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GICA: Imperialist competitive algorithm with globalization mechanism for optimization problems

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Abstract: The imperialist competitive algorithm (ICA) is a recent global search strategy developed based on human social evolutionary phenomena in the real world. However, the ICA has the drawback of trapping in local optimum solutions when used for high-dimensional or complex multimodal functions. In order to deal with this situation, in this paper an improved ICA, named GICA, is proposed that can enhance ICA performance by using a new assimilation method and establishing a relationship between countries inspired by the globalization concept in the real world. The proposed algorithm is evaluated using a set of well-known benchmark functions for global optimization. Obtained results show the efficiency and effectiveness of the method and show that this strategy can deal with the local optimum problem.

Key words: Imperialist competitive algorithm, optimization, local optimum, globalization, segmented assimilation, crossover

1. Introduction

Fundamentally, most optimization problems are hard. Linear programming and dynamic programming techniques or conventional mathematical methods often fail in solving this kind of problems with large numbers of variables, but evolutionary algorithms (EAs) can be effective in these problems and provide near optimal solutions for them due to their random nature.

Several EAs have been proposed for searching near-optimum solutions to NP-hard problems. These algorithms are stochastic search methods inspired from natural processes, e.g., the genetic algorithm (GA) [1], which derives its behavior from the process of natural evolution; particle swarm optimization (PSO) proposed by Kennedy and Eberhart [2] in 1995, inspired by the social behavior of bird flocking; ant colony optimization (ACO) [3], which mimics the behavior of ants investigating from nest to food source; and artificial honey bee (AHB) [4], based on the foraging behavior of bees.

The imperialist competitive algorithm (ICA) is a new evolutionary algorithm proposed by Atashpaz-Gargari and Lucas [5] in 2007. The ICA is not inspired by natural processes; instead, it uses the phenomenon of sociopolitical competition among human empires in the real world. Like other evolutionary algorithms, the ICA begins with an initial population, normally randomly generated. In this algorithm, an individual of the population is called a country. The ICA divides its population into several groups, called empires, and allows these empires to evolve concurrently. In each empire, the best country is called imperialist and the others are

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called colonies. The ICA moves all colonies toward the imperialist through assimilation policy in each empire. The basic feature of the ICA is that it permits all empires to interact via imperialist competition policy. The competition policy simply moves a colony from the weakest empire to another empire [5].

The ICA algorithm has been successfully applied to a variety of optimization problems [6–8]. The results reported in these studies confirm its competitiveness over other EAs. The ease of performing neighborhood movement, less dependency on initial solutions, and having a better convergence rate are other advantages of the ICA, but due to some insufficiencies, it often gets trapped in the local optimum area, especially in multimodal and high-dimensional problems [7,9].

One of the drawbacks of the ICA is that is mechanism for improving the quality of imperialist countries is weak. The power of imperialist countries is improved just by exchanging positions with their colonies, but in this case the convergence speed becomes slow. Having a more efficient mechanism for improving the quality of imperialists can accelerate the algorithm to reach the location of the globally optimal position in the search space. On the other hand, although the assimiliation operation in each iteration of the algorithm improves the quality of each empire, but it is not satisfying, especially in high-dimensional problems, it could not be adapted with the search process because of its monotonic nature [9]. Another drawback of the ICA is competition among empires. If the quality improvement approach for empires is not strong enough, competition occurs too often and weak empires get eliminated quickly. In this condition, population diversity quickly degrades and consequently the algorithm is trapped in local optima due to loss of diversity. These negative points may cause premature convergence to a local optimum in the ICA.

In this paper, inspired by the concept of globalization in the real world, we have proposed an improved ICA called GICA that uses a different assimilation mechanism and an extra method for establishing effective relationships between countries to enhance explorative and exploitation search abilities to improve the convergence speed of the original ICA. The proposed method efficiently deals with the premature convergence problem and promotes the global search capability of the algorithm by better improving the quality of empires. Compared with some EAs and other variants of the ICA, experimental results demonstrate that the proposed algorithm (GICA) can effectively overcome trapping in the local optimum problem and achieve the global optimum with fewer iterations.

The rest of the paper is structured as follows: Section 2 presents a brief review of some related works. Section 3 provides an introduction to the original ICA. Section 4 describes the proposed algorithm. Section 5 discusses experimental results. Finally, Section 6 is devoted to conclusions and future work.

2. Related work

For dealing with premature convergence in the ICA, some previous works applied an improved assimilation operator for doing better local search and keeping diversity in the population [9–11]. Other methods take advantage of the strength of other EAs and ICA together in an algorithm (e.g., [12–14]). In this section, we briefly review these methods.

Abderchini et al. [9] proposed a variant of ICA called the adaptive imperialist competitive algorithm (AICA), in which the absorption policy is changed dynamically to adapt colonies' movement for an effective search. Talatahari et al. [10] introduced a chaotic imperialist competitive algorithm. In this study different chaotic maps were utilized to determine the moving direction for the assimilation operation. Lin et al. [11] proposed 2 variants of ICA named ICALSI and ICALSB, where they perform a local search method called random line search on the best solution. Behnamian et al. [12] used GA operators to make a feasible assimilation mechanism. Godrati et al. [14] presented a new hybrid method using PSO and ICA by adding independent countries for large-scale global optimization. Lin et al. [15] presented 2 variants of ICA called ICAAI and ICACI; the former one controls frequency of the competition process by introducing a new parameter, ρ, and the latter one applies uniform crossover between imperialists for exchanging information about the imperialist with other empires. Ramezani et al. [13] proposed a new hybrid method called SBA, which combines evolutionary algorithm and ICA features. They presented promising results from their proposed algorithm.

3. Basic imperialist competitive algorithm

The ICA starts with an initial random population of size N_{pop}, where each member of the population is referred to as a country. A predetermined number of these countries that have the best fitness, N_{imp}, are selected as imperialists and the others are considered as the colonies of these imperialists. For an N-dimensional optimization problem (N_{var}), a country is defined as in Eq. (1) and its cost is defined with the fitness function f as in Eq. (2).

$$country_i = [p_{i1}, p_{i2}, p_{i3}, \ldots, p_{iN}] \tag{1}$$

$$cost_i = f\left(country_i\right) = f\left(p_{i1}, p_{i2}, p_{i3}, \ldots, p_{iN}\right) \tag{2}$$

Empires are formed by distributing colonies between imperialists based on their power. Thus, each empire consists of an imperialist and some colonies, where the stronger imperialists have more colonies than the weaker ones.

The main core of the ICA is the assimilation process that is shown in Figure 1. The assimilation process causes the colonies to move x distance along d direction towards their related imperialist. The total power of each empire is defined by the power of its imperialist and a fraction of the power of its colonies, as Eq. (3):

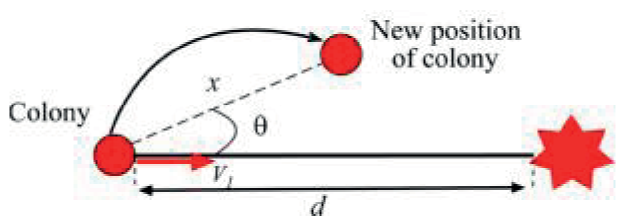


Figure 1. Movement of a colony toward its imperialist.

$$TC_n = cost\left(imp_n\right) + \zeta \times mean\left\{cost(colonies\, of\, emp_n)\right\}, \tag{3}$$

where TC_n is the total cost of the nth empire and $0 < \zeta < 1$ (usually near zero).

In the assimilation process, each colony moves towards the imperialist by a random unit and a random deviation angle, θ, on the vector that connects the colony to its imperialist. This angle is a random number with uniform (or any proper) distribution. The movement is made by Eq. (4).

$$\{x\}_{new} = \{x\}_{old} + \beta \times d \times \{rand\} \otimes \{V_1\} \tag{4}$$

where, β is a positive number between 1 and 2 (usually near 2) and d is the distance between the imperialist and colony. $\{V_1\}$ is a vector; its start point is the previous location of the colony and its direction is towards the imperialist location. The length of this vector is set to unity.

Some colonies may withstand absorption by the imperialists. These colonies make some improvements in their attributes, and this process is called revolution in the ICA. Revolution operation occurs after the assimilation process and causes unexpected random changes in one or more parameters of the problem. This operation increments exploration and prevents fast convergence of countries toward local minima. After performing assimilation and revolution operations on colonies of an empire, the costs of the colonies and imperialist are compared. If a colony has less cost than the imperialist, the imperialist is swapped with that colony.

The next step in the ICA is imperialistic competition, in which all empires try to possess the colonies of other empires. During imperialistic competition, weaker empires lose their colonies gradually to stronger ones. Thus, one of the weakest colonies of the weakest empire will be possessed by another empire during a competition between empires. The probability of the stronger empires possessing the weakest colonies is higher. Therefore, the power of stronger empires is increased gradually, while the power of weaker ones is decreased.

The ICA is executed until the termination condition is achieved. The ideal termination condition is when just one empire exists in the world. However, preset running time or a predefined number of iterations or having no advance in the results for several successive iterations is generally used as the termination condition of the ICA. In these conditions, the solution of the problem is defined by the imperialist of the strongest empire.

4. The proposed algorithm

In the real world, *globalization* takes the form of increasing relations and assimilation between the cultures, business enterprises, economies, and governing bodies of countries throughout the world. In other words, globalization can be described as a process of rapid pressures for assimilation towards international standards. It involves relationships that transcend national boundaries [16]. In the globalization system, the most powerful countries have a main role in the world. Most of the time, the powerful country is mainly involved in establishing international standards and enforces other countries to apply these standards.

Inspired by this phenomenon, we have modified the original ICA by contributing the greatest imperialist in the assimilation process (segmented assimilation) and establishing relationships between countries for sharing experiences between them. The proposed modifications can increase the quality of each empire in each generation and overcome the ICA deficiencies described in Section 1.

In this section, we describe the segmented assimilation process and the method of establishing relationships between/within empires to form a globalization concept in the GICA algorithm.

4.1. Segmented assimilation process

As described in Section 3, in the assimilation method of the original ICA, colonies move toward the imperialist. In other words, the imperialist uniformly assimilates all variables of its colonies such as economy, language, religion, etc. However, in the real world this rarely happens and some variables of countries are affected by the other most important countries apart from which empire they belong to. For example, all of the countries in the world use the English language and it is becoming a global language. This represents the globalization concept and it has a tendency to lead to a significant increase in sameness throughout the world and often overwhelms local realities.

For modeling this fact in the GICA, we utilize a segmented assimilation mechanism in which some of the variables of the colonies are assimilated to the global best imperialist and the others are assimilated to their relevant imperialist country. Eq. (4) is changed as follows:

$$\{x_{\varphi}\}_{new} = \{x_{\varphi}\}_{old} + \beta \times d_2 \times \{rand\} \otimes \{V_{\varphi}\}, \tag{5}$$

$$\{x_{N-\varphi}\}_{new} = \{x_{N-\varphi}\}_{old} + \beta \times d_1 \times \{rand\} \otimes \{V_{N-\varphi}\}, \tag{6}$$

$$\{x\}_{new} = \{x_{\varphi}\}_{new} \circ \{x_{N-\varphi}\}_{new}\,, \tag{7}$$

where $\varphi$is a random number in [1, $N_{var}/2$], d_2 is the distance of φ randomly selected variables between the global best imperialist and colony, d_1 is the distance of $N-\varphi$ variables between the imperialist and colony, $\{V_{\varphi}\}$ is a vector and its start point is the previous location of the φ randomly selected variables from the colony and its direction is toward the location of the same selected variables in the global best imperialist, and $\{V_{N-\varphi}\}$ is a vector and its start point is the previous location of $N-\varphi$ variables in the colony and its direction is toward the location of $N-\varphi$ variables in the imperialist.

In other words, each colony moves toward the global best imperialist by using Eq. (5) according to φ randomly selected variables, and, at the same time, moves toward the relative imperialist by using Eq. (6) according to the other remaining variables (N-φ). It is clear that $\varphi \leq N-\varphi$, because φ is in [1, N/2]. Finally, a new position is formed by using Eq. (7). Figure 2 shows an example of segmented assimilation in graphical mode.

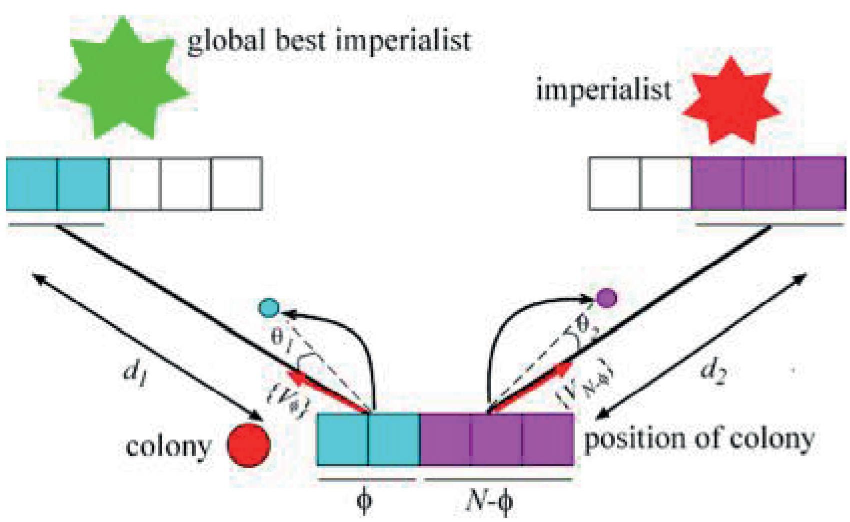


Figure 2. An example of segmented assimilation.

4.2. Countries' relationships

As described in Section 4, globalization involves relationships that transcend national boundaries. The process of globalization consists of interactions and integration among people, companies, and governments of different nations. By this fact, we adopt the crossover operator of the GA for establishing relationships between countries in the GICA. Two kinds of relationship are taken: the first is the relationship between empires, and the second is the neighboring relationship within empires. Both of them are described in the following subsections.

4.2.1. Relationship between empires

The relationship between empires is done by using an imperialist country in each empire. For establishing this form of relationship, heuristic crossover [17] is used. However, other kinds of crossover can be used. In heuristic crossover, 2 selected individuals x_1 and x_2 create a new solution y by Eq. (8):

$$y = \alpha \left(x_2 - x_1 \right) + x_2, \tag{8}$$

where α is a uniform random variable over [0, 1].

Before applying crossover, selection is used. The selection mechanism determines which individuals are chosen for creating new solutions. Our strategy is selecting the global best imperialist country and randomly selected samples of other weaker imperialists. Figure 3 displays the steps of this relationship and Figure 4 shows it in graphical mode.

1. Select the global best imperialist, G
2. Select random samples of other imperialist countries, S
3. **For each** S_i perform crossover on pair $\{G, S_i\}$ by using Eq. (8) and generate a new solution, y
4. Evaluate y, if its cost is better than S_i, replace S_i with y
5. **End For**

Figure 3. Steps of relationship between empires.

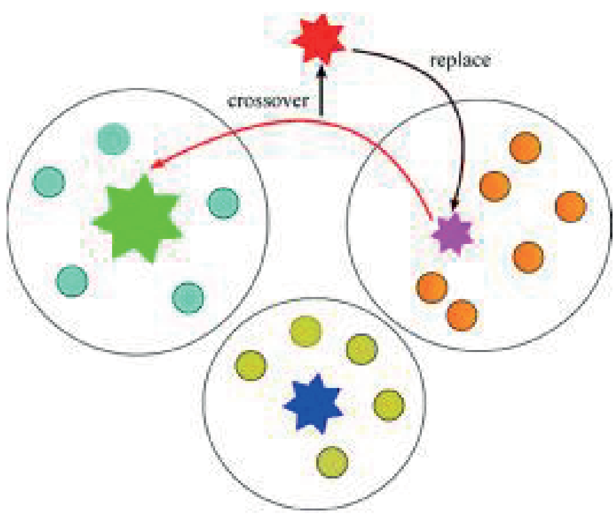


Figure 4. A graphical model of relationship between empires.

4.2.2. Neighboring relationship within empires

In the case of the neighboring relationship, we use the uniform crossover operation [1]. The crossover acts on 2 selected individuals x_1, x_2 and creates 2 new solutions, y_1 by Eq. (9) and y_2 by Eq. (10).

$$y_1 = \alpha x_1 + \left(1 - \alpha \right) x_2 \tag{9}$$

$$y_2 = \alpha x_2 + (1 - \alpha)\, x_1 \tag{10}$$

Here, α is a uniform random variable over [0, 1].

For establishing a neighborhood relationship between countries in each empire, the colonies are listed in ascending order based on their cost and then from the beginning of the list to the end, uniform crossover is done on the selected country and its neighbor in the list. From 2 generated solutions, the better one is chosen and substituted for the selected country if its cost is better. Figure 5 shows the steps of this process and Figure 6 shows it for an empire in graphical mode.

```
For each empire_i Do
Sort all colonies and imperialist in ascending order, L_i: c_1, c_2, ..., imp_i
For j=1 to Length(L_i – 1) Do
Perform crossover on pair {L_i(j), L_i(j+1)} by using Eqs. (9), (10) and
  generate two new solutions, y_1, y_2, Select the best one, y
Evaluate y; if its cost is better than L_i(j), replace it
End For
End For
```

Figure 5. Steps of neighboring relationship within empires.

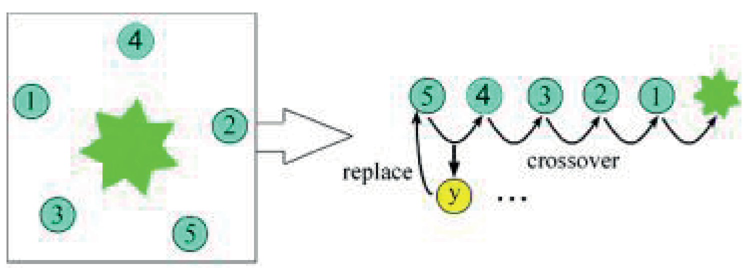


Figure 6. Neighboring relationship within an empire.

5. GICA framework

The pseudocode of the GICA is presented as follows:

Procedure for GICA

Step 1: Initialize population;

Step 2: Main loop

Countries Segmented Assimilation; *Separate variables of each colony into 2 subsets and move smaller one toward the global best imperialist and the other one toward relative imperialist.*

Countries Revolutionary;

Relationship between empires; *Do heuristic crossover between the best imperialist and the other randomly selected imperialists; if imperialist is worse than the new generated solution, replace it.*

Relationship within empires; *Sort colonies in ascending mode and from the beginning to the end do crossover on them two-by-two.*

Exchange Imperialist;

Unite the similar empires;
Update TotalCost;
Imperialistic competition;
Step 3*: Terminate the algorithm if a terminating criterion is satisfied.*

6. Computational experiments

We have implemented the GICA in MATLAB. Our implementation was done in a machine built with an Intel Core i3 processor, 2-GB RAM, and the platform used was Windows 7. In computational study, the GICA was compared with the most outstanding variants of the ICA (SBA [13], ICAAI [15], ICACI [15]) and 3 other EAs (ABC [18], PSO [2], SaDE [19]).

6.1. Testing functions

To evaluate the optimization performance of the GICA, we have selected a set of benchmark functions from previous evolutionary computation studies in which functions F1–F4 are unimodal and functions F5–F8 are multimodal. All these functions are minimization optimization problems and they are set to 30 dimensions (D = 30). All the benchmark functions are listed in Table 1 from F1 to F8.

Table 1. Benchmark functions with global solutions and search ranges.

Title	Function	Search range	Min
F1	$\sum_{i=1}^{D} x_i^2$	$-100 \leq xi \leq 100$	0
F2	$\sum_{i=1}^{D} \lvert x_i \rvert + \prod_{i=1}^{D} \lvert x_i \rvert$	$-10 \leq xi \leq 10$	0
F3	$\sum_{i=1}^{D} \sum_{j=1}^{i} x_j^2$	$-100 \leq xi \leq 100$	0
F4	$\max_i \{\lvert x_i \rvert, 1 \leq i \leq D\}$	$-100 \leq xi \leq 100$	0
F5	$\sum_{i=1}^{D-1} 100(x_i^2 - x_{i+1})^2 + (1 - x_i)^2$	$-100 \leq xi \leq 100$	0
F6	$\sum_{i=1}^{D} (x_i^2 - 10\cos(2\Pi x_i) + 10D)$	$-10 \leq xi \leq 10$	0
F7	$1 + \sum_{i=1}^{D} \left({x_i^2}/{4000} \right) - \prod_{i=1}^{2} (cos({x_i}/{\sqrt{i}}))$	$-600 \leq xi \leq 600$	0
F8	$-20e^{-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}} - e^{\frac{1}{D}\sum_{i=1}^{D} cos(2\Pi x_i)} + 20 + e$	$-32 \leq xi \leq 32$	0

6.2. Parameter settings

In all of the ICA variant algorithms, the initial parameters such as number of countries, number of imperialists, β, and ζ were set to 88, 8, 2, and 0.02, respectively. For both SBA and ICACI, the crossover rate was set to 0.8 and for both ICACI and ICAAI, the parameter p was set to 1.

In the other EAs, the population size was set to 88. The basic ABC used in this study utilizes only one control parameter, which is called *limit* and it was set to (*employed bees* $\times$ *Dimensions*) [18]. In the

PSO, $C_1 = C_2 = 2$ and the interia weight (w) was decreasing linearly from 0.9 to 0.4. In the SaDE, F was self-adaptive and initially set to 0.9, while CR was self-adaptive and initially set to 0.5.

6.3. Results

The number of iterations for all of the algorithms is set to 1000. The experiment on each function was repeated 30 times and the mean of the best results was obtained. In addition, in order to make a fair comparision the same set of initial solutions was generated for all algorithms.

Table 2 presents the mean and standard deviation results of the minimum values for each function and algorithm. The convergence characteristics of all functions are presented with a logarithmic scale of base 10 for the y-axis in Figures 7 and 8. To compare the different algorithms, a statistical test called nonparametric the Wilcoxon rank-sum test [19], at the 5% significance level, is conducted. By using a statistical test we can judge whether the obtained results from the proposed algorithm are significantly different from the other algorithms and have not occured by chance [20]. The results of p-values for this test between the GICA and other algorithms over all the test functions are presented in Table 3. The p-values below 0.05 indicate that the Wilcoxon test rejects the null hypothesis and the differences between the GICA and other compared algorithms are significant; they are marked by italic font.

Table 2. Comparision of results for GICA and other algorithms by average and standard deviation of the best obtained fitness values over 30 runs after 1000 generations.

F		SBA	ICAAI	ICACI	ABC	PSO	SaDE	GICA
F1	Mean	$9.4e^{-19}$	$1.8e^{-8}$	$5.4e^{-6}$	$5.1e^{-16}$	$2.5e^{-23}$	$1.3e^{-10}$	$5.4e^{-39}$
	Std.	($2.0e^{-18}$)	($5.8e^{-8}$)	($2.8e^{-5}$)	($3.4e^{-16}$)	($4.8e^{-23}$)	($6.1e^{-11}$)	($1.4e^{-38}$)
F2	Mean	$3.3e^{-12}$	$9.7e^{-6}$	$8.9e^{-6}$	$8.5e^{-8}$	$1.8e^{-15}$	$4.4e^{-7}$	$9.5e^{-25}$
	Std.	($9.6e^{-12}$)	($1.0e^{-5}$)	($2.5e^{-5}$)	($9.2e^{-8}$)	($1.6e^{-15}$)	($1.2e^{-7}$)	($2.4e^{-24}$)
F3	Mean	$3.4e^{-16}$	$3.0e^{-7}$	$6.6e^{-6}$	$5.9e^{-15}$	$6.0e^{-16}$	$1.1e^{-9}$	$8.8e^{-38}$
	Std.	($1.4e^{-15}$)	($1.3e^{-6}$)	($2.2e^{-5}$)	($3.4e^{-15}$)	($1.9e^{-15}$)	($4.1e^{-10}$)	($2.5e^{-37}$)
F4	Mean	$2.9e^{-1}$	$1.7e^{-1}$	8.3	2.8	0.2	2.0	$5.9e^{-3}$
	Std.	($1.6e^{-1}$)	($1.5e^{-1}$)	(2.7)	(0.4)	(0.1)	($2.8e^{-1}$)	($3.1e^{-3}$)
F5	Mean	96.6	49.0	194.8	28.7	70.8	37.8	50.8
	Std.	(111.3)	(43.0)	314.6	(4.0)	(74)	(31.0)	(57.2)
F6	Mean	35.8	2.5	7.3	1.7	48.8	$1.1e^{2}$	0.2
	Std.	(15.5)	(2.7)	3.8	(7.7)	(15.1)	(7.1)	(0.4)
F7	Mean	$1.6e^{-2}$	$9.2e^{-3}$	$2.6e^{-2}$	$4.3e^{-8}$	$1.3e^{-2}$	$3.4e^{-9}$	$7.3e^{-3}$
	Std.	($1.4e^{-2}$)	($1.2e^{-2}$)	($2.4e^{-2}$)	($1.9e^{-7}$)	($1.2e^{-2}$)	($1.0e^{-8}$)	($8.4e^{-3}$)
F8	Mean	$6.7e^{-8}$	$5.9e^{-5}$	$5.6e^{-4}$	$2.3e^{-8}$	$4.9e^{-13}$	$2.9e^{-6}$	$2.3e^{-14}$
	Std.	($1.5e^{-7}$)	($8.1e^{-5}$)	($8.8e^{-4}$)	($1.1e^{-8}$)	($4.7e^{-13}$)	($6.6e^{-7}$)	($4.7e^{-15}$)

The Wilcoxon signed-rank test shows that the GICA outperforms all of the algorithms on unimodal benchmark functions. In multimodal functions, the GICA provides better results for F6 and F8, but the algorithms ABC and SaDE provide better results for F5 and F7, respectively. However, better results might be obtained for these functions from the GICA by applying other ranges for parameter φ. From Figures 7 and 8 we can observe that the GICA has significantly better convergence speed than the other algorithms in all of the functions.

Table 3. *p*-values calculated for Wilcoxcon's rank-sum test between the GICA and other algorithms for all test functions.

GICA vs. alg.	F1	F2	F3	F4	F5	F6	F7	F8
SBA	$3.03e^{-11}$	$3.01e^{-11}$	$3.01e^{-11}$	$3.01e^{-11}$	0.08	$3.01e^{-11}$	0.001	$2.03e^{-11}$
ICAAI	$3.01e^{-11}$	$3.01e^{-11}$	$3.02e^{-11}$	$3.03e^{-11}$	0.35	$1.54e^{-9}$	0.04	$2.03e^{-11}$
ICACI	$3.01e^{-11}$	$3.02e^{-11}$	$3.00e^{-11}$	$3.03e^{-11}$	0.02	$3.68e^{-11}$	$1.49e^{-5}$	$2.03e^{-11}$
ABC	$3.02e^{-11}$	$3.01e^{-11}$	$3.01e^{-11}$	$3.01e^{-11}$	0.34	$2.87e^{-11}$	0.66	$2.03e^{-11}$
PSO	$3.01e^{-11}$	$3.01e^{-11}$	$3.01e^{-11}$	$3.02e^{-11}$	0.05	$3.01e^{-11}$	0.04	$2.68e^{-10}$
SaDE	$3.01e^{-11}$	$3.01e^{-11}$	$3.01e^{-11}$	$3.01e^{-11}$	0.24	$3.01e^{-11}$	0.6	$2.03e^{-11}$

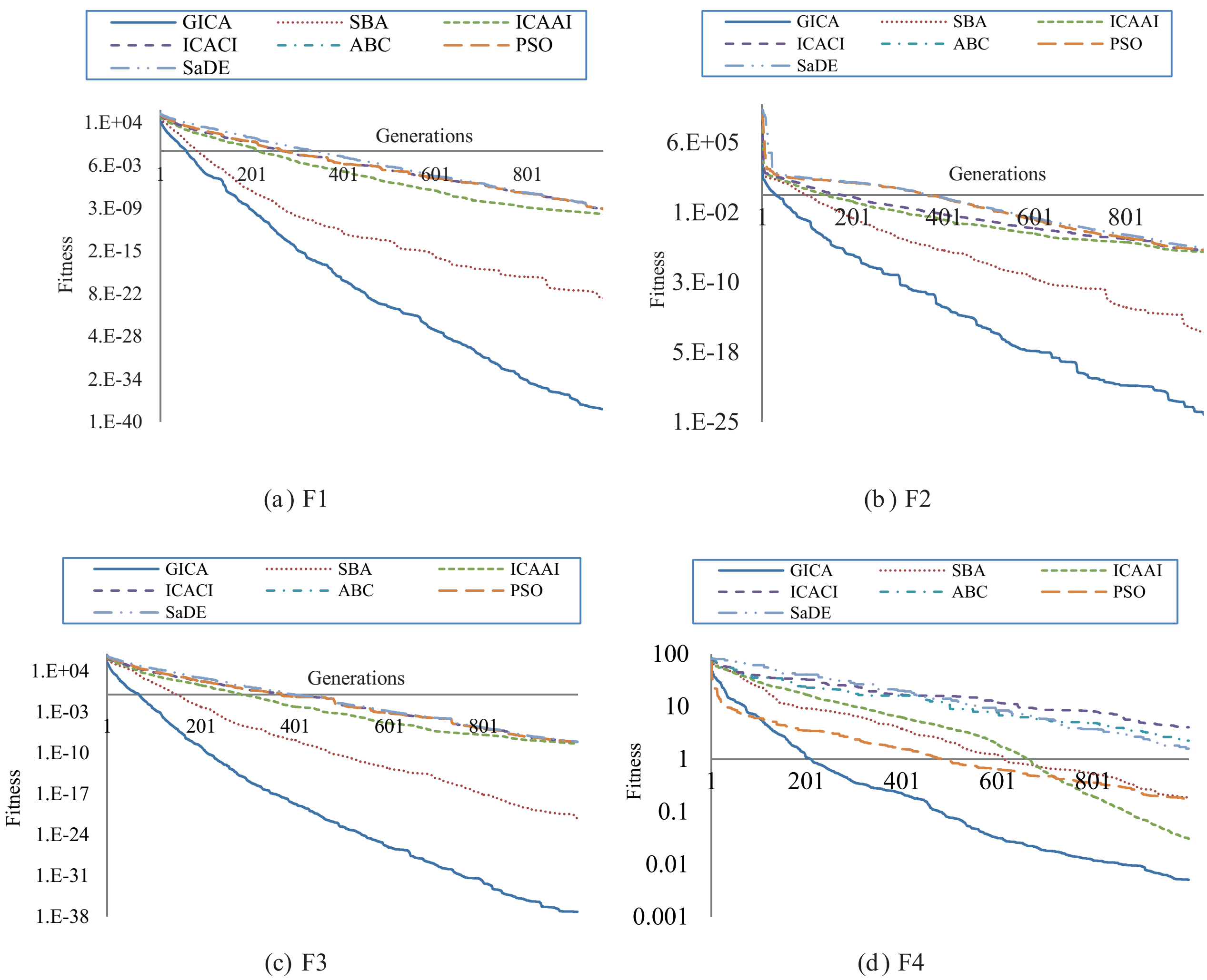
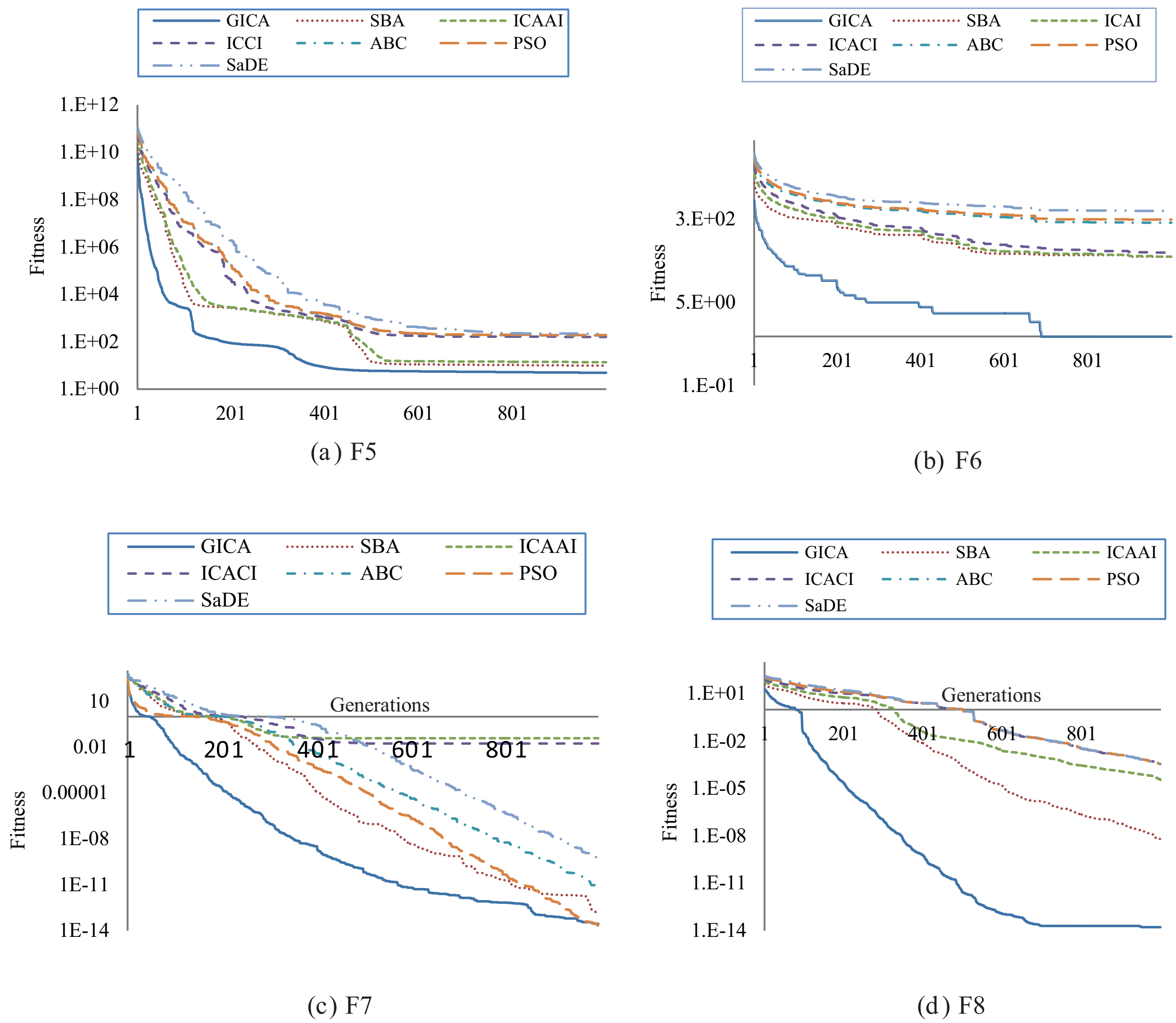


Figure 7. Convergence diagrams for unimodal functions. The horizontal axis is generations and the vertical axis is the fitness.

7. Conclusion and future work

In this paper, we have presented an improved ICA algorithm, called GICA. Inspired by the globalization concept, we have produced 2 modifications to the original ICA; one is introducing a new assimilation method called segmented assimilation, and the other one is establishing relationships between countries by a crossover operator.



(a) F5 (b) F6

(c) F7 (d) F8

Figure 8. Convergence diagrams for multimodal functions. The horizontal axis is generations and the vertical axis is fitness.

In the segmented assimilation process, each country moves toward the global best imperialist country according to a randomly chosen part of variables and, at the same time, moves toward a relative imperialist according to the other part of variables.

In the relationship process, 2 kinds of relationship are used, the relationship between empires and the neighboring relationship between countries within the empire, by performing crossover operation on them.

The empirical results showed that the proposed modifications have a great effect on improving the performance of the original ICA and enhance its global search capability to escape from the local optima. Furthermore, the modifications improved algorithm converges to the global optimum quickly.

Possible avenues of future works include: considering other kinds of crossover operators; introducing other methods for establishing relationships between countries and increasing connectivity between them; simulating other aspects of globalization and assessing their effects on the performance of the proposed algorithm, as globalization has more details in the real world and they can be brought into the algorithm via simulation; contributing more imperialist countries in the segmented assimilation process and investigating its effect on the performance of the proposed algorithm; and testing and assessing the proposed algorithm on complex engineering problems.

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