Improving Numerical Model Specifications for Cardiac Electrical Excitation

Abstract

Mathematical cardiac electrical excitation models describe the electrical activity of the heart. They play a crucial role in understanding its electrophysiological behaviour and form the foundation of computational cardiac medicine for instance by predicting arrhythmias. This research proposes the integration of a small neural network to enhance the accuracy and efficiency of a simple numerical cardiac model which approximates components of cardiac excitation dynamics and explore the systems behaviour. This will hopefully lead to improvements in simulation speed and accuracy. This study may help to develop more efficient cardiac simulations with potential future applications in real-time patient monitoring and treatment.

Background and literature review

Numerical models describing electrical impulses of cells including the Hodgkin-Huxley model, developed for nerve cells and the Luo-Rudy models for cardiac cells have advanced the understanding of electrophysiology [1, 2]. They describe variables associated with cell membrane potential and ionic concentrations as a set of partial differential equations (PDEs) [3]. Comprehensive models such as the Ten Tusscher-Nobel-Nobel-Panfilov model or the Iyer-Mazhari-Winslow (IMW) model use many variables; for instance, the IMW model uses 67 variables [4]. This provides mathematical interpretability and computational consistency. However, these highly non-linear systems suffer from great computational cost which restricts their real-time applicability [5]. Simpler models such as the Minimal Model by Bueno-Orovio et al. [6] improve computational tractability but show limitations in capturing complex dynamics. They make assumptions about observable biological phenomena and the associations they represent.

Recent advancements in artificial intelligence (AI), particularly neural networks (NNs), offer opportunities to refine these models. Machine learning (ML) models use a larger set of parameters to model relationships between in and outputs directly and statistically but suffer from poor extrapolation. NNs don't contain primary information of underlying physical or mathematical laws governing the system, a significant weakness [5]. Recent literature describes how neural network NNs have been adapted to improve large numerical electrophysiological cardiac models to improve computational efficiency [7, 8].

This research aims to explore combining a simple cardiac model such as the Minimal Model by Bueno-Orovio which uses 4 variables with a small neural network and observe how the systems behaviour changes. It is hoped that the use of small NNs can improve computational efficiency while preserving the physiological accuracy of the numerical model.

Research Objectives

- Develop small NNs-architectures to approximate key components of cardiac excitation models.
- Integrate these NNs into existing numerical frameworks describing cardiac excitation.
- Validate the proposed models against high-fidelity simulations and experimental data.
- Assess trade-offs between model size, accuracy, robustness, computational cost and interpretability.

Research Methodology

- Language selection: A JIT-compiled language such as Julia will be selected.
- Model Selection: An simple model such as the Minimal Model by Bueno-Orovio will be selected [6, 9].
- NN Design: Small NNs will be designed to approximate specific excitation components.
- Training and Optimisation: Networks will be trained using supervised learning with datasets generated from high-fidelity simulations.
- Integration and Evaluation: The trained networks will be embedded into numerical solvers and tested for accuracy, stability, and computational efficiency.
- Validation: Performance will be assessed through comparison with traditional models and experimental data from literature.

Expected Outcomes and Output

- Faster numerical simulations with reduced computational complexity.
- Retention of physiological accuracy in excitation dynamics.
- Insights into advantages and trade-offs between NN enhanced models and classic numerical models.
- Poster presentation at the Laidlaw Scholars conference/ report.

Workplan

- Before summer research period: Familiarise with selected programming language. Start literature review.
- Week 1: Literature review and selection of baseline cardiac models.
- Week 2-3: Development and training of NNs.
- Week 4: Integration of NN into numerical solvers.
- Week 5: Validation, testing, and refinement of models.
- Week 6: Documentation.
- After summer research period: Preparing conference poster.

Impact and Benefits

While the proposed project is fundamental basic research there are several potential future applications if an improved model can be designed:

- Faster more accurate cardiac simulations could potentially enhance monitoring and diagnosis of patients with heart conditions.
- AI-driven cardiac models could in the future enable patient-specific simulations offering personalised medicine.
- Efficient models could be eventually integrated in wearable medical devices.
- Small NNs could help reduce computational costs.
- Speeding up simulations of cardiac models used for drug safety testing (assessing proarrhythmic risks) may reduce pharmaceutical development cost, reduce the need for animal testing and accelerate marked introduction.
- Integration of AI-driven models into medical decision making however raises regulatory and ethical consideration to ensure models are transparent.
- Faster efficient and therefore cheaper models could improve access to diagnostic tools in resource poor settings.

The project sits at the intersection of multiple disciplines:

- Biomedical engineering – development of AI-enhanced numerical models.
- ML – designing small NNs or PINNs networks for time-series modelling.
- Applied mathematics – solving PDEs governing cardiac excitation.
- Medical research – ensuring clinical relevance for future applications.
- Ethics – addressing AI transparency, bias and medical safety standard issues.

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