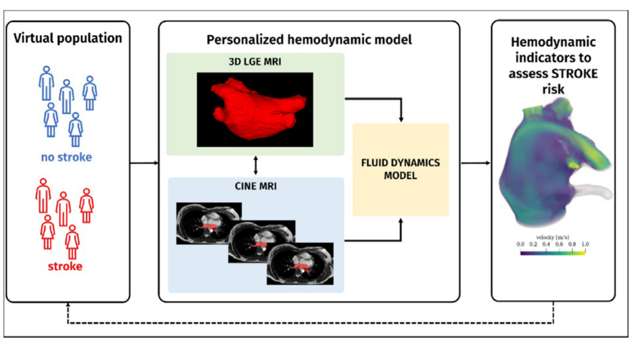
Objective: To quantify thrombotic stroke risk using hemodynamic indicators for disturbed blood flow in the left atria by means of personalized fluid dynamics modeling.
Methods: Our patient cohort consists of subjects who experienced a thrombotic stroke and those who did not. In a novel approach, we merge static 3D LGE MRI images with CINE MRI data to accurately construct the LA endocardial geometry over time. This allowed us to construct a framework to simulate, quantify and compare left atrial hemodynamics in these patients in terms of multiple indicators such as flow stasis, time-averaged wall shear stress, relative residence time, and mean age of blood particles (see Figure).
Results: Patients who experienced stroke exhibited regions of the left atrium with stagnant blood flow, especially in the LAA. The comparison of mean age of blood particles and flow stasis revealed a distinct division between the no-stroke and stroke groups; the stroke group exhibited larger values for both indicators, promoting optimal conditions for clot formation. Furthermore, we investigated the importance of including the atrial contraction in the model in terms of stroke risk assessment. We found that the usage of CINE MRI data in our personalized fluid dynamics model is crucial since it significantly improves our results when compared with a simplified model with a rigid atrial endocardium.
Conclusion: Fluid dynamics modeling showed that stroke risk is strongly correlated with an abnormal rinsing of the left atrium, promoting the stagnation of particles, especially in the LAA. The development of personalized frameworks, with the inclusion of functional data as the endocardial displacement, can distinctively quantify atrial hemodynamic anomalies, allowing for accurate prediction of stroke risk.



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LONG-TIME MACHINE-LEARNING PREDICTION OF COMPLEX SPATIOTEMPORAL DYNAMICS DURING FIBRILLATION IN LIVE EXPLANTED PIG AND HUMAN HEARTS

Flavio H. Fenton; Shahrokh Shahi; Ilija Uzelac; Shahriar Iravanian; Neal K. Bhatia; Michael Burke; Anand D. Shah; Faisal M. Merchant and Elizabeth Cherry

Background: Fibrillation is characterized by complex spatiotemporal electrical dynamics often driven by the continuous creation and annihilation of reentrant waves. While it has been shown that this dynamics can be chaotic and deterministic, it is hard to describe its evolution, which could help define for example the best times to defibrillate using the lowest energy. To date it has been impossible to predict the dynamics of reentrant waves once initiated in space, not only in experiments but also in simulations using the most up-to-date ionic cell models.
Objective: To accurately forecast the complex dynamics of cardiac fibrillation in time and space several periods in advance.
Methods: Using an autoencoder echo state network (AE-ESN) approach introduced earlier, we present a novel integrated deep-learning architecture, called convolutional echo state network (Conv-ESN), in which an echo state network (ESN) is incorporated into a convolutional autoencoder (CAE) architecture. Using spatiotemporal signals from optical-mapping experiments and/or numerical simulations, the CAE model is constructed and trained to learn a compressed representation of the samples in its bottleneck layer. The ESN, placed between the trained encoder and decoder, receives the extracted features and predicts the representation for the next time step, which then is passed to the trained decoder to reconstruct the spatiotemporal dynamics.
Results: We applied our developed Conv-ESN approach to both 2D simulated data of the 41-variable O'Hara-Virag-Varro-Rudy ventricular model and high-spatiotemporal-resolution experimental datasets obtained using optical mapping from live explanted pig and human hearts during fibrillation, representing complex cardiac spatiotemporal electrical dynamics. After training, our technique could successfully forecast these complex spatiotemporal dynamics over a clinically relevant prediction horizon, from about 600 ms for short training datasets of 5s of VF up to about 2 s for long training datasets of 25s. Figure shows AP and APD from 2 sites from optical mapping human VF data (prediction in black), and MAE from all pixels during the same time.
Conclusion: We show for the first time that it is possible to predict the complex spatiotemporal dynamics generated by multiple reentrant waves (both in simulations and experiments) using a novel deep-learning technique. Accurate predictions of the spatiotemporal patterns can be made up to 8-10 dominant-frequency periods in advance.