

Local Decomposition Method based on physical criterion for meta-modeling with aeronautics applications

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Abstract:

The conception of new civil aircraft relies increasingly on numerical simulations, in particular Computational Fluid Dynamics (CFD). However, simulations may run for several hours over hundreds of processor cores. Due to the short time period available in an industrial design phase, only few simulations taken into account dozen of variables can be computed. The aim of this presentation is to introduce the process of a global surrogate model capable of substituting the CFD part, while minimizing the number of simulations with an acceptable accuracy to perform sensitivity analysis, uncertainty quantification or multiphysics coupling.

Such a problem consists in modeling a vector function $f: \Gamma \subset \mathbb{R}^d \rightarrow \mathbb{R}^p$ where Γ is the parameter's domain, d the number of variables and p the size of the output, typically the mesh size of a CFD simulation. The method for building surrogate models is summarized in Figure 1 and is implemented in the CERFACS in-house code JPOD. First a Design of Experiment (DOE) method produces a set of training snapshots. Then, the dimension of the problem is reduced using Proper Orthogonal Decomposition (POD) that transforms a vector function f in M scalar functions a_k , also called reduced coordinates, such as $f(x) = \sum_{k=1}^M a_k(x) \times \phi_k$, with $\phi_k \in \mathbb{R}^p$ the orthogonal basis vectors. A Gaussian Process Regression (GPR) model is built for each reduced coordinate a_k and resampling techniques can be applied to improve the accuracy.

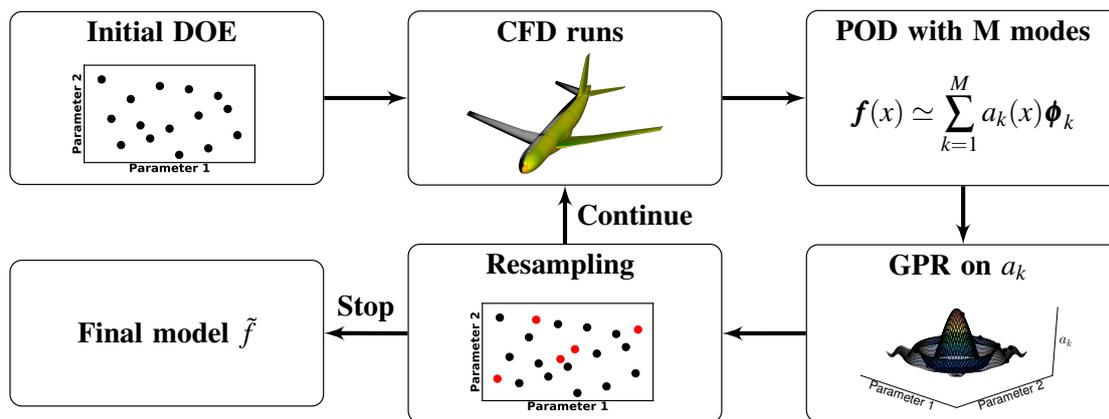


Figure 1: JPOD metamodeling process

This classical approach exhibits satisfactory results for continuous or weakly discontinuous output. However, large discrepancies occur when the problem presents different physical regimes with respect to the inputs [1], such as flight missions. A particular interest is given to problems with

transition from linear to nonlinear response, very common in aerodynamics with shock waves. The original Local Decomposition Method (LDM), based on mixtures of experts [2] and local reduced-order bases [3], has been developed to address this problem. It has started with an observation: using classical approach, residual discontinuities occur in the predictions with inputs far from nonlinear flow regime. The primary reason is that discontinuities appear as dominant structures in the POD bases. Therefore, small errors in the reduced coordinate modeling propagate these discontinuous structures in the predictions.

The LDM improved the aforementioned classical approach by replacing the global POD with several local POD, in order to associate a POD subset to each physical regime. First, a shock sensor is computed for all snapshots which are then clustered into subsets using an unsupervised learning algorithm. Second, the POD is computed on each subset and GPR models are built on the corresponding local reduced coordinates. Third, a supervised learning algorithm (Gaussian Process Classification) is used to map the subsets with the corresponding input spaces. This final step allows predicting the cluster to which the unknown points to compute belong.

This approach has been tested for an analytical case, the Burger equation, and a more complex and realistic case, a 2D flow around RAE2822 airfoil with 4 parameters of large variation. A clear improvement in the quality method is observed in the Figure 2 for the LDM for both mean root mean square error ($\langle \text{RMSE} \rangle$) and mean predictivity coefficient ($\langle \text{Q}^2 \rangle$).

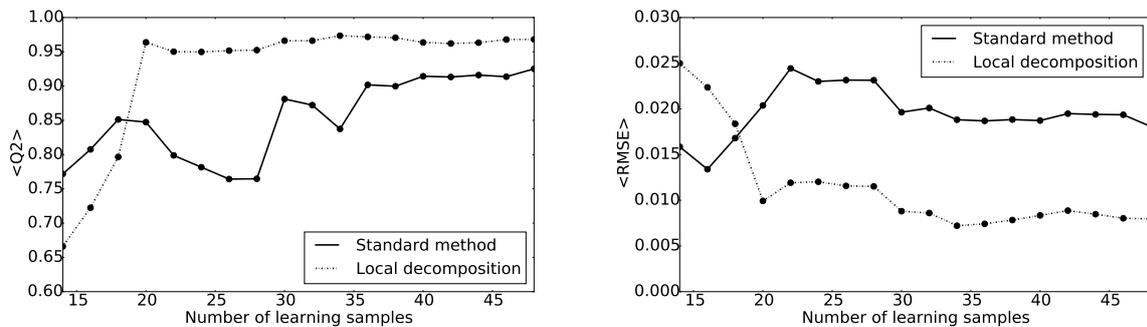


Figure 2: $\langle \text{Q}^2 \rangle$ and $\langle \text{RMSE} \rangle$ of the pressure signal at the extrados of RAE2822 airfoil

Finally an adaptive resampling technique has been developed, based on local decomposition, by computing new points only in the regions corresponding to nonlinear physical regimes. First results for the RAE2822 case seem promising with a reduction of the RMSE of about 20%.

References

- [1] E. Iuliano and Domenico Q. Proper Orthogonal Decomposition, surrogate modelling and evolutionary optimization in aerodynamic design. *Computers & Fluids*, June 2013.
- [2] R. P. Liem et al. Surrogate models and mixtures of experts in aerodynamic performance prediction for aircraft mission analysis. *Aerospace Science and Technology*, 43, June 2015.
- [3] K. Washabaugh et al. Nonlinear model reduction for cfd problems using local reduced-order bases. *42nd AIAA Fluid Dynamics Conference and Exhibit*, 2012.

Short biography – Romain Dupuis received his engineering degree in Energy, Fluid and Thermal Power from Mines Nancy and Cranfield University in 2014. After a year working in the automotive industry, he started his PhD thesis in October 2015, funded by IRT Saint Exupéry and in collaboration with Airbus. His PhD topic focuses on aerothermal coupling using dimension reduction and surrogate models with application to aeronautics problems.