DEEP LEARNING THORACIC AORTA SEGMENTATION FOR FEATURE EXTRACTION AND HEMODYNAMIC ANALYSIS FROM 3D PC-MRI

Simone Garzia (1,2), Martino Andrea Scarpolini (1,3), Katia Capellini (1), Vincenzo Positano (1), Filippo Cademartiri (4) and Simona Celi (1)

1. BioCardioLab, Fondazione Toscana Gabriele Monasterio, Italy; 2. Department of Information Engineering, University of Pisa, Italy; 3. Department of Industrial Engineering, University of Rome "Tor Vergata", Italy; 4. Clinical Imaging Department, Fondazione Toscana Gabriele Monasterio, Italy

Introduction

The analysis of blood flow and of the morphological features plays an important role in the understanding, evaluation, and prevention of cardiovascular diseases. Currently, three-dimensional (3D) phase contrast (PC) magnetic resonance imaging (MRI) has seen broad clinical acceptance for the visualization and quantitative evaluation of blood flow in the heart, aorta and large vessels [1]. At the same time 3D PC-MRI allows the reconstruction of the anatomical structures. However, the associated segmentation process is high time consuming due to the image's quality and their spatial resolution. Recently, to overcome this limitation, 3D PC-MRI-based segmentations of the aorta using deep learning neural network was proposed [1-2] by processing 1018 and 205 datasets, respectively. In this work, we propose a novel and optimised AI-based multidomain pipeline for the automatic segmentation of the thoracic aorta (TA) from 3D PC-MRI images and for the extraction of the patient-specific hemodynamic and morphological features.

Materials and methods

A collection of 50 3D PC-MRI volumes were acquired by two different clinical scanners: a 3 T Philips Ingenia scanner (Philips Healthcare) (N = 24), and a 1.5 Optim MR450w (GE Medical Systems) (N = 26). The acquired volumes cover the whole thoracic aorta. Magnetic Resonance Angiography (PC-MRA) images were generated for each patient and manually segmented to identify the thoracic aorta (TA). An automated segmentation system, using a 3D U-Net implemented with Tensorflow and Keras libraries, was trained to segment TA from the PC-MRA images. The system was tested using 10 PC-MRA images and generated patient-specific surfaces. A tool was developed using mainly the PyVista library to extract geometric and hemodynamic features from the patient-specific TA geometry and PC-MRI data respectively. Moreover, the tool accounts for a specific module that allows for the computation of MRI Wall Shear Stress (WSS) with different interpolation methods [3]. All the features were mapped for each phase of the cardiac cycle on the segmented volumetric mesh volume and on a customizable number of slices along the centerline of the geometry.

Results

The developed U-Net was tested on a test dataset. A mean DICE score (DSC) of 0.80 was measured. Fig.1d and Fig.1f show respectively the network segmentation and the characteristics that were retrieved for the given geometry. The results indicate how the general trend of the flow curves, flow value ranges and WSS correspond to the physiological examples presented in the literature for TA [4].

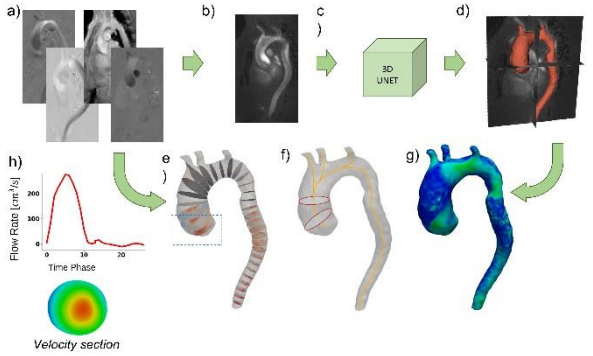

Figure 1: Workflow pipeline: 3D PC-MRI dataset *(a) 3D PC-MRA creation (b). 3D U-Net (c) vessel segmentation (d). Velocity data extraction and mapping at different sections (h), morphological features (f) and WSS mapping (g).*

Discussion

In clinical practice, segmentation processes that are manual or semi-automatic take a lot of time and effort. Furthermore, specialized software that isn't always user-friendly is needed for the examination of hemodynamic characteristics. The suggested pipeline was created as a small, efficient stream of connected, sequential processes that automate and customize the extraction of geometric and hemodynamic parameters as well as the automatic production of vascular surfaces that are patient specific. Segmentation accuracy of the 3D U-Net, even if on a smaller dataset, obtained comparable results to [1] (0.951 DSC) and [2] (0.91 DSC).

References

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