Active learning based Cardiac Tissue Parameter Estimation for Personalized model exploiting predictive uncertainty

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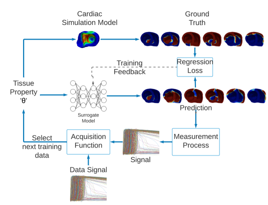
Background: Personalized cardiac models are crucial intervention tools for a multitude of cardiac health issues. As cardiac simulations become more complex and expensive, machine learning (ML) models demonstrated the potential to enable efficient model personalization and cardiac tissue parameter estimation. Prior studies however depend on "globally" accurate ML models trained with large simulation data to predict tissue parameters. Such a global ML model is not only expensive to train, but its success also relies on the assumption that real-world data would fall within the range of the training data.

Objective: Our goal is to establish a novel active-learning method for cardiac parameter estimation by steering the training of the ML model towards the unknown region of interest in the parameter space.

Method: We train a ML model on a small labeled dataset that maps tissue properties to observable data. During testing, the model's uncertainty in predicting the difference between the signal and its estimation is used to optimize for the tissue parameters. As a by-product, the training data is augmented with new data, at regions of interest, from the optimized space. The iterative process results in an efficient parameter estimation model that needs significantly less simulation data than existing methods. Furthermore, the ML model is steered to be locally accurate around the given data.



Block Diagram of the proposed method

Results: We evaluated the presented approach on two datasets: spatially varying cardiac tissue properties (>1000 locations) and another with low dimensional properties (∼20) that specify the location of activations. The results demonstrated improved accuracy of parameter estimation compared to a global-ML model, and this performance gap increases as the test data lie further away from the data used to train the global model.

Conclusion: We introduce and demonstrate that personalizing cardiac models can be improved by using an active-learning method based on predictive uncertainty