Editorial for "Automatic Time-Resolved Cardiovascular Segmentation of 4D Flow MRI Using Deep Learning"

Flow quantification using 2D phase-contrast cine MRI (PC-MRI) has long been a part of clinical cardiovascular protocols and is extremely useful in the evaluation and quantification of cardiac and valve function (1). Over the last decade, 3D cine PC-MRI (more often called 4D flow MRI) has received increasing research interest and undergone important developments that have brought it closer to widespread clinical adoption (2). Unlike standard PC-MRI, 4D flow MRI offers comprehensive 3D anatomic coverage and flow quantification in all three spatial directions.

This is beneficial for three main reasons. Firstly, it allows visualization of 3D anatomy and flow patterns, using techniques such as streamlines, vector fields, isosurfaces and volume renderings. Secondly, it enables retrospective multiplanar analysis at any location. This simplifies imaging protocols when it is necessary to measure flow in multiple locations, such as in cases of complex congenital heart disease (CHD). Finally, it enables the computation of advanced hemodynamic parameters, such as vorticity, helicity, wall shear stress, kinetic energy, viscous energy loss and blood stasis. Many useful applications of this type of analysis have been demonstrated (2, 3), and further research is warranted to establish its clinical value in different settings.

However, the analysis of 4D flow MRI and the reduction of this high-dimensional data into easily interpretable metrics requires advanced post-processing. An essential step in many applications is the segmentation of the cardiovascular structures under examination. Unfortunately, manual segmentation of time-resolved 3D imaging requires significant expertise and is extremely time-consuming. In practice, automatic segmentation methods are essential. Previous automatic segmentation methods have relied on registration with atlases, which contain information about the expected locations and shapes of the different structures (4). The problem with atlas registration methods is that they are often computationally expensive and may be limited in their ability to generalize to abnormal anatomies. Another way to incorporate data-driven prior information is the use of deep learning, in which neural networks (often a convolutional neural network) are trained to perform the segmentation using a set of labelled data. Deep learning methods are now firmly established as the state-of-the-art in medical image segmentation (5).

In this issue of *JMRI*, the article “Automatic time-resolved cardiovascular segmentation of 4D flow MRI using deep learning” (6) presents a method for segmentation of the

cardiac anatomy from 4D flow MRI. Using 205 4D flow magnitude images with manually corrected, atlas-based ground truth labels, the authors trained a convolutional neural network (CNN) to segment the left and right atria, the aorta and the pulmonary arteries. They used a 3D U-Net, a proven CNN architecture widely used in medical imaging, which they apply to each timeframe independently in order to obtain a time-resolved segmentation. They report very good agreement between the predictions and ground truth labels, with a mean Dice score of 0.908. Agreement was slightly better on the left heart than the right heart, a common finding in cardiac segmentation (7). The proposed CNN can segment all volumetric time frames in only 6 seconds.

This excellent performance was achieved without any task-specific optimizations of the network architecture, and despite the poor contrast inherent to 4D flow magnitude images. Furthermore, training was accomplished with a relatively modest amount of training data, although the dataset was artificially augmented using various transforms to decrease the network's variance. The method is also more comprehensive (in terms of structures labelled) than previous deep learning methods (7, 8). The main use of this segmentation would be in analysis of intracardiac and great vessel blood flow conditions. Segmentation of cardiovascular structures in 3D should also enable simpler automated extraction of standard 2D planes required for routine clinical flow quantification. Finally, comprehensive cardiovascular segmentation results in indirect localization of the cardiac valves, common areas of interest in the evaluation of heart disease using flow quantification.

Segmentation and post-processing remain an important barrier to both further research and the widespread clinical adoption of 4D flow MRI. This study is a very important step towards lowering this barrier, although further work will be needed for more thorough validation. Specifically, future efforts should consider network performance and generalizability in wider data distributions. Although this study included data from patients with heart disease, most of them will have been structurally normal, given the reported demographic data. Future studies should also target structurally abnormal anatomies, such as those found in congenital heart disease, since this is one of the most important applications of 4D flow MRI. It is also important that future work considers more varied data sources, i.e., images from different scanners and centres, with varying acquisition protocols and different image

reconstruction technologies. This additional validation will be essential in the development of robust clinical solutions.

In conclusion, this study presents a deep learning-based automatic segmentation method for 4D flow MRI with promising results. This tool could significantly enhance the utility of 4D flow MRI in both clinical and research settings.

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