Reinforcement machine learning-based aortic anatomical landmarks detection from phase-contrast enhanced magnetic resonance angiography

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Funding Acknowledgements: Type of funding sources: Public grant(s) – National budget only. Main funding source(s): Spanish Ministry of Science, Innovation and Universities; La Marató de TV3

Introduction: Automatic analysis of medical imaging data may improve their clinical impact by reducing analysis time and improving reproducibility. Many medical imaging data, like 4D-flow magnetic resonance imaging (MRI), are often quantified regionally, implying the need for anatomical landmark identification to locate correspondences in the extracted data and compare among patients. Machine learning (ML) techniques hold potential for automatic analysis of medical imaging. Phase-contrast enhanced magnetic resonance angiography (PC-MRA) is a class of angiograms not requiring the administration of contrast agents.

Purpose: We aimed to test whether a machine learning algorithm can be trained to identify key anatomical cardiovascular landmarks on PC-MRA images and compare its performance with humans.

Methods: Three-hundred twenty-three aortic PC-MRA were manually annotated with the location of 4 landmarks: sinotubular junction, pulmonary artery bifurcation and first and third supra-aortic vessels (Figure 1), often used to separate the aorta in sub-regions. Patients included in the training dataset comprised healthy volunteers (40), bicuspid aortic valve patients (141), patients with degenerative aortic disease (60) and patients with genetically-triggered aortic disease (82), all without previous aortic surgery and with native aortic valve. PC-MRA images and manual annotations were used to train a DQN, a reinforcement learning algorithm that combines Q-learning with deep neural networks. The agents can navigate the images and optimally find the landmarks by following the policies learned during training. Data from thirty patients, distributed in terms of aortic condition as the training set, unseen by the algorithm in the training phase, were used to quantify intra-observer reproducibility and to assess ML algorithm performance. Distance between points was used as metric for comparisons, original human annotation was used as ground-truth and repeated-measures ANOVA was used for statistical testing.

Results: Human and machine learning performed similarly in the identification of the sinotubular junction (distance between points of 11.0 ± 8.1 vs. 11.1 ± 8.6 mm, respectively, $p = 0.949$) and first (6.6 ± 3.9 vs. 6.8 ± 5.6 mm, $p = 0.886$) and third (6.8 ± 4.0 vs. 8.4 ± 7.4 mm, $p = 0.161$) supra-aortic vessels branches but human annotation outperformed ML landmark detection in the identification of the pulmonary artery bifurcation (10.2 ± 7.0 vs. 15.2 ± 13.1 mm, $p = 0.008$). Computation time for landmark detection by ML was between 0.8 and 1.6 seconds on a standard computer while human annotation took approximatively two minutes.

Conclusions: ML-based aortic landmarks detection from phase-contrast enhanced magnetic resonance angiography is feasible and fast and performs similarly to human. Reinforced learning anatomical landmark identification unlock automatic extraction of a variety of regional aortic data, including complex 4D flow parameters.

Abstract Figure