Hybrid Model Base on Artificial Immune System and Fuzzy Cellular Automata (FCA-AIS)

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Abstract—**The Artificial immune system is computational system that mimics the process of principles and processes of the vertebrate immune system when combine with fuzzy cellular automata that is a discrete model studied in computational, mathematics, physics, complexity science then we have powerful tools to solve many of problems. The hybridization of artificial immune system with fuzzy cellular automata (FCA-AIS) is a novel approach. In this hybrid model, the fuzzy cellular automaton within each cell deploys the artificial immune system algorithm under optimization context so that by applying its neighbors' and its own experiences tries to improve its fitness. The hybrid model FCA-AIS is introduced to fix the standard artificial immune system's weaknesses. The propose of this model is localize communication between the antibody and use of expert knowledge with using fuzzy membership function that maps into cellular Automata to determine the basic parameters as well as. The credibility of the proposed approach is evaluated by simulations which show that the proposed approach achieves better results compared to hybrid model based on artificial immune system with cellular automata (CA-AIS) and standard artificial immune system.**

Keywords-Artificial Immune System, Artificial Intelligence, Cellular Automat, Fuzzy Cellular Automata

I. INTRODUCTION

The necessity 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 employment. Artificial immune system algorithms are among metaheuristics used for the information clustering, pattern recognition and optimization problems. These algorithms lie under the optimization metaheuristic subcategory in which they use the biological immune system rules for optimization and are based on clonal selection, mutation and choosing the best antibodies[1-4].

Account of simplicity and obviating the need for complex differential equations, traditional immune system algorithms are used in solving complex problems with non-smooth search space and they outperform genetic algorithms in optimization and in the problems where more than a single optimum point is desired. Slow convergence to the global optimum and instability in multiple runs are major drawbacks of these algorithms. The stochastic nature of these algorithms makes the quality of the results from various runs to be very different. 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 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 based on hybridization of artificial immune system and fuzzy system is presented in which antibodies employ expert knowledge and local dependency to estimate important parameters such as mutation rate 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 on artificial immune system in the first section. In the second section fuzzy cellular automata is surveyed. Section three introduces the hybrid model of artificial immune system with fuzzy cellular automata and in section four the credibility of this model is examined. Conclusions are provided in the final section of paper.

II. BIOLOGICAL AND ARTIFICIAL IMMUNE SYSTEMS

Immune system consists of cells, molecules and mechanisms which prevent external agents such as pathogens from harming the host body. Antigen is part of pathogen recognized by immune system. Kind of immune cells named lymphocytes detect and kill pathogens and are 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

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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. Within the produced receptor cells some are picked to be memory cells which yield to an enhanced response from immune system to secondary 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 the affinity with antigen, higher 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] (Fig. 1).

III. Cellular Automata, Learning Automata, Fuzzy logic and Fuzzy Cellular Automata

A. Cellular Automata

Cellular automata are models to study the behavior of complex systems. In cellular automata space is defined as a grid composed of cells, time is supposed to be discrete and rules are global. By using rules in every generation each cell calculates its new state with respect to its neighbors. Cellular automata rules describe how each cell is affected by its neighbors [5,6].

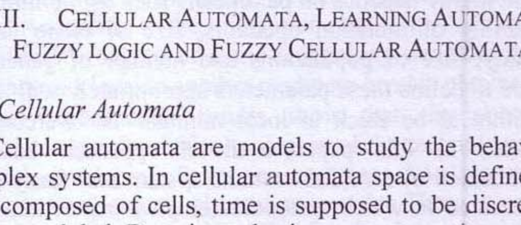

Figure 1. A taxonomy for AIS algorithms.

B. Learning Automata

Automata are adaptive decision-making devices that operate on unknown random environments. A learning Automaton has a finite set of actions to choose from and at each stage, its choice (action) depends upon its action probability vector. For each action chosen by the automaton, the environment gives a reinforcement signal with fixed unknown probability distribution. The automaton then updates its action probability vector depending upon the reinforcement signal at that stage, and evolves to some final desired behavior (Fig.2). A class of learning automata is called variable structure learning automata and are represented by quadruple $\{\alpha, \beta, p, T\}$ in which $\alpha = \{\alpha_1, \alpha_2, \cdots, \alpha_r\}$ represents the action set of the automata, $\beta = \{\beta_1, \beta_2, \cdots, \beta_r\}$ represents the input set, $p = \{p_1, p_2, \cdots, p_r\}$ represents the action probability set, and finally $p(n+1) = T[\alpha(n), \beta(n), p(n)]$ represents the learning algorithm. Let α_i be the action chosen at time n, then the recurrence equation for updating p is defined as

$$\begin{aligned} p_i(n+1) &= p_i(n) + a.(1 - p_i(n)) \\ p_j(n+1) &= p_j(n) - a.p_j(n) \qquad \forall j \;\; j \neq i \end{aligned} \tag{1}$$

For favorable responses, and

$$\begin{aligned} p_i(n+1) &= (1-b).p_i(n) \\ p_j(n+1) &= \frac{b}{r-1} + (1-b)p_j(n) \qquad \forall j \;\; j \neq i \end{aligned} \tag{2}$$

For unfavorable ones. In these equations, a and b are reward and penalty parameters respectively. If a = b, learning algorithm is called L_{R-P} [1], if a << b, it is called L_{ReP} [2], and if b = 0, it is called L_{R-I} [3]. The environments could be classified into tree classes: P-, Q- and S-models. The output of a P-model environment has two values of success or failure. In Q-model environments, the output of environment can take a finite number of values in the interval [0,1] while in S-model environments, the output of environment could be a real number lied in the interval [a,b]. For more information about learning automata the reader may refer to [7][8][9].

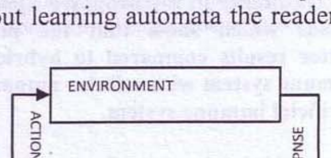

Figure 2. Learning Automata and Environment.

C. Fuzzy Logic

Fuzzy logic was originally proposed in 1965 by Lotfi A.Zadeh as a generalization of binary logic [10]; is used to model imprecision, vagueness and uncertainty in real world. In fuzzy logic, variables consist of partially overlapping fuzzy sets, which form qualitative groups of values within given ranges of values. A linguistic variable is assigned to

[1] Linear Reward-Penalty
[2] Linear Reward epsilon Penalty
[3] Linear Reward Inaction

each fuzzy set in order to describe its properties. In order to convert crisp numerical variables into fuzzy, fuzzy sets are fully defined by membership functions, which return a membership value (μ) within [0,1] for a given crisp object in the fuzzy set. The knowledge base is represented as "IF…THEN" rules, connecting hypotheses to conclusions through a certainty factor. Fuzzy inference is divided into the stages of aggregation, implication and accumulation [10, 11]. Aggregation returns the fulfillment of hypothesis for every rule individually, implication combines aggregation's result to the rule's certainty factor (CF) resulting to the degree of fulfillment for each rule's conclusion, while accumulation corresponds to compromising different individual conclusions into a final fuzzy result [12].

D. *Fuzzy Cellular Automata*

Major problem in modeling complex systems by Cellular Automata, is that cannot define precise relationship between action and reaction in normal behavior. Precise definition of system behavior requires accurate knowledge of system conditions and system state changes under different entries. To solve this problem fuzzy logic is a useful technique by using it can be defined parameters that can be vague and non accurate to decision about transition law and changing system modes. According to the ability of fuzzy logic in data processing in non-deterministic, have been proposed a structural of cellular automata where instead of using absolute values and transmission functions in cells the uncertain value and fuzzy values are used. Different definitions of Fuzzy Cellular Automata provided specific characteristics and behaviors in fuzzy cellular Automata.

IV. Hybrid Model Base on Artificial Immune System and Fuzzy Cellular Automata (FCA-AIS)

In the proposed method fuzzy cellular automata used for determine the appropriate antibody's hyper mutation rate in parallel. Fuzzy rules within each cell responsible for determining the appropriate hyper mutation rate of own cell. Indeed, the fuzzy system sets in each antibody determine low or high mutation rate for each antibody mutation rates should be considered low or high respectively.

For this purpose, in situations that antibodies' affinity to in depended of the best antibodies in the neighborhood is not high must be high hyper mutation rate and otherwise antibodies' affinity to in depended of the best antibodies in the neighborhood is high must be low hyper mutation rate. The aim of this model is using concepts of fuzzy cellular automata to determine properly and efficiently hyper mutation rate for each antibody. Also, using the concepts of fuzzy cellular automata can be calculations performed in parallel and seem be distributed models. To determine the hyper mutation rate have been used of a two-dimensional cellular automata (Fig.3). Each antibody in the artificial immune system is one of the cells onto cellular automata. In this model, the Von Neumann neighborhood with one radius neighborhood is used. Fig.4 depict a cell in the proposed hybrid model.

Because no prior knowledge of the global optimum, it is difficult for artificial immune system algorithms to determining the appropriate hyper mutation rate. This hybrid method benefits affinity evaluation in fuzzy mode. The whole of antibody maturation, affinity evolution, fitness calculation and colony process occur in local environment and in parallel and fuzzy context. In order to use expert knowledge, fuzzy set and fuzzy theory provide a powerful tool and process human knowledge in the form of "IF…THEN" rule. To determine an efficient hyper mutation rate using the hybrid model, there is need to identify quality of antibodies affinity. For this purpose, used the belonging value of antibodies affinity to the Near and Far fuzzy membership function that Figure 4 depicted it. The centers of this membership function on the dependence of the best antibodies are in the neighborhood and hyper mutation rate is determined based on simple equation (3) and (4).

If Affinity is Near Then Mutation is Low (3)

If Affinity is Far Then Mutation is High (4)

In Near and Far fuzzy membership functions (Fig.5), Ab* is the best antibodies in the neighborhood of that antibody is in processed. The value of α is equal to the absolute value of difference between the best and worst antibody affinity in the neighborhood antibody is in processed. This makes the domain of Near and Far fuzzy membership function dynamically adapt to environmental conditions and it is adjusted for every antibody in the cellular grid separately and in parallel. This mean the domain of membership functions for every antibody to another in different. The points 'a', 'b', 'c' and'd' in Low and High membership function (Fig.6), equal to 0, 1, 2 and 3 respectively. This fuzzy system used of Product inference mechanism and center average for defuzzier.

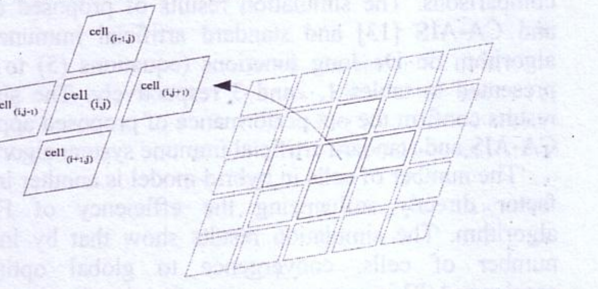

Figure 3. Von Neumann neighborhood with a neighborhood radius one in two-dimensional fuzzy cellular Automata in the proposed model

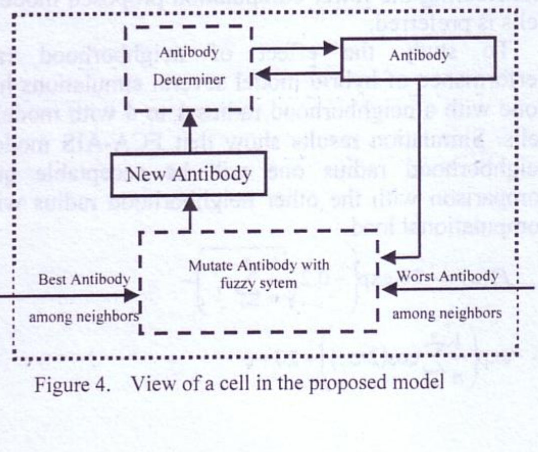

Figure 4. View of a cell in the proposed model

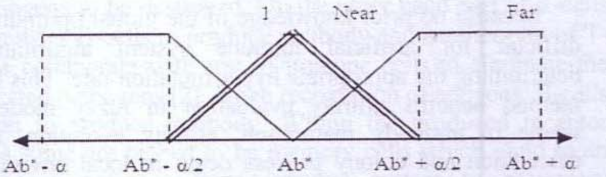

Figure 5. Near and Far membership function

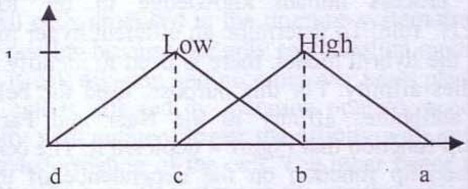

Figure 6. Loe and High membership function

V. EXPERIMENTAL RESULTS

This section the results of simulating proposed hybrid model (FCA-AIS) on four standard benchmark functions are compared to the results of hybrid model based on cellular automata with artificial immune system (CA-AIS) and 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. Based on best artichecture obtained of this model have been used 36 antibodies in fuzzy cellular automata. Taking into account the nature of statistical tests, by running each function 30 times consecutively, average and best of solutions measures are used for efficiency comparisons and variance measure is used for stability comparisons. The simulation results of proposed approach and CA-AIS [13] and standard artificial immune system algorithm on De Jong functions (equations (5) to (8)) are presented in tables 1, 2and 3 respectively. The simulation results confirm the out performance of proposed approach to CA-AIS and standard artificial immune system algorithm.

The number of cells in hybrid model is another important factor directly influencing the efficiency of FCA-AIS algorithm. The simulation results show that by increasing number of cells, convergence to global optimum is accelerated. This convergence acceleration is not noticeable anymore after increasing cells to more than 36 cells. Considering the fewer computation proposed model with 36 cells is preferred.

To study the effect of neighborhood radius to performance of hybrid model several simulations have been done with a neighborhood radius 1 to 4 with model with 36 cells. Simulation results show that FCA-AIS model with a neighborhood radius one will be acceptable quality in comparison with the other neighborhood radius with fewer computational load.

$$F_1(x) = -20.\exp\left(-0.2\sqrt{\frac{1}{n}.\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + e \quad (5)$$

$$F_2(x) = \sum_{i=1}^{n} x_i^2 \quad (6)$$

$$F_3(x) = 10n + \sum_{i=1}^{n}\left(x_i^2 - 10\cos(2\pi x_i)\right) \quad (7)$$

$$F_4(x) = \sum_{i=1}^{n}\frac{x_i^2}{4000} - \prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1 \quad (8)$$

TABLE I. SIMULATION RESULTS OF PROPOSED APPROACH (FCA-AIS).

Function	Average	Variance	Best Result
F1	1.0264e-012	1.4165e-024	1.6875e-014
F2	1.1135e-012	9.6587e-024	2.0139e-015
F3	2.0192e-011	9.4741e-020	1.5616e-014
F4	4.9519e-014	4.3580e-025	1.9095e-015

TABLE II. SIMULATION RESULTS OF HYBRIDE MODEL BASE ON CELLULAR AUTOMAT AND ARTIFICIAL IMMUNE SYSTEM(CA-AIS).

Function	Average	Variance	Best Result
F1	2.1766e-006	1.6210e-08	2.24837e-08
F2	50.6920e-07	3.8048e-09	8.4184e-010
F3	1.6544e-07	1.3234e-08	2.8599e-09
F4	5.6090e-07	2.8527e-08	3.5083e-09

TABLE III. SIMULATION RESULTS OF 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-003	3.75e-004	5.68e-005

VI. CONCLUSION

In this paper a novel hybrid models based on artificial immune system and fuzzy cellular automata for localization between antibodies and use of expert knowledge to determine the basic parameters has been introduced and studied. In this hybrid models antibodies that maps into fuzzy cellular network are considered together and antibodies are placed on a cellular grid beside each other. At every point on time all cells are activated synchronously and fuzzy system into each cell with membership function and fuzzy rule determine efficiently hyper mutation rate according to its and its best and bad neighbors' antibody value. In next step, another antibody is produced which will substitute the former antibody if it has better quality.

The simulation results confirm the out performance of proposed approach to CA-AIS and standard artificial immune system algorithm. The results show that the proposed model in addition to accelerating the calculations with more accurate than the standard artificial immune system algorithm. Meanwhile 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 neighborhood radius have been implemented. 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 neighborhood radius does not have great impact on convergence speed and fuzzy cellular automata with neighborhood radius one is commonly used because of its fewer computational load. Moreover another advantage of this approach is that it is distributed.

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