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Physics-Informed Emulation of Systemic Blood Circulation

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Extended Abstract

There have been impressive advancements in the application of physics to the modelling of complex cardio-physiological systems, including the dynamics of the blood flow-pressure dependence in the vasculature connected to the heart [1,2]. In principle this affords opportunities for deeper insight into the nature, cause and best treatment of cardio-physiological diseases. However, the corresponding mathematical models typically do not accommodate closed form solutions and entirely rely on numerical simulation procedures instead. This becomes problematic in clinical applications, where model calibration and patient specific parameter estimation are indispensable, calling for repeated forward simulations from the model as part of an iterative optimisation or sampling procedure at substantial computational costs. A potential workaround is to rely on surrogate models which approximate the simulations [3]. The present work introduces an efficient method of predicting fluid dynamics in systemic arterial networks via physics-informed neural networks [4]. In particular, we explore predictions associated with a 1D-fluid dynamics network model [5] that accepts biophysical parameters as inputs, and as such functions as a surrogate model for numerical solvers of the fluid dynamics problem. The focus of our work lies on patient-specific modelling and requires a ventricular geometry profile as well as blood flow measurements in the ascending aorta which define the inlet boundary condition. Once fully trained, the machine learning model predicts blood flow and pressure waveforms in a fraction of the time taken by the numerical solver, allowing for fast uncertainty quantification of the parameters in the system given observational data using Markov chain Monte Carlo. Our inference framework is applied to magnetic resonance imaging (MRI) and magnetic resonance angiography (MRA) data from four patients diagnosed with double outlet right ventricle (DORV) [5], a congenital heart defect where both the aorta and pulmonary artery originate from the right ventricle, instead of the left and right ventricle respectively. We show that our method provides an accurate non-invasive method of predicting blood pressure in the arteries surrounding the heart, accounting for uncertainty in inferred physiological parameters.

References

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