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A Comparative Investigation of a new Multi-fidelity Bayesian Optimization Framework for Surrogate-Based Design Optimization

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ABSTRACT

The Gaussian process is a frequently used machine learning model in surrogate-based design optimization and it can even be superior with some improvements, such as the applications of multi-fidelity and Bayesian optimization. Therefore, finding an efficient multi-fidelity Bayesian optimization framework is of great importance. In this respect, the current work tries to introduce an improved multi-fidelity Bayesian optimization framework and compares it with the other frameworks (Ficini et al., 2021; Moss et al., 2020). The present algorithm consists of outer and inner loops. The Bayesian optimization continues until the convergence criterion is calculated from the optimization of the black-box function executed for each outer loop. Subsequently, the optimum point is added to the dataset. Meanwhile, an acquisition function such as lower-confidence-bound (LCB) or max-value entropy search (MES) is calculated to get the candidate design point(s) in each inner loop. The optimums of the black-box or acquisition function are obtained by a technique consisting of the genetic algorithm and a gradient-based method. The benchmark study is carried out by using some analytical functions as observation methods recommended by Mainini et al. (2022) and Paleyes (2019). In addition, the performances are evaluated by the procedure and the criteria proposed by Mainini et al. (2022). The frameworks are examined in a way that different multi-fidelity models, linear and nonlinear auto-regressive Gaussian processes, are tested to represent proper analytical functions. Secondly, the other acquisition functions are inquired by adapting them to each multi-fidelity framework. Finally, the performances the acquisition functions used with different frameworks are analysed for different computational cost ratios (η) between the low-accuracy and high-accuracy observation methods. As shown in Figure 1, the present framework (MF-BO) with MES is superior to MUMBO, but LCB(MF-BO) does not converge according to the RRMSE criterion.

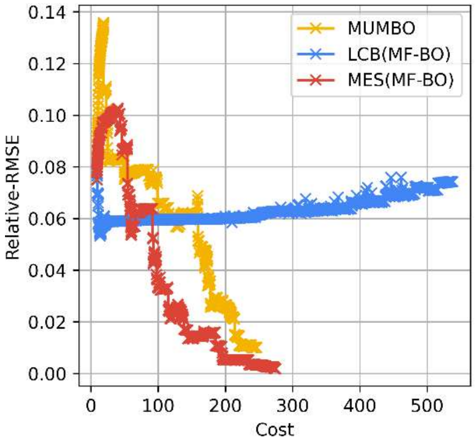

Figure 1: Relative-RMSE of two-fidelity (η=0.1) auto-regressive Gaussian process model vs. computational cost in each iteration to optimize 3D Hartmann Function.

References

S. Ficini, R. Pellegrini, A. Odetti, A. Serani, U. Iemma, M. Caccia, M. Diez. Uncertainty Quantification of an Autonomous Surface Vehicle by Multi-fidelity Gaussian Process. In COUPLED 2021-IX International Conference on Coupled Problems in Science and Engineering, 2021.

L. Mainini, A. Serani, M. P. Rumpfkeil, E. Minisci, D. Quagliarella, H. Pehlivan-Solak, S. Yildiz, S. Ficini, R. Pellegrini, F. Di Fiore, et alia. Analytical Benchmark Problems for Multifidelity Optimization Methods. Research workshop AVT-354 on Multifidelity Methods for Military Vehicle Design, 2022.

H. B. Moss, D. S. Leslie, P. Rayson. Mumbo: Multi-task max-value Bayesian optimization. InMachine Learning and Knowledge Discovery in Databases: European Conference, ECML PKDD 2020, Ghent, Belgium, September 14–18, 2020, Proceedings, Part III 2021.

A. Paleyes, M. Pullin, M., Mahsereci, N. Lawrence, J. Gonzalez. Emulation of Physical Processes with Emukit, Second Workshop on Machine Learning and the Physical Sciences, NeurIPS, 2019.