Deep learning-based reduced order models in cardiac electrophysiology

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S1 File.

Features maps. Here we report the feature maps of the DL-ROM neural network. In Figs 1 we show the feature maps of the first convolutional layer of the encoder function $\sigma_1(W_1^k * \mathbf{u}^1(\boldsymbol{\mu_{test}}) + b_1^k)$, for $k = 1, \ldots, 8$, in the DL-ROM neural network when the FOM solution for the testing-parameter instances $\boldsymbol{\mu}_{test} = (3.75, 3.75)$ cm and $\boldsymbol{\mu}_{test} = (6.25, 6.25)$ cm at $t = 0.2$ ms, are provided as inputs. At this stage, the feature maps retain most of the information present in the FOM solution. Moreover, by considering the two testing-parameter instances, we observe the translation equi-variance property [1] that convolutional layers hold when applied to the part of cardiac tissue corresponding to the scar. Moving to deeper layers, feature maps become increasingly abstract, and less visually interpretable; however, the extracted high-level features are still related both to the ischemic region and the electrical activation pattern.

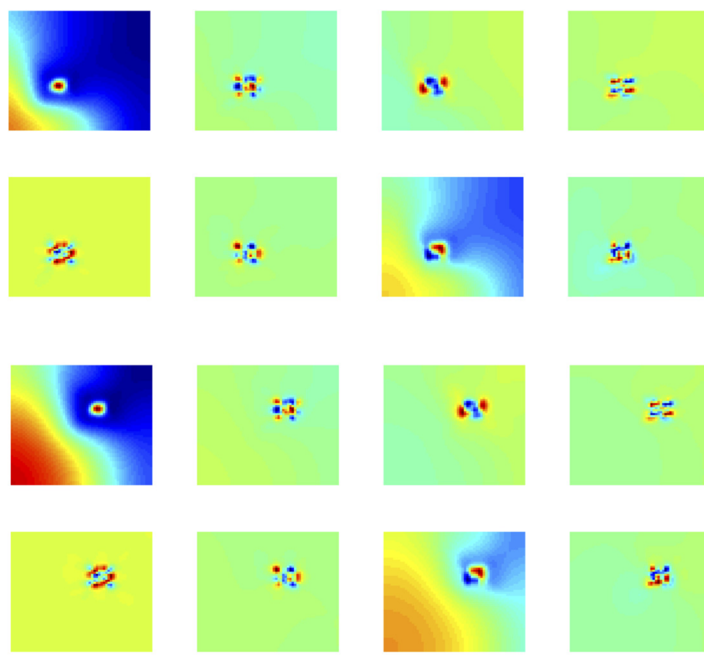

Fig 1. Test 1: activations of the first convolutional layer of the encoder function for a testing-parameter instance. Feature maps of the first convolutional layer of the encoder function in the DL-ROM neural network for the testing-parameter instances $\boldsymbol{\mu}_{test} = (3.75, 3.75)$ cm (top) and $\boldsymbol{\mu}_{test} = (6.25, 6.25)$ cm (bottom) at $\tilde{t} = 0.2$ ms.

References

1. Goodfellow I, Bengio Y, Courville A. Deep Learning. MIT Press; 2016. Available from: `http://www.deeplearningbook.org`.