EP-Net 2.0: Out-of-Domain Generalisation for Deep Learning Models of Cardiac Electrophysiology

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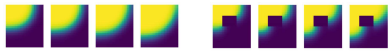
Problem

How can we predict the evolution of cardiac electrical activity:

- System is highly complex and nonlinear;
- Model must be data-driven so that it can be adapted to individuals;
- We have access only to partial measurements of the system;
- Presence of scar or of multiple onsets changes electrical dynamics.



Approach

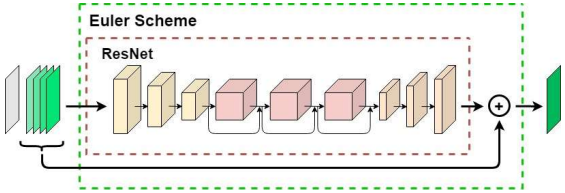
In this work, we use:

- **Mitchell-Schaeffer model** (two variables);
- Tissue slab of 24×24 mm^2 with an ischaemic (non conductive) region (scar);
- **Observation operator $\mathcal{H}$ to replace the hidden variable h ;**
- **$\mathcal{L}_{scar}$ loss to include the constraint corresponding to the presence of the scar.**

We consider the **statistical learning problem** as:

$$minimize_{\theta}\ \mathrm{E}_{V\in Dataset}\ \mathcal{L}\left(V,\mathcal{H}(X^{\theta})\right), subject\ to\ \frac{dX_t}{dt}=F_{\theta}(X_t),\ X_0=g_{\theta}(V_{-k})$$

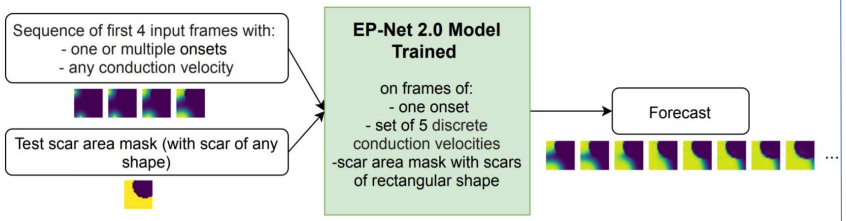
where operators F, g are implemented via ResNet model, and solve it via **training our EP-Net 2.0.**



Figures: The EP-Net 2.0 architecture. It has 5 input frames (mask frame plus 4 frames of transmembrane potential) and 1 output frame of forecast.

Results

After training of **EP-Net 2.0** on data with base conditions we obtain **the model which is able to predict any given cardiac electrical activity** simulated via Mitchell-Schaeffer model*. The figure below presents the **general experimental setting** used in our work:



*You can try the performance of our trained model via a Jupyter notebook on our github page. To access use the QR code on the top of this poster or direct link (https://github.com/KVict-new/EP-Net-2.0)

Generalisation Ability of EP-Net 2.0: Scars of Various Shapes and Multiple Onsets.

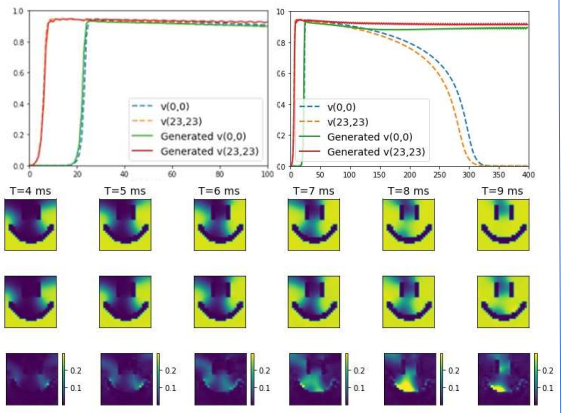
In order to evaluate the model capability to generalise to conditions outside the training environment, we performed two types of tests:

- with scars with different shapes (when training was performed only with rectangular shapes);
- with multiple onset (when training considered only one onset).

The tables and figures below demonstrate that the model shows good results for forecasting on the different scar shapes and of multiple depolarisation waves on one cardiac slab tissue, which is essential to capture correctly for ventricular tachycardia simulation.

Tables: Relative mean-squared error (MSE) of transmembrane potential forecasting and comparison with the baseline model (LBM method with time step equal to 1.0)

	MSE (6 ms)	MSE (12 ms)	MSE (24 ms)
Baseline	$1.1*10^{-1}$	$2*10^{-1}$	$3*10^{-1}$
EP-Net 2.0 (one onset)	$1.8*10^{-4}$	$4.45*10^{-4}$	$6.8*10^{-4}$
EP-Net 2.0 (multiple onset)	$4.7*10^{-4}$	$5.8*10^{-4}$	$6.9*10^{-4}$
EP-Net 2.0 (complex scar)	$4.6*10^{-4}$	$1.9*10^{-3}$	$6.36*10^{-3}$



Figures: (Bottom) Results of trained EP-Net 2.0 model (9 ms of forecast). (Top) Transmembrane potential graph at the leftmost upper point (0, 0) and the rightmost bottom point (23, 23) in the slab with different forecasting horizons.

Limitations

Although our approach can achieve compelling results, there are still limitations:

- Model does not work properly on thin scars
- Model has been trained only to model depolarization of the cardiac slab tissue and cannot predict its repolarisation

Conclusion

In this work, we show :

- EP-Net 2.0 DL model to learn the cardiac EP dynamics in presence of complex initial boundary conditions (like scar area of any form, multiple onsets and various conduction velocities);
- Great generalisation ability of EP-Net 2.0 to unseen complex conditions.

We believe that in future our approach can help upgrade and personalise mathematical model via additional data.

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