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Global aerodynamic design optimization based on data dimensionality reduction

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Abstract In aerodynamic optimization, global optimization methods such as genetic algorithms are preferred in many cases because of their advantage on reaching global optimum. However, for complex problems in which large number of design variables are needed, the computational cost becomes prohibitive, and thus original global optimization strategies are required. To address this need, data dimensionality reduction method is combined with global optimization methods, thus forming a new global optimization system, aiming to improve the efficiency of conventional global optimization. The new optimization system involves applying Proper Orthogonal Decomposition (POD) in dimensionality reduction of design space while maintaining the generality of original design space. Besides, an acceleration approach for samples calculation in surrogate modeling is applied to reduce the computational time while providing sufficient accuracy. The optimizations of a transonic airfoil RAE2822 and the transonic wing ONERA M6 are performed to demonstrate the effectiveness of the proposed new optimization system. In both cases, we manage to reduce the number of design variables from 20 to 10 and from 42 to 20 respectively. The new design optimization system converges faster and it takes 1/3 of the total time of traditional optimization to converge to a better design, thus significantly reducing the overall optimization time and improving the efficiency of conventional global design optimization method.

1. Introduction

With the development of high performance computing, aerodynamic shape optimization has been widely used in the process of aircraft shape design. Aerodynamic shape optimization based on Genetic Algorithm (GA) is distinguished from regular optimization by its focus on finding the maximum or minimum over all input values, as opposed to finding local minima or maxima. However, it still faces many challenging problems and issues. One of them is the large num-

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ber of shape Design Variables (DV) which lead to prohibitive computational cost. Another one is that high-fidelity aerodynamic model based on the Reynolds-Averaged Navier-Stokes (RANS) equations takes up the majority of the overall optimization time.

There are several approaches to deal with large number of design variables. Gradient-based methods with adjoint gradients,[1] which can efficiently compute gradients without restriction of the number of design variables, have been widely used in aerodynamic shape optimizations.[2,3] However, gradient-based methods are more likely to find local optima especially in multi-modal problems. On the other hand, gradient-free methods are more likely to find the global optimum, but the computational cost is higher when dealing with large numbers of variables. Currently, there are two possible solutions widely used to reduce the number of DVs. One is variable screening[4,5] which can identify some design variables that contribute to the objective function most and leave out the others to reduce the dimensionality of design space. However, this method will reduce the size of design space and even cannot find the optimal designs that can only be found in original design space. The other is data dimensionality reduction method which can reduce the number of DVs under the precondition of maintaining the generality of original design space. For example, Ghisu et al.[6] applied Principal Components Analysis (PCA) to reduce the number of DVs in the design of a core compression system for turbofan engine. Similarly, Ghoman et al.[7,8] studied the application of Proper Orthogonal Decomposition (POD) in multi-disciplinary optimization framework. Toal et al.[9,10] used POD to filter badly performing geometries and thus reduced the design space. Gao et al. used PCA in many-objective engineering problems.[11] Besides, some nonlinear data dimensionality reduction methods have been gradually used in aerodynamic shape optimization, such as Generative Topographic Mapping (GTM) studied by Viswanath et al.[12], Active Subspace Method (ASM) used by Lukaczyk et al.[13] and ISOMAP applied by Qiu.[14]

As for the second problem, namely high computational cost of the CFD solver, there are several methods used in aerodynamic shape optimization. Among all of them, the Surrogate-Based Optimization (SBO)[15–17] is the most popular since it can build an inexpensive response surface approximation of high-fidelity model. However, when dealing with large number of DVs, the surrogate model approaches become prohibitive since the large number of samples for surrogate model training and tuning processes require huge computational time. Another approach is proposed by LeGresley and Alonso.[18–20] They applied POD to build Reduced Order Model (ROM) for an inverse design optimization problem. Then Bui-Thanh et al.[21,22] extended gappy POD to the inverse airfoil design problem which demonstrated a great simplification. Qiu and Bai[23] proposed POD-surrogate ROM to predict stationary flow fields, which also reduced the computational time in optimization.

The focus of this paper is to reduce the overall computational cost and improve the efficiency of global optimization by data dimensionality reduction method—POD. For this purpose, typical surrogate-based optimization system is introduced in Section 2. In Section 3, POD is applied in dimensionality reduction of design space and acceleration approach for samples calculation in surrogate modeling. The new optimization system is proposed in Section 4 based on the work mentioned above. Following that, the optimizations of a RAE2822 airfoil and ONERA M6 wing are used as test cases to demonstrate the effectiveness of the proposed strategy. Finally, conclusions are drawn in Section 5.

2. Typical aerodynamic shape optimization based on surrogate model

Surrogate-based optimization is the base of our research. This section describes the components of a typical SBO system: aerodynamic shape parameterization method—Free Form Deformation (FFD), high-fidelity aerodynamic analytical method based on solving RANS, kriging surrogate model and genetic algorithm.

2.1. Aerodynamic shape parameterization method

In this paper, we choose to use FFD to parameterize the aerodynamic shape. It was first proposed by Sederberg and Parry[24] in 1986 based on the idea that an object is elastic and easy to change shapes under the influence of external forces. If the object is enclosed in a framework and external force is applied to the framework to make it deform, the shape of the object would change as well. Thus, we can control the shape of the object by controlling the shape of FFD framework or the position of FFD control points. A detailed introduction to the method can be found in Ref. 25. Fig. 1 shows the FFD control framework and the deformation of airfoil.

2.2. High-fidelity aerodynamic analytical method based on solving RANS

The accuracy of CFD method is the guarantee of the quality of aerodynamic shape optimization. In this paper, the aerodynamic performance of different aerodynamic configurations is obtained by solving the RANS equation.

$$\frac{\partial}{\partial t}\iiint_{\Omega} \boldsymbol{Q} dV + \iint_{\partial\Omega} \boldsymbol{F}(\boldsymbol{Q}) \cdot \boldsymbol{n} ds = \iint_{\partial\Omega} \boldsymbol{G}\boldsymbol{Q} \cdot \boldsymbol{n} dS \tag{1}$$

where $\boldsymbol{Q}$ is conserved variable, $\boldsymbol{F}(\boldsymbol{Q})$ is inviscid flux vector, and $\boldsymbol{G}(\boldsymbol{Q})$ is viscous flux vector; $\partial\Omega$ is the boundary of control

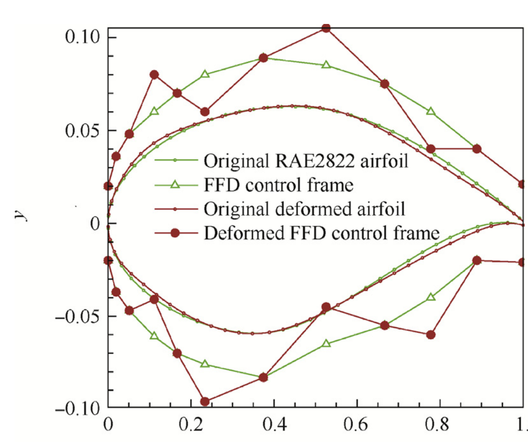

Fig. 1 FFD control framework and deformation of RAE2822 airfoil.

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