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DOMAIN-AWARE MULTIFIDELITY LEARNING FOR DESIGN OPTIMIZATION

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Accurate physics-based models are essential to the design and optimization of engineering systems, to compute key performance indicators associated with alternative design solutions. The implementation of high-fidelity models in simulation-based design optimization poses significant challenges due to the relevant computational cost frequently associated with their execution. However, real world engineering systems can rely on the availability of multiple models or approximations of their physics, representations characterized by different computational complexity and accuracy. Those alternative models can be cheaper to evaluate and can thus be exploited to enhance the efficiency of the optimization task. Multifidelity methods allow to combine multiple sources of information at different levels of fidelity, potentially exploiting the affordability of low fidelity evaluations to massively explore the design space, then enriching the accuracy through a reduced number of high-fidelity queries [1]. Many multifidelity optimization methods combine data from multiple models into a probabilistic surrogate, frequently delaying the identification of promising design alternatives that could rather be more efficiently captured if domain specific expertise were also used to inform the search [2]. To address this challenge, we present original domain-aware multifidelity frameworks to accelerate design optimization and improve the quality of the solution. In particular, our strategy is based on an active learning scheme that combines data-driven and physics-informed utility functions, to include the expert knowledge about the specific physical phenomena during the search for the optimal design. This allows to tailor the selection of the physical model to evaluate and increase the efficiency of the learning process, using at best a limited amount of high-fidelity data to sensitively improve the design solution. We discuss several applications of the proposed framework for aerospace design optimization problems, considering atmospheric flight at low and high altitudes for both aeronautics and space applications.

REFERENCES

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