IMPROVED PARTICLE SWARM OPTIMIZATION BASED ON SOCIAL MODEL FOR AERODYNAMIC DESIGN

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Keywords: *particle swarm optimization; artificial fish swarm algorithm; social model; searching efficiency; aerodynamic optimization design*

Abstract

It is becoming more and more important to do aerodynamic design optimization with numerical methods and it is also a good way to apply intelligent algorithms which have sprung up recently to aerodynamic design optimization skillfully. However, the balance between global search ability and local search ability in intelligent algorithms is always not easy to be implemented. For this problem, here, a universal strategy named social mode is developed and a new algorithm named Improved Particle Swarm Optimization Based on Social Model (IPSOSM) is proposed. The social model is analyzed to some extent and with the guidance of it the collective action which belongs to Artificial Fish Swarm Algorithm (AFSA) is introduced into Particle Swarm Optimization (PSO) algorithm to form IPSOSM algorithm. Function test results show that IPSOSM algorithm has much better optimal ability than PSO algorithm. IPSOSM algorithm is also applied to the airfoil aerodynamic design and the wing aerodynamic design. The satisfying optimal results are obtained, which proves the simplicity and efficiency of the social model.

1 Introduction

With the fast development of the computer technology, the efficiency of optimization in aerodynamic design could be improved dramatically by combining the computational fluid dynamics (CFD) and the numerical methods together. However, most of the traditional optimization algorithms such as gradient algorithms, quasi-Newton approach are easily strapped into a local minimum which could not satisfy the requirement of practical engineering. Although some of the meta-heuristic intelligent algorithms such as genetic algorithm perform good global search ability, it is still inefficient to the aerodynamic optimization system for their much higher computational cost. Therefore, it is of great significance to develop some new algorithms that have good global search ability and good local search ability as well as lower computational cost in the field of aerodynamic design.

In this paper, inspired by a kind of social phenomenon, social model which is an efficient universal strategy to improve the intelligent algorithms' performance is developed and analyzed. With the guidance of this model, the collective action which belongs to AFSA is introduced into PSO algorithm and a new algorithm named Improved Particle Swarm Optimization Based on Social Model is proposed. The new algorithm is also applied to the 2D airfoil design and the 3D wing design and the results validate the efficiency of the new algorithm.

2 Social Model

It is said that the unique behavior owned by human being rather than animals is that human being could learn from the surroundings and the procedure of labor and then apply what they

Foundation item: the National Natural Science Foundation of China(11172242)

have learned into practice with their much thinking. Not only does this behavior depends on the experience of individuals themselves, but also depends on the knowledge learned from the whole society. That is, human being improve their cognitive ability by making good use of the information. Getting back to the time when R.Boyd and P.J.Richerson[1] lived in, after doing some research work on how people making their decisions, both of them pointed out that the decisions were determined by two important factors. One is the information got from people themselves and the other is the information learned from other people. It means promising decisions will not be made if the information around us is not taken good advantage of. Since the intelligent algorithms are usually based on natural and social phenomenon, it may be a good way to introduce such phenomenon into intelligent algorithms. With the help of information learned from the individuals themselves and others, intelligent algorithms can be driven forward which may result in better solutions as well as lower computation cost. This is the social model developed in this paper. The social model is a universal strategy and the following takes PSO algorithm for example.

3 Optimization Strategies

3.1 Particle Swarm Optimization

The Particle Swarm Optimization[2] was proposed in 1995 by a social psychologist J.Kennedy and an electrical engineer R.C.Eberhart. It simulates the behaviour of birds finding food. The design parameters in the solution space are viewed as a group of birds (which are also named as particles) without volume and quantity. The best solution of the problem is interpreted as the food which the birds are looking for. With the guidance of the individual minimum value *pbest* and the swarm minimum value *gbest*, all of the birds changes their directions and distance adaptively by updating their velocities and locations so that they may tend to be close to the food. Here, the velocity and the location can be renewed by the following formulas:

$$v_{ij}^{t+1} = \omega v_{ij}^{t} + c_1 r_1 (pbest_{ij}^{t} - x_{ij}^{t}) + c_2 r_2 (gbest_{j}^{t} - x_{ij}^{t}) \quad (1)$$

$$x_{ij}^{t+1} = x_{ij}^{t} + v_{ij}^{t} \quad (2)$$

Where x, v are the current locations and velocities of the particles respectively. Subscript i and j denote the sequence number and dimension of each particle respectively. t is the number of iteration cycles. w denotes the inertial weight which plays an important role in the performance of this algorithm. The study factors c_1, c_2 are used to adjust the step intervals by which particles move to *pbest* and *gbest*. r_1 and r_2 are the random float numbers belonging to (0,1).

Compared with other algorithms, PSO algorithm has been widely applied to the field of design for its reliability and simplicity. The disadvantage of it may be that it is easily strapped into a local minimum with the disappearance of population diversity after some iteration steps[3-4].

3.2 Artificial Fish Swarm Algorithm

Artificial Fish Swarm Algorithm[5] which belongs to the swarm intelligent algorithms is based on the behavior of fish swarm. It implements the optimization by simulating the habit of fish on preying, collecting and so on. AFSA is supposed to be good at getting rid of local minimum that could result in a global minimum. Here, the collective action is specified and highlighted.

The collective action represents the behavior of fish collecting together when the food is found. This phenomenon is the product of evolution which may help fish prey easily and survive from their enemies. The collective action is specified in ref. [5]. We assume that $\boldsymbol{X_i}$ denotes current status of the fish. n_f and $\boldsymbol{X_C}$ are the number of fish in neighborhood ($d<Visual$) and central position respectively. If $Y_c/n_f > \delta\, Y_i$ (for the maximized problem), it indicates that the food in the central position is abounding and the fish are not crowded. Then, the fish will move to the central position for one step. Otherwise, the preying actions will be employed.

On the above formula, $\boldsymbol{X}=(x_1, x_2, x_n)$ and Y are the status of the artificial fish and the objective function respectively. d is the distance between two fish. *Visual* is the domain which a fish could detect, δ signifies the crowded factor. The collective action may improve the ability of communication among the fish and result in a global minimum rather than local minimum[5-6].

3.3 Improved Particle Swarm Optimization based on social model

Particle Swarm Optimization which was proposed by Kennedy and Eberhart is based on the simulation for birds finding food. It considers the information inherited from both the individual best information and the swarm best information. However, in view of the mechanism mentioned in social model, we could find that this inheriting mechanism in PSO is still not sufficient. The drawback is that only individual best information and swarm best information are under consideration whereas the information hided in other particles is ignored which may have negative effect on driving the algorithm forward. In fact, the best information of the swarm could not summarize the information of the whole swarm. Taking function optimization for example, the best information in each dimension of the solution space is selected on criterion that the function value of the individual is the best. It does not mean the actual information in each dimension of the solution space is the best. Much useful information may also exist in other individuals which are quite different from the best one. Making good use of this information, we may get better results. Based on above, a new algorithm named Improved Particle Swarm Optimization based on Social Model (IPSOSM) is proposed. In this new algorithm, AFSA's collective action coming from the guidance of social model is simplified and then introduced into PSO algorithm skillfully. By this way, each particle in PSO algorithm inherits the property which belongs to collective action. This makes particles analogous to artificial fish, i.e. The particles also have their own view. Furthermore, the visual is zoomed to the whole solution space boundary which results in the disappearance of crowded the factor δ. In addition to that, the distance between two artificial fish d is changed and covers the whole design parameter space. The simplified collective action in IPSOSM algorithm can be expressed by adding the additional parts on the velocity formulation, that is

$$v_{ij}^{t+1}=\omega v_{ij}^{t}+c_1 r_1(pbest_{ij}^{t}-x_{ij}^{t})+c_2 r_2(gbest_{j}^{t}-x_{ij}^{t})+c_3 r_3(X_c-x_{ij}^{t}) \quad (3)$$

$$X_c=\sum_{i=1}^{n}x_{ij}\Big/n \quad (4)$$

Where subscript i and j denote the sequence number and dimension of each particle respectively. t is the number of iteration cycles; study factors c_1, c_2 and c_3 are expected to adjust the scale inherited from individual best information, swarm best information and simplified collective action information. Since simplified collective action does not always dedicate positive contribution to the algorithm, study factor c_3 should be smallest in these three factors; r_1, r_2 and r_3 are arbitrary float numbers between 0 and 1; n is the population of particles

Besides the merit owned by PSO algorithm, IPSOSM algorithm also benefits from the information of the whole particles by introducing simplified collective action. It abounds the best information and could guide particles flying to the food by a more efficient flight route. The flowchart of IPSOSM algorithm is presented in Fig.1.

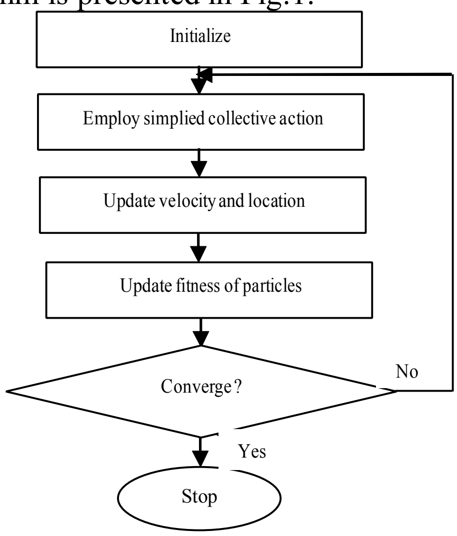


Fig.1 flow chart of IPSOSM

The procedure of IPSOSM algorithm is carried out as follows.

1. Initialize: initialize the parameters including population, the number of iteration cycles, the inertial weight, the study factors etc.

2. Employ simplified collective action: use the formula (4) to calculate the simplified collective action.

3. Update velocity and location: use the formula (3) and the formula (2) to renew the velocity and the location of each particle which could result in a new population.

4. Update the fitness of particles: renew the fitness and *pbest* of individual as well as the fitness of swarm *gbest*.

5. If the abort criterion is satisfied, then STOP, otherwise GOTO 2.

4 Function Test

In order to test and analysis the performance of different algorithms, we apply three typical test functions to both PSO algorithm and IPSOSM algorithm. These test functions are showed as follows.

(1) Sphere function

$$f_1(x) = \sum_{i=1}^{n} x_i^2 \quad -100 \le x_i \le 100$$

The optimal solution is:

$$\min(f_1) = f_1(0,\cdots,0) = 0$$

This is a nonlinear symmetric function.

It only has one peak with respect of solution space. Most algorithms can perform well on this simple function and it is usually used to test the accuracy of the algorithms.

(2) Rastrigin function

$$f_2(x) = \sum_{i=1}^{n}[x_i^2 - 10\cos(2\pi x_i) + 10] \quad -5.12 \le x_i \le 5.12$$

The optimal solution is:

$$\min(f_2) = f_2(0,\cdots,0) = 0$$

This function contains a plenty of local minimum which are ranged on the trend of Sine function. Many algorithms are easily strapped into a local minimum on the way to global minimum when doing function test.

(3) Ackley function

$$f_3(x) = -20e^{-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}} - e^{\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)} + 20 + e \quad -32 \le x_i 32$$

The optimal solution is:

$$\min(f_3) = f_3(0,\cdots,0) = 0$$

Many peaks in the solution space is the characteristic of this function. Algorithms are easily strapped into a local minimum when doing function test.

In the test presented here, the dimension of each variable is 15. The inertial weight w is reduced from 0.9 to 0.4 linearly[7]. In order to eliminate the influence of the study factors, in PSO algorithm, $c_1=c_2=2$ while in IPSOSM algorithm, $c_1=1.5$, $c_2=2$, $c_3=0.5$. It means the summations of study factors in each algorithm are the same and could also be viewed as that the information inherited in different algorithms are the same. In the function test, both of the algorithms are executed 100 times. For each time, there are 400 iteration cycles allowed for the algorithms to search for the minimum. The final results are statistical in terms of mean value and minimum value which based on these 100 times. The performance of the algorithms is showed in Table.1.

Table.1 Performance of algorithms

	Result	PSO	IPSOSM
f_1	Mean	2.8927e-005	3.2926e-009
	Minimum	4.0481e-007	3.4018e-011
f_2	Mean	2.5136e+001	2.1028e+001
	Minimum	8.9547e+000	7.9597e+000
f_3	Mean	1.0954e-003	1.9272e-005
	Minimum	2.3363e-004	9.1106e-007

We may see that with the identical computational cost IPSOSM algorithm performs better accuracy and convergency ability on both the mean value and the minimum value, which also validate that with the guidance of social model the way to introduce simplified collective action into PSO algorithm could enhance the performance of PSO algorithm dramatically. It is also due to the fact that social model emphasizes paying additional attention to the information among the whole swarm rather than only on the individual best information and the swarm best information.

5 Airfoil Optimization Design

The optimization model generally consists of three key components: objective functions, constraints and design variables. On a given design point of the airfoil aerodynamic optimization design, the aerodynamic feature ingredients such as lift, drag, pitch moment coefficient etc can be selected as objective functions and the airfoils' thickness, area etc can be restrained to a limited range as the constraints. Besides, the variables in the parameterization of the airfoil shape can be viewed as the design variables of the airfoil optimization[8-10].

5.1 Parameterization of Airfoil

The parameterization of the airfoil has great influence on airfoil optimization design. Several schemes such as the polynomial interpolation approach, the analytical function approach and so on can be used. Inspired by Hicks-Henne bump function [11] and binomial, a new method developed here is given as follows [12-14]. The new airfoil can be obtained by adding the perturbation of the airfoil's thickness function and the camber function on baseline.

$$y = y_0(x) + \sum_{k=0}^{n-1} D_K f_k(x)$$

$$f_k(x) = \begin{cases} x^{0.25}(1-x)e^{-20x}, k=0 \\ \dfrac{n!}{k!(n-k)!}x^k(1-x)^{n-k}, k=1,2\ldots n-1 \end{cases}$$

Where $y_0(x)$ is the baseline of airfoil and n is the number of the thickness function or the camber function. D_k which represent the factors of basis function are also the design variables. When k=0, the corresponding formula aims at controlling the variation of the leading edge.

In this paper, 14 design variables are used in airfoil optimization design, where 7 design variables are expected to serve for the thickness function and the others are for the camber function.

5.2 Airfoil Optimization Model

The optimized case is on the RAE2822 airfoil in height of 11000m at cruise condition aiming at minimizing the drag.

The given design point is as follows:

$$Mach = 0.74, \alpha = 2.3^\circ, \mathrm{Re} = 5.59 \times 10^6$$

The objective function is to minimize the drag coefficient. Additionally, the lift coefficient is kept constant and the pitch moment is not allowed to reduce. Besides, the area and the maximum thickness of the airfoil are also constrained to larger than the initial's. The Reynolds-average Navier-Stokes (RANS) equations and k- ω SST turbulence model are used to get aerodynamic dates. The macro function is employed to adapt the mesh to a new deformed airfoil automatically.

In the airfoil optimization design, many methods can be applied to the multiple constraint problems while the penalty function is one of the most popular methods. However, considering aerodynamic dates can be obtained after high computational cost while the geometry profile could be well observed before the flow computation, here, the penalty function is only applied to aerodynamic characteristic and the geometry constraints are executed by regenerating a new airfoil. That is, a new airfoil profile will be regenerated until it satisfies the specified geometry constraints. The purpose of tacking constraints like this is to alleviate the pressure of the penalty function and simplified the problem.

5.3 Optimization Strategies

PSO algorithm and IPSOSM algorithm are applied to airfoil optimization design. They have the same initial population and both the population numbers are 25. The iteration cycles is set 39. It means there is 1000 (25+25 × 39=1000) times flow computation in the whole process of airfoil optimization. The inertial weight is reduced from 0.9 to 0.4 linearly. In PSO algorithm, the study factors are c_1=c_2=2 while in IPSOSM algorithm the study factors are c_1=1.5, c_2=2.0 and c_3=0.5.

5.4 Optimization results and analysis

Fig 2 and Fig 3 present the comparison of the airfoil shape and the pressure distribution before and after the optimization respectively. Table 2 presents the performance of the initial airfoil and the optimal airfoils.

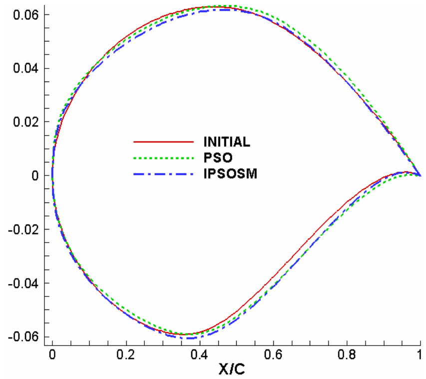


Fig.2 Comparison of the airfoil shape

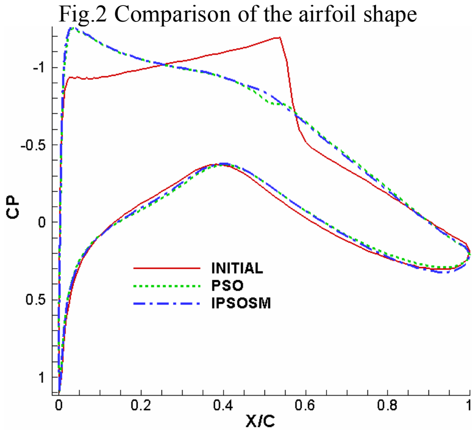


Fig.3 Comparison of the pressure distribution

Table.2 Comparison of performance

	Initial airfoil	PSO	IPSOSM
Lift coefficient	0.686	0.686	0.686
Drag coefficient	0.017627	0.013933	0.013683
Pitch moment	-0.0926	-0.0748	-0.0772
Maximum thickness	0.121	0.121	0.121
Area	0.0778	0.0798	0.0788

We may find from these figures and table that both of the algorithms achieve the goal to reduce the drag of airfoil within expected constraints. Fig 2 and Fig 3 show that the upper crest position and the maximum thickness position of the airfoil move backward. The loads located on the leading edge and the trailing edge are strengthened and the strong shock wave on the upper surface is also eliminated. In particular, compared with PSO algorithm, the pressure distribution obtained by IPSOSM algorithm is smoother which implies better aerodynamic results. The results learned from Table 2 show that with the identical computational cost, drag reduces 20.96% by using PSO algorithm while in IPSOSM algorithm, drag reduces 22.37%. All of these validate that analysis before, i.e., the social model helps the algorithm make good use of the information among the individual. Not only the information can be got from the best individuals and the best populations, but also the information hided in other non-best individuals is emphasized which finally drives the algorithm forward and results in better optimal ability.

6 Wing optimization design

The configuration used for wing design is clarified as follows[15]. Three control sections which locate at the root, the break -station and the tip of the wing are selected to express the section shape of the whole wing. The parameterization of each airfoil is similar to section 5.1. The difference is that, here, for each airfoil, 10 design variables are used for reducing the number of the design parameters, 5 for the thickness functions and the others for the camber functions. By this way, the total variables of three section airfoils are up to 30. Besides, the semi-span, the leading edge sweep, the length of root chord, the break-station chord and the tip chord, the twist of break-station airfoil and the tip airfoil, the position of the break-station are also under consideration which are so called the wing geometry parameters. So, the total variables of the whole wing amount to 38. In particular, the initial airfoils of the three sections are NACA0012. The optimization goal is to reduce the drag of the wing at cruise condition.

The design point is:

$$Mach = 0.78, \alpha = 3^\circ, \mathrm{Re} = 5.89 \times 10^6$$

The objective function is to minimize the drag coefficient. The maximum thickness of each airfoil and the reference area of the wing are not allowed to reduce. The lift is kept as constant. The mathematical model of this optimization case can be described as follows:

$$\min : f(x) = C_d$$

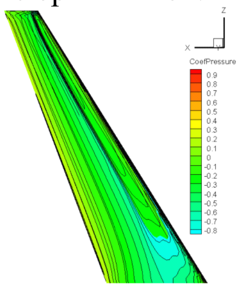
$$s.t:$$

$$t_{root\_\max} \geq 0.123, t_{break\_\max} \geq 0.122$$

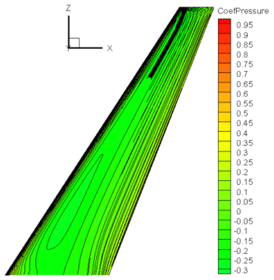
$$t_{tip\_\max} \geq 0.120, S \geq 64, C_l = 0.25$$

The RANS equations and k-w SST turbulence model are used to calculate the aerodynamic dates. The macro function is employed to generate the unstructured mesh automatically.

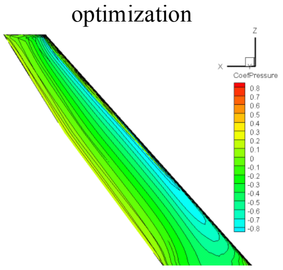
In IPSOSM algorithm, the number of the population is 25. The iteration cycles are 19. The study factors are c_1=1.5, c_2=2.0, c_3=0.5. The inertial weight w reduces from 0.9 to 0.4 linearly. Based on above, there are 500 (25+25×19=500) times flow computation in the whole optimization.



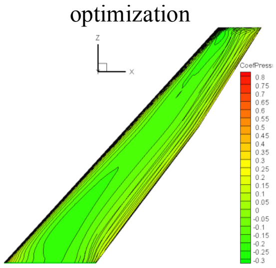
a. Pressure distribution of the upper wing before optimization



b. Pressure distribution of the lower wing before optimization



a. Pressure distribution of the upper wing after optimization



b. Pressure distribution of the lower wing after optimization

Fig.4 Pressure counter comparison of the wing

Table.3 Comparison of the wing parameter

Geometry parameters of the wing				
	Upper boundary	Lower boundary	Initial wing	Optimized wing
Semi-span	15m	17m	16m	16.2269 m
Leading sweep	22.25°	42.25°	32.25°	42.25°
Root chord	3m	9m	6m	6.2732 m
Break chord	1m	7m	4m	4.7917 m
Break position	5m	11m	8m	8.6310 m
Break twist	-3°	3°	0°	1.4315°
Tip chord	1m	3m	2m	2.7156 m
Tip twist	-3°	3°	0°	-1.8945°
$t_{root-max}$	0.120	——	0.120	0.1260
$t_{break-max}$	0.120	——	0.120	0.12301
$t_{tip-max}$	0.120	——	0.120	0.1213
Area	64 m^2	——	64 m^2	76.2631 m^2

Aerodynamical parameters of the wing		
	Initial wing	Optimized wing
Lift coefficient	0.25	0.25
Drag coefficient	0.011327	0.010751

Fig 4 presents the comparison of the pressure counter distribution of the wing and table 2 shows the comparison of the wing performance. Learned from these results, we may see that the drag is reduced with the expected constraints. The drag of the wing is reduced about 5.09%. Compared with the initial wing, all of the values except for twist of tip airfoil are enlarged. In particular, the leading edge sweep changes from 32.5° to 42.5° which slow down the effective velocity of the flow stream. As a result, the drag is also reduced correspondingly. The negative twist angle appearing on the tip airfoil can reduce partially the load of the tip which is favourable to avoid the appearance of shock wave on the wing tip. All of these validate that IPSOSM is still efficient in a more complex wing optimization case which also proves the efficiency of the social model.

7 Conclusions

(1) In this paper, social model is developed and validated to be an efficient universal strategy to improve the performance of intelligent algorithms. With the guidance of it, the collective action belonging to AFSA algorithm is simplified and introduced into PSO algorithm and a new algorithm named Improved Particle Swarm Optimization Based on Social Model is proposed correspondingly. The results of the function test and the aerodynamic optimization prove that IPSOSM algorithm performs better optimal ability than PSO algorithm.

(2) Currently, the computational cost of aerodynamic optimization in the framework of CFD is still prohibitively large. It is promising to develop some algorithms that are good at both low computational cost and optimal ability. To this end, much investigation may be done in the future.

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