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Surface shape design in fluid flow problems via hybrid optimization algorithms

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ABSTRACT

Shape design problems, in general, and inverse design problems, in particular, are often solved via optimization techniques. Evolutionary algorithms provide robust and efficient solution methods for such problems. This paper focuses on the application of genetic algorithms (GA), particle swarm optimization (PSO), and two hybrid variants of GA and PSO. Optimum shapes in five shape design problems are found by the proposed hybrid algorithms. Potential, Euler and both laminar and turbulent Navier–Stokes flow solvers are employed in the test problems which include internal and external flows and convection heat transfer. Computational results show that hybridization of GA and PSO improves the convergence rate in all test cases. Up to 30% speed up is observed in the numerical test cases when the hybrid methods are employed and it is also shown that hybrid methods find a better solution in the design space as compared to either GA or PSO.

1. Introduction

The objective in a surface shape design in the context of fluid flow problems is to compute both the flow and the surface shape corresponding to a given performance criterion. In other words, a shape is sought which provides a performance as close as desired to a specified performance. When the target is to achieve a given surface pressure, or a given surface tangential velocity in the case of an ideal flow model, the problem is known as inverse shape design or more commonly as inverse design [3].

Dulikravich [8] provides a general review of shape design methods. These methods can be broadly categorized in two groups, i.e. coupled or direct design methods and uncoupled or inherently iterative design methods. In direct methods [3,4,29] parameters or coordinates that define the surface shape appear as dependent variables in the equations to be solved. Uncoupled methods, in general, and optimization methods, in particular, call a flow solver iteratively in a shape update routine until the required performance is achieved. Fig. 1 shows a general optimization design loop.

Among uncoupled methods, optimization techniques have been used extensively to solve inverse design problems. In general, the minimum of a cost function is sought subject to the constraint that the flow governing equations be satisfied. The minimum can be found by monitoring the gradients of the objective function with respect to the design variables [6]. Since gradient computation can often be a complex and time consuming process, attempts have been made to propose simpler and less expensive gradient calculation methods, e.g. methods based on adjoint equations and control theory [2,16].

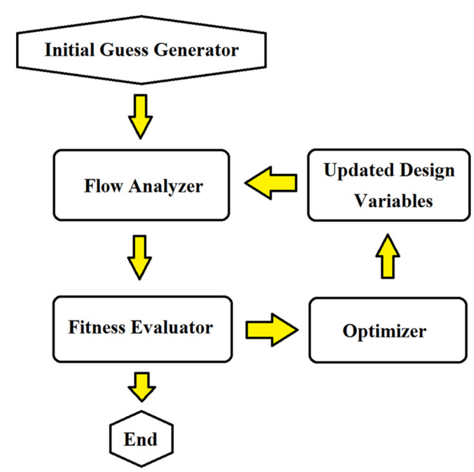

Fig. 1. A general optimum shape design loop.

The optimum can also be found by repeated function evaluations as is the case in evolutionary algorithms. Among evolutionary methods, Genetic Algorithm (GA) has gained popularity.

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Genetic algorithm is a search method based on the principles of natural selection, genetic and evolution. The information regarding the objective function is obtained through simultaneous multipoint search instead of a point by point search. Therefore, GA is capable of finding the global optimum in contrast to gradient-based methods which can easily be trapped in a local minimum. In spite of many desirable features, GA can be very computationally expensive. This happens when the evaluation of the fitness function requires large number of calculations which is often the case when computational fluid dynamics is used for the function evaluation. Different techniques have been proposed for improving the performance of GA in CFD-based optimization problems, including the use of improved genetic operators [11,23] and parallel processing [13,20].

Another population-based search algorithm, originally proposed by Eberhart and Kennedy [19], is the particle swarm optimization (PSO) method. The development of PSO is based on the observation of social behaviors of particular types of populations, e.g. birds flocking and fish schooling. In this class of heuristic algorithms the position update of each individual, or particle, in the search space is based on the previous position and displacement of the particle, best recorded position of the particle during the past updates, and the best recorded displacement in the entire population. The PSO algorithm has been applied to a wide range of engineering problems including aerodynamic optimization problems. Considering the fact that PSO faces premature convergence in most of the aerodynamic applications, the research in this area has been focused on convergence acceleration. Venter and Sobieski [30] optimized aircraft wing with PSO algorithm. Wang et al. [33] introduced an oscillating term to the update formula of the particle displacement to speed up the convergence in an airfoil shape design problem. Huang et al. [15] designed a hydrofoil section with an improved PSO algorithm in which some of the weight factors change during the evolution. In contrast to the genetic algorithm, which has been widely used in aerodynamic shape design, the use of PSO in these problems is relatively new.

The idea of combining different optimization techniques to achieve better convergence has also been attempted. Different hybridization scenarios, including the combination of gradient-based and evolutionary methods [5,31], and combined artificial neural network and evolutionary algorithms [9] have already been tried.

Combination of GA and PSO has also been proposed and tested on some function minimization problems [1,10,26,28]. The results show that this hybridization provides an effective search strategy and performance improvement has been reported in all test cases.

In this article the idea of hybridization of GA and PSO is further examined in the context of two-dimensional aerodynamic as well as convection heat transfer shape design problems. Four inverse design problems, which include both internal and external flows as well as inviscid and viscous flow models, are solved as aerodynamic test cases. Furthermore, a shape design problem is also solved in the context of laminar convection heat transfer in a wavy channel. Proposed hybrid algorithms are shown to be superior in terms of both convergence speed and accuracy in all cases. On average, hybridization improves the convergence rate by about 15% in our test cases.

Considering the major subroutines in the design loop, shown in Fig. 1, optimizers are discussed next. Genetic algorithm, PSO and proposed hybrid algorithms, which are used as optimizers in this study, are presented in some details in Section 2. Afterwards, the test cases are introduced in Section 3 of the paper. In Section 4 the objective or fitness functions are presented as well as the design variables, i.e. the control points of some Bezier curves. Brief explanations regarding the flow solvers used in this study are given in Section 5 followed by Section 6 on computational results and comparisons of different optimization algorithms. The paper is wrapped up by Section 7.

2. Description of the implemented optimization algorithms

2.1. Genetic algorithm

Genetic algorithm has been proposed by Holland [14] and further improved by Goldberg [12]. The GA is a stochastic global search technique based on the mechanics of natural selection, genetic and evolution, in which a set of candidate solutions, called population, evolve during the iterations. Each solution, known as a chromosome, is encoded by one of the commonly used encoding strategies, i.e. binary, real-valued or complex-valued encoding. The encoding method is chosen based on the problem type and application. In continuous GA, a real variable is replaced by a new random real variable. Joodaki et al. [17] have shown that continuous GA provides better convergence rate in fluid flow shape design problems. Therefore, continuous real-valued encoding is used in this paper.

The chromosomes are then evaluated and the fitness of each decoded chromosome is examined using the objective function formula. Upon completion of the evaluation, pairs of better chromosomes are selected to undergo genetic operations. Again, there are various ways of doing this. Here, the Roulette Wheel Selection method is used in which each individual is assigned a space on the roulette wheel depending on its relative fitness.

Crossover is the main genetic operator representing the mating and consists of swapping chromosome parts between individuals. The crossover is not performed on every pair of individuals. Its frequency is controlled by a crossover probability factor. Crossover process provides a mechanism to allow new chromosomes to inherit the properties from old ones. A single point crossover is used in this article.

Mutation is another genetic operation. This operation induces random variations in the population and prevents the inadvertent loss of useful genetic material. The mutation rate is the portion of bits or values within a population that will be changed. Here a single-point random mutation is used.

In order to enrich the future generations with specific genetic information of the parent with the best fitness in the current generation, that particular parent is preserved in the next generations. This operation, which is also used in this study, is known as elitism.

After the completion of selection, crossover and mutation processes, a new population is obtained. Genetic algorithm iterates over a large number of generations until a termination criterion is satisfied. The flow chart for the genetic algorithm is shown in Fig. 2.

2.2. Particle swarm optimization

Particle swarm optimization (PSO) is one of the latest population-based optimization methods [11]. This algorithm mimics the flocking and swarm behavior of birds and is initialized with a population of random solutions, called particles. Each particle is represented by a point in the search space in which particles fly around. During flight, each particle adjusts its position according to the best position encountered by itself and its neighbors. Let $X_i(t)$ denote ith particle position in the search space at time (iteration level) t and $V_i(t)$ denote ith particle velocity at the same iteration level. Assuming each solution (particle) is a d-dimensional quantity, i.e. d design variables in the corresponding optimization problem, the ith particle position (or state) can be written as $X_i(t) = (x^t_{i,1}, x^t_{i,2}, \ldots, x^t_{i,d})$ and the best previous position of the ith particle as $X_{i,p}(t) = (x^t_{i,p1}, x^t_{i,p2}, \ldots, x^t_{i,pd})$. Position of the best particle in