Hybrid Model Based on Artificial Immune System and Cellular Automata

Ramin Javadzadeh., Zahra Afsahi and MohammadReza Meybodi

***Abstract*—**The hybridization of artificial immune system with cellular automata (CA-AIS) is a novel method. In this hybrid model, the cellular automaton within each cell deploys the artificial immune system algorithm under optimization context in order to increase its fitness by using its neighbor's efforts. The hybrid model CA-AIS is introduced to fix the standard artificial immune system's weaknesses. The credibility of the proposed approach is evaluated by simulations and it shows that the proposed approach achieves better results compared to standard artificial immune system.

***Keywords*—**Artificial Immune System, Cellular Automat, neighborhood

I. Introduction

THE necessary of searching in solving applied problems is inescapable and yet difficult. This has led to existence of many searching algorithms with different notions and different scope of application. Artificial immune system algorithms are among 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 based on clonal selection and mutation [1-4].

Slow convergence to the global optimum and instability in multiple runs are major drawbacks of artificial immune system algorithms. The stochastic nature of these algorithms makes the quality of the results to be very different in various runs. The behavior 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 population 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 is presented based on hybridization of artificial immune system and cellular automata in which antibodies employ cellular automata neighborhood instead of mutation operator to achieve best value. In addition, using cellular automata concept will initiate the implementation of parallel computing in artificial immune systems. In this paper, there is a concise review of artificial immune system in the first section. In the second section cellular automata is surveyed. Section three introduces the hybrid model of artificial immune system with cellular automata and in section four the credibility of this model is examined. Conclusions are provided in the final section of paper.

Ramin Javadzadeh., Bojnourd Branch, Islamic Azad University-Bojnourd, Iran (Email: javadzadeh.r@srbiau.ac).

Zahra Afsa, Jr., Bojnourd Branch, Islamic Azad University-Bojnourd, Iran (Email: Afsahi_ai@yahoo.com.).

MohammadReza Meybodi Dept. Computer Engineering and Information Technology Amirkabir University of Technology, Tehran, Iran (Email: mmeybodi@aut.ac.ir).

II. Biological and Artificial Immune Systems

Immune system consists of cells, molecules and mechanisms which prevent harming the host body by external agents such as pathogens from. Antigen is part of pathogen recognized by immune system. Kind of immune cell named lymphocyte detects and kills pathogens and it 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 they 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]. Upon recognition of antigens, B-cells begin to produce antibody. Some of the produced receptor cells are selected as memory cells which result in an enhanced secondary response from immune system and they encounter 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 depending on its affinity with antigen as lower the affinity with antigen, higher is the transformation of the 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 is called Affinity maturation [1, 2]. For the sake of simplicity B-cells and T-cells are considered to be a unique 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 two population-based and network-based categories and thereby put the negative and clonal selection in first category and immune network model, subcategorized to continuous network and discrete network, in the second category [1].

III. Cellular Automata

Cellular automata (CA) is mathematical model for systems consisting of large numbers of simple identical components with local interactions. CA is non-linear dynamical systems in which space and time are discrete. They are called cellular, because they are made up of cells like points in the lattice or

like squares of the checker boards and they are called automata, because they follow a simple rule [5]. The simple components act together to produce complicated patterns of behavior. They are specially suitable for modeling natural systems to be described as massive collections of simple objects interacting locally with each other [6, 7]. The cells update their states synchronously on discrete steps according to a local rule. The new state of each cell depends on the previous states of a set of cells, including the cell itself, and constitutes its neighborhood [8]. The states of all cells in the lattice are described by a configuration, as the state of the whole lattice. The rule and the initial configuration of the CA specify the evolution of CA and indicate how each configuration is changed in one step [9,10,11].

IV. Hybrid Model Based on Artificial Immune System and Cellular Automata (CA-AIS)

In the proposed hybrid model, the population of antibodies is conformed to a cellular grid and within each CA cell there are genomes equal to the number of variables forming antibody (problem space dimension) and antibody value is determined as its value and its neighborhoods value based on algorithm Strategy. Nevertheless, the structure of artificial immune system algorithms is preserved in this model. Assuming that problem space is finite, the optimization problem can be represented in form of equation (1):

$$\max\{f(\underline{X}) \mid \underline{X} \in B^n\} \tag{1}$$

Where $f(.)$ is a real function and $B^n = \Re^n$ is the desired real search space.

To this end, 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. Antibody in this model achieves global optimum based on their own and other genomes experiences. As a result, the evolution process improves the antibody value according to the evaluation function

Antibodies in this models, evolve and cloned through interactions with its neighbors simultaneously. Each cell in cellular automata is comprised of many genes based on number of variables forming antibody and each antibodies are the intermediate solutions to the specified problem. In addition, genes represent the state of the cell in cellular automata. Subsequent case of Cellular Automata is produced by using colony and mutation law, as the basic law of artificial immune system algorithms. In table 1, the concepts of proposed approach and artificial immune system algorithm are compared. As noted in this model, antibodies evolve based on concept of neighborhoods in Cellula Automata and interactions with neighbors and localized artificial immune system algorithms operation. Purpose of localizing artificial immune system operators is to build colonies with appropriate Efficiency of colony size based on neighborhood, predefined for each antibody in process also in the mutation operator determining the appropriate mutation rate in predefined neighborhood radius.

TABLE I
Similarities and differences between standard AIS and proposed approach

AIS	CA-AIS
Antibody	cell
Colony of Antibody	Cells Grid
Antibody Value	Cell Status
AIS Operators	Rules
-	neighbours

Parameters affect the colony size of each antibody, the antibody fitness, in comparison with its neighbor fitness and neighborhood predefined radius and neighborhood type. In addition, parameters that affect on mutation operator are the inverse of the antibodies fitness in comparison with neighboring antibodies fitness, in the neighborhood-predefined radius. In the proposed approach, the Von Neumann neighborhood with one- radius neighborhood and two-dimensional structure of the cellular grid is used in the simulations. In the standard artificial immune systems algorithms, in each iteration, each antibody in the population according to their fitness in comparison with other antibodies selected for colony, and influence on the mutation operator. However, in the proposed approach each antibody in cellular automata based on its fitness in compare of the closed antibodies affected to artificial immune system operators. This produces the best rates for artificial immune systems operators to be selected locally. Based on this suitable rate for each antibody, the antibody will be commensurate with the position and absolutely the rate is different for each antibody. In Cellular automaton $CA(\underline{L}_1,...,\underline{L}_k)$ with k cells and in each cell, there is one string in real domain that represents the state of that cell. This string is the antibody in the proposed algorithm. Assuming that CA is synchronous, in time t every cell, i, investigates its own and its neighbor's antibody and selects some of them to be appropriate neighbors according to the evaluation function. Each cell develops an artificial immune system operator rate according to its selected neighbors. Then, it intervenes to improve antibodies in reaching global optimum. According to artificial immune system algorithms, every antibody establishes clone based on the values provided by this way. Afterwards, X^i_{t+1} best antibody of the clone is selected to produce the new antibody. The new antibody, new^i_{t+1}, will substitute the old antibody if it has better value than old antibody, otherwise the old antibody is preserved for cell (according to Eq. (2)). Subsequently memory antibodies are updated and algorithm moves on with the evolution process.

$$X^i_{t+1} = \begin{cases} X^i_t & f(X^i_t) > f(new^i_{t+1}) \\ new^i_{t+1} & f(X^i_t) \le f(new^i_{t+1}) \end{cases} \tag{2}$$

Fig. 1 illustrates a cell within the proposed CA-AIS model. Also in table 1, the features of CA-AIS and AIS are compared. In the proposed approach, the cellular automata rule is made

of two sections. First section of the rule is selection strategy. Selection strategy of cell i, chooses specified number of cells Se, $1 \le Se \le m$, out of m neighbor cells, P^i. The employed strategy selects Se cells with best antibody values of P^i cells which are named P^{Se}. The second section of rule is artificial immune system operator by using P^{Se} set.

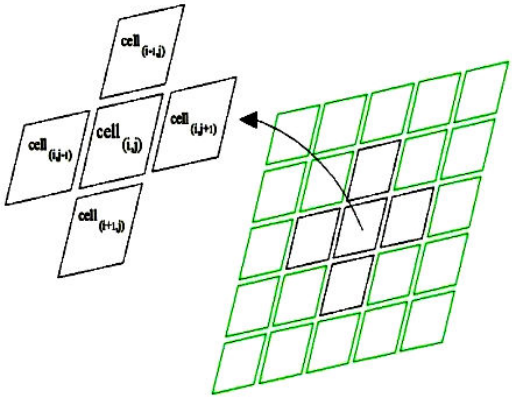

Fig. 1 A cell within the proposed CA-AIS model

V. Experimental Results

In this section the results of simulating CA-AIS hybrid model on eight standard benchmark functions (table.2) are compared to the results of standard artificial immune system. For evaluation, functions are 30 dimensional and 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, average and best solution are measured for efficiency comparisons and variance assessment is used for stability comparisons. The simulation results of proposed approach and artificial immune system algorithm on standard benchmark functions are presented in tables 3 and 4 respectively. The simulation results confirm the out performance of proposed approach to standard artificial immune system algorithm.

TABLE II
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	$f_4(x) = \sum_{i=1}^{D}\frac{x_i^2}{4000} - \prod_{i=1}^{D}\cos(\frac{x_i}{\sqrt{i}}) + 1$	$[-600,200]$
Weierstrass	$f_5(x) = \sum_{i=1}^{D}(\sum_{k=0}^{kmax}[a^k\cos(2\pi b^k(x_i + 0.5))]) - D\sum_{k=0}^{kmax}[a^k\cos(2\pi b^k 0.5)]$	$[-0.5,0.2]$
Rastrigin	$f_6(x) = \sum_{i=1}^{D}(x_i^2 - 10\cos(2\pi x_i) + 10)$	$[-5.12,5.12]$
Noncontinue sRastrigin	$f_7(x) = \sum_{i=1}^{D}(y_i^2 - 10\cos(2\pi y_i) + 10)$ $y_i = \begin{cases} x_i & \lvert x_i\rvert < 1/2 \\ \frac{rand(2x_i)}{2} & \lvert x_i\rvert \ge 1/2 \end{cases}$	$[-5.12,2]$
Schwefel	$f_8(x) = 418.9829 * D - \sum_{i=1}^{D} x_i \sin\left(\lvert x_i\rvert^{\frac{1}{2}}\right)$	$[-500,500]$

TABLE III
The result for 30 dimensional functions with using standard AIS

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 IV
The result for 30 dimensional functions with using CA- AIS

Function	Average	Variance	Best Result
F1	127.4351e-14	2.587e-24	761.1404e-24
F2	764.3751e-10	1.52e-31	132.9727e-19
F3	145.5401e-11	7.43e-16	231.1782e-21
F4	872.9233e-09	5.12e-15	657.4187e-11
F5	184.3391e-10	10.56e-11	391.9367e-12
F6	271.8761e-08	19.96e-17	656.4917e-10
F7	154.3491e-14	3.2e-98	394.8107e-21
F8	744.3271e-12	7.44e-76	681.0711e-18

The results show that the proposed approach (CA-AIS) achieves better results compared to standard artificial immune system and it converges better to optimum solutions. The number of CA-AIS cells is another important factor, and 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 the cell increased to more than 25 cells. Considering the fewer computations for the proposed model with 25 cells is preferred.

VI. Conclusion

In this paper a novel distributed artificial immune system based on the model of cellular automata has been introduced and studied. In the proposed approach each antibody is string and antibodies are placed on a cellular grid beside each other. At every point on time all cells are activated synchronously and they compute their values according to their own and their neighbor's antibody value. In next step, this will substitute the former antibody if it has better quality. 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.

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