International Journal of
Intelligent Systems and
Applications in Engineering
ISSN:2147-6799 www.atscience.org/IJISAE
Advanced Technology and Science
Original Research Paper

A Modified Artificial Algae Algorithm for Large Scale Global Optimization Problems

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Accepted : 18/12/2018 Published: 31/12/2018

Abstract: Optimization technology is used to accelerate decision-making processes and to increase the quality of decision making in management and engineering problems. The development technology has made real world problems large and complex. Many optimization methods that proposed for solving large-scale global optimization (LSGO) problems suffer from the “curse of dimensionality”, which implies that their performance deteriorates quickly as the dimensionality of the search space increases. Therefore, more efficient and robust algorithms are needed. When literature on large-scale optimization problems is examined, it is seen that algorithms with effective global search ability have better results. For the purpose, in this paper Modified Artificial Algae Algorithm (MAAA) is proposed by modifying original version of Artificial Algae Algorithm (AAA) inspiring by Differential Evolution Algorithm (DE)’s mutation strategies. AAA and MAAA are compared with each other by operating with the first 10 benchmark functions of CEC2010 Special Session on Large Scale Global Optimization. The results show that hybridization process that applied by updating an additional fourth dimension with mutation strategies of DE after the helical motion of the AAA algorithm, contributes exploration phase and improves the AAA performance on LSGO.

Keywords: *artificial algae algorithm,CEC2010 benchmark,large scale global optimization*

1. Introduction

There are various high dimensional problems in the modern world. Because most modern data, such as computational biology, data from consumer preferences, images, videos, are often high dimensional. Optimization is a technique for solving problems and it is the calculation of the parameters that will produce the best result of a function. However, as the dimension of problem increases, the process of reaching a definitive solution becomes very complex, difficult and costly. This is because when the dimensionality increases, the volume of the space increases exponentially and probability of finding good solutions with limited search amount decreases dramatically. R. Bellman used "curse of dimensionality" term in the introduction of his book “Dynamic programming” in 1957 for this situation [1]. This term refers to the difficulties of finding optimum in high-dimensional space using extensive search. Therefore, there is a need to use effective and efficient new techniques beyond what exists to solve large-scale optimization problems.

Metaheuristic methods that find the most suitable solution around the real solution at an acceptable time, are preferred as an effective solution technique for large-scale optimization problems. While metaheuristic algorithms are shown excellent search abilities when applied to some small dimensional problems, usually their performance deteriorates quickly as the dimensionality of search space increases. Therefore, a more efficient search strategy is required to explore all the promising regions in a given time or fitness evaluation count limits.

Some attempts have been made by the researchers, such as modify original version of an algorithm [2,3], hybridize with another algorithm [4], using additional local search methods [5,6] or develop solution techniques [7] to make metaheuristic algorithms suitable to overcome the difficulties of solving large-scale optimization problems.

Inspired by Differential Evolution mutation strategies, this paper presents an improved variant of the AAA algorithm called Modified Artificial Algae Algorithm(MAAA) for solving large-scale global optimization problems.

The rest of the paper is organized as follows. First, Artificial Algae Algorithm, Differential Evolution are described briefly. Then Modified Artificial Algae Algorithm is described. In the following section benchmark set used in tests, parameters of algorithms and working environment are analyzed. Finally, results and interpretations are given and are followed by conclusions and recommendations.

2. Artificial Algae Algorithm

Artificial Algae Algorithm (AAA) is a bio-inspired meta-heuristic optimization algorithm designed to solve continuous and real-value optimization problems. It is developed by inspiration of foraging behaviour of micro-algae. In this population-based algorithm each individual is named as artificial algal colony and each artificial algal colony corresponds to a solution in the problem space. Artificial algae, like algae in real life, moves to the light source (better solutions) in order to do photosynthesis. Their movement is in the form of helical swimming. Their life cycle consists of adapting to the environment, changing the dominant species and multiplying by mitosis. AAA mimics these lifecycle

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behaviours in three phases. These phases are helical movement, evolutionary process and adaptation. Pseudo-code of AAA is given in Table 1 [8,9].

AAA is proposed in 2015 by Uymaz et al. [8]. In the same year Uymaz et al. made a modification on AAA by multi light source [9]. And then many researchers have been worked on AAA. For example, Babalık et.al. studied AAA for multi-objective optimization [10], Zhang et al. studied binary version of AAA [11], Kumar & Dhillon studied hybrid version of AAA by hybridized with simplex search method (SSM) [12]. AAA applied on real-world problems such as wind turbine placement problem [13], economic load dispatch problem [12]. But there is no study on large-scale optimization with AAA. The lack of a study of AAA on a large-scale optimization is the motivation of this work. Results of the original version of AAA were promising, so a modification was applied on AAA to increase the performance on LSGO.

Table 1. AAA pseudo-code

1 :	generate an initial population of n algal colonies with random solutions
2 :	evaluate $f(x_i)$, $i = 1, 2, \ldots, D$
3 :	while stopping condition not reached do
4 :	for i = 1 to n do
5 :	while energy of i^{th} colony not finished do
6 :	modify the colony with helical movement
7 :	end while
8 :	end for
9 :	apply evolutionary strategy
10 :	apply adaptation strategy
11 :	end while

3. Differential Evolution

Differential evolution (DE), proposed by Storn and Price [14], is an efficient and versatile population-based direct search algorithm. Among its advantages are its simple structure, ease of use, speed, and robustness, which enables its application on many real-world applications.

DE is an effective algorithm frequently used in the LSGO [15,16,17]. The algorithm achieved third rank in CEC 2008 special session and competition on high-dimensional real-parameter optimization [18]. Therefore, effects of crossover and mutation operators of DE algorithm [19,20] for LSGO performance is also investigated.

Mutation is treated as a random change of some parameter. Thanks to the changes in the mutation phase, the solution point representing the chromosome is moved in the solution space. In DE-literature, a parent vector from the current generation is called target vector, a mutant vector obtained through the differential mutation operation is known as donor vector and finally an offspring formed by recombining the donor with the target vector is called trial vector [20]. In mutation stage, several DE trial vector generation strategies have been proposed. Well-known mutation strategies were listed in [21,22]. One of the DE mutation strategies in the literature defined as follows:

$$V_{g+1} = x_g + F\left(x_{bg} - x_g\right) + F\left(x_{r1g} - x_{r2g}\right) + F(x_{r3g} - x_{r4g}) \qquad (1)$$

In (1) which calculates the donor vector V, the index $g + 1$ indicates the next generation and the index b refers to the best individual. In this equitation, four distinct parameter vectors $r1, r2, r3, r4$ are sampled randomly from the current population. The difference of these vectors is scaled by a scalar number F and the scaled difference is added to the grand total.

4. Modified Artificial Algae Algorithm

In order to achieve successful results in the LSGO field, it is necessary to use an algorithm which has powerful exploration and exploitation. While the evolutionary and adaptation processes of AAA support exploitation mechanism, the process of helical movement contributes to both exploration and exploitation mechanisms. In other words, exploration and exploitation process of AAA are provided by a spiral movement through modification of algal colonies. Therefore, in order to increase the search capabilities, we made the modification in the process of helical movement. Helical movement pattern like as follow Fig. 1 [23].

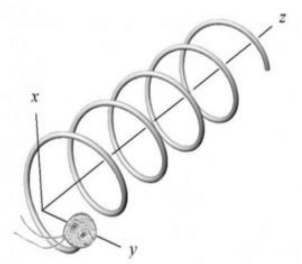


Fig. 1. Helical movement pattern of Algae.

Helical movement is a process which updates each algal colony. In this process, colony is selected with tournament selection and only three algal cells of each algal colony, which are also selected randomly and represented as *k, l and m*, are modified by the following formulas:

Calculation for Linear Movement:

$$x_{im}^{t+1} = x_{im}^{t} + \left(x_{jm}^{t} - x_{im}^{t}\right)(\Delta - \tau^{t}(x_i))p \qquad (2)$$

Calculation for Angular Movement:

$$x_{ik}^{t+1} = x_{ik}^{t} + \left(x_{jk}^{t} - x_{ik}^{t}\right)(\Delta - \tau^{t}(x_i)) \cos\alpha \qquad (3)$$

$$x_{il}^{t+1} = x_{il}^{t} + \left(x_{jl}^{t} - x_{il}^{t}\right)(\Delta - \tau^{t}(x_i)) \sin\beta \qquad (4)$$

Parameters which are used in (2), (3), (4) , are Δ and τ , shear force and friction surface of algal colonies, respectively.

It was thought that making an update in a fourth algal cell of each algal colony immediately after the helical movement in AAA could be useful for increasing exploration capability of the algorithm. Therefore, a modification has been made in AAA inspired by Differential Evolution mutation strategy in (1) and this approach was called as MAAA. While DE uses differences of random vectors in current population, we used difference of helical movement calculation results($x_{im}^{t+1}, x_{ik}^{t+1}, x_{il}^{t+1}$). Random selected fourth algal cell (n) of same algal colony are modified by following formula:

$$x_{in}^{t+1} = x_{best}^{t} + (x_{im}^{t+1} - x_{ik}^{t+1}) + (x_{ik}^{t+1} - x_{il}^{t+1}) + (x_{il}^{t+1} - x_{im}^{t+1}) \qquad (5)$$

Pseudo-code of MAAA is given in Table 2.

Table 2. Pseudo-code of modification in AAA helical movement phase for every algal colony (second and fourth steps)

1 :	Select another colony with tournament selection
2 :	Select four algal cells (*k, l, m and n*) in the colony randomly
3 :	Modification the algal cells(*k, l and m*) of the colony with (2), (3) and (4)
4 :	Modification the fourth cell (*n)* of the same colony with (5) which uses the results of (2), (3), (4).
5 :	Decrease energy caused by movement
6 :	If new solution is better, move new position else decrease energy by metabolism
7 :	If energy of the colony did not finish go to step 1
8 :	If the colony did not find better solution increase starvation of the colony

5. Performance Evaluation

5.1. Experimental Environment

The computer platform used to perform the experiments was based on an Intel(R) Xeon(R) CPU E5-2650 2.00 GHz processor, 8.70 GB of RAM, and the Microsoft Windows Server 2012 operating system. All experimental works were conducted by using Matlab (Release R2010a). Matlab code v.1. of Artificial Algae Algorithm is released in [24]

5.2. Benchmark Set

Since 2005, competitions have been organized in the LSGO field traditionally at CEC (IEEE Evolutionary Computing Congress) private sessions. Common rules and benchmark sets were presented in 2008, 2010 and 2013 to evaluate algorithms fairly in these competitions. In this paper, we used 10 functions of CEC 2010 benchmark set given in Table 3. All functions are the minimization problems and the optimum function values are zero for all the problems. Detailed information about benchmark set is provided in [25].

Table 3. Used benchmark function set of CEC2010 LSGO

No	Name	Range
F1	Shifted Elliptic Function	[−100, 100]
F2	Shifted Rastrigin	[−5, 5]
F3	Shifted Ackley	[−32, 32]
F4	Single-group Shifted and m-rotated Elliptic	[−100, 100]
F5	Single-group Shifted and m-rotated Rastrigin	[−5, 5]
F6	Single-group Shifted and m-rotated Ackley	[−32, 32]
F7	Single-group Shifted m-dimensional Schwefel's Problem 1.2	[−100, 100]
F8	Single-group Shifted m-dimensional Rosenbrock	[−100, 100]
F9	D/2m -group Shifted and m-rotated Elliptic	[−100, 100]
F10	D/2m -group Shifted and m-rotated Rastrigin	[−5, 5]

5.3. Parameter Settings

For this study, the recommendations in [8] were followed by setting the energy loss, e = 0.3, the shear force, Δ = 2, the adaptation parameter, Ap = 0.5 and the population size, N=40.

5.4. Testing Procedure

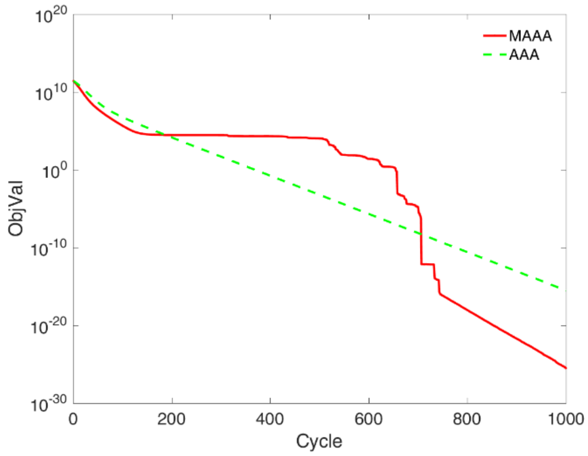
All reported results in this study were the averages over 25 simulations. In ordered results, the results of the 1st (Best), 13th (Median), and 25th (Worst) trial, as well as the trial mean (Mean), and standard deviation (Std.) are presented.

Dimension of problems in the benchmark set are 1000. Maximum fitness evaluation (MaxFEs) was set to 3e6.

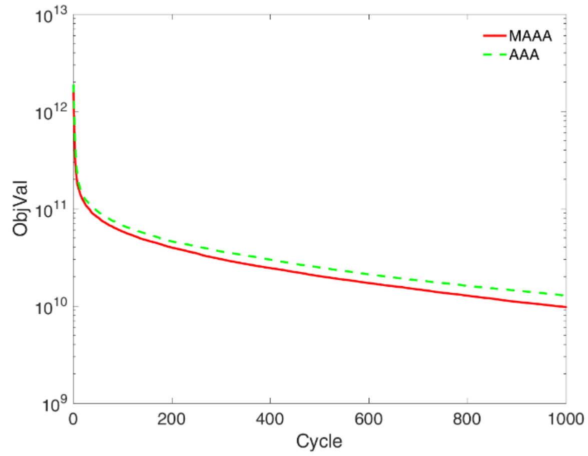
6. Results and Discussion

The original version of AAA and the proposed modified version of AAA, called MAAA, are run on the benchmark set in Table 3, in equal conditions and same parameters. Table 5 shows the results of AAA and MAAA. For remarking the best algorithm, we have put minimum values for each function in bold.

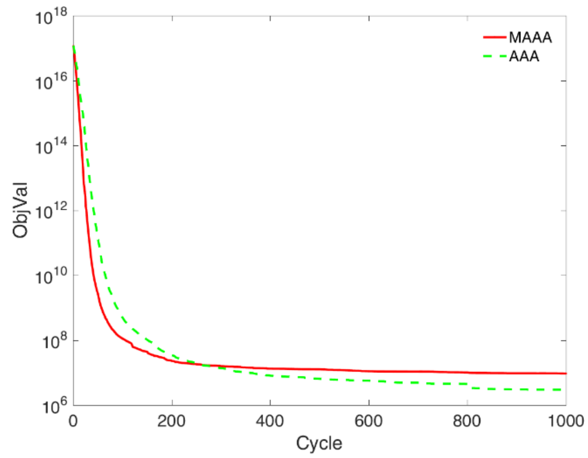
According to Table 5, the proposed MAAA algorithm obtained better results in seven functions of ten than AAA algorithm in both average and best values. In F1 and F2 functions, MAAA showed a significant improvement over AAA. Proposed MAAA has also reached the optimum solution in F1. MAAA and AAA have similar standard deviations.



(a) F1



(b) F7



(c) F8

Fig. 2. Convergence curves of sample functions for AAA and MAAA

The convergence curves of the AAA and MAAA for the following selected three problems: F1, F7, F8 are presented in Fig. 2. Y axis represents mean values of 25 independent runs of related function. X axis represents a recorded point in each 3000 fitness evaluations. For example, 200 value at x axis corresponds to 6e5 FEs.

Fig.2a shows that MAAA much faster than AAA until 6e5 FEs. After that point, AAA continues to find better results but MAAA draws a constant graph until 1.5e6 FEs. After that point, MAAA convergence to optimum very fast.

Fig.2b shows that MAAA has same convergence characteristic with AAA and therefore they draw parallel convergence graphic. But MAAA slightly faster so find better results than AAA.

Fig.2c shows that MAAA much faster than AAA until around 8e5 FEs. However, after that point, AAA pass MAAA with very close performance.

Table 4. Summary Information of Compared Algorithms

Algorithm	Description
SDENS [26]	Sequential Differential Evolution enhanced by neighborhood search
DNSPSO [27]	A hybrid PSO algorithm which employs a diversity enhancing mechanism and neighborhood search strategies
DASA [28]	Differential Ant-Stigmergy Algorithm is an Ant-colony optimization-based algorithm.
DECC-G [7]	Differential Evolution Cooperative Co-evolutionary with random grouping and adaptive weighting
LOCUST SWARMS (LS) [29]	A multi-optima search technique explicitly designed for non-globally convex search spaces.

Table 6 shows the test results of MAAA and other methods given in Table 4. Comparisons are drawn from the mean of 25 independent runs at 3.0e+6 FEs. MAAA results are obtained from running own codes. Results of other LSGO algorithms are directly taken from references which mentioned in header of the Table 6 columns.

While MAAA obtains best results in F1, F3 and F8, DASA obtains best results in F2, F4, F7 and F9. Therefore, MAAA is the second algorithm after DASA. Ranks part of Table 6 shows that the order of each algorithm among all algorithms. Average ranks of each algorithm proves that MAAA is the best second algorithm among six algorithms.

7. Conclusion

Metaheuristic optimization algorithms often show sufficient search capabilities on small optimization problems, but when applied to large and complex problems with more than a hundred decision variables, often lose their efficacy and performance [23]. Therefore, there is a need to develop effective and efficient new modifications or techniques. For this purpose, we made a modification on original version of AAA and investigated effects on LSGO performance.

The obtained results show that additional dimension modification after helical movement of AAA algorithm by inspired from DE algorithm mutation strategies let the AAA algorithm perform better in large dimension problems.

For future works, the performance of AAA can be improved by applying LSGO solutions techniques or hybridizing with another powerful optimization algorithm.

Table 5. Test results of AAA and MAAA

	AAA				MAAA			
	Best	Median	Mean	Std.	Best	Median	Mean	Std.
F1	4.39E-17	2.60E-16	3.02E-16	2.42E-16	**0.00E+00**	**2.71E-28**	**3.06E-26**	**1.24E-25**
F2	**2.98E+00**	**6.26E+00**	**8.14E+00**	**5.29E+00**	6.08E+01	8.08E+01	8.06E+01	1.45E+01
F3	2.89E-11	8.99E-11	5.48E-03	2.51E-02	**2.52E-13**	**4.12E-13**	**4.71E-13**	**2.06E-13**
F4	1.23E+13	1.89E+13	1.86E+13	**4.35E+12**	**8.22E+12**	**1.55E+13**	**1.62E+13**	4.62E+12

Table 6. Comparison with other algorithms

	Mean Values						Ranks					
	MAAA	**SDENS[26]**	**DNSPSO[27]**	**DASA[28]**	**DECC-G[6]**	**LS[29]**	**MAAA**	**SDENS**	**DNSPSO**	**DASA**	**DECC-G**	**LS**
F1	**3.06E-26**	5.73E-06	1.87E+07	1.52E-21	2.93E-07	3.48E+05	1	4	6	2	3	5
F2	8.06E+01	2.21E+03	5.85E+03	**8.48E+00**	1.31E+03	1.24E+03	2	5	6	1	4	3
F3	**4.71E-13**	2.70E-05	1.93E+01	7.20E-11	1.39E+00	2.67E+00	1	3	6	2	4	5
F4	1.62E+13	5.11E+12	2.25E+12	**5.05E+11**	1.70E+13	6.65E+12	5	3	2	1	6	4
F5	4.24E+08	**1.18E+08**	1.57E+08	6.20E+08	2.63E+08	3.60E+08	5	1	2	6	3	4
F6	1.94E+07	**2.02E-04**	1.75E+06	1.97E+07	4.96E+06	1.91E+07	5	1	2	6	3	4
F7	9.72E+09	1.20E+08	8.60E+06	**7.78E+00**	1.63E+08	6.32E+08	6	3	2	1	4	5
F8	**9.38E+06**	5.12E+07	1.31E+07	4.98E+07	6.44E+07	3.10E+07	1	5	2	4	6	3
F9	1.91E+08	5.63E+08	3.16E+08	**3.60E+07**	3.21E+08	2.22E+08	2	6	4	1	5	3
F10	6.78E+03	6.87E+03	6.90E+03	7.29E+03	1.06E+04	**6.04E+03**	2	3	4	5	6	1
						Average Rank =	**3.0**	**3.4**	**3.6**	**2.9**	**4.4**	**3.7**

Acknowledgment

This study was financially supported by The Coordinatorship of Scientific Research Projects of Selçuk University [Grant no: 18101012].

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