INTEGRATING CFD AND DEEP LEARNING FOR ENHANCED HEMODYNAMIC PREDICTIONS IN THE LEFT VENTRICLE.

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Introduction

In recent years, cardiovascular disease has remained the leading cause of death worldwide, encouraging the exploration of innovative approaches to address this challenge. In particular, the integration of new engineering perspectives has significantly enhanced cardiovascular research. Techniques such as computational fluid dynamics (CFD) have been used to study hemodynamics within the heart [1], while machine learning tools have been applied to classify and predict these diseases using medical data [2]. Our study builds on these advances by combining left ventricular simulations from commercial CFD software (Star-CCM+) with deep learning architectures based on autoencoders. This combination aims to create high quality, converged databases efficiently and at low computational cost.

Methods

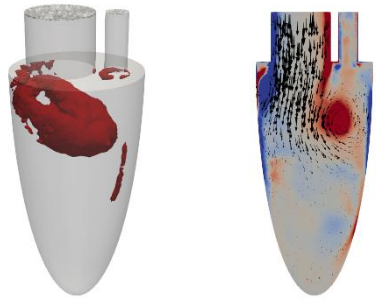
We began our research by using a CFD code to generate a detailed, high-dimensional database of the hemodynamics within the left ventricle using Star-CCM+ software. We modeled the blood as an incompressible laminar fluid and implemented specific inlet and outlet conditions corresponding to the mitral and aortic valves, respectively, based on medical data. In addition, a moving wall boundary condition replicated the ventricular pumping action during a cardiac cycle. These conditions were essential to accurately capture key flow features such as the primary vortex ring. Our simulations were thoroughly validated against reference data and subjected to extensive convergence studies.

After generating a sufficiently converged database, we employed a symmetric autoencoder with a prediction layer in latent space. The encoder consists of three-dimensional convolutional layers, paired with max-pooling to reduce spatial dimensions while improving learning capabilities. It then transitions to dense layers to further compress the data into a 32-state latent dimension, a technique adapted from Hamidreza et al [3]. In the latent space, we applied a matrix rotation method to predict subsequent temporal states training the frequency λ^k for each state couples.

$$\begin{bmatrix} z_{i+1}^{k} \\ z_{i+1}^{k+1} \end{bmatrix} = \begin{bmatrix} cos(\lambda^k \Delta t) & -sin(\lambda^k \Delta t) \\ sin(\lambda^k \Delta t) & cos(\lambda^k \Delta t) \end{bmatrix} \begin{bmatrix} z_{i}^{k} \\ z_{i}^{k+1} \end{bmatrix} \quad (1)$$

Results

From the CFD simulations, we extracted data for four heart cycles equispaced in time. Figure 1 illustrates some of these results, including vorticity and velocity fields that highlight the dynamics within the ventricle, such as the vortex ring and blood recirculation. We used this comprehensive database to train our neural network, allowing it to encode the data, predict future time instances in latent space, and reconstruct these new snapshots back into the original space. Our results show that our model can predict over a third of a cardiac cycle with an absolute error of less than 15%. This demonstrates the potential of combining CFD simulations with deep learning techniques to improve predictive accuracy in cardiovascular research, and offers promising directions for future investigation.



a) b)

Figure 1: Left ventricle simulation results for t = 0.20 s: a) Q-criterion isosurface, b) Contours of the plane-normal vorticity field with xy velocity vector.

We use this database to train our neural network to be able to encode the data, predict following time instances in the latent space, and reconstruct this new snapshots to the original space. Our results show that we are able to predict more than a third of a cycle with an absolute error lower than 15%.

References

1. Zingaro et al, arXiv:2110.02114, 2021.
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