

Bayesian Inference, Emulation and Deep Learning in Cardiac Mechanics

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Extended Abstract

There have recently been impressive developments in the mathematical modelling of cardiac mechanic physiological and pathophysiological processes [1,2]. This allows us to gain, in principle, deeper insight into the state of a variety of cardiovascular diseases. However, model calibration and cardiac mechanic parameter inference for patient-specific diagnosis is challenging due to the high computational costs of the numerical solutions, which have to be carried out repeatedly as part of an iterative optimization or sampling process [3].

For the present study, an image-based method has been developed to estimate the volume of the left ventricular cavity using cardiac magnetic resonance (CMR) imaging data [4]. Deep learning and Gaussian processes have been applied to bring the estimations closer to the cavity volumes manually extracted. CMR data from 339 patients and healthy volunteers have been used to train a stepwise regression model that can estimate the volume of the left ventricular cavity at the beginning and end of diastole. We have decreased the root mean square error (RMSE) of cavity volume estimation approximately to about 8 ml. Considering the RMSE of manual measurements is approximately 4 ml on the same dataset, 8 ml of error is notable for a fully automated estimation method, which needs no supervision or user-hours once it has been trained.

Next, we have focused on inferring patient-specific cardiac mechanic parameters, which are critical for understanding myocardial functions and performance. Our work is primarily motivated to determine the passive stiffness of the myocardium (the muscular tissue of the heart) from the measurement of the left ventricle (LV) volume, which is crucial for diagnosing cardiac physiological conditions. We adapt Gaussian processes to construct a statistical surrogate model for emulating LV cavity volume during diastolic filling to overcome this challenge. As the LV volumes, obtained at different time points in diastole, constitute a time series, we apply the Kronecker product trick to decompose the complex covariance matrix of the whole system into two separate covariance matrices, one for time and the other for biophysical parameters. To proceed towards personalized health care, we integrate patient-specific LV geometries into the Gaussian process emulator using principal components analysis. Utilizing the deep learning neural network for extracting time-series left ventricle volumes from CMR scans as described above (in the second paragraph), Bayesian inference is applied to determine the posterior probability distribution of critical cardiac mechanic parameters. Tests on real-patient data illustrate the potential for real-time estimation of myocardial properties for clinical decision-making. These advancements constitute a crucial step toward clinical impact, offering valuable insights into posterior uncertainty quantification for complex cardiac mechanics models.

References

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