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Aerodynamic shape optimization by variable-fidelity computational fluid dynamics models: A review of recent progress

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ABSTRACT

A brief review of some recent variable-fidelity aerodynamic shape optimization methods is presented. We discuss three techniques that—by exploiting information embedded in low-fidelity computational fluid dynamics (CFD) models—are able to yield a satisfactory design at a low computational cost, usually corresponding to a few evaluations of the original, high-fidelity CFD model to be optimized. The specific techniques considered here include multi-level design optimization, space mapping, and shape-preserving response prediction. All of them use the same prediction–correction scheme, however, they differ in the way the low-fidelity model information it utilized to construct the surrogate model. The presented techniques are illustrated using three specific cases of transonic airfoil design involving lift maximization and drag minimization.

1. Introduction

Aerodynamic (or hydrodynamic) shapes and surfaces are encountered in numerous engineering systems, such as aircraft, automobiles, ships, rockets, bicycles, turbines, and pumps; just to name a few. The task of the aerodynamic engineer is to find a shape (or adjust the existing one) that improves a given aerodynamic measure of merit while adhering to appropriate constraints. The complexity of engineering systems is growing and computer simulations are needed to provide a reliable evaluation of system performance. Given the nonlinear behavior of fluid systems it is often an impossible task to improve a given design by using a hands-on approach. Numerical design techniques are, therefore, essential to assist the engineer in solving the challenging task. Aerodynamic shape optimization (ASO) involves the use of search algorithms for the design of aerodynamic surfaces. This paper provides a review of recent progress in this field. In particular, several variable-fidelity optimization algorithms, which have been shown to be very efficient, will be described and compared with benchmark techniques.

Hicks et al. [1] are generally credited for the first practical application of ASO. They used a conjugate-gradient method to design two-dimensional airfoil shapes in transonic flow. Later, Hicks and Henne [2] extend the work to three-dimensional transonic wing design with a steepest-descent gradient method. Nowadays, gradient-based methods are considered the state-of-the-art in ASO and are the most widely used approaches; see for example [3–6]. The key to using gradient-based ASO is the adjoint approach, first introduced by Pironneau [7], and later developed for aerodynamic design by Jameson [8]. The main advantage is that the cost of a gradient calculation can be made nearly independent of the number of design variables. This opens the gateway for applying ASO to problems with a large design space.

Various other types of algorithms are used for ASO, such as derivative-free methods, one-shot methods, and surrogate-based methods. Evolutionary algorithms, such as genetic algorithms, are the most popular derivative-free methods for ASO; see for example Holst and Pulliam [9], and Epstein and Peigin [10]. The fundamental advantage of evolutionary algorithms (or, more broadly, population-based metaheuristics) over gradient-based ones is their ability to perform global search. However, this comes at a price since a large number of model evaluations are needed, especially for a large design space. One-shot methods are based on the same Lagrangian formulation as the gradient-based methods, but the flow equations and the first-order optimality conditions are solved simultaneously, and, thereby, avoiding repeated flow and gradient evaluations. An overview of the approach can be found in Gunzburger [11] and applications can be found in Gatsis and Zingg [12], and Iollo et al. [13].

In surrogate-based optimization (SBO), a computationally expensive model is replaced by a cheap surrogate model [14,15].

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The main objective is to accelerate the optimization process and obtain an optimized design by using fewer evaluations of the expensive model. Typically, the surrogates are functional ones, i.e., constructed by using design of experiments and data fitting. A variety of techniques are available to create function-approximation surrogate models. These include polynomial regression [14], radial basis function interpolation [15], kriging [16], and support vector regression [17]. Function-approximation models are versatile, however, they normally require substantial amount of data samples to ensure good accuracy. Examples of SBO with various function–approximation models related to aerodynamic design can be found in Forrester et al. [18], Jouhoud et al. [19], and Brooks et al. [20].

Variable-fidelity optimization (VFO) refers to a certain type of SBO where the surrogate models are constructed using corrected physics-based low-fidelity models [21–29]. The low-fidelity models can be obtained using one of, or a combination of the following: simplified physics models (also called variable-fidelity physics models), the high-fidelity model with a coarser computational mesh discretization (called variable-resolution models), and relaxed flow solver convergence criteria (called variable-accuracy models). The surrogate model needs to be a reliable representation of the high-fidelity model. This is typically achieved by correcting the low-fidelity model. Examples of correction techniques for aerodynamic models include space mapping (SM) [24,27], shape-preserving response prediction (SPRP) [25,28], and adaptive response correction (ARC) [29]. The key benefit of the VFO approach is that compared to function-approximation surrogates, less high-fidelity model data may be needed to construct a physics-based one to obtain a given accuracy level, which will lead to improved algorithm efficiency.

In this paper, we provide a brief summary of recently developed VFO algorithms for the design of aerodynamic surfaces. In particular, we describe the multi-level optimization (MLO) algorithm [23], and the SM [24] and SPRP [28] correction techniques. The algorithms are applied to aerodynamic shape optimization of transonic airfoils.

2. Aerodynamic shape optimization

This section provides a discussion on the basic properties and characteristics of aerodynamic surfaces pertaining to the geometry and the performance measures, as well as an example of design objectives. A mathematical formulation of the ASO problem is given.

2.1. Basic characteristics of aerodynamic surfaces

Aerodynamic shapes are typically described by a set of parameters and shape functions. For example, the aircraft wing shown in Fig. 1 can be described on one hand by planform variables, such as the span (b), sweep (Λ), and chord lengths (c) shown in Fig. 1(a), and, on the other hand by the airfoil shapes at each spanstation, such as the root, kink, and tip. Each airfoil section, such as the one in Fig. 1(b), can be described by a set of shape functions and parameters.

2.2. Aerodynamic performance metrics

The measure of merit is a quantity that characterizes the performance of the aerodynamic surface. The characteristics of an aerodynamic surface are typically represented with the non-dimensional coefficients of forces, pressures, and moments acting on it, such as the coefficients of lift (C_l), drag (C_d), pressure (C_p), and pitching moment (C_M).

The performance metrics are, typically, obtained by aerodynamic analysis of the streamlined surfaces through computational fluid dynamics (CFD) simulations. CFD models contain, in general, the following elements: geometry modeling and parameterization, computational grid generation, flow solution, and a calculation of the measures of merit. The entire process is automated and integrated within an optimization framework. The simulation of the flow about a typical transport wing could take around 24 h (assuming a parallel computation on 8 processors). Obviously, a more powerful hardware will reduce the computational time. A computation of the two-dimensional flow past an airfoil needs around 0.5 million grid cells and takes around half an hour (on a similar machine).

Typically, the objective is to minimize the drag. For example, in the design of transonic wings one of the main objectives is to minimize the drag induced by a pressure shock, such as the one shown in Fig. 2. Often, in low speed design the objective is to maximize the lift. Maximization of the lift to drag ratio can also be considered. Anderson [30] provides an excellent discussion of aerodynamic design of transonic airfoils and wings.

2.3. Constraints

There can be constraints pertaining to various aspects of the engineering system under consideration. Aircraft design is highly multi-disciplinary and the constraints can be related to the aerodynamics, structures, propulsion system, and control systems. As all the disciplines are highly coupled, ASO needs to account for that in some way. For example, the wings of an aircraft have many structural, mechanical, and electrical components. There needs to be space for these components. This is often accounted for in ASO by thickness constraints.

2.4. Problem formulation

ASO can be formulated as a constrained nonlinear minimization problem, i.e., for a given operating condition, solve

$$x^* = \underset{x}{\operatorname{argmin}} H(f(x)), \ \text{s.t.} g_j(x) \le 0, \ h_k(x) = 0, \ l \le x \le u, \tag{1}$$

where H is the objective function, $f(x)$ is the high-fidelity model, x* is the optimized design, x is the design variable vector (describing the airfoil shape), arg min represents minimization, $g_j(x)$ are the inequality constraints with $j = 1, \ldots, M$, $h_k(x)$ are the equality constraints with $k = 1, \ldots, N$, and l and u are the lower and upper bounds of the design variables, respectively.

The detailed formulation then depends on the particular design scenario. Typically, lift maximization and drag minimization can

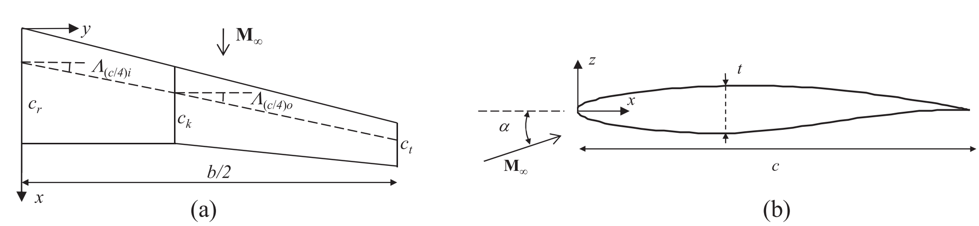

Fig. 1. Nomenclature for typical transonic aircraft wing geometry, (a) planform view, (b) airfoil section.