slices.

The computation of the NRMSE for each predicted 3DCT images of the additional test set shows that the further the intermediate phase is from the reference phase N , the higher the NRMSE.

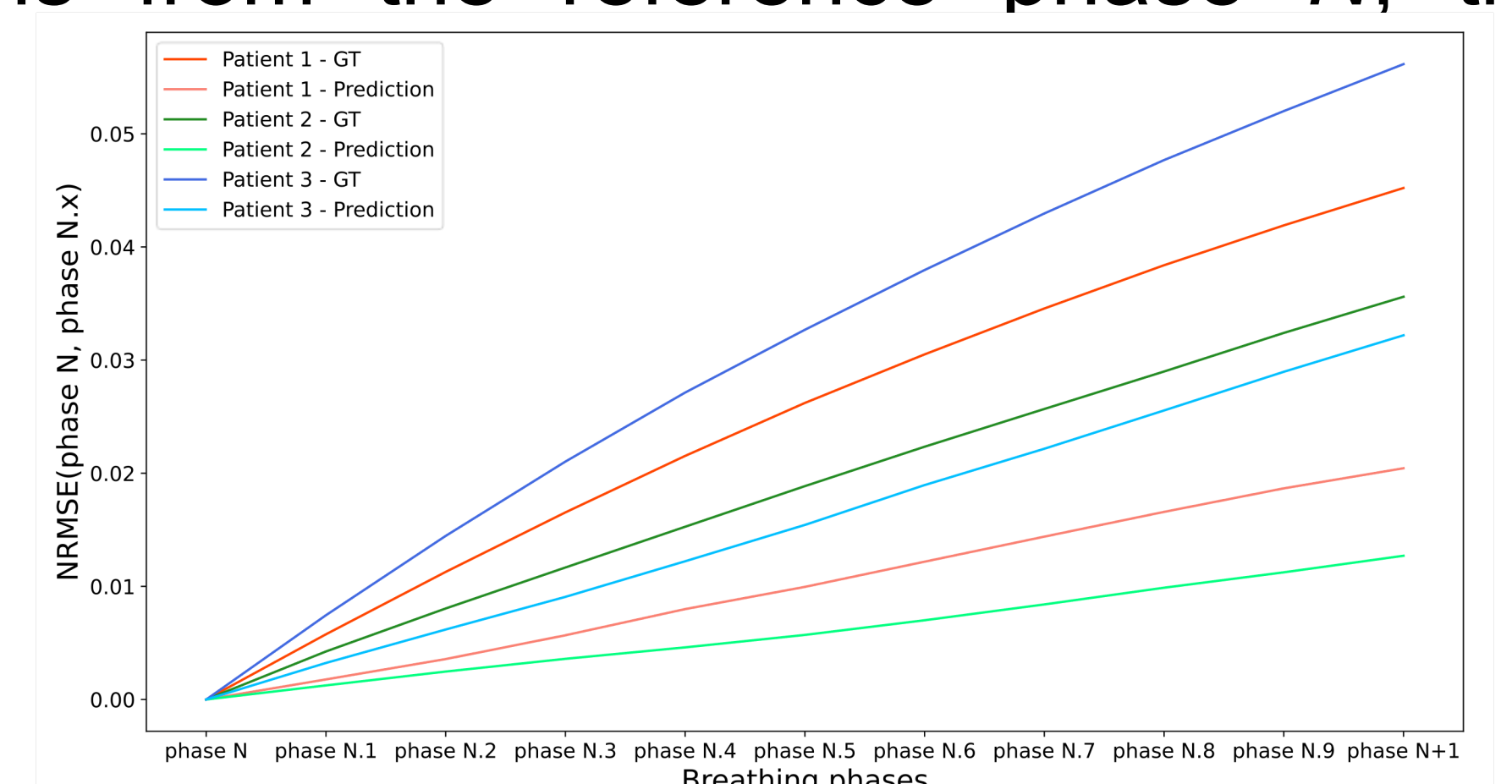


Figure 4: Results of the NRMSE between the 11 intermediate 3DCTs and the reference phase N for each patient.

Conclusion

The proposed method allows the reconstruction of a 3DCT image from a single DRR which can be used in real-time for a better tumor localization and improve treatment of mobile tumors.

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References

- [1] – J. Dhont, S.V. Harden, L.Y.S. Chee, K. Aitken, G.G. Hanna, J. Bertholet, Image-guided Radiotherapy to Manage Respiratory Motion: Lung and Liver, Clinical Oncology, vol. 32, pp. 792-804, Dec. 2020.
- [2] – P. Henzler, V. Rasche, T. Ropinski, T. Ritschel, Single-image Tomography: 3D Volumes from 2D Cranial X-Rays. arXiv:1710.04867v3 [cs.GR] (2018) (available at: <https://arxiv.org/abs/1710.04867>)