A New Approach for Biological Complex Adaptive System Modeling and Simulation

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Abstract: By considering definitions of complex adaptive systems, the fundamental features of them are determined. Furthermore, Capra Cognitive Framework for better understanding of living systems is introduced and described. Based on the Santiago Theory of Cognition, Capra Cognitive Framework and Complex Adaptive System features, a model for Biological Complex Adaptive System is proposed and explained. The proposed model includes the main characteristics of Complex Adaptive System like adaptation, Learning and Evolution. Furthermore, for simulating the model by computer, the functionality of Biological Immune System as a Biological Complex Adaptive System is considered and based on; an agent for simulating the Biological Immune System is modeled and designed. The behavior generation of the agents and decision making of them, is presented. By simulating the Biological Immune System based on proposed model the effect of some characteristics in robustness of the system is illustrated.

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1. Introduction

Complex Adaptive Systems (CAS) refers to a field of natural, biological and artificial systems that defy reductionist (top-down) investigation. In a general manner, such systems are composed of adaptive agents with ability of interactions in complex non-linear dynamics [1]. Emergent [2] is one of the basic results of the interactions between agents and it is an important aspect of CAS [3].CAS is concerned with:1-comparing natural and artificial examples of CAS to distil general properties and processes and 2-investigate computer simulations of simplified models of natural systems. By modeling and simulation of CAS, proposing a conceptual model for computational system will be accessible [1].

As John H. Holland Saied, CASs are systems that have a large numbers of components (agents) that interact and adapt or learn. He believes CAS share four major features: 1- Parallelism, 2- Conditional action, 3-Modularity and, 4- Adaptation and evolution. The agents in a CAS change over time. These changes are usually adaptations that improve performance, rather than random variations [4].

By considering CAS it is evidence that understanding behavior of agents in CAS have not been enough to achieve a precise comprehension about it, rather the effect of components and agents on each other should be traced [5]. Time and emergence [6] have been considered as effective parameters in CAS. Time brings the birth, growth, changes, death and destruction of the system and emergence which has caused the ultimate behavior to be the result of all system agents' behaviors [7].

Social living systems like biological immune system, ant colony, and honey bee colony would be considered as a Biological Complex Adaptive System (BCAS) including complex elements with complex interactions. A cell as a fundamental component of living system would be considered as a basic living system. In a cell membrane and chemical metabolism are vital characteristics [8]. In metabolism process, chemical network of processes could be observed and, by exact consideration on BCAS this would be perceived that a network could be noticed as a common pattern for all living systems [9]. For better understanding of BCAS it is necessary consider biological system by CAS approaches.

In the following Section Capra Cognitive Framework (CCF) will be described, then related work will be considered. A through description basic characteristic of BIS and its modeling including a model for antibody behavior, modeling of BIS as a BCAS and behavior generation of agents in BIS, will be explained. In section V the result of BIS simulation based on proposed BCAS model will be illustrated. Conclusions will end the paper.

2. Capra Cognitive Framework (CCF)

Living systems interact with the environmental by Structural changes. Structural changes results in changing later behaviors of the living system. It would be considered as Learning in living system [10]. The Structure of a living system would change while it interacts with its environment and finds the ability of Evolution as time goes on. Through the interactions living system keeps its former Structural changes and applies the changes of new Structures on future behaviors [11].

Considering mentioned issues and due to the Santiago Theory of Cognition [12 and 13], Structural changes of a system form the rules of cognition [9]. Every living system is autonomous in reaction of environment acts and gives the appropriate reaction among all reactions which have been learned in its Structure [14].

Capra Cognitive Framework (CCF) has been represented for understanding the biological and cognitive phenomena. CCF considers living systems through three viewpoints; Pattern, Structure and Process. The Pattern valuates the relations between living agents of a system. In this viewpoint the Pattern of a living organization is mentioned which determines the main characteristic of the system. Physical embodiment of an agent or organization is Structure. Structure has an evolutionary process and gets more complete as time goes on. The Process point of view emerges the first two viewpoints together [15]. Figure 1 illustrates the Capra Cognitive Framework for a single living creature.

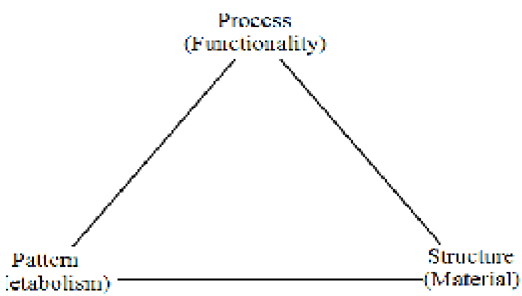

Figure 1. Capra Cognitive Framework (CCF)

In a living system like BIS each component could be mentioned as an element of a CAS: a cell as a Structure (material), cells' metabolism as the Pattern (form), and the chemical interaction among them (their functionality) as the Process. The Pattern and Process are not material and have been emerged from material actions and reactions. To generalize life to the social dominant, the Meaning viewpoint has been added to the three previous points of view. Therefore social phenomena could be evaluated from four viewpoints of Pattern, Structure, Process and Meaning [15].

In order to make the Capra Cognitive Framework (CCF) to be adapted to the existed context in CAS, Network (the relations between the components) would be used for the Pattern and Agent will be mentioned as the Structure. Therefore in CCF, Network would be the selected flow of connections. Structure or Agents are information resources and services. The Process includes every agent's decision making methods. The Process is a function of Structure and Network which means that all affairs in the Process dimension would be affected by the Network and Agents of system. Figure 2 illustrates Adapted Capra Cognitive Framework (ACCF) for CAS.

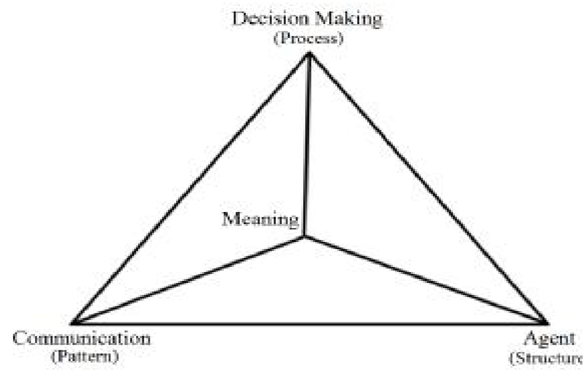

Figure 2. Adapted Capra Cognitive Framework (ACCF) for a CAS

Meaning dimension, as the fourth dimension is a concept that results in convergence and robustness of a biological system. It determines the main system objectives. Also the group of each data and its sources and objectives will be mentioned and clarified in this dimension.

3. Related Work

The field of Complex Adaptive Systems (CAS) was founded at the Santa Fe Institute (SFI) in about 1987 [16].Many methods have considered complexity, complex systems and CAS. Anderson provides an insightful summary of eight popular theories and methods of thinking about complexity, which highlights the diversity of such approaches [17]. However, a clear definition of a CAS has been not presented, but sets of principles and properties in different researches presented different definition of CAS [18]. John H. Holland conceptualized an "adaptive plan", which was the progressive modification of structures by means of suitable operators [19]. He would like to find out how computers could be programmed so that problem solving capabilities are built. In the 1992, he provided ECHO [20]. It was a summary of CAS with a computational example [1].

Furthermore, Waldrop provided a detailed review of the science of complexity [21]. Gell-Mann [22] also produced a seminal work on complexity theory including many detailed illustrative examples. Arthur presented a definition of complex systems as studied in economics with six properties [23]. K. Dooley provided a definition that in it, agents are the base elements of the system and they adapt in response to

interactions [24]. S. A. Levin considered some of the mathematical challenges of CAS. He notifies the limited predictability of results from simulation to the natural systems [25]. J. Jost explained the environment of a CAS is more complex than the CAS itself and that CAS depends on regularities in its environment [26].
Base on the mentioned points, BIS is a CAS includes complex components with complex interactions, distributed throughout our body, with ability of adaptation, learning, evolution, emergence that defense against antigens [9].There are several methodologies for modeling BIS based on an analytical approach [27], Cellular Automata [28] and some others based on Multi Agent System [29]. Differential equations systems based on analytical approach set up to represent some part of BIS [27].
Complex generalized Cellular Automata is simulations based on the global consequences of local communications of members of a population and have been proposed as models of BIS [30]. IMMSIM is a cellular automata base simulation to simulate clonotypic cell types and their communication with other cells. Pappalardo et al. [31] explicitly implement the cellular and humoral immune responses in a set of rules relating to the communication of cellular entities.
SIMISYS is a model and simulates some aspects of the human immune system based on the computational framework of cellular automata. SIMISYS 0.3 model and simulate the innate and adaptive components of the human immune system [32]. Bandini et al. modeled BIS by Situated Cellular Agents (SCA). They introduced the SCA model [33] and exploited to represent their model [34].
Furthermore, some researchers tried to model and simulate BIS for increasing robustness of computer systems. For example, Jabbour and Menasce presented a security policies framework. The security policies consist of several layers in a way that significantly increases the difficulty of attacking the system [29].Y. Ishida proposed the self-identification mechanism based on the value sharing among agents. He has suggested the computer network requires “population thinking” and provided a platform for testing the evolutional system including the immunity-based systems [35].
Dasgupta et al. [36] proposed an immunity-based IDS framework for a multi-agent architecture. The proposed system followed the multi-level detection feature of the immune system [37]. They used ART-2 neural network for detecting anomalies of all monitoring levels and fuzzy logic was proposed to combine four different levels of warnings into a final threat warning [38].
Chandrasekaran adopted Bio-Inspired approach for making the network to automatically detect and tolerate the previously unseen normal behavior [39]. De Paula et al. proposed ADENOIDS [40], an intrusion detection system based on immune system. They have introduced different components taken from BIS.

4. Immune System Modeling

Based on the Santiago Theory of Cognition every living system is a cognition system. In the other word, Living is equal with cognition and living systems are cognition systems. On the other hand, regarding the CAS definitions, a system with adaptation, learning, emergence and evolution ability with the interaction between elements is a CAS. Therefore, can be claimed living system like BIS is a cognitive CAS or Biological CAS (BCAS).
BIS can be able to recognize self/non-self and has some characteristics like adaptation, learning, emergence, evolution and communication. For modeling BIS, its elements, structure and function should be studied carefully. BIS is consisting of different antibodies (self elements) which resist antigens (non-self elements).

4.1. Behavior Modeling of Antibody

Each antibody has two different receptors; Paratope uses for antigens recognition and Idiotope uses for communicate between antibodies. Furthermore the part of antigens that recognized by antibodies called Epitope [41]. Figure 3 shows the different parts of an antibody. Antibody memorizes some antigens' structure and can only confront with them, in the other words; these antigens are known for the antibody [42].

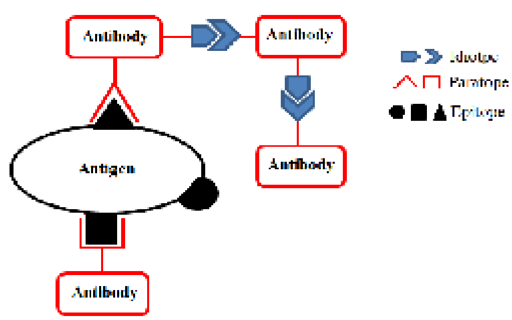

Figure3. Different parts on an antibody

Antibodies monitor the environment and determine self and non-self elements by Paratopes. If the element was non-self, its structure would be checked by the antibody’s memory. If it was matched, the antibody would be able to confront that antigen. Otherwise, antibody tries to adapt its Paratope with antigen's Epitope.If the antibody could have the ability to confront; it would migrate to the lymph nodes, and if it was not able, would keep on moving in the environment [43]. On the other hand, in first step every antibody monitors its environment and tries to get data by Paratope and Idiotope. In the second step antibody analyze the data and recognize self and non-self. Furthermore, in this step it considers its memory for recognizing the kind of non-self antigens. In third step, it plans to confront with antigen. The reaction of antibody in this step depends on its memory. If it recognizes the kind of antigen, it migrates to lymph's node and autopoiesis [9]; else it moves in environment and communicates with other antibodies. The model of antibody's behavior is illustrated in figure 4. More details about BIS behavior are presented in [41-44].

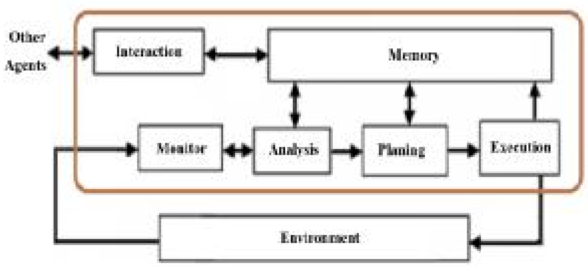

Figure4. Proposed Model for Behavior of an Antibody

For BIS modeling, agent with four processes would be designed. Every agent (antibody) as shown in figure 4 obeys a behavior generation circle with four states. In Monitor state, an agent observe the environment; in Analyse state, recognize self and non-self; in Planning state, generate a suitable behavior and in Execute state, execute the behavior in environment.

4.2. Modeling of BIS as a BCAS

Based on Capra Cognitive Framework and the Santiago Theory of Cognition, by Structural changes a living system would react to the actions of their environment. It would be happen through the two forms of self-renovation and structural changes. In the first one, the organizational structure of the living creature has been kept and it could be assumed as Adaptation. In the second one, new communicational structures have been generated which could cause further changes in creature's behavior and this process has to be called Learning. Through the time Learning could direct the living creature to Evolution.

Awareness about the environment is a necessary for elements in biological adaptive systems (BAS).Without the Awareness, BAS would not be able to make an appropriate adaptation in order to the Meaning. Furthermore, the Meaning provides suitable purpose for action and reaction of living system. When a BAS considered as a social system, Shared Awareness as one of the other major parameters is appeared. The Shared Awareness has been generated from sharing the Awareness of an organization or a system's elements. In basic BCAS like ant colony and BIS, Shared Awareness is caused of chemical interactions such as pheromone and enzymes. But in more advanced social-systems like mammals societies, it happens through conversation and information transmission. Regarding to the mentioned issues and using the CCF, a cognitive model in three tiers could be proposed for an agent in the social dominant as what has been illustrated in figure 5. This model proposes a Meta Model for Biological System Modeling (MMBSM).

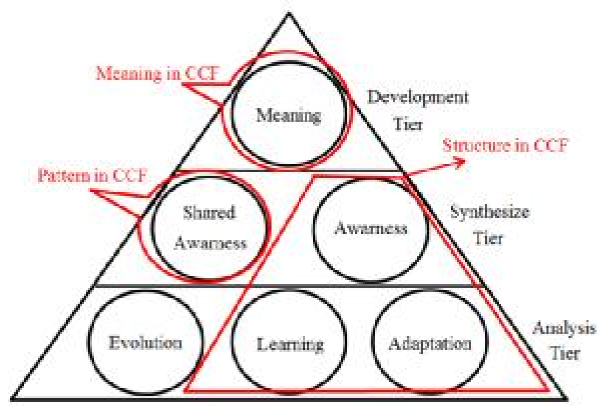

Figure5. The Approach of MMBSM.

The Awareness, adaptation and learning in the MMBSM could be considered equivalent to the Structure dimension in CCF and Shared Awareness has been the consequence of the existence of Pattern and communicational network in CCF. The Meaning dimension has been equivalent in the MMBSM and CCF. The Meaning could determine the amount of threshold for all contexts and depends on the environmental conditions it could be changed for any of contexts. The Process has been considered as an independent dimension in the CCF and MMBSM. The Process is the consequent of the Structure and the Pattern and result of it is behavior generation. The comparing of the MMBSM and CCF is shown in figure 5. More details about the MMBSM have been presented in [45]. By comparing the MMBSM and CAS definitions [1-5, 17 and 18], it is evidence the proposed model contain many concepts of CAS.

4.3. Agent Definition and Antibody Behavior Flowchart

For simulation the proposed model, presenting a precise algorithm or formalism is necessary. By considering BIS, it could be found that it is a BCAS consist of heterogeneous, autonomous and mobile elements. Agent as an independent and mobile entity can be used for simulation of BIS [9]. For simulating BIS by computer, a Multi Agent System (MAS) would be a suitable option. Relation (1) defines MAS for simulating BIS by MMBSM based on ACCF and CAS.

$$< Space, Agent, Object > \qquad (1)$$

Where *Space* is a single layered environment where agents are situated, act autonomously and interact; *Agent* is including antibody and antigen agents and *object* is some defined object in the space.
Antibodies and antigens are implemented by reaction agent. As describe in Eqs. (2) and (3), two different agent use for proposed modeling simulation.

$$Agent_{self} \equiv antibody \qquad (2)$$
$$Agent_{nonself} \equiv antigen \qquad (3)$$

Every self and non-self agent defines by Eqs. (4) and (5).

$$Agent_{self} \equiv \delta\,(Aw, Id, Po, Mo,\ En, Me) \qquad (3)$$
$$Agent_{nonself} \equiv \delta\,(Aw, Id, Po, Mo, En) \qquad (4)$$

Where *En* is the energy of each agent and adjusted by user at the initializing time. When the energy of agent finish, the agent is killed; *Mo* is an agent movement, *Po* is an agent coordinates; *Id* is every agent identification code; *Aw* indicate the information of agent about the other agents, who are located in same *Po*, and *Me* in antibody agent shows the memory of an antibody. δ is a function defines an agent according mentioned characteristics.
Behavior generation of antibody agent obey figure 6. The presented flowchart is adapted by behavior generation in figure 4.
Important definitions used in simulation are defined below:

1- Memory of antibody is randomly initialized.
2- Agent movement is based on Random Walk [2].
3- Neighborhood; Two agents are neighborhood with each other if they have a same location.
4- Adaptation; when Paratope of an antibody has a little difference with Epitope of an antigen, the Paratope of antibody can change and adapt with the Epitope. This process named adaptation. For applying this process in the simulation, minimum Hamming distance (mHd) [46] is used. By changing mHd amount in initializing time, user can adjust the different ability of adaptation for antibodies.
5- Learning; the adaptation causes a change in antibody's memory. If the changing would be saved in memory of antibody, the process named learning.
6- Communication is data transferring between two antibodies. For communication, the position of antibody agents (*Po*) would be same.
7- Robustness Time: since agents can reproduce themselves robustness time would be defined the time antibodies kill all antigens and vice versa.

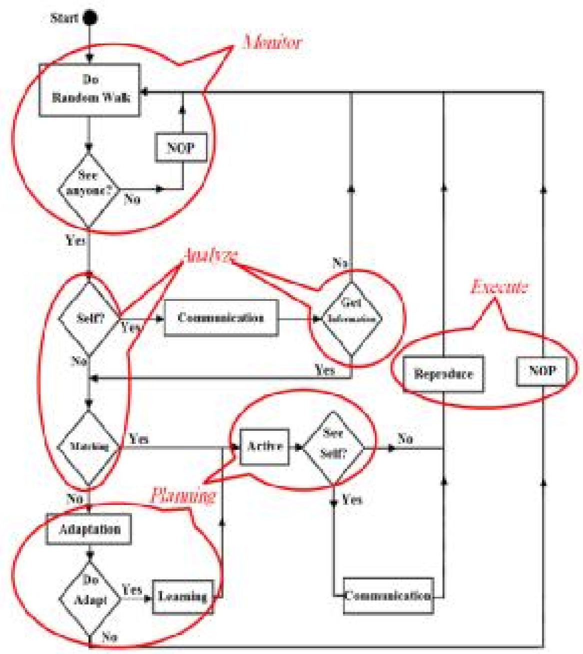

Figure 6. Behavior generation of an antibody agent [47]

5. Results of Simulation

For simulating BIS, Netlogo environment has been used, and agents have been categorized in self and non-self. All antibodies obey flowchart of figure 6 for behavior generation. Antibodies have same codes and recognize each other, but antigens have different random codes and identify antibodies. Each antibody agent has a memory of antigens' code with random data.
For considering the effect of adaptation, learning and communication in robustness of BIS, effect of mentioned parameters in robustness of BIS is considered by 100 running. By considering the results in figure 7, it is evidence; by increasing adaptation the robustness time is increased. In figure 7, Y axis shows the average of robustness time for 100 running and, X axis shows the ability of adaptation, learning and communication.
Also, the results of the running show, learning is another effective characteristic increases robustness of the system. Furthermore, results show in same situation antibodies with communication is more robust than without it.

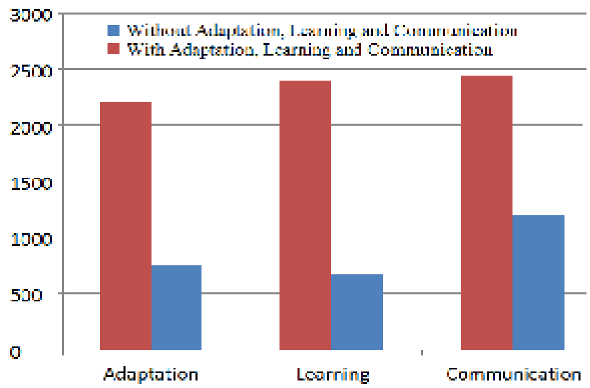

Figure 7. Effect of adaptation, learning and communication

6. Conclusions

Complex Adaptive Systems were described and their features introduced. Also, Capra Cognitive Framework was explained and based on it the characteristics of living systems were detailed. Regarding the CCF and the Santiago Theory of Cognition every living system was cognition system.

Biological Immune System and Ant Colony as a Biological Complex Adaptive System (BCAS) have complex component with complex interaction. By introducing BCAS, it was described by CAS definitions and CCF. Furthermore, a Meta Model for Biological System Modeling was proposed and adapted with CCF and CAS definitions. For simulating a BCAS in a computer, an agent was introduced and the behavior model of the agent for BIS modeling and simulation was presented. By simulating BIS as a BCAS the effect of some characteristics in robustness of system was illustrated.

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