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Development of a pipeline for fully automated masking of 4D-MRI images for future hemodynamic analysis

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INTRODUCTION

The need to obtain deeper insights about patient's health from medical images has made the field of automated analysis and extraction a hot research topic in the last years. This thesis aims to create a pipeline for fully automated segmentation of the aorta in four-dimensional (4D) flow magnetic resonance images (MRI). The generated segmentation is further needed to extract hemodynamic information and provide insights on the blood flow and even allow classification of cardiovascular diseases in the future.

CONCEPT

To do so 4D flow MRI images and already segmented computer tomography (CT) images of thirteen patients are used to develop two different approaches for automated segmentation of the aorta. Images from an additional patient are used to compare these approaches to each other using dice score, Hausdorff distance and average symmetrical surface distance. All patients underwent an aortic valve replacement in the same hospital and each a 4D flow MRI image was ac-quired in the pre- and post-operative phase using a SIEMENS Aera 1.5 T scanner.

4D flow MRI are consisting of several 3D images of different timepoints along the heart cycle and contain for each timepoint a magnitude image as well as three velocity images.

The two approaches are visually presented in Fig.1 as well as the developed first draft of a hemodynamic extraction pipeline.

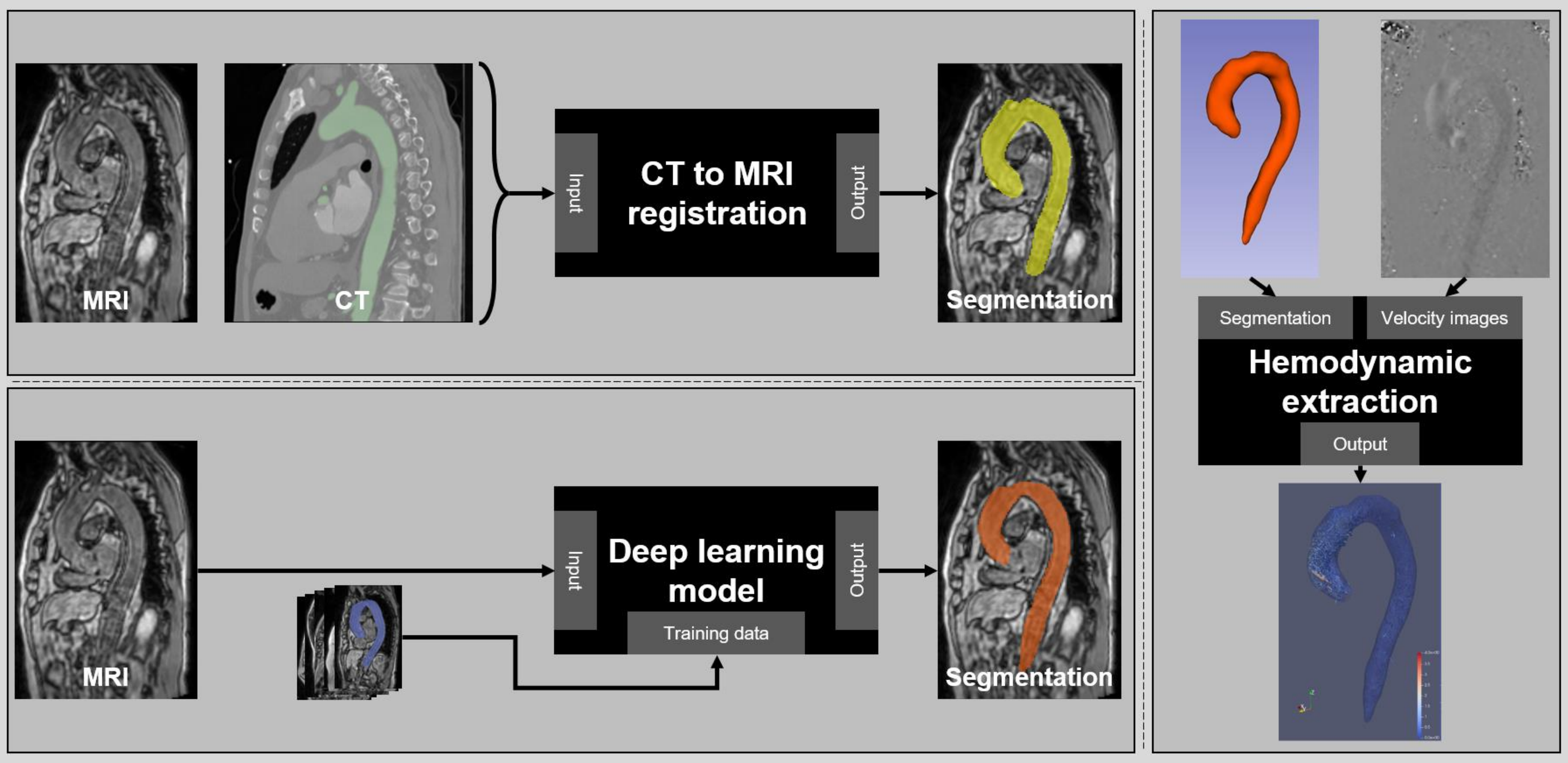

Fig. 1: Visual presentation of the developed approaches for automatic aortic segmentation as well as a first draft of a hemodynamic extraction pipeline. Top: the CT to MRI registration using the 4D flow MRI and the corresponding segmented CT. Bottom: the deep learning approach using separate data to train a model which is further used to predict the segmentation on unseen 4D flow MRI images directly.

CT to MRI registration

The first approach aims to leverage the availability of segmented CT images with corresponding 4D flow MRI images for several patients by registering the CT segmentation to the 4D flow MRI. For this a multi step approach was developed in Python using different image processing and registration algorithms.

The velocity images are pre-processed according to [1] and further thresholded to obtain a binary image which can be registered to the binary CT segmentation of aorta, left ventricle and pulmonary artery using registration methods from the SimpleITK library. After an initial registration, the two binary images are further aligned using a rigid registration while a BSpline registration finalizes the process. The obtained transformations are applied to the CT Aorta segmentation before smoothing and island filter creates the final MRI segmentation.

Deep learning MRI segmentation

The second approach aims to train specific deep learning models to segment the aorta directly in the provided 4D flow MRI images. Since this approach is declared as confidential no detailed methodology is presented here.

RESULTS

The CT to MRI registration approach resulted in a dice score of 0.783 ± 0.016, Hausdorff distance of 23.689 ± 0.580 pixels and average symmetrical surface distance of 1.456 ± 0.053 pixels for the data using for comparison.

The deep learning MRI segmentation approach resulted in a dice score of 0.873 ± 0.003, Hausdorff distance of 9.555 ± 0.445 pixels and average symmetrical surface distance of 0.758 ± 0.014 pixels using the same input data.

Fig. 2 shows the generated segmentation for timestep at peak systole of PATIENT14 preoperational for CT to MRI registration (yellow) and deep learning MRI segmentation (orange) along with the CT (green) and manual MRI segmentation (blue). The CT segmentation shows lot more details due to the higher resolution of the respective image data. The differences between the two developed approaches (yellow and orange) are best visible in the root region of the aorta as well as in the coverage of the descending aorta.

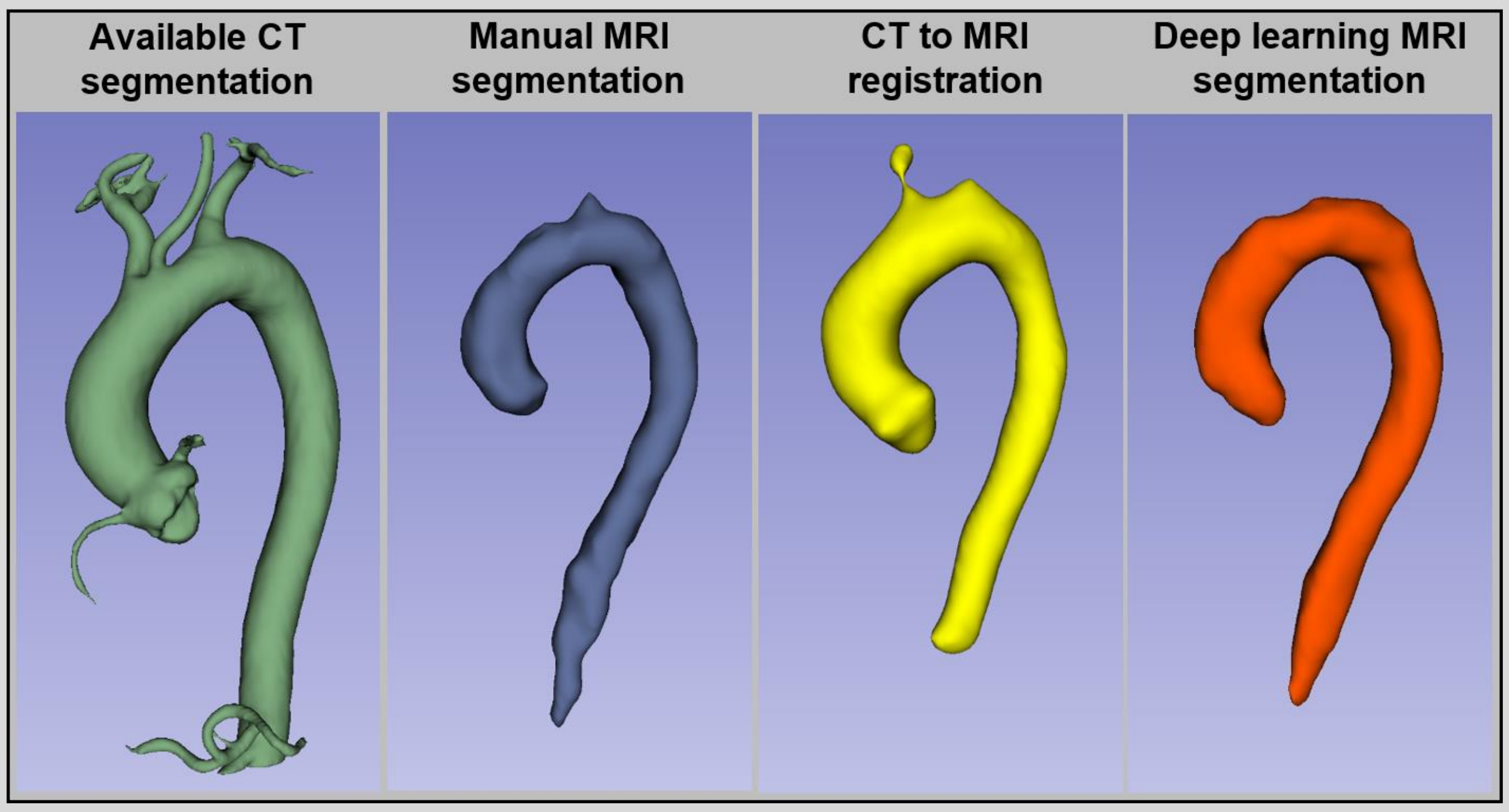

Fig. 2: 3D visualizations of PATIENT14 preoperational image data for timestep at peak systole. From left to right: green the available CT segmentation used for the CT to MRI registration approach, blue the manual segmentation used for calculation of the validation scores, yellow the result of the CT to MRI registration approach and orange the result for the deep learning MRI segmentation approach.

CONCLUSION

The comparison of the two approaches showed that the deep learning MRI segmentation approach reaches the higher scores plus covers the root area and the descending aorta better. This also will lead to more accurate hemodynamic information in the future. Nevertheless, both scores are lower than published results in the literature using big datasets for deep learning such as [2] which reached a dice score of 0.951 using data from 1018 patients.

Due to the unique trained model which can be used for several prediction this approach also needs less time for the segmentation generation itself compared to the registration approach. Of course, the time needed during training exceeds the time needed for a single registration. For the registration approach the field of view is limiting since if the CT do not cover the complete aorta the resulting MRI segmentation will also only cover at most the same field of view even if there a bigger field of view would be present.

On the other hand, the CT to MRI registration do not need - in contrast to the deep learning approach - a big or balanced dataset to be trained on and can work with a small amount of data. Since for this thesis only a very limited number of datasets was available these scores are very specific and not necessarily true for other data especially from different hospitals or scanner. A short robustness evaluation showed that the predictions are affected by artificial modification to the data which could be solved using more training data or data augmentation in the future. Nevertheless, the developed pipelines are ready for upcoming trainings and covers all necessary processing steps to be used in the future.

REFERENCES

[1] Bock, J. et al. (2007) 'Optimized pre-processing of time-resolved 2 D and 3 D Phase Contrast MRI data'

[2] Berhane, H. et al. (2020) 'Fully automated 3D aortic segmentation of 4D flow MRI for hemodynamic analysis using deep learning', Magnetic Resonance in Medicine, 84(4), pp. 2204–2218. doi: 10.1002/mrm.28257

HiD imaging