Constraint Multi-objective Optimization based on Genetic Shuffled Frog Leaping Algorithm

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Abstract: To solve the convergence problem of the constrained multi-objective optimization, combining the advantages of genetic algorithm and shuffled frog leaping algorithm，a method based on genetic shuffled frog leaping algorithm. To use the genetic operators and the packet improved shuffled frog leaping algorithm and avoid falling into local optimal, accelerating the convergence speed. Experiments show that the improved algorithm is efficient and reasonable, can reduce the execution time of the multi-objective optimization problem, improve the quality of optimal solution.

1 THE CONSTRAINT MULTI-OBJECTIVE OPTIMIZATION

In the real world, the problem of optimization with multi-objective constraint, under certain conditions, the optimization problems are multi-objective, in most cases, multi-objective to be optimized attributes with conflicting. For example, the investment problem, we hope to use the least investment cost and the lowest risk, to gain the maximum benefit. If there is no priori knowledge, this kind of problem solving is very difficult by the single objective optimization. The multi-objective optimization problem (MOP)[1], which is defined as follows:

If there are n variables and k objective function of multi-objective problem, describe its formalization:

$$\begin{cases} \max \ y = \{ f_1(x), f_2(x), \ldots, f_k(x) \} \\ S.T. e(x) = \{ e_1(x), e_2(x), \ldots, e_m(x) \} \le 0 \end{cases} \quad (1)$$

Among them, x= (x1, x2,... , xn) ∈X, X is the decision vector, X represent the decision space formed by the decision vector y= (y1, y2,... , yK) ∈ Y, y is the target vector, Y formed by the target vector target space constraints, e (X) ≤ 0 determines the range of x.

Constrained multi-objective optimization goal can not find a single solution, the optimal solution is a set, is to ensure that the set of Pareto optimal solutions close to the true Pareto optimal solution set and evenly distributed on the basis of satisfying the constraints, the complexity of the greater. At present, the traditional method of constrained multi objective optimization are[2]:① objective weighting method, the multi-objective optimization problem into a single objective optimization problem;② the single objective function as the optimization objective, the other goal function to solve the constraints; ③the goal programming method to set the objective function for the intended target, find out the closest or expected value solution. Traditional multi-objective optimization methods is difficult, mainly reflected in: ①one can only obtain a Pareto optimal solution; ②the Pareto frontier is concave,

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can not find the Pareto optimal solution; the traditional method requires the priori knowledge.

Evolutionary algorithm is a group search algorithm, can have multiple Pareto optimal solutions in a single execution, and the different problems (non continuous, non differentiable problem solving)[3]. In the optimization of constrained multi objective treatment, improves the convergence and diversity algorithm. More and more studies the evolutionary algorithm, and achieved great success, but the number of multi-objective evolutionary algorithms are generally not more than 4 , its stability is relatively poor, to find the optimal solution efficiently and further research is needed.

2 SHUFFLED FROG LEAPING ALGORITHM

Shuffled frog leaping algorithm is a heuristic search algorithm.in 2003, Eusuff and Lansay formally proposed shuffled frog leaping algorithm[4][5], search by heuristic function, and find the optimal solution. In this algorithm, the memetic algorithm as the foundation, combined with the optimization algorithm and particle swarm optimization.

2.1 The Principle of the Algorithm

In 1989, Moscato proposed Memetic algorithms (MA, meme) as chromosomes carry genetic information, only to be transmitted or repeated when it can be called memo, the algorithm uses the competition and cooperation mechanism in the local strategy, which can be used to solve large-scale discrete optimization problem, can solve the other algorithm cannot solve the problem.

In 1995, Eberhart and Kennedy proposed particle swarm optimization algorithm according to the birds of prey behavior simulation of simplified social model[6]. The algorithm is composed of a plurality of particle groups to a certain speed in D dimensional search space flight, each particle to search other particles within the relevant range phase of merit, and on the basis of the position change[7]. The particle velocity and position formula as follows:

$$V_{iD}^{k+1} = V_{iD}^{k+1} + c_1\xi(p_{iD}^{k} - x_{iD}^{k}) + c_2\eta(p_{gD}^{k} - x_{gD}^{k}) \quad (2)$$

$$x_{iD}^{k+1} = x_{iD}^{k} + V_{iD}^{k+1} \quad (3)$$

The C1, C2 as the study factor, the particles have the ability to self summary and excellent learning within the field of particles, the particles into the history of the advantages of continuous approximation; ξ, η ∈[0,1], is a uniform distribution random number intervals, xi=（$x_{i1}, x_{i2}, \ldots, x_{iD}$) is the i particle position (P_{i1}, P_{i2}, p_{i3},... P_{iD}), best historical point particles experienced pg=($pg_1, pg_2, \ldots, pg_D$) the best point particle through.

In 1998, Shi and Eberhart into the inertia weight in the algorithm, improves the convergence performance of the algorithm, the velocity formula (2) to:

$$V_{iD}^{k+1} = \omega v_{iD}^{k} + c_1\xi(p_{iD}^{k} - x_{iD}^{k}) + c_2\eta(p_{gD}^{k} - x_{gD}^{k}) \quad (4)$$

Among them, Omega is the inertia weight, its value can make the particles with balancing exploration ability and exploitation ability. When ω= 1, the basic particle swarm optimization algorithm is a standard.

A group of cooperative search algorithm shuffled frog leaping algorithm by simulating the frog foraging and produce[8], transfer by individual and group information, the global information exchange and local search effectively combined. The whole wetland frog is set to a population, the population is divided into several sub populations in small populations, each has its own culture, every frog also have other effects and individual self culture, and

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with the evolution of the population evolution, when these sub populations evolve to a certain extent, will these sub populations were mixed, realize information exchange, until a termination condition is satisfied. The global leap exchange and the local depth search strategy so that the algorithm can jump out of local optimum to the global optimum direction, evolution.

2.2 The Algorithm Flow

Step 1: population initialization: within the feasible solution space, randomly generated initial population of F, the whole population containing k＝m*N frog. Where m is the number of sub populations, namely the number of memeplex, n is the number of each sub population contains frog. Dimension D, each frog position represents a candidate solution, the I frog position F (i) adaptive value is denoted by fi.

Step 2: the entire population in the k frog according to the fitness values in descending order, generating a group number X＝{F(i),f_i;i=1,2,…,k}, when i=1, said the frog's best position.

Step 3: on the whole population according to k=m*n divided into m groups $Y_1,Y_2,\ldots,Y_m$, expressed
as:

$$Y_k=[F(j),f_j \mid F(j)=F(k+m(j-1)),f_j=f(k+m(j-1)),j=1,2,...,n]_T$$

he first frogs into Y_1 subgroup, second frogs into Y_2, so tired, the m frog into the Ym, the m+1 frog is divided into Y_1, until all the frogs distribution date.

Step 4: in each sub population memeplex, every frog affected other frogs, keep close to the goal. Mainly uses the memetic evolution, the process is as follows:

(1) counting im initialization of Memeplex ,im= 0, iterations iN=0 ,each evolution, the frog information exchange between individuals, the worst frog position to improve position;

（2）im=im+1；

（3）iN=iN+1；

(4) for moving the position of each frog, frog mobile distance cannot exceed the maximum distance moved;

(5) if the frog to move to a better location, representation yields better solutions, with the new location of the frog instead of frog, or use the best point in the history of frog pg replace the position of sub populations best frog pb, repeat the above action;

(6) if the operation does not produce new, then randomly generated a new location instead of the sub populations at the worst frog pw;

(7) if iN<N, then go to the (2);

(8) if im<m, then go to the (1).

Step 5: the frog after memetic evolution, the sub populations were mixed, to adapt to the values are sorted, and update the best position of the whole population of frogs.

Step 6: a termination condition is satisfied, then the end, or to jump to the Step 3.

2.3 The Algorithm Parameter Setting

The algorithm needs to set 5 parameters: the number of initial clusters in the frog k, k value is greater, showing the number of initial samples of the larger, compute the optimal solution is more likely; number of sub populations of m because k=m*n, m size of the direct impact of the a number of frogs each subgroup of n, if the n value is too small, the advantages of memetic evolutionary search will not exist; allows the frog to move the maximum distance , the values and the ability to control algorithm for global search, the value is too large, may skip the optimal solution, capacity is too small will reduce global search; maximum algebra of the entire population, and scale proportional to the size of the value of the maximum number of iterations; sub populations of N, might fall into the local optimal

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value is too large, too small will weaken the information exchange between individuals.

3 IMPROVED SHUFFLED FROG LEAPING ALGORITHM

Shuffled frog leaping algorithm is relatively strong ability in global search, but if the problem is more complex, then the problems of slow convergence speed and easily falling into local extremum problem, genetic algorithm has the ability to jump out of the local optimum, therefore, will be shuffled frog leaping algorithm combined with genetic algorithm to form the genetic shuffled frog leaping algorithm (G-SFLA).

Differences between G-SFLA and SFLA is to adopt the genetic algorithm crossover and mutation operations on packet evolution, these two operations used in the process of Step 4.

The crossover operation refers to the same position of random performance best frog Pb and the poor performance of frog Pw set breakpoints, the right part of the breakpoints are exchanged, generating two new process called cross. If the new position is better than Pw, instead of Pw. If the solution is not superior to Pw, the random Pw bits of mutation operation, thus creating new solutions instead of Pw.

G-SFLA, the group also makes some improvements, the grouping method of SFLA, the last group of individual relative fitness of relatively poor individuals in the whole population, even if the group members constantly through the information exchange and learning, it is unable to get a better evolution results. Because of uneven packet, limitation of the study amplification. A new way of grouping is based on the original packets, randomly from the other group took several individuals joined the group, the number of the members of the group are n+m-1, diversity is obtained with genetic arithmetic, play the advantage of. Note that, when the team re merged into a population, the number of individuals in a population increase of m* (m-1), sorted again for all individuals, remove duplicate individual. The number of individuals removed more than k, from the previous K individuals to iterate the next round, if less than k individuals, randomly generated individuals, make up the K for the next round of iteration.

4 SIMULATION EXPERIMENTS

This experiment in order to verify the performance of G-SFLA, comparing with the shuffled frog leaping algorithm, the experimental results are analyzed. The experimental function using 3 benchmark functions, as shown in table 1: The experimental parameters are set as follows: the population of 500 frog, is divided into 25 sub groups, frogs have 20 each subgroup of SFLA, G-SFLA in 25 (adding 5), in the subgroup of 20 times of iteration, the individual search range is Xmax/5, evolutionary iteration times is 1000, the algorithm running 25 time. In the condition of same parameters, the experimental results on SFLA and G-SFLA two kinds of algorithm (Table 2) were compared, analysis of the pros and cons.

Table 1: The Test Object.

Function	Function Expression	Range	Standard Solution
Sphere	$\sum_{i=1}^{D} x_i^2$	[-100,100]	0
Schwefel	$-\sum_{i=1}^{n}(x_i \sin\sqrt{\lvert xi \rvert}) + 418.9829n$	[-500,500]	0
Ackley	$-20\exp[-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}]-\exp[\frac{1}{n}\sum_{i=1}^{n} 2\pi$	[-32,32]	0

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Table 2: The experimental results.

Function	Algorithm	The average optimal value	standard deviation
Sphere	SFLA	0.00573	0.00286
	G-SFLA	2.3E-16	4.72E-16
Schwefel	SFLA	0.92186	0.18636
	G-SFLA	0.00304	0.00017
Ackley	SFLA	0.79385	0.65802
	G-SFLA	1.82E-13	5.42E-13

Figure 1- Figure 3 are three curves that function respectively by SFLA and G-SFLA algorithm independent running average value obtained after 25 times of evolution.

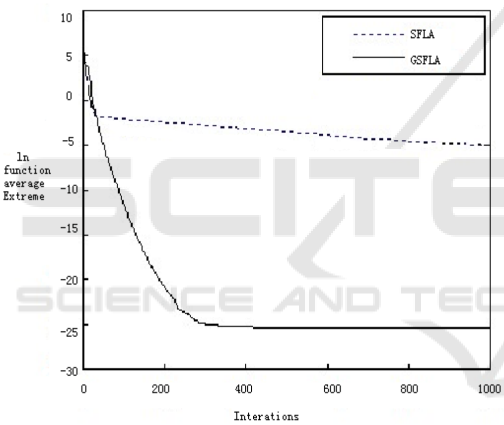

Figure 1: The evolutionary curve of Sphere.

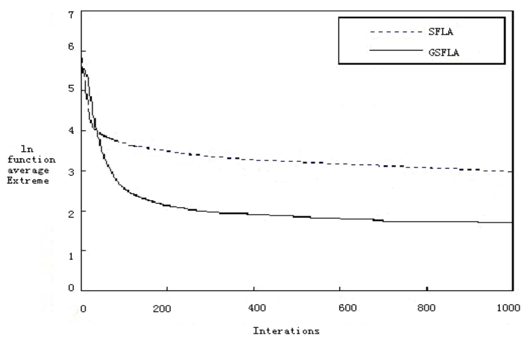

Figure 2: The evolutionary curve of Schwefel.

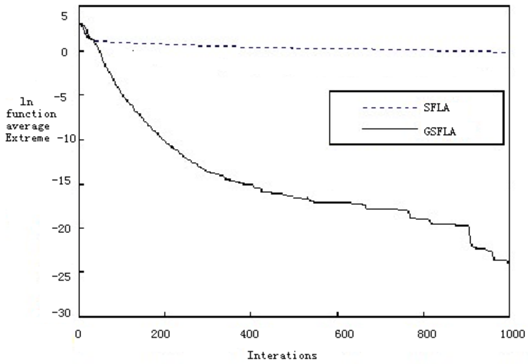

Figure 3: The evolutionary curve of Ackley.

Through the above three in the chart, the constrained multi objective optimization, the performance of G-SFLA is better than SFLA, in the target optimization accuracy under the same number of iterations, G-SFLA is obviously lower than SFLA. The above results show that, G-SFLA has better stability and convergence.

5 CONCLUSION

Based on the advantages of shuffled frog leaping algorithm and genetic algorithm, design a constraint multi-objective genetic algorithm based on shuffled frog leaping algorithm. Experiments show that, in the parameter is small, the G-SFLA algorithm has faster convergence speed, can in the iteration times less access to better solutions.

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