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Exploiting of Adaptive Multi Agent System Theory in Modeling and Simulation: A Survey

Rabia Korkmaz Tan, Şebnem Bora

Department of Computer Engineering, Ege University, Izmir, Turkey

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Corresponding author: Rabia Korkmaz Tan, Department of Computer Engineering, Ege University, Izmir, Turkey
Email: rabia_korkmaz@yahoo.com

Abstract

In this paper, we present a survey on the studies using Adaptive Multi Agent System Theory. This theory has been developed to use cooperation as an engine for designing complex systems which is very difficult to observe and analyze in environment. While modeling a complex system in an agent based environment, the main goal of Adaptive Multi Agent System Theory is to model interaction between agents and/or between agents and the environment in a cooperative manner. In addition, the Adaptive Multi Agent System Theory is able to find its right configuration in an environment for its functional adequacy with its environment. This theory has been largely and successfully applied while modeling complex systems in agent-based environments. We examine the provided solutions to different complex systems and discuss the key points of these studied projects. At the end of the paper, we explain the pros, cons and problems of these studies.

Keywords

Adaptive Complex System, Self-Organize Agent, Agent Based Modeling and Simulation, Adaptive Multi Agent System (AMAS) Theory.

1. Introduction

Complex Adaptive Systems search how the order emerged from complexity in such nonlinear systems as galaxies, ecology, social systems and neural networks. These systems are created by getting inspired from living organisms. They continuously change and progress, because they have to be in accord with the events inside themselves and around them, as well as adapting or reorganizing themselves to ensure their own continuity. The main features of the complex adaptive systems are evolution, collective behavior and pre-estimation. As the time passes, the system components interacting with the components around, also, evolve in order to increase the expectation of life. The components' ability to evolve is the characteristic feature of these systems. In complex adaptive systems they display a collective behavior that the components simply cannot show by themselves. Rather, it comes up as all the systems come together. This behavior comes up as the components interact with each other or display combined behavior. Lastly, in variable situations the components of the system apply constructive rules by estimating certain answers when the system adjusts itself.

Agent Based Modeling and Simulation is a widely applied method to analyze complex adaptive systems, and to assess theories and models. Complex systems consist of many components interconnected with each other. The properties emerging as a result of the individuals' interactions enable the system to seem as a whole. Complex adaptive systems, represented by agent-based modeling, and simulation vary to a great degree. They range from social and economic simulations, biological systems, and traffic and society simulations to space studies (**Macal at all, 2006**).

As a result of the comprehensive studies carried on the properties and structures of complex adaptive systems, Adaptive Multi Agent System (AMAS) Theory was developed. AMAS Theory presents completely different approach compared to other available agent- based models when complex systems are patterned. Various complex systems have been overcome and the scheme of the systems has been created with their guidelines by applying this theory. The theory is based on the principles of autonomy, cooperation and self-organization (**Giovanna Di Marzo at all, 2011**). We show how the theory was applied to the current complex systems and patterned. Also, we present the working principle of an AMAS Theory through these studies. The common feature of the studies patterned by using AMAS Theory is that the environment can adjust itself as it is the case in real complex systems. This feature belonging to AMAS Theory allows the designed models to be applied independently without any central control.

2. Adaptive multi agent system (AMAS) theory

This theorem explains the relationship between the cooperation inside the system and the acquired functional adequacy of the system. There is at least one cooperative system in the adequate system in terms of any functionality. A cooperative system does not include non-cooperative situations (NCS). For a cooperative situation, there must be cooperation among agents, and also between the agent and the environment (**Giovanna Di Marzo at all, 2011**). Generally, it is accepted that estimating how a complex system will behave in a dynamic environment is really difficult, because there are many situations in space searches. It is not possible to discover all of them in a proper time. The goal of the AMAS theory is to find a true configuration in a certain environment and to provide necessary configurations for this. The AMAS Theory focuses on the components of the agent system. The main subject is to design the interaction of the local information and autonomous agents (**Giovanna Di Marzo at all, 2011**).

The main subject of the self-organizing systems is the engineering of the right self-organizing behavior. How is the desired behavior that appears designed properly? How can be the undesired behaviors prevented according to the given necessities and application platform? In order to handle these issues the AMAS theory has been suggested (**Kaddoum at all, 2012**).

3. Applications based on the adaptive multi –agent system (AMAS)

3.1 Mechanical System Design Application

A prototype is made using the components while the mechanisms synthesize. The faults, encountered after the prototype is used, are determined. Then, they are tried to be made up and the same procedures are reiterated by designating a new prototype. These procedures were tried to be implemented by making use of the simulation environment, because this is a long and tiring procedure. In the simulation created by using the AMAS Theory, the Nozzle component of the jet engine was patterned. Also, every component of it was designated as an agent. The most important task of the agents representing the components is to determine non-cooperative situations (NCS). When the first simulation is operated, the agents determine NCS situations. The agents in NCS situation are either rendered cooperative or recreated by a demolishment. In the next step the cooperative agents will try to form the proper mechanism by ensuring the proper connections and interactions. If the impracticability of the attained mechanism to the desired one was detected, the ideal mechanism was tried to be achieved. This was done by changing the mechanism in every simulation, detecting again the interaction among agents, and the new connections and new orbits. This study was not tested in a real system. It is planned to be furthered in the future by adding such behaviors as the creation of new agent components and the self-organization of the agents (**Capera at all, 2004**).

3.2 Ambient System Design Application

The aim of this study is to observe the user behavior in the environment and to realize the practices made in the name of users. The main feature of this application, performed by using the AMAS Theory, is that it does not use any present data and not filter data from the database. Centralized management solutions arising from the heterogeneous devices and mobile devices in the environment were refrained. A distributed solution was offered by enabling heterogeneous devices to interact with each other. An effecter and a sensor were embedded in the devices in the environment. The 3 different types of agents in the system are current data, context and controller agents. Data agent processes the digital data which it took from the sensors. Context agent generates an interval called the adaptive range tracker (ART) within the frame of the agent data. Then, with the help of the AVT (adaptive value tracker), a device based on AMAS, it tries to find the most real-like value by the context agent's estimation of the user agent satisfaction rating. The value that the context agent obtains is reported to the controller agent. Comparing the values obtained from context agent with the estimations, the controller agent chooses the most favorable context agent to perform the action. The chosen context agent starts performing the action in the name of the user. The habits of the user can change in time. The controller agent creates a context agent for the new habits. The context agents that are not used any more are deleted. The learning activity takes place depending on the user's repetition number of the action. It is a considerably successful application. The fact that it hasn't been tested on bigger data is a disadvantage, though (**Guivarch at all, 2012**).

3.3 Complex Product Design Application

When we analyze a product, we see that it has many components. A complex product is a system consisting of a number of connected parts and components, representing generally a certain discipline. This system's functions are composed as the parts interact. When a new element is created for the product, already existing or obtained information is used. Sought characteristic (SC) can be estimated. For the estimation, it is closely related with the known elements (KE) and their characteristics, because the connections between the characteristics are crucial. With this study, a solution was provided by using SAPBR (Self-Adaptive Population Based Reasoning), which is based on cooperation. KC, CW, SC agents are created with AMAS theory and a cooperative interaction occurs among them. **Characteristic Weight (CW) Agent**'s aim is to calculate the weight of the characteristic value given for a certain factor. It takes a request from KE and KC factors for the algorithm processes. CW agent sends a new value for the KE and KC agents, where the new requests are formulated and the information is updated, after the every adjustment step. For the each CW element in the each lifecycle, weighted values are looked. KC agent weight effect is calculated and then compared with the agent's rank. If the value of both is equal, as the KC agent has reached the desired value, it doesn't make any request from the CW agent any more. If not, it continues to send questions to the CW in order to equal. Adjusting the KC's own value and those of the agents that request is a repetitive process. After every 100 lifecycles, solution processes come to a halt. As a result of this study, the products are determined as an original method to design complex products related to their current family. But nevertheless, some improvements are necessary. It must be tested on bigger databases and its sensitivity must be searched (**Kaddoum at all, 2012**).

3.4 Sea Surveillance System Application

This study recommends AMAS, where every agent is responsible for a ship. The ship agent detects local anomalies and uses an initiator connected with critical values. The importance of the anomalies is the necessity for how to combine the cooperative's self-adjustment procedure, in order to regard the feedback. It is patterned, using maritime legislation rules. The violation of the unknown and the rules are accepted as an anomaly behavior. There new behaviors waiting for discovery. Thus, a sea surveillance system should determine new anomaly behaviors. After the agents analyze the behaviors, a sea-agent calculates its own criticality. This could cause the warning to be triggered. The criticality of a ship agent is a function, determining whether a trigger is necessary or not by comparing the warning threshold value with its own value. The criticality of a ship agent is calculated through a function generated by using such parameters as the number of anomalies and ship agent. As the ship agent exceeding the criticality value starts to give signal, the danger is perceived and necessary precautions are taken (**Brax at all, 2013**).

3.5 Bioprocess Control Application

This study makes use of AMAS theory in order to cope with the control of such complex systems as bioprocess. Bioprocess is like a black box, just having partial information and few sensors on it. The goal of the CAMAS (Control Adaptive Multi Agent System) is to control the developments on the bioprocess to give decide on some special actions.

Variable agent provides the connection between the system and CAMAS. The aim is to transmit the change in the real system to the CAMAS system. Every observable variable, heat and sub layer quantity on the bioprocess is represented with a variable agent.

Control agent (Ctr) is an agent responsible of modifying the variables. This agent depends on the whole variable agent of the system and takes all the possible alteration notifications from variable agents. Control agent has been designed to choose the best action among context agents. This comparison is made thanks to the estimation of the context agent.

The context agent (C) reports control agents of this when it is triggered. It sends the control agent a recommendation to perform the action, relying on its own knowledge and estimation.

CAMAS was applied on the prey-hunter problem that has two populations. It succeeded on this population (**Videau at all, 2011**).

3.6. Dynamic Ontology Application

A method called DYNAMO has been suggested when composing ontology, because the ontology expands and it takes time to learn by using AMAS. We benefited from the distributed hierarchical clustering algorithms. DYNAMO forms the concept network with MAS in order to process the results of the text analysis and to create more productive ontologies. DYNAMO provides the hierarchical organization of the concepts. Modification, verification and refinement procedures are repeated until the user gets satisfied. The ontology modification here is the experimental complexity of the agents' relation among them. A self- organized process happens as a new text is added to a dynamic ontology. A number of rules have been defined in the DYNAMO method for this method. This method is based on used and cooperative agents.

The DYNAMO method makes use of distributed clustering algorithm, and makes classification relying on the similarities. A root agent without any parent is created. For the each term an agent is created. The parent of all of them is the firstly created agent. Then, a dual tree is generated until a balance is caught. Childs send the messages stating their choices to the parent. The parents make a classification among their own children. The most voted child is different from the other children to a great degree. Those having the same number of votes are chosen randomly. P creates a new agent: P'. P' becomes the parent of the new group. When only one sibling of an agent remains, its activity comes to a halt. The biggest problem of this study is that it can't manage to get connected to the root, from which a new term is wanted to be added into the current network. The emphasis was put on the fact that this problem will be solved with the cooperative method (**Ottens at all, 2007**).

3.7 A Biological Application That Patterns the Yeast Cell

In this study, a four-layered system including also the agents' self-organize, self-tune and self-assemble abilities is recommended. The aim is to pattern a single-celled yeast behavior. Agents display behaviors according to the local and limited information. The complexity of the pattern design gets reduced to a great extent with the cooperation of the agents with each other and with the self-adaptation ability. The Figure 1 shows this four-layered construction.

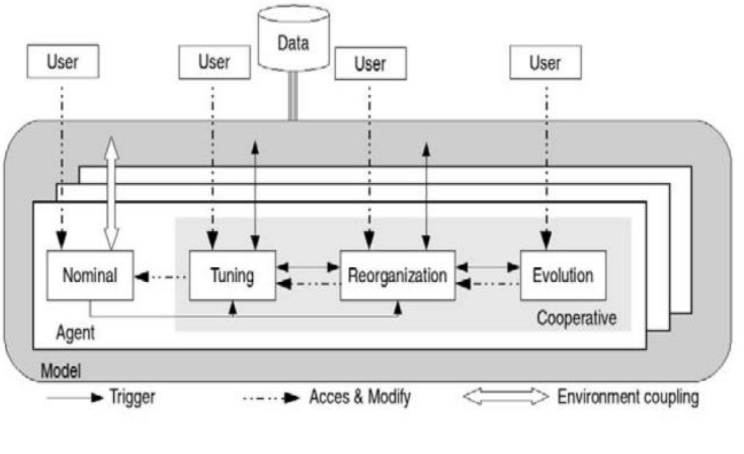

Figure 1. A four-tier model of a collaborative agent.

The agents used in this study have Nominal Behavior, Tuning Behavior, Reorganization Behavior and Evolution Behavior.

When the yeast cell is patterned, 3 types of agents that have these behaviors have been designed: Element, reaction and observant agents. Element agent comprises the components of the yeast cell whereas reaction agent carries out the agent transfer and transformation. Observant agent observes the other agents and prevents the NCS situation related to their behavior.

With this method it has been observed that the simulation tolerates possible malfunctions on its own. Moreover, in this method one can benefit from genetic algorithms and artificial neural networks to adjust the rules designated for the yeast cell and the happening reactions in the best possible way (**Bernon at all, 2009**).

3.8 Flood Forecast Application

This study is a multi-agent system called STAFF that organizes on its own. The aim of the STAFF system is to make flood forecast in every hour by measuring the change in the level of water. Two different agents have been used in this system. These are hourly agents and sensor agents. The purpose of the hourly agent is to measure the change in the level of water at the unit in an hour. Two types of data coming from the sensors exist: 1) the change in the level of water, 2) the measurement of the precipitation.

Here, it has been shown that STAFF has a functional adequacy according to the AMAS theory’s terminology. When a system’s components are in a cooperative situation, system agents display favorable behaviors. Successful estimations made in the STAFF system decrease the conflicts between the agents at the same time (**Georg éat all, 2003**).

3.9 User’s Profile Application

This study mentions an algorithm that observes and can adapt user behaviors on a document. User’s interest or behaviors on the document can change in time. User’s profile is updated by taking these behaviors into consideration. The system focuses on two types of feedbacks. In an **explicit** feedback a user has to evaluate the results that the system gives. **Implicit** feedback tries to solve this problem (time spent on the document, the number of mouse clicks etc.). This problem, which is observable by the feedback system’s interaction, is based on understanding the implicit user preferences automatically. Each and every observation is a critic showing user’s interest. The function defining the user’s interest consists of dynamics defining each criticality’s importance. Real-time learning algorithm aims to deduce the critical behavior. The intended assessment function cannot be controlled by an external audit.

The system calculates a critical value in order to solve and fix possible faults. This value depends on the feedback from the environment. If an agent detects a conflict, it increases the criticality value to repress this situation and sends feedback to the environment. If it sends low feedback, it decreases the criticality value. For the cooperation, each agent must arrange the criticality value. If the normalized value of an agent ends up low, the agent takes the role of solving the present faults on and improves the criticality value. During the criticality value adjustment process, agents are not in interaction with each other. In the criticality phrase, the main function sends feedback to the target function, so it adjusts itself. In this model the multi-criteria criticality function has been updated adaptively. In fact, this function provides assessing the criteria related to the user’s decision making process (**Lemouzy at all, 2010**).

3.10 Biological Neural Network Application

As the aim of this study is to pattern a biological process, this system could be thought as a group where its behavior should be defined. Thus, it involves the environment and all the agents that can interact with this group. The accuracy of the nerves constituting the network and the number of the synapses between them appears as this network’s self-construction is made possible. In this study, Nerve Agents and Synapses, Sensory Nerve Agent, Motor Nerve Agents, Intermediate Nerve Agents, and Observer Agents have been used.

The agents other than the observant agent make a direct contact via their synapses. An observant agent stimulates sensory nerve agents randomly. When triggered, sensory nerves exceed their fire-up levels at that moment and they transmit a spike to postsynaptic nerves. These postsynaptic nerves can be intermediate nerves or motor nerves. Intermediate nerve agents produce and transmit a spike when they receive enough inputs to reach fire-up threshold from their own pre-synaptic agents. Unlike other nerves, motor nerve agents produce spikes consistently. So, the arrival of spikes to a motor nerve just changes its fire-up activity. Once the spikes produced by motor nerves reach muscles, the observant agent records their arrival time. Cooperation faults might occur when the taken spikes become ineffective for the receiver agents.

This situation might appear in two ways. The receiver agent is an intermediate nerve agent, and the temporal correlation as well as the power of the inputs is not enough for the intermediate nerve to exceed the fire-up level. Or, receiver agent is a motor nerve agent, and the temporal correlation of the inputs does not create the expected warning-triggered behavior. Possible cooperation faults (infeasibility) could appear, also, when the results of an agent behavior is not beneficial for the other agents. What's more, an observant agent can assess and ascertain the faults, as well. According to AMAS, every agent should define a criticality function. Every agent detects their relationship with other agents and the NCSs among them. So, they overcome these with their collaborative behavior. In the model, all the NCSs show a biologically unwanted situation. According to the AMAS theory, several agents interacting locally are needed to display collective behaviors functionally in conformity with their biological systems (**Gürcan, 2013**).

4. Conclusion

In this study, the AMAS theory has been analyzed. The AMAS Theory is an important theory for the multi-agent based modeling and simulation. It plays an active role in creating models that resembles the most similar complex systems in the real world. At the AMAS applications in the complex systems, agents represent the components in the complex system while agent relations represent components' interaction processes. This study has presented a list of some important applications related to the artificial simulations of the complex systems that makes use of AMAS. The AMAS Theory will continue to be used in new artificial life simulations day by day. It can generate a solution for several complex systems.

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