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MULTI-FIDELITY ACTIVE LEARNING FOR SHAPE OPTIMIZATION PROBLEMS AFFECTED BY NOISE

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A multi-fidelity (MF) active learning method is presented for design optimization problems based on noisy evaluations of the performance metrics. The method is intended to accurately predict the design performance while reducing the computational effort required by simulation-driven design (SDD) to achieve the global optimum. A generalized MF surrogate model is used for design-space exploration, exploiting an arbitrary number of hierarchical fidelity levels, i.e., performance evaluations characterized by different accuracy, coming from different models, solvers, or discretizations.

The overall MF prediction is evaluated as a low-fidelity trained surrogate corrected with the surrogates of the errors between consecutive fidelity levels [1]. The surrogate models use stochastic radial basis functions (SRBF) with least squares regression and in-the-loop optimization of hyperparameters to deal with noisy training data. The method chooses new training points in an adaptive manner, selecting both the design points and the required fidelity level via an active learning approach. This approach is based on the lower confidence bounding method, which combines performance predictions and their associated uncertainty to select the most promising design regions. Subsequently, the fidelity level to be sampled is decided considering the cost-benefit ratio associated with its choice for the training.

The method's performance is evaluated using analytical tests and SDD cases based on (noisy) computational fluid dynamics (CFD) simulations, namely the shape optimization of a NACA hydrofoil and the DTMB 5415 destroyer [2]. Wherever possible, statistical results based on several realizations of the test cases are used to assess the effects of the random noise. Different fidelity levels are provided by CFD with adaptive grid refinement. Under the assumption of a limited budget of function evaluations, the proposed MF method shows better performance in comparison with models trained on high-fidelity data only.

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