Adaptive Multifidelity Shape Optimization based on Noisy CFD Data

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ABSTRACT

The aim of metamodelling in CFD-based automatic shape optimization is to replace expensive CFD computations in the optimization process by evaluations of a cheap surrogate model, created from a limited training set of simulations. Multi-fidelity metamodels [1] make this process even more efficient by basing a part of the metamodel on inexpensive low-fidelity simulations and introducing a correction based on a few high-fidelity simulations. To adaptively define the training sets of the low-fidelity and correction metamodels, different sampling strategies can be used [2].

However, the CFD results on which the metamodels are based contain numerical errors. Especially if new grids are generated for each simulation, the numerical errors for two similar geometries may be different. These differences manifest themselves as numerical noise in the training sets for the metamodels. Adaptive sampling strategies which determine new training points by evaluating the uncertainty of the metamodel, may react to this noise by placing new points in noisy regions, rather than in places where the overall metamodel is unreliable. This deteriorates the metamodel quality.

In this paper, we study multifidelity metamodeling approaches which eliminate a part of the numerical noise in the metamodel. For metamodels based on Dynamic Radial Basis Functions [3], this is obtained by introducing less RBF degrees of freedom than training points and computing the RBF fits using least-squares approximation. The number of DoF will be defined adaptively as the training progresses, based on a metric like leave-one-out cross-validation combined with in-the-loop optimization of the metamodel.

Applications to the shape optimisation of 2D NACA four-digit airfoils and a destroyer-type vessel will be presented. The CFD simulations are based on a Reynolds-averaged Navier Stokes solver that uses adaptive grid refinement to create the meshes.

REFERENCES

[1] Pellegrini, R., Iemma, U., Leotardi, C., Campana, E.F., and Diez, M. Multi-fidelity Adaptive global metamodel of expensive computer simulations. *2016 IEEE Congress on Evolutionary Computation* (2016).

[2] Pellegrini, R., Serani, A., Diez, M., Wackers, J., Queutey P., and Visonneau, M. Adaptive sampling criteria for multi-fidelity metamodels in CFD-based shape optimization. *ECCOMAS CFD 2018*, Glasgow, UK (2018).

[3] Volpi, S., Diez, M., Gaul, N.J., Song, H., Iemma, U., Choi, K.K., Campana, E.F., and Stern, F. Development and validation of a dynamic metamodel based on stochastic radial basis functions and uncertainty quantification. *Struct. Multidiscipl. Optim.*, Vol. **51**(2), pp. 347–368, (2015).