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AIRFOIL SHAPE OPTIMIZATION USING IMPROVED SIMPLE GENETIC ALGORITHM (ISGA)

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Abstract

To study the efficiency of genetic algorithms (GAs) in the optimization of aerodynamic shapes, the shape of an airfoil was optimized by a genetic algorithm to obtain maximum lift to drag ratio and maximum lift. The flow field is assumed to be two dimensional, Invicsid, transonic and is analyzed numerically. The camber line and thickness distribution of the airfoil were modeled by a fourth order polynomial. The airfoil chord length was assumed constant. Also, proper boundary conditions were applied. A finite volume method using the first order Roe’s flux approximation and time marching (explicit) method was used for the flow analysis. The simple genetic algorithm (SGA) was used for optimization. This algorithm could find the optimum point of this problem in an acceptable time frame. Results show that the GA could find the optimum point by examining only less than 0.1% of the total possible cases. Meanwhile, effects of parameters of GA such as population size in each generation, mutation probability and crossover probability on accuracy and speed of convergence of this SGA were studied. These parameters have very small effects on the accuracy of the genetic algorithm, but they have a sensible effect on speed of convergence. The parameters of this genetic algorithm were improved to obtain the minimum run time of optimization procedure and to maximize the speed of convergence of this genetic algorithm. Robustness and efficiency of this algorithm in optimizing the shape of the airfoils were shown. Also, by finding the optimum values of its parameters, maximum speed and minimum run time was obtained. It is shown that for engineering purposes, the speed of GAs is incredibly high, and acceptable results are sought by a fairly low number of generations of computations.

Introduction

Computational fluid dynamics (CFD) and numerical optimization techniques are being used widely in the field of aerodynamic shape optimization. This growing interest is owing to the fact that CFD is making fast progress using advanced computer technology and available efficient numerical algorithms. This helps faster computation of the flow field which is necessary for the optimization. Also, efficient numerical algorithms for optimization are available so that the combined effort makes it possible to compute optimum solution in realistic time periods. This helps saving the cost incurred in experimental methods [1].

Optimization in aerodynamics can be categorized in two kinds: Gradient based and non-gradient based methods. In gradient based methods, the gradient of the objective function with respect to design variables plays an important role in optimization process. The finite difference and Newton's method are examples of gradient methods.

In non-gradient based methods, the gradient of the objective function is not needed and an optimum configuration is chosen among different possible models. These methods are also called search methods; Random search and Genetic Algorithm [2] are examples of such methods.

Genetic Algorithm (GA) which is based on natural selection mechanism and natural genetics is recognized as a robust method among optimization techniques. Since genetic algorithm uses information of objective function instead of derivative values or other information used by gradient based methods for optimization, it is different from the other optimization methods. In addition, genetic algorithm finds the optimum point of a problem through a simultaneous multipoint search instead of a point by point search. These two properties give genetic algorithms a wide range of applications in engineering problems. As an example, in recent years, genetic algorithm is accompanied by the usual methods of computational fluid dynamics and therefore it is used for optimizing aerodynamic shapes [1, 3-4]. This algorithm is very attractive for use in the design and optimization of aerodynamic shapes because unlike the gradient based methods, it can find the global optimum point of an optimization problem [5].

Optimization of aerodynamic shapes includes determining the values of design parameters that generate the geometric details of the aerodynamic shapes, in a way that objective function values are optimized while the aerodynamic constraints are satisfied.

It is interesting that genetic algorithm is independent of the solution method which is used in CFD software. That is, if a proper numerical solution method is chosen then the genetic algorithm can be applied for any kind of aerodynamic optimization problem [6, 7]. Design parameters which determine the shape geometry, must satisfy the geometric constraints of that problem for finding a reasonable shape. For example, in aerodynamic shape optimization of a wing, geometric parameters such as wing span, wing chord, wing twist angle, maximum chord thickness, radius of trailing edge and radius of leading edge, in different cross sections of the wing must be limited to reasonable values.

However, we expect that details of GA algorithm affect the speed of convergence in different physical problems. For example, one may find that while a certain set of details would be most appropriate for transonic invicsid flows, another one results in shorter run-times for hypersonic viscous flows.

In this study, simple genetic algorithm whose parameters are improved [8], is used for performing the optimization procedure. In this paper we try to find an optimized airfoil profile. To do this, optimization is initiated from a given airfoil and the flow field is solved; then, this improved simple genetic algorithm (ISGA) calculates the best of each generation on the basis of its maximum fitness value with respect to the design variables. With new design variables the flow field is solved again, and this procedure is iterated to reach the maximum value of the objective function. The final design variables which lead to the maximum value of the objective function are optimum ones. Design variables are coefficients of a polynomial equation defining the upper and lower airfoil profiles. An aerodynamic characteristic namely the lift/drag ratio $\frac{C_l}{C_d}$ is assumed as an objective function. Optimization of a given airfoil (NACA 0012) is studied using this objective function.

Optimization Approach

Genetic algorithm (GA) is a mathematical algorithm which uses operational patterns of Darwin's principle in accordance with survival of fitness on the basis of natural genetic processes such as mating, crossover, mutation and etc.; also it can change the population of single mathematical objects (chromosomes) with a special fitness level to a new generation. Although genetic algorithms are stochastic methods they have simple deterministic processes. They use the information of previous generations with high efficiency to find new points. These algorithms attempt to avoid being completely random and as mentioned in genetic algorithm literature, usually a process can not be found that is completely random. This algorithm does not need derivative values of an objective function for optimization, and only uses objective function value in each point. Also, the genetic algorithm can be applied to any objective function such as continuous or discrete functions, and in each step it surveys a set of points and therefore more than one optimized result can be obtained [9].

In this study the profile of a NACA 0012 airfoil is chosen as an initial shape, and the improved genetic algorithm is applied to perform optimization of this shape for maximizing $\frac{C_l}{C_d}$.

The upper and lower profiles of the airfoil are defined by a polynomial and its coefficients are chosen as design variables. These coefficients change to binary codes (genes) and produce the required chromosomes for this improved simple genetic algorithm. In each generation some different shapes are produced while each chromosome introduces a specific profile for the airfoil. The first generation is produced randomly. By using a mutation operator which is applied on a random bit of the chromosome and therefore the population that produces the first generation already exists. The fitness evaluation is the basis of genetic algorithm and it has a great role in its selection procedures.

The genetic algorithm recognizes chromosomes that have higher fitness values and selects them as parents for producing the next generation. Finding profile of an airfoil which produces maximum $\frac{C_l}{C_d}$ is the goal of this optimization procedure. Hence the $\frac{C_l}{C_d}$ is used as the fitness value (objective function value) in this algorithm.

The CFD solver calculates $\frac{C_l}{C_d}$ of the airfoil. For a chromosome in each generation the solver should be called at least once. Therefore, the CFD solver must be called many times to complete the optimization. The numerical experiences show that the run-times of numerical computations of the genetic algorithm in comparison with the CFD solver run-times are negligible. The selection of parents is based on Roulette wheel [9] and the probability that a parent is selected depends on its fitness value. Each pair of parents produces two offspring (two new chromosomes) by using a crossover operator. The mutation operator is applied to offspring on the basis of its probability. One-point crossover is used here. The crossover point which is on the parent chromosome is selected randomly. The mutation operator is performed on a gene in a chromosome which is selected randomly, and changes its value (if it is zero, it will become one and vice versa). Although the reproduction and crossover procedures are done randomly on the basis of the fitness value, they may destruct valuable strings and therefore the genetic algorithm can not converge uniformly to the global optimum of the problem. To have a uniform and faster convergence, the best chromosome of each generation can be transferred to the next generation. This operator is named elitism [10].

Flow Field Governing Equations

Euler equations are adopted as the flow field governing equations and have an essential role in the determination of the objective function. These equations are developed from the laws of conservation of mass, momentum and energy. The vector from of these equations is:

(1)

$$\frac{\partial U}{\partial t}+\frac{\partial F}{\partial x}+\frac{\partial G}{\partial y}=0$$

where:

(2)

$$U=\begin{bmatrix}\rho\\ \rho u\\ \rho v\\ \rho e_t\end{bmatrix}\qquad F=\begin{bmatrix}\rho u\\ \rho u^2+P\\ \rho uv\\ \rho u h_t\end{bmatrix}\qquad G=\begin{bmatrix}\rho u\\ \rho uv\\ \rho v^2+P\\ \rho v h_t\end{bmatrix}$$

F And G are flux vectors in x and y directions, respectively. U is the vector of conserved variables, and e_t and h_t are total energy and total enthalpy, respectively.

The above set of equations contains four equations with five unknowns. To close this set, we need an extra equation which will be the equation of state. For an ideal gas this equation is:

(3)

$$\frac{p}{\rho}=(\gamma-1)e$$

where e is internal energy and γ is the specific heat ratio.

Numerical Methods

A finite volume technique is used for spatial discretization of the governing equations. After integration from equation 4 over triangular control volumes shown in Figure 1, we have:

(4)

$$\frac{\partial \overline{U}_j}{\partial t}A_j+\sum_{j=1}^{3}\left(\overline{F}_{nj}+\overline{G}_{ni}\right)\Delta s_i=0$$

where $\overline{U}_j$ represents the numerical approximation of U in cell j and $\overline{F}_{nj}$, $\overline{G}_{ni}$ are approximations to the normal components of F, G on edge i of the control volume, Δs_i is the length of the control volume edge, and A_j denotes the area of the control volume j. The next step is the determination of fluxes on the edge of the control volume. Here the invicsid fluxes are approximated using Roe's scheme [11]. This scheme, called flux difference splitting, belongs to the upwind schemes category, which use approximate Riemann solvers for flux to capture flow field discontinuities such as shock waves.

After special integration of the Euler equations, the equations are converted to ordinary differential equations:

(5)

$$\frac{d\overline{U}_j}{dt}=R\left(\overline{U}_i+\overline{U}_j\right)$$

where R is the numerical flux function. Equation (5) is an ordinary differential equation which may be solved using classical methods such as the 4th order Runge-Kutta method [11]:

(6)

$$U^k=U^{k-1}+\frac{\Delta t}{4-k+1}R^{k-1}\qquad ,\quad k=1,\ldots,4$$

Grid Generation

As stated before, the discretization of the equations is carried out in triangular cells. Here, the Delaunay triangulation method [12] is chosen to discretize the physical domain. An advancing front algorithm is used to generate the Delaunay triangulation, which is both robust and fast enough. The Delaunay triangulation has many properties, and from some view points is the best possible triangulation.

Since the geometry of the airfoil varies during the optimization process, a new grid is needed for the new geometry. A procedure called spring based smoothing method [13] is used to adapt the grid to slow movements of the boundaries. In the spring-based smoothing method, the edges of the mesh are idealized as a network of interconnected springs. The initial length of the edges before any boundary motion constitutes the equilibrium state of the mesh. A displacement at a given boundary node will generate a force proportional to the displacement along all the springs connected to the node. Figure 2 represents the results of this displacement procedure.

Results

Since the flow field solver evaluates the objective function, the flow filed solver should be validated; therefore results of the present solver are compared with those of reference [14]. Figure 3 gives the pressure coefficient distribution over the lower and upper surface of a NACA 0012 airfoil for free stream conditions of $M=0.7$ and $\alpha=1.49$, where M is the Mach number and α is the angle of attack. It can be seen that the present results have good agreement with the experimental data of Mirzaei et al. [15]. Figure 4 shows the pressure contours of the present solver for this case.

To estimate the performance of the improved simple genetic algorithm as the optimization procedure, an airfoil with initial profile of NACA 0012 is adopted for free stream conditions of $M = 0.7$ and $\alpha = 1.49$ and the objective function is $\frac{C_l}{C_d}$.

This objective function will help us to verify our genetic algorithm method. Table 1 shows the results of this optimization. In this table the initial and optimized values of design variables and objective function are presented. The airfoil profile is:

$$y = \frac{t}{0.2}\left(a_1\sqrt{x} + a_2 x + a_3 x^2 + a_4 x^3 + a_5 x^4\right) \quad (7)$$

$a_1, \ldots, a_5$ are design variables, and for this airfoil t is 0.12. Figure 5., depicts the convergence history of the objective function. Figure 6 shows the optimized airfoil and the initial airfoil – which has been NACA 0012. As can be seen, the airfoil thickness has considerably decreased. As we know thinner airfoils tend to have lower drag. This characteristic is magnified in transonic flows as the shock wave is avoided by decreasing the flow velocity above the airfoil. In figures 7 to 9 the pressure coefficient over the airfoil and also the Mach and pressure contours are depicted. It is obvious that no shock waves are present and consequently as the field is solved invicsid ly, the only possible source of drag, pressure drag, is avoided. In other words, genetic algorithm has successfully minimized the drag while increasing lift, by eliminating the major source of drag, namely pressure drag. The only remaining source is the drag which is not physical and is a part of the artificial viscosity which exists intrinsically in the flow solver. In this case the lift is also increased because the thin airfoil allows the upper surface flow to reach its maximum velocity without being forced to lessen, due to shock wave.

Note that the ISGA method is converged after 50 generations. Comparing with the other usual methods such as gradient based methods [15] and simple genetic algorithm, it has converged faster, and it calls the CFD solver less than 0.1% of all possible cases; hence, it is a fairly time saving approach.

	a1	a2	a3	a4	a5	Cl/Cd
NACA 0012	0.2969	-0.126	-0.3516	0.2843	-0.1015	16.2
Optimized	0.4965	-0.3601	-0.2336	0.2974	-0.2002	1037

Table 1. Design results

Conclusions

The improved simple genetic algorithm (ISGA) is presented and applied for airfoil shape optimization. According to the results, this method is very effective and robust and can be used for the optimization of simple NACA series airfoils. For this test case, with the objective function of $\frac{C_l}{C_d}$, optimization leads to an increase in $\frac{C_l}{C_d}$ ratio in comparison with the initial airfoil (NACA0012) after 50 generations.

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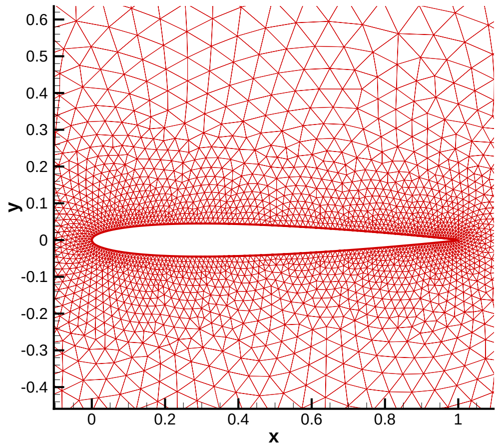

Figure1. Triangular control volume

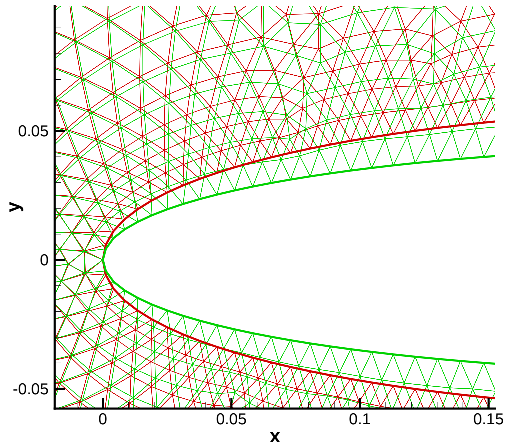

Figure 2. Spring-based smoothing method

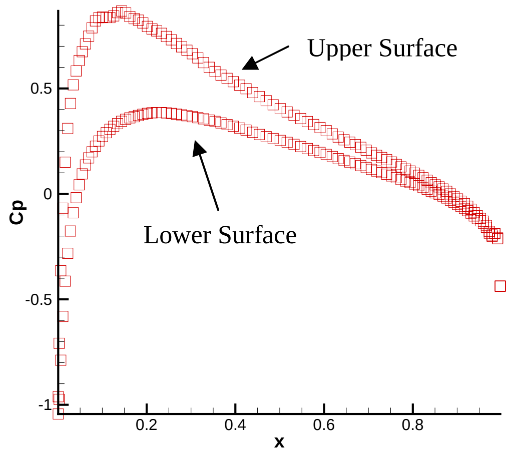

Figure 3.The pressure coefficient distribution over lower and upper surface of NACA 0012 airfoil

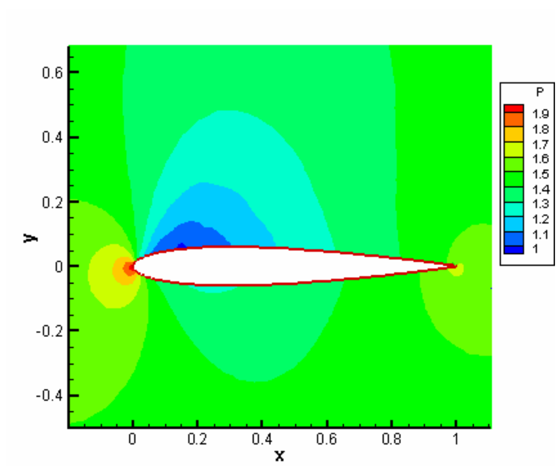

Figure 4. Pressure contours of the present solver for validation case (Non-dimensionalized by $\rho_\infty U_\infty^2$)

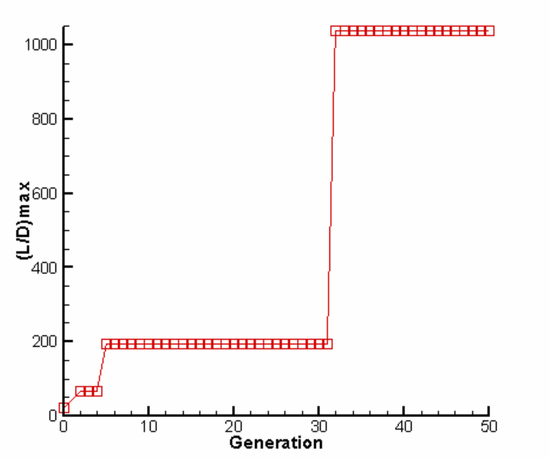

Figure 5. Growth trend of L/D through the optimization process

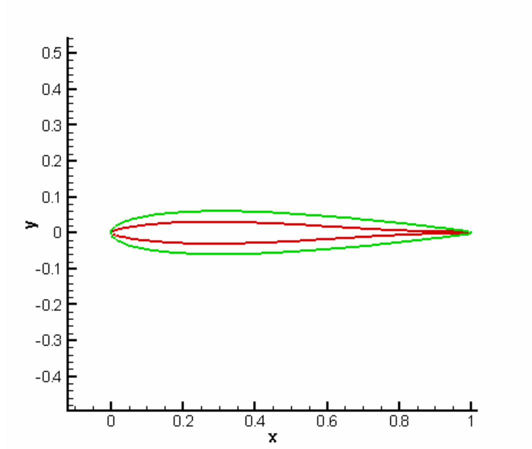

Figure 6. Optimized airfoil (Red) with L/D objective function in comparison with NACA 0012(Green)

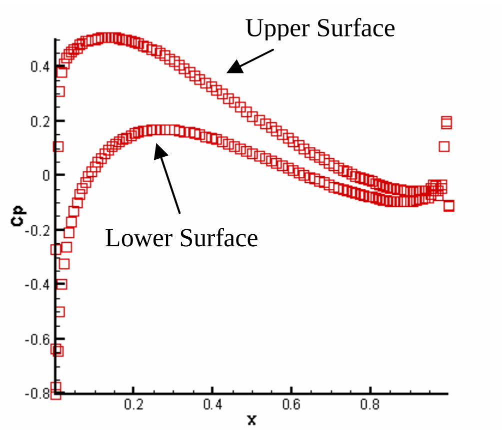

Figure 7. Pressure coefficient along the optimized airfoil

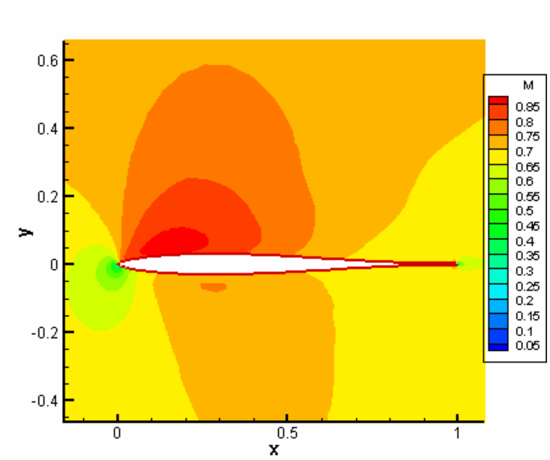

Figure 8. Mach contour for the optimized airfoil

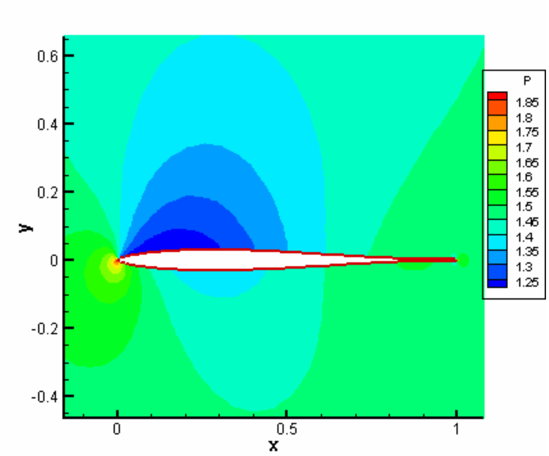

Figure 9. Pressure contour for the optimized airfoil (Non-dimensionalized by $\rho_\infty U_\infty^2$)