

Fast Characterization of Inducible Regions of Atrial Fibrillation Models with Multi-Fidelity Gaussian Process Classification



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Goal

Given: atrial model on the geometry $\Omega \subset \mathbb{R}^3$ and atrial surface $\mathcal{S} \subset \Omega$.

For any $\mathbf{x} \in \mathcal{S}$, determine if a pacing protocol applied at \mathbf{x} induces an Atrial Fibrillation event ($y = 1$) or not ($y = 0$). The mapping $F: \mathcal{S} \rightarrow \{0, 1\}$, $\mathbf{x} \mapsto y$ is called **inducibility map** [2].

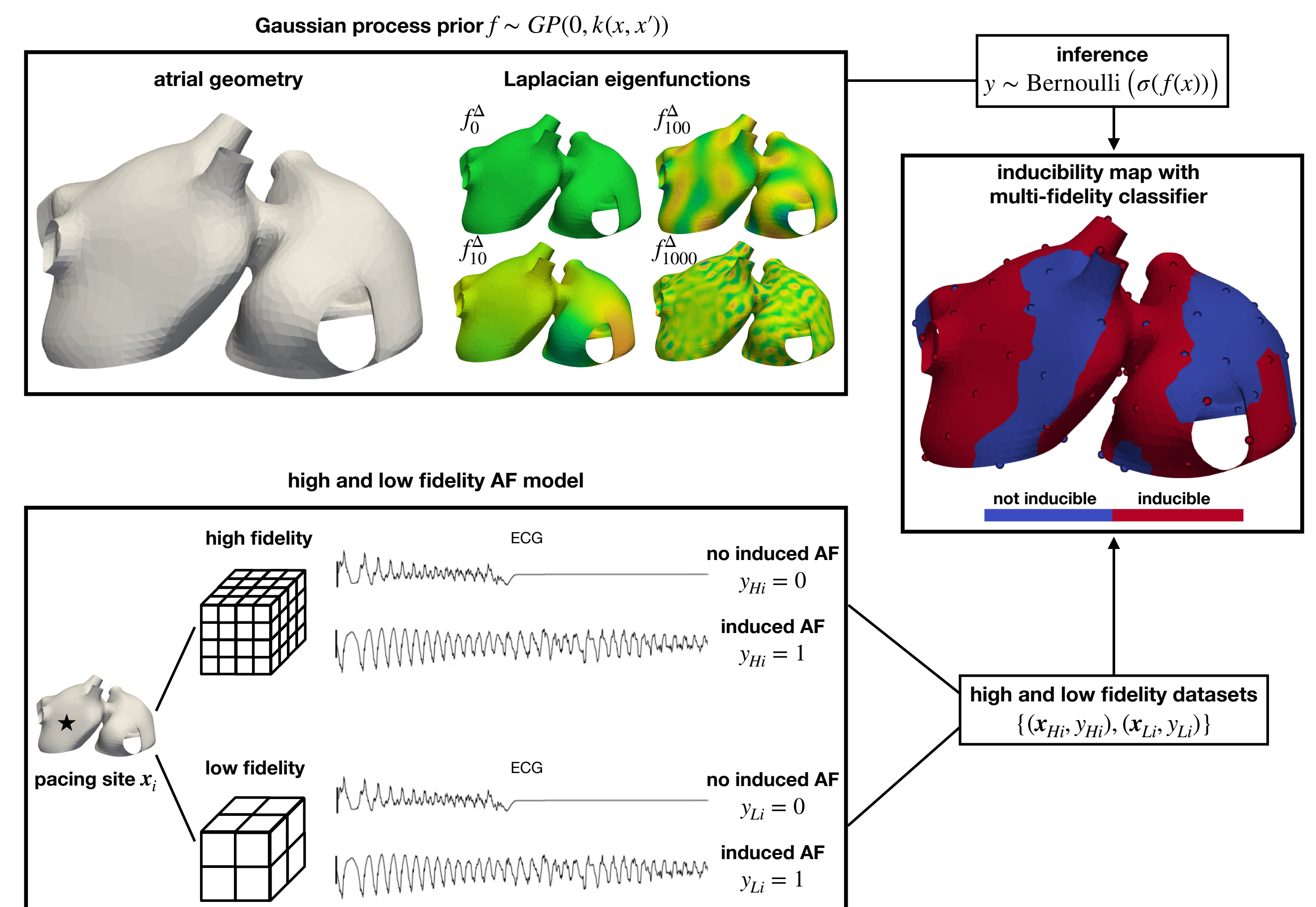
Method

- High fidelity model and **low fidelity model based on a coarser discretization** of the monodomain equation in space and time. The low fidelity model is **16 times faster than the high fidelity one**
- Multi-fidelity Gaussian Process classification [3]
 - Train set $\{(\mathbf{x}_{Hi}, y_{Hi})_{i=1}^{N_H}, (\mathbf{x}_{Li}, y_{Li})_{i=1}^{N_L}\}$
 - Latent functions $f_H(\mathbf{x}) = \rho f_L(\mathbf{x}) + \delta(\mathbf{x})$
 - Gaussian Process (GP) priors on f_L and δ , and prior distributions over ρ , θ_L and θ_H

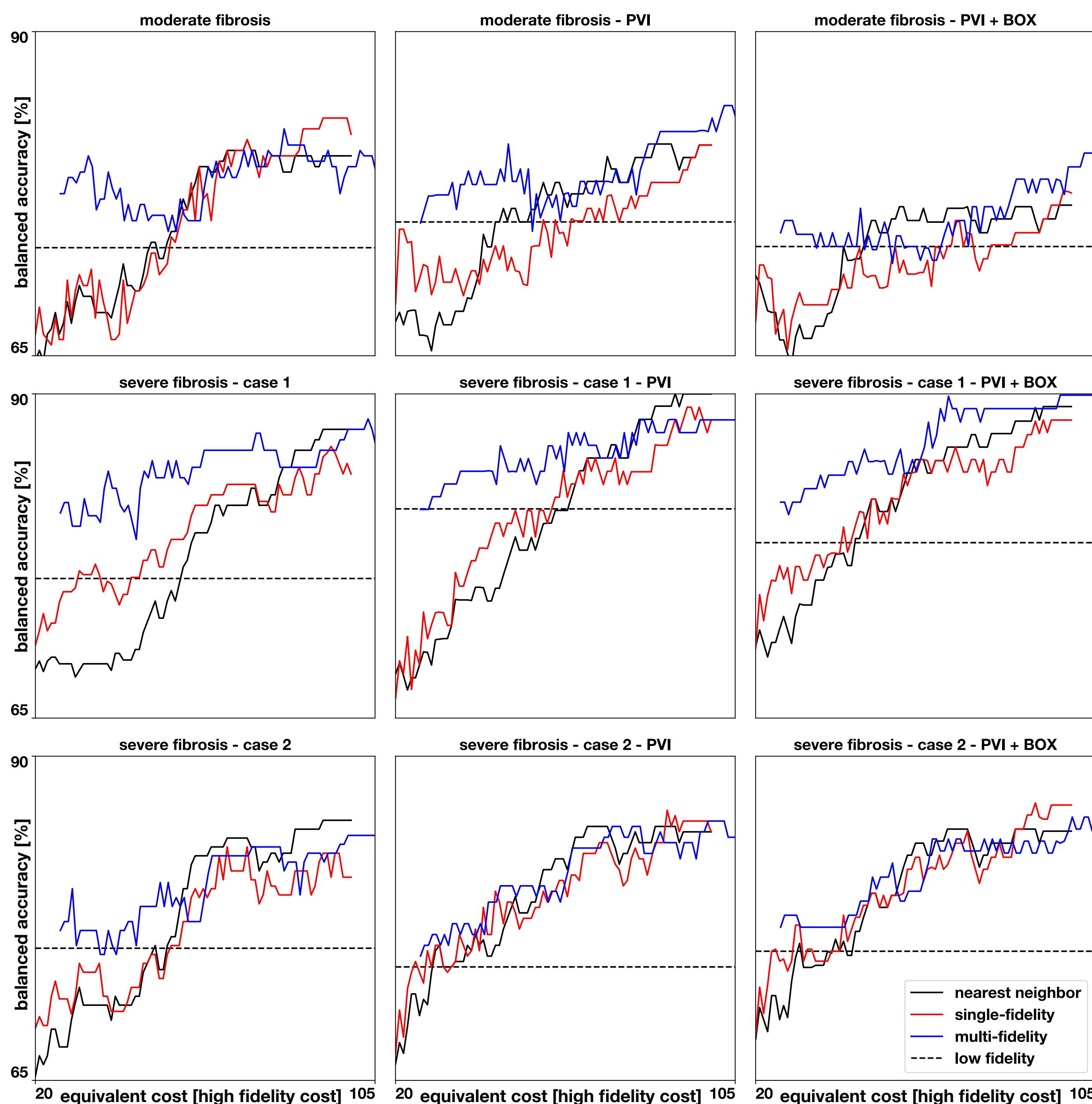
$$f_L \sim \mathcal{GP}(0, k(\mathbf{x}, \mathbf{x}'; \theta_L))$$

$$\delta \sim \mathcal{GP}(0, k(\mathbf{x}, \mathbf{x}'; \theta_H))$$

- Matérn kernel k on the manifold based on the eigenpairs of the Laplacian [1]
- Bayesian inference of the posterior distributions of ρ , θ_L , θ_H and $\mathbf{f} = \begin{bmatrix} f_L \\ f_H \end{bmatrix}$
- Posterior distribution of the predictive latent function $\mathbf{f}^*(\mathbf{x}^*)$ at a new location \mathbf{x}^* obtained by conditioning on the train data
- Prediction $y^* = \sigma(\mathbf{f}^*(\mathbf{x}^*))$, where $\sigma: \mathbb{R} \rightarrow [0, 1]$ is the sigmoid function

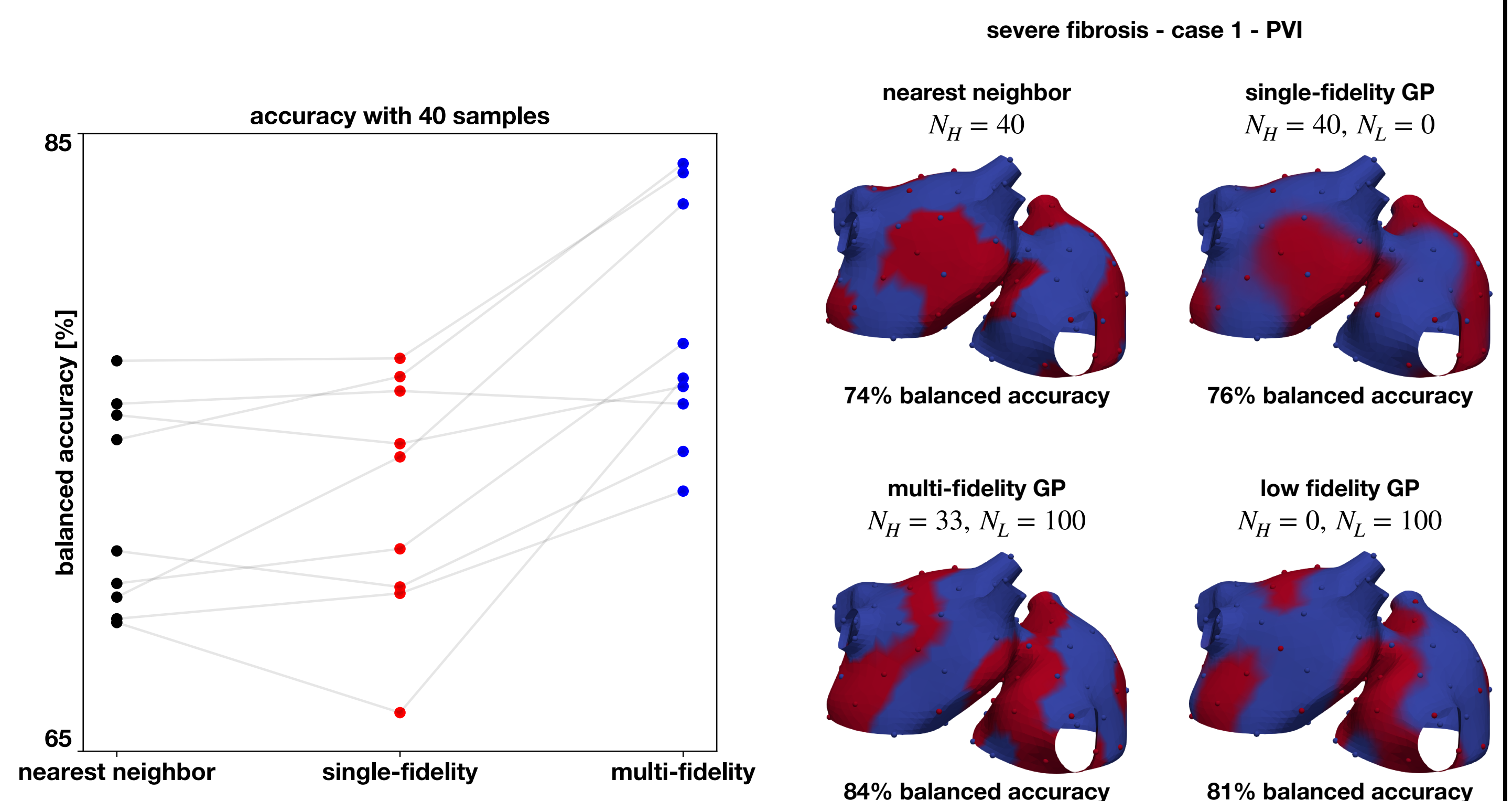


Numerical Results



- 9 atrial models
- Comparison of 4 classifiers for N_H ranging from 20 to 100
 - nearest neighbor
 - single-fidelity GP
 - multi-fidelity GP with $N_L = 100$
 - low fidelity GP with $N_H = 0$ and $N_L = 100$
- Balanced accuracy computed on a test set

For small train sets the multi-fidelity GP classifier performs better than the single-fidelity GP and the nearest neighbor classifiers.



- In clinical studies a typical choice is $N_H = 40$ high fidelity simulations
- The multi-fidelity classifier with $N_H = 33$ has equivalent cost

On average, with the multi-fidelity GP classifier we gain 5.4% accuracy compared to the single-fidelity GP classifier and 5.7% accuracy compared to the nearest neighbor classifier.

Conclusion

- It is worth taking advantage of the cheap low fidelity model in a multi-fidelity framework
 - higher accuracy can be achieved with fixed computational cost
 - a target accuracy can be achieved with lower computational cost
- The multi-fidelity strategy is interesting for clinical applications, where patient-specific results need to be delivered within practical time constraints
- **The multi-fidelity GP classifier is efficient in evaluating the effect of personalized ablation therapies**

References

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- [2] L. Gander, S. Pezzuto, A. Gharaviri, R. Krause, P. Perdikaris, and F. Sahli Costabal. Fast Characterization of Inducible Regions of Atrial Fibrillation Models with Multi-Fidelity Gaussian Process Classification. *Frontiers in Physiology*, 13:757159, 2022.
- [3] F. Sahli Costabal, P. Perdikaris, E. Kuhl, and D. E. Hurtado. Multi-Fidelity Classification using Gaussian Processes: Accelerating the Prediction of Large-Scale Computational Models. *Computer Methods in Applied Mechanics and Engineering*, 357:112602, 2019.