AN IMPROVED MULTI-OBJECTIVE EVOLUTION ALGORITHM BASED ON SHUFFLED FROG LEAPING

Jianping Luo
Shenzhen Key Lab of Advanced Communications and Information Processing, College of Information Engineering, Shenzhen University, China
camelrock@126.com

Xia Li
Shenzhen Key Lab of Advanced Communications and Information Processing, College of Information Engineering, Shenzhen University, China

Min-Rong Chen
Shenzhen Key Lab of Advanced Communications and Information Processing, College of Information Engineering, Shenzhen University, China
mrongchen@126.com

Hongwei Liu
Shenzhen Key Lab of Advanced Communications and Information Processing, College of Information Engineering, Shenzhen University, China
36541562@qq.com

Abstract:
In this paper, we present a meta-heuristic base on improved shuffled frog leaping algorithm (SFLA) to tackle the multi-objective problem (MOP). The SFLA is suitable to solve the single objective problem. For the multi-objective problem, one main issue is that how to evaluate the quality of two optional solutions and select the better one from them. The traditional Pareto dominance cannot generate a strong selection pressure toward the Pareto front when we have many objectives (since almost all solutions in the current population become non-dominated). In our algorithm, we propose a relaxed dominance mechanism to promote the selection pressure in evolution. The comparison between two frogs proposed in this work takes the modified Pareto dominance relations into account. At the same time, the number of frog in each memeplex of SFLA is not too much, we only select two individuals (the best and the worst) to perform the memetic evolution. Therefore, the algorithm has the better selection pressure toward to the Pareto front. The experimental results show that our algorithm processes good performance to solve the MOP.

Keywords: multi-objective optimizatio, shuffled frog leaping algorithm, dominance mechanism

1. INTRODUCTIONS

An m-objective optimization problem (MOP) can be described as in the following equation:

$$\mathit{Minimize}\ \mathrm{F(x)}=(f_1(\mathrm{x}), f_1(\mathrm{x}),..., f_k(\mathrm{x}))^T \ \text{Subject to } \mathrm{x} \in \mathrm{S} \qquad (1)$$

where S is the decision (variable) space, x is a decision vector, $\mathrm{F}{:}\mathrm{S} \rightarrow \mathrm{R}^k$ consists of k real-valued objective functions and R^m is called the objective space. Pareto dominance is formally defined as follows:

A vector $\mathrm{x_A}$ is said to dominate $\mathrm{x_B}$ if $\mathrm{x_A}, \mathrm{x_B} \in \mathrm{S}$, $f_i(\mathrm{x_A}) \le f_i(\mathrm{x_B})$ $(i \in \{1,2,...,k\})$, and there is at least one $j \in \{1,2,...,k\}$ such that $f_i(\mathrm{x_A}) < f_i(\mathrm{x_B})$, written as $\mathrm{x_A} \prec \mathrm{x_B}$.

$\mathrm{x'}$ is said to be a non-dominated solution, or a Pareto optimum solution, if $\mathrm{x'} \in \mathrm{S}$ and there are no others that dominated $\mathrm{x'}$ in S.

Since the objectives in (1) contradict each other, no point in S maximizes all the objectives simultaneously. One has to balance them. The best tradeoffs among the objectives can be defined in terms of Pareto optimality. When all non-dominated solutions are plotted in objective function space, the non-dominated vectors are collectively known as the Pareto Front (PF). Formally:

$$PF := \{(f_1(\mathrm{x}), f_1(\mathrm{x}),..., f_k(\mathrm{x})) \mid \mathrm{x} \in PS\} \qquad (2)$$

Shuffled Frog Leaping Algorithm (SFLA), which was developed by Eusuff and Lansey[1], belongs to the MA family. It is a meta-heuristic optimization method inspired from the memetic evolution of a group of frogs when seeking for food. In this algorithm, the evolution of memes is driven by the exchange of information among interactive individuals. SFLA combines the advantages of the genetic-based MA and the social behavior-based PSO algorithm. It has been tested on several combinatorial problems and found to be effective in searching the global solutions [2-4]. In this work, we present a general framework based on the SFLA to solve the MOP.

2. SHUFFLED FROG LEAPING ALGORITHM (SFLA)

Shuffled Frog Leaping Algorithm (SFLA) is a meta-heuristic optimization method that mimics the memetic evolution of a group of frogs when seeking for the location that has the maximum amount of available food. It is described in detail as follows. First, an initial population of F frogs is created randomly. For the d-dimensional problem, the position of the 'ith' frog is represented as $x_i = (x_{i1}, x_{i2,}, ..., x_{id})$. Afterwards, the frogs are sorted in a descending order according to their fitness.

Afterwards, all the frogs in population P are sorted in a ascending order according to their fitness to form m memeplexes $\Psi^1, \Psi^2, ..., \Psi^m$, which can be created by

$$\Psi^k = \{X_i^k \mid X_i^k = X_{k+m(i-1)}, i = 1,2,...,n\} \quad k = 1,2,...,m \qquad (3)$$

where n is the number of frog in every memeplex. It is obvious that $F = m \times n$. The worst frog in each memeplex is updated according to the following rule:

$$B = r(X_b - X_w) \qquad (4)$$

$$X_w^{'} = X_w + B, \quad \| B_{\min} \| \le \| B \| \le \| B_{\max} \| \qquad (5)$$

where B denotes the leaping step size; X_w and X_b stand for the worst frog and the best frog, respectively, in the memeplex; r is a random number between (0, 1) and $\| B_{\min} \|$ and $\| B_{\max} \|$ are the maximum and minimum allowed change in a frog's position, respectively. If $X_w^{'}$ is better than X_w,

X_w is replaced by $X_w^{'}$. Otherwise, the global best frog X_g is used instead of X_b to carry out the above updating strategy, i.e.,

$$B = r(X_g - X_w) \quad (6)$$

If there is still no improvement, X_w is replaced by a random solution. The process continues for a pre-defined number of iterations within each memeplex. Afterward, all frogs are shuffled for global information exchange. Local exploration and global shuffling alternate until a pre-defined convergence criterion is satisfied.

3. SFLA FOR MOP

In this paper, we present a meta-heuristic base on the SFLA to tackle the multi-objective problem. The main working process of algorithm is similar to the introduction of section 1. The SFLA is suitable to solve the single objective problem. For the multi-objective problem, one main issue is that how to evaluate the quality of two optional solutions and select the better one from them, e.g., consideration the updating of the worst frog, how to judge whether the $X_w^{'}$ is better than X_w. In this paper, we propose a relaxed dominance mechanism to improve the effectiveness of algorithm.

3.1. Fitness evaluation

Traditionally, the fitness assignment scheme is composed of two important ingredients. One is Pareto dominance relationship, which divides individuals into dominated and non-dominated categories. And the latter ones are always preferable to the formers when referring to fitness values. The other ingredient is usually represented by the density information of an individual. In our algorithm, we adopt and modify a simple but effective method initially proposed in Non-dominated sorting genetic algorithm II to sort the frogs. Non-dominated sorting genetic algorithm II (NSGA-II): NSGA-II [5] was advanced from its origin, NSGA [6]. In NSGA-II, a non-dominated sorting approach is used for each individual to create Pareto rank, and a crowding distance assignment method is applied to implement density estimation. In a fitness assignment between two individuals, NSGA-II prefers the point with a lower rank value, or the point located in a region with fewer numbers of points if both of the points belong to the same front. Therefore, by combining a fast non-dominated sorting approach, an elitist scheme and a parameterless sharing method with the original NSGA, NSGA-II claims to produce a better spread of solutions in some testing problems [5].

3.2. Relaxed dominance mechanism

In memetic evolution of SFLA, the comparison of two frogs ought to be implemented to judge whether the mutation solution replace the worst frog. The traditional Pareto dominance cannot generate a strong selection pressure toward the Pareto front when we have many objectives (since almost all solutions in the current population become non-dominated). In our algorithm, we propose a relaxed dominance mechanism to promote the selection pressure in evolution. The comparison between two frogs proposed in this work takes the modified Pareto dominance relations into account. At the same time, the number of frog in each memeplex of SFLA is not too much, we only select two individuals (X_b and X_w) to perform the memetic evolution. Therefore, our algorithm has the better selection pressure toward to the Pareto front.

The slightly dominance is defined as:

A vector $\mathrm{x_A}$ is said to slightly dominate $\mathrm{x_B}$ if

$$|fs_{\mathrm{A}}| > |fs_{\mathrm{B}}|$$

where $fs_{\mathrm{A}} = \{i \mid f_i(\mathrm{x_A}) < f_i(\mathrm{x_B})\}$, $fs_{\mathrm{B}} = \{i \mid f_i(\mathrm{x_A}) > f_i(\mathrm{x_B})\}$, $\mathrm{x_A}$, $\mathrm{x_B} \in \mathrm{S}$, $\mathrm{x_A}$ and $\mathrm{x_B}$ are not dominate each other, and $|fs_{\mathrm{A}}|$ is the number of elements in the set fs_{A}.

In order to say that a solution slightly dominates another one, such a solution needs to have a more number of the better objectives. Therefore, when we are comparing two different solutions, the following procedures are performed as Algorithm 1 shown, where Dis_x denote the crowding distance. Note that the return value of algorithm 1 is 1,-1 or 0, which is corresponding to x_A is better than x_B, x_A is inferior than x_B and x_A is equal to x_B, respectively. The comparison of two solutions is performed only in the procedure of memetic evolution in each memeplex, in which the algorithm determinates whether the X_w frog is replaced by the new frog generated using updating formula.

Picture 1: Algorithm 1 - Comparison of two solutions

Algorithm 1: Comparison of two solutions

```
Input: xA, xB
If xA dominate xB
    return 1
Else If xB dominate xA
    return -1
If xA slightly dominate xB
    return 1
Else If xB slightly dominate xA
    return -1
If Dis_xA > Dis_xB
    return 1
Else If Dis_xA < Dis_xB
    return -1
Else
    return 0
```

4. PERFORMANCE ASSESSMENTS

We evaluate the performance of the proposed algorithm, i.e., SFLA with relaxed dominance mechanism (SFLA-RD) and the SFLA with Non-dominated sorting mechanism[5] (SFLA-NS) on a set of 13 benchmark functions [7], which include 7 two-objective test functions, 3 three-objective test functions and 3 five-objective test functions.

A. Performance Metric (IGD)

Let P* be a set of uniformly distributed points along the PF (in the objective space). Let *A* be an approximate set to the PF, the average distance from P* to *A* is defined as [7]:

$$IGD(A, P^*) = \frac{\sum_{v \in P^*} d(v, A)}{|P^*|} \qquad (7)$$

where *d*(*v*, *A*) is the minimum Euclidean distance between *v* and the points in *A*.

B. PC Configuration:

System: Windows XP Professional; CPU: Intel Pentium® 4 CPU 2.8 GHZ; Ram: 1GB of memory; Computer Language: Visual C++.

C. Algorithmic Parameter Setting

The parameters setting of SFLA are performed, $m = 10, n = 10,$ and the generation number for the memeplex is equal to 8. These values are found suitable to produce good solutions in terms of the processing time and the quality of the solution in accordance with our observation in experiments. The maximum shuffling iterations is set as 2000.

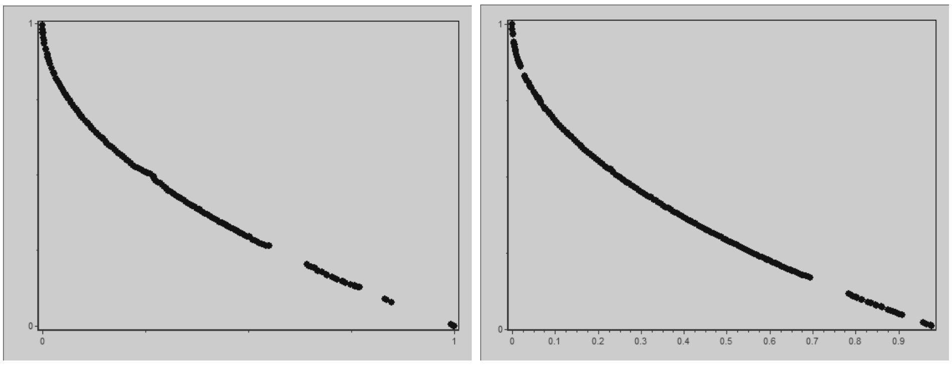
D. Experimental Results

For all the test functions, we recorded the approximate set every generation in each run. According to these approximate sets, we calculated the performance metrics IGD [7]. The mean, the best, the worst and the standard deviation of the IGD values obtained for each test instance of the 10 runs are presented in Table I for SFLA-RD and the mean of the IGD values obtained by SFLA-NS is also shown in the table. Smaller IGD values indicate better results. For the SFLA-RD, the plot of the final approximation set with the smallest IGD value in the objective space for some test instances with 2 objectives are shown in Figs. 1. From IGD values shown in Table I, among all the 13 test problems, SFLA-RD performs better than the SFLA-NS on all the 13 benchmark test functions. It demonstrates that SFLA-RD improves upon the search ability of the original SFLA with Non-dominated sorting mechanism. Therefore, our proposed improved algorithm is effectiveness to solve the MOP.

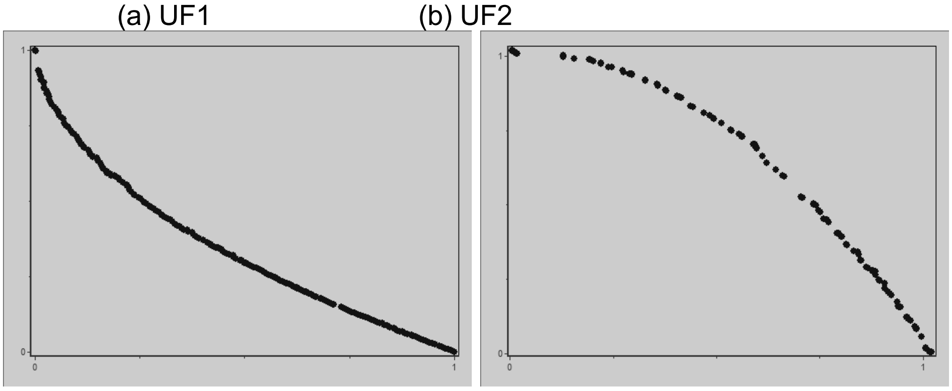
Table 1: the IGD statistics based on 10 independent runs

Instance	SFLA-RD				SFLA-NS
	Mean	Best	Worst	Std	Mean
UF1	0.00821	0.00789	0.00896	0.002	0.01231
UF2	0.00652	0.00623	0.00701	0.025	0.0136
UF3	0.00535	0.00498	0.00595	0.014	0.00962
UF4	0.02258	0.02105	0.02478	0.056	0.0325
UF5	0.02157	0.02024	0.02225	0.012	0.04123
UF6	0.01482	0.013014	0.01515	0.002	0.01954
UF7	0.00954	0.00892	0.01025	0.007	0.02541
UF8	0.08916	0.08517	0.09358	0.092	0.1025
UF9	0.09801	0.09661	0.09986	0.085	0.11258
UF10	0.65842	0.64215	0.65952	0.535	0.68452
UF11	0.21052	0.20221	0.22102	0.124	0.32864
UF12	138.2257	137.2785	139.2248	0.985	158.56425
UF13	1.02555	1.00258	1.1258	0.0523	1.45862

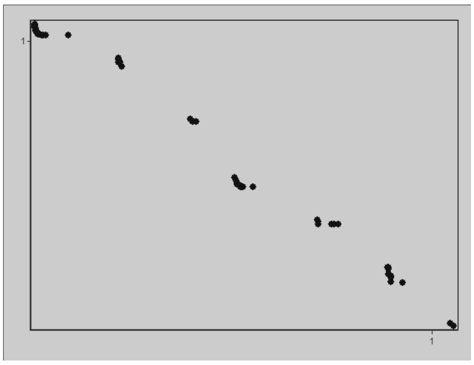
Picture 2: The best approximation to UF1-UF7



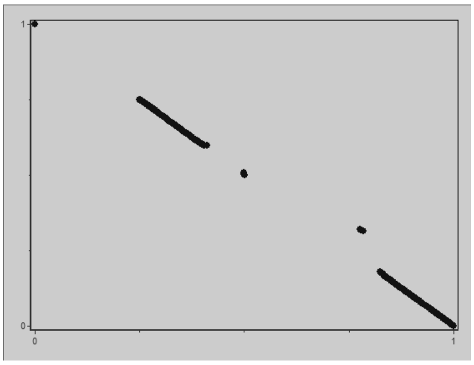
(a) UF1 (b) UF2



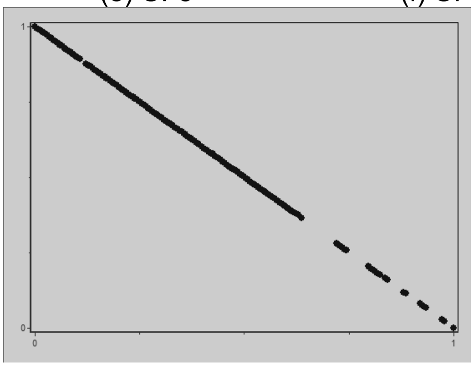
(c) UF3 (d) UF4



(e) UF5



(f) UF6



(g) UF7

5. CONCLUSIONS

In this paper, we present a meta-heuristic base on SFLA to solve the multi-objective problem (MOP). The SFLA is suitable to solve the single objective problem. For the multi-objective problem, one main issue is that how to evaluate the quality of two optional solutions and select the better one from them. The traditional Pareto dominance cannot generate a strong selection pressure toward the Pareto front when we have many objectives (since almost all solutions in the current population become non-dominated). In our algorithm, we propose a relaxed dominance mechanism to promote the selection pressure in evolution. The comparison between two frogs proposed in this work takes the modified Pareto dominance relations into account. At the same time, the number of frog in each memeplex of SFLA is not too much, we only select two individuals (the best and the worst) to perform the memetic evolution. Therefore, the algorithm has the better selection pressure toward to the Pareto front. The experimental results show that our algorithm processes good performance to solve the MOP.

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