First International Conference on Emerging Technologies in Computational Science for Industry, Sustainability and Innovation – M2P 2023
May 30th - June 1st, 2023, Taormina, Italy

COMPUTATIONAL MEDICINE: DATA-DRIVEN AND PHYSICS-BASED TOOLS FOR CLINICAL APPLICATIONS

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ABSTRACT

Clinical treatment is moving towards a personalized approach that can be achieved or integrated with computational modeling. However, for this to be possible, very efficient and cost-effective tools and products must be developed. Due to the computational cost of forward models, obtaining model parameters is unfeasible or very costly in biophysical applications, restricting clinical use. Current parameter estimation methods use stochastic or variational data assimilation techniques, which involve expensive forward model evaluations. This requires alternative methodologies for near-real-time model predictions. Data-driven modeling and machine learning offer a promising research direction. These methods provide reliable surrogates of considered phenomena based on enough data at a lower computational cost. Standard black-box function approximations, like Artificial Neural Networks, require substantial data collecting. Physics-informed machine learning can help overcome the limitations of traditional machine learning approaches. Using synthetically generated data, first attempts have been made to apply these models to Computational Fluid Dynamics [1] and biomechanics. However, more research is needed to measure their robustness and accuracy. In model order reduction, a well-known data-driven strategy to reduce the complexity of the underlying partial differential equations is Proper Orthogonal Decomposition (POD), which however still requires a substantial number of input snapshots (produced by the high-fidelity model) to assure a satisfying output [2]. Novel contributions combine POD and Gaussian Process Emulators to circumvent this constraint. In this mini-symposium, we will bring together applied mathematicians and biomedical engineering experts who study personalized computational medicine technologies. The mini-symposium will allow worldwide academics and entrepreneurs to share their latest results, collaborate, and network, supporting future advancements and expanding the international research network in this emerging subject.

REFERENCES

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