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Improved Artificial Immune System Algorithm with Local Search

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***Abstract*—**The Artificial immune systems algorithms are Meta heuristic optimization method, which are used for clustering and pattern recognition applications are abundantly. These algorithms in multimodal optimization problems are more efficient than genetic algorithms. A major drawback in these algorithms is their slow convergence to global optimum and their weak stability can be considered in various running of these algorithms. In this paper, improved Artificial Immune System Algorithm is introduced for the first time to overcome its problems of artificial immune system. That use of the small size of a local search around the memory antibodies is used for improving the algorithm efficiently. The credibility of the proposed approach is evaluated by simulations, and it is shown that the proposed approach achieves better results can be achieved compared to the standard artificial immune system algorithms

***Keywords*—**Artificial immune system, Cellular Automata, Cellular learning automata, Cellular learning automata,, Local search, Optimization.

I. Introduction

In the field of science and engineering, sometimes we face with variety of complexity and extent of the problem space, in which it is not possible to achieve global optima in a reasonable time by using classical techniques. Artificial immune system algorithms are metaheuristics used for clustering, pattern recognition and optimization problems. These algorithms lie under the optimization metaheuristic subcategory in which the biological immune system rules are used for optimization and in the first step, they are based on clonal selection and mutation [1-6]. in the first steps similar to other metaheuristics, they quickly identifying the state space including local and global optimum but the major drawback of these algorithms is their slow convergence to the global optimum as well as their instability in multiple runs. The stochastic nature of these algorithms makes the quality of the results very different from others runs. The behaviour of an artificial immune system highly depends on parameters such as definition and probability of mutation operators, size of clone for each antibody, size of populations and number of generations. Failure to define these parameters appropriately will lead the algorithm to be stuck in local minima. To overcome this problem, in this paper a novel approach, improved artificial immune system is introduced. In addition to use of local search in memory antibodies area, it is attempted to strengthen this proposed approach. For local search the CA-AIS, CLA-AIS, GA have been used.

In the first section, there is a concise review on biological and artificial immune system. In the second section CA-AIS, CLA-AIS and GA are surveyed. Section three introduces the new artificial immune system algorithm and in section four the credibility of the proposed approach is examined. Conclusions are provided in the final section of paper.

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II. Biological and Artificial Immune Systems

Immune system consists of cells, molecules and mechanisms in which external agents such as pathogens are prevented harming the host body. Antigen is a part of pathogen and it is recognized by immune system. A type of immune cells called lymphocytes detects and kills pathogens. This type of immune cell is composed of two groups of cells, each with different structure and function: B-cells and T-cells. B-cells produce antibody and by attaching themselves to antigens which cause pathogens to be destroyed. On the other hand part of T-cells stimulates B-cells to produce antibody and another part of T-cells collaborate with rest of immune cells to eliminate the detected pathogens [2]. After recognition of antigens, B-cells begin to produce antibody. Some of produced receptor cells are selected as memory cells to yield an enhanced response of immune system to the secondary once which encounters with the same specific antigens or similar structure.

All cells produced in the immune system are identical to their parents because the only reproduction method for these cells is cell division and no crossover takes place. However, each cell is affected by mutation operator according to its affinity with antigen; lower affinity with antigen lead to higher transformation of cell. The other factor that depends on the affinity with antigen is the number of cells that each cell can reproduce. Parent cell reproduces more cells when the affinity is higher. Selection and mutation process are called Affinity maturation [1, 2]. For the sake of simplicity B-cells and T-cells are considered to be a an integrated set in artificial immune system. Samples of immune system algorithms customized for optimization problems are ClonalG and opt-aiNet. Furthermore, aiNet algorithm can be placed within the clustering algorithms. Castro and Timmis classified artificial immune system algorithms into population-based and network-based categories and thereby, the negative and clonal selection are included in first category and immune network model are categorized into continuous network and discrete network, in the second category [1].

III. CA-AIS, CLA-AIS and GA

A. CA-AIS

In the CA-AIS method, of antibody population are conformed to a cellular grid and within each CA cell there are

genomes equal to the number of variables forming antibody and antibody value determined according to its value and its neighbourhoods value based on algorithms strategy. Nevertheless, the structure of artificial immune system algorithms is preserved in this model. It is assumed that in this model each cell in the cellular grid of CA has antibody model. Antibodies are the intermediate solutions to the specified problem. Antibodies in this model achieve global optimum based on their own value and other genomes values. As a result, the evolution process improves the antibody value according to the evaluation function. Antibodies in these models are evolved and cloned through interactions with their neighbors simultaneously [7].

B. CLA-AIS

In the CLA-AIS method, antibody population is conformed to a cellular grid and within each CA cell there are learning automata equal to the number of variables forming antibody. The antibody value is determined according to the learning automata. It is assumed that in this model each cell in the cellular grid of CLA has two components; antibody and antibody model. Antibodies are the intermediate solutions to the specified problem. Antibody model is comprised of some learning automata that learn how to assign antibody values in order to achieve global optimum based on their own and other genomes' experiences. The evolution process improves the antibody value according to the evaluation function. The learning automata are assigned to antibodies such that every antibody variable has one learning automaton assigned to [8].

C. GA

In a genetic algorithm, string population called chromosomes or the genotype of the genome, encode candidate solutions called individuals, creatures, or phenotypes to an optimization problem, moves toward better solutions. Traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible. The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), and modified (recombined and possibly randomly mutated) to form a new population. The new population is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population. If the algorithm has terminated due to a maximum number of generations, a satisfactory solution may or may not have been reached.

IV. Improved Artificial Immune System with Local Search

AIS algorithms are adaptive systems inspired by theoretical immunology and observed immune functions, principles and models, which are applied to complex problem domains. In particular, inspiration has been taken from the antigen driven affinity maturation process of B-cells, with its associated hypermutation mechanism. AIS also often utilises the idea of memory cells to retain good solutions to the problem being solved.

In other words, memory cells with antibodies against the antigens in the evaluation of algorithms have been improved and will be updated.

Thus memory cells will earn the highest affinity. The idea of this method to improve its accuracy is using local search in memory cells space. Local search around the best antibodies will be achieved in the small scale. Thereby, the memory cells affinity, convergence speed, and algorithm accuracy significantly increase. Also stability of the responses will in cure significant influence. The searching occurs only in the memory cell space and in small case and it is why it is called local search.

After improving the memory cells, according to the algorithm, in addition to adding a random antibodies to population of antibodies, some of memory cells are added to the population for faster convergence.

In the purposed algorithm, the CA-AIS method, CLA-AIS method and GA are used for local search. In addition, the results obtained from the combination of these methods are mentioned as follows.

V.. Experimental Results

In this section the results of simulating proposed approach with CA-AIS method, CLA-AIS method and GA as local search on eight standard benchmark functions (table.1) are compared to the results of standard artificial immune system. For evaluation, functions are 30 dimensional, antibodies are encoded as real numbers, and proposed system runs 100 iterations to find the optimum solution. Taking into account the nature of statistical tests by running each function 30 times consecutively, the average and best solution are measured for efficiency comparisons and variance assessment is used for stability comparisons. The simulation results for the proposed approach and artificial immune system algorithm based on standard benchmark functions are presented in tables 2-4. The simulation results confirm the outperformance of proposed approach to standard artificial immune system algorithm.

Tabel I
Benchmark function list

Name	Function Formula	Search range
Sphere	$f_1(x) = \sum_{i=1}^{D} x_i^2$	$[-100,50]$
Rosenbrok	$f_2(x) = \sum_{i=1}^{D-1}(100(x_i^2 - x_{i-1}^2)^2 + (x_i^2 - 1)^2)$	$[-2.048,2.048$
Ackley	$f_3(x) = -20\exp\left(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}\right) - \exp\left(\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi x_i)\right) + 20 + e$	$[-32.768,16]$
Greiwank	$f_4(x) = \sum_{i=1}^{D}\frac{x_i^2}{4000} - \prod_{i=1}^{D}\cos(\frac{x_i}{\sqrt{i}}) + 1$	$[-600,200]$

Name	Function Formula	Search range
Weierstrass	$f_5(x) = \sum_{i=1}^{D}\left(\sum_{k=0}^{kmax}\left[a^k \cos\left(2\pi b^k (x_i + 0.5)\right)\right]\right) - D \sum_{k=0}^{kmax}[a^k \cos(2\pi b^k 0.5)]$	$[-0.5,0.2]$
Rastrigin	$f_6(x) = \sum_{i=1}^{D}(x_i^2 - 10\cos(2\pi x_i) + 10)$	$[-5.12,5.12]$
Noncontinue sRastrigin	$f_7(x) = \sum_{i=1}^{D}(y_i^2 - 10\cos(2\pi y_i) + 10)$ $y_i = \begin{cases} x_i & \lvert x_i\rvert < 1/2 \\ \frac{rand(2x_i)}{2} & \lvert x_i\rvert \geq 1/2 \end{cases}$	$[-5.12,2]$
Schwefel	$f_8(x) = 418.9829 * D - \sum_{i=1}^{D} x_i \sin\left(\lvert x_i\rvert^{\frac{1}{2}}\right)$	$[-500,500]$

TABEL II
STANDARD AIS RESULT

Function	Average	Variance	Best Result
F1	3.21e-002	6.36e-003	1.34e-006
F2	9.37e-004	3.19e-006	4.76e-008
F3	2.31e-002	5.26e-003	9.24e-006
F4	7.20e-002	3.75e-004	5.68e-004
F5	1.41e-002	7.22e-004	2.31e-005
F6	5.17e-003	4.29e-005	1.06e-004
F7	1.54e-003	1.33e-004	7.09e-005
F8	4.07e-004	2.49e-004	7.33e-006

TABLE III
RESULTS FOR PROPOSED APPROACH WITH CA-AIS AS LOCAL SEARCH

Function	Average	Variance	Best Result
F1	0.0	0.0	0.0
F2	0.0	0.0	0.0
F3	1. 07e-0124	2. 01e-0332	0.0
F4	0.0	0.0	0.0
F5	0.0	0.0	0.0
F6	6. 12e-0354	6. 32e-0741	0.0
F7	4. 12e-0212	9. 03e-0654	0.0
F8	0.0	0.0	0.0

TABLE IV
RESULTS FOR PROPOSED APPROACH WITH CLA-AIS AS LOCAL SEARCH

Function	Average	Variance	Best Result
F1	0.0	0.0	0.0
F2	0.0	0.0	0.0
F3	0.0	0.0	0.0
F4	0.0	0.0	0.0
F5	0.0	0.0	0.0
F6	0.0	0.0	0.0
F7	0.0	0.0	0.0
F8	0.0	0.0	0.0

TABLE V
RESULTS FOR PROPOSED APPROACH WITH GA AS LOCAL SEARCH

Function	Average	Variance	Best Result
F1	0.0	0.0	0.0
F2	0.0	0.0	0.0
F3	5. 41e-0325	2. 14e-0357	0.0
F4	0.0	0.0	0.0
F5	0.0	0.0	0.0
F6	0.0	0.0	0.0
F7	3. 21e-0145	6. 84e-0249	0.0
F8	0.0	0.0	0.0

The results show that the proposed approach (CA-AIS) achieves better results compared to standard artificial immune system and converges better to optimum solutions. The number of CA-AIS cells is another important factor directly influencing the efficiency of CA-AIS algorithm. The simulation results show that by increasing number of cells, convergence to global optimum is accelerated. The convergence acceleration is not noticeable anymore after increasing cells to more than 25 cells. Considered the fewer computation in proposed model with 25 cells is preferably.

VI. SUMMARIES

In this paper a novel artificial immune system algorithm has been introduced and studied. In the proposed approach memory cells and antibodies together have been improved against the antigens in the evaluation of algorithms, and will be updated. Thus, memory cells will gain the highest affinity. Local search will be achieved around the best antibodies in the small scale. Thereby the memory cells affinity, convergence speed, and algorithm accuracy significantly increase. Also stability of the responses will have significantly influence.

One advantage of this approach is that it is distributed. Moreover, the simulation results show that within this approach, problems with many variables can be optimized with few numbers of antibodies where this is not true for typical artificial immune system algorithms.

To investigate the influence of various parameters on convergence, parameters such as number of grid cells and neighbourhood radius have been included. The results indicate that by increasing number of cells, the proposed hybrid model converges faster to the global optimum where in a cellular grid, increasing neighbourhood radius does not have great impact on convergence speed and cellular automata since commonly neighbourhood raduis is used and the computational loads are fewer. The results also show that the proposed approach with CLA-AIS as local search has higher speed in converging to global optimum compared to other local searches.

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