Engineering Applications of Artificial Intelligence 57 (2017) 1–15

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

An improved TLBO based memetic algorithm for aerodynamic shape optimization

Xinghua Qu[b], Ran Zhang[b], Bo Liu[a,*], Huifeng Li[b,*]

[a] Academy of Mathematics and Systems Science, Chinese Academy of Sciences, Beijing 100190, China
[b] Astronautics School, Beihang University, Beijing 100191, China

A R T I C L E I N F O

Keywords:
Aerodynamic shape optimization
Teaching-Learning based optimization
Memetic algorithm

A B S T R A C T

Aerodynamic shape optimization (ASO) for aircraft is the focus of concern as well as the subject of substantial research issue in aerospace engineering. This paper proposes a novel TLBO (teaching-learning based optimization based) memetic algorithm (TLBO-MA) for optimizing the aerodynamic shape. In the proposed TLBO-MA, an adaptive teaching factor, conservation of information inspired operator and multi-meme learning are incorporated to enhance the searching behavior of standard TLBO. Simulation based on well-known benchmarks and ASO for HTV-2 prototype demonstrates the efficiency of the proposed TLBO-MA.

1. Introduction

The task of aerodynamic shape optimization (ASO) in aerospace engineering is to search for optimal settings of shape parameters (e.g., length of body, width of wing, angle of sweepback etc.) which have significant impacts on aerodynamic characteristics of vehicle. The ASO in essence is a kind of multimodal continuous optimization problem in which geometric shape and performance constraints (e.g., lower bound on thickness of an airfoil (Hazra, 2007)) should be satisfied, meanwhile certain objectives should be met (e.g., maximizing lift-drag ratio (Neville, 2015), minimizing the peak heat (Neville, 2015; Jameson and Kim, 2003), minimizing drag coefficient (Jameson and Kim, 2003) or multiple objectives (Anderson et al., 2000; Gauger et al., 2007)). Due to its difficulties in optimization and significance in vehicle design, ASO has been becoming the focus of concern as well as the subject of substantial research in fields of aeronautics/astronautics engineering, and mathematics.

During the past decades, lots of researches have been focused on the shape optimization of airfoil (Morris et al., 2009), wing (Morris et al., 2009; Nabawy et al., 2012; Watanabe et al., 2008), turbine blades (Olhofer et al., 2001) and hypersonic vehicle (Ma et al., 2014, 2015; Bowcutt, 2001). The motivation lies in on the one hand, the fact that ASO has coupled effects on other subsystems (Ma et al., 2015), such as thermal protection system, propulsion system, structure and control system (Feng et al., 2014); on the other hand, the fact that high computational costs with using high-fidelity simulation models bring about unique challenge to optimization algorithms. Considerable research efforts in designing optimization methods for ASO have been carried out which can be roughly divided into two basic categories: 1) traditional optimization methods (e.g., gradient-based methods (Hazra, 2007; Tanrikulu and Ercan, 1998; Burgreen et al., 1994; Hazra et al., 2008; Hazra and Schulz, 2006; Hazra, 2008) and direct search methods (Cui and Yang, 2010; Foster and Dulikravich, 1997)) and 2) meta-heuristics (e.g., genetic algorithm (Anderson et al., 2000; Ma et al., 2014, 2015; Poloni and Mosetti, 1996; Jahangirian and Shahrokhi, 2011; Antunes and Azevedo, 2014; Karakasis et al., 2003), particle swarm optimization (Nejat et al., 2014; Zhang and Sun, 2014; Yang et al., 2015)).

Due to their fast convergence speed and low calculation costs, traditional optimization algorithms have been investigated for ASO, including gradient-based methods (such as steepest-decent method (Tanrikulu and Ercan, 1998) and Newton's method (Burgreen et al., 1994)), and direct search methods (such as Nelder-Mead simplex method (Cui and Yang, 2010; Foster and Dulikravich, 1997)). For instance, Carlos et al. Orozco and Ghattas (1996) proposed a tailored sequential quadratic programming (SQP) to solve the aerodynamic design problems in nonlinear transonic flow. Hazra (2007, 2008), Hazra et al. (2008) and Hazra and Schulz (2006) introduced pseudo-time stepping method into SQP for accelerating the convergence process of ASO. Leung et al. Kraiko (2010) presented a Newton-Krylov algorithm for ASO, where quasi-Newton method was used to find the optimal geometry. Nemec et al. (2004) introduced a gradient-based Newton-Krylov algorithm for both single and multipoint ASO problems. Burgreen and Baysal (1994) applied the preconditioned conjugate-gradient method to ASO of airfoil in the inviscid transonic flow. Beyond the gradient-based methods, many direct search methods

* Corresponding authors.
E-mail addresses: bliu@amss.ac.cn (B. Liu), lihuifeng@buaa.edu.cn (H. Li).

http://dx.doi.org/10.1016/j.engappai.2016.10.009
Received 7 May 2016; Received in revised form 16 October 2016; Accepted 16 October 2016
0952-1976/

have been investigated and applied to ASO problems. For instance, Kraiko (2010) proposed a direct search method based on Bézier spline approximation to solve optimization problem of supersonic part of an axisymmetric de Laval nozzle. Cui and Yang (2010) utilized Nelder-Mead simplex algorithm to improve the aerodynamic performance of generic hypersonic missiles by searching for optimal parameters of the leading edge and the fixing angle. Foster and Dulikravich (1997) introduced the Nelder-Mead simplex method into genetic algorithm (GA) for shape optimization of ogive-shaped, and spiked projectiles in a hypersonic flow. Although traditional optimization methods have been successfully applied to ASO, they are sensitive to the initial guess and easy to get stuck into local optima (Anderson et al., 2000).

To avoid the above mentioned defects from the traditional methods, as kinds of general optimization solvers (Pedrycz et al., 2009; Pedrycz and Song, 2011; Wang and Pedrycz, 2015), population-based meta-heuristics (PBMH), such as differential evolution (DE) (Derksen and Kraj, 2007; Song et al., 2011), genetic algorithm (GA) (Anderson et al., 2000; Ma et al., 2014, 2015; Poloni and Mosetti, 1996; Jahangirian and Shahrokhi, 2011; Antunes and Azevedo, 2014; Karakasis et al., 2003) and particle swarm optimization (PSO) (Nejat et al., 2014; Zhang and Sun, 2014), have been intensively investigated for optimization of aerodynamic shape (Chen and Ong, 2012; Ong and Keane, 2004; Ong et al., 2007; Ong et al., 2009). For instance, Jahangirian and Shahrokhi (2011) proposed an improved GA to the optimization of aerodynamic shape of transonic airfoils, where the RAE-2822 was chosen to be the original airfoil and the optimization target was defined as a maximized lift-drag ratio. The simulation results indicated that the total computational time of the proposed GA was decreased up to 60% compared with the primary GA. Antunes and Azevedo (2014) applied GA to decrease the drag of aerofoil. Song et al., (2011) proposed a parallel version of adaptive DE for optimizing aerodynamic shape of NASA rotor 37 with the constraints of total pressure ratio and mass flow rate, where the optimal objective was to maximize the isentropic efficiency. Derksen and Kraj (2007) applied DE to a biplane configuration design, aiming to maximize the lift-drag ratio. Furthermore, to deal with the constraints, various kinds of constraints handling techniques (Zhang and Rangaiah, 2012), such as penalty function method (Mezura-Montes and Coello, 2011), multi-objective method (Mezura-Montes and Coello, 2011), as well as the level comparison (Wang and Li, 2011), have been investigated to solve the constrained optimization problems of ASO (Mezura-Montes and Coello, 2011; Coello, 2002).

Recently, memetic algorithms (MAs) (Liang et al., 2012; Wang et al., 2011; Wu et al., 2015; Liu et al., 2010; Mashinchi et al., 2011; Wang et al., 2014; Chen et al., 2015; Marinakis et al., 2010; Zhu et al., 2010, 2016) have become a hot topic in the fields of operational research and engineering (Foster and Dulikravich, 1997; Liang et al., 2012; Gao et al., 2015; Basak et al., 2013; He and Wang, 2007; Niknam and Farsani, 2010), in which multiple searching strategies (multi-meme) work complementarily to produce more effective and efficient optimizers. For instance, Foster and Dulikravich (1997) proposed two hybrid methods (i.e. GA with Nelder-Mead simplex method as well as the Rosen's projection method) to optimize three-dimensional shapes in a hypersonic flow with respect to maximization of the lift-drag ratio.

As a newly developed PBMH, Teaching-Learning based Optimization (TLBO) (Rao et al., 2011; Rao et al., 2012) is motivated by the behaviors of the teacher and students in the classroom. Compared with other PBMH algorithms, TLBO can be characterized by two attractive features, 1) differential information among individuals is employed to formulate prospect candidates, in which way the promising searching direction is determined; 2) only a single parameter (the population size) is needed in TLBO to be tuned. Due to its efficacy and easy tuning, lots of efforts in theoretical research and technical application of TLBO has been made.

To further enhance the performance of TLBO, considerable efforts have been made, which are mainly focused on the improvements of the three components which the TLBO could be abstracted as, i.e. self-adaptation, social-cooperation, and competition components (Liu et al., 2011). Teaching phase can be viewed as the social-cooperation of TLBO, in which the improvements are mainly about modification of the number of teacher and teaching factor (e g., multiple teachers and adaptive teaching factor (Rao and Patel, 2013; Chen et al., 2015; Venkata Rao and Patel, 2013)). For instance, Rao and Patel (2013) proposed an improved TLBO by introducing the concept of number of teachers, adaptive teaching factor, tutorial training and self motivated learning. Particularly, the adaptive teaching factor varies automatically during the search by which the performance of the algorithm had been improved. Ouyang et al. (2015) replaced the rand vector in teaching operation with Gaussian distribution. Pickard et al. (2016) mentioned that the TLBO has origin bias affecting the population convergence and success rates of benchmark with origin solutions when teaching factor takes the value of 2. In original TLBO, the value of teaching factor varies randomly for each iteration either as 1 or 2 and it will not remain as 2 during all the iterations. And Pickard et al. (2016) proposed modification using the “biasing” property to “assist in locating better solutions”. The work of Pickard et al. (2016) has the same idea with the work of Crepinsek et al. (2012) which was commented upon by Waghmare (2013). However, TLBO could provide better results for benchmark whose solutions are not located at the origin (Rao and An, 2012). The TLBO has obtained the optimum results irrespective of whether the solution to the objective function is located at the origin or not (Rao, 2016). Rao (2015) had already discussed on the unusual concept of function evaluations required for duplicate removal. The fact is that the TLBO has been applied by many researchers to many real life applications (whose solutions are not located at origin) in different engineering disciplines and obtained better results as compared to the other advanced optimization algorithms.

Learning phase can be regarded as the self-adaptation of TLBO, the modification of which covers self-adaptive learning, self-learning and diversified learning. For instance, to strengthen the mutation ability and accelerate the convergence speed, the mutation operator of DE was incorporated into learning phase (Ouyang et al., 2015). Chen et al. (2015) and Venkata Rao and Patel (2013) presented a modified TLBO with self-motivated learning which assigned each learner to a unique teacher. Shabanpour-Haghighi et al., (2014) incorporated a self-adapting wavelet mutation strategy. In addition, Rao and Patel (2013) enhanced the searching ability of learning phase by three improvements: 1) learning through tutorial which adds the direct differential information between each individual not just between individual and mean; 2) self-motivated learning which enhances the mutation of the individual; and 3) external archive which keeps the historical information of the population. Ghasemi et al., (2015) introduced Gaussian sampling into the learning phase to strengthen the capability of local search. Competition component is mainly with regard to the selection strategy in TLBO. Most of the selection strategies between individual and its candidate are based on greedy law. To overcome these limitations, elitism strategy (Rao and An, 2012) was introduced to replace the greedy selection strategy.

Except the improvements aforementioned, TLBO based memetic algorithms (Wang et al., 2016; Qu et al., 2016a, 2016b; Liu et al., 2016; Zhang et al., 2015) are hot topics as well. There are several studies which have been dedicated to address the issue on how to propose effective TLBO based MA, that is, how to design MA algorithm in which TLBO serves as the population based global search, while some other algorithms or search operators perform as local refinement searches (i.e., meme learning). For instance, Dokeroglu (2015) proposed a hybrid TLBO-RTS which introduced Tabu search into TLBO to enhance the balance between exploration and exploitation. Xie et al. (2014) enhanced the performance of TLBO by incorporating variable neighborhood search and simulated annealing. Wang et al. (2014) hybridized TLBO with DE, aiming at integrating the merits of both TLBO and DE. Zou et al. (2013) developed a multi-objective TLBO called