An Adaptive Agent Model for Self-Organizing MAS

(Short Paper)

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ABSTRACT
Self-organizing multi-agent systems (MAS) use different mechanisms to mimic the adaptation exhibited by complex systems situated in unpredictable and dynamic environments. These mechanisms allow a collection of agents to spontaneously adapt their behavior towards an optimal organization. This paper presents a self-organization approach that exploits several self-organizing principles through an agent adaptive architecture and a reinforcement mechanism. This mechanism was designed and implemented using the INGENIAS methodology.

Categories and Subject Descriptors
I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence – *Multi-agent Systems, Intelligent agents, Languages and structures, Coherence and coordination.*

General Terms
Algorithms, Design, Languages, Theory.

Keywords
Multi-agent systems (MAS), Self-organizing systems, Complex Adaptive Systems (CAS), Agent-based Modeling, INGENIAS.

1. INTRODUCTION
The theory of self-organization has inspired numerous mechanisms [2] to design and implement artificial self-organizing systems in order to provide insights of the behavior of complex adaptive systems on one hand, and to develop practical applications to solve complex problems on the other hand. Self-organizing systems are characterized by a spontaneous dynamical augmentation of order as a consequence of the interactions of their components without an external influence. When this global order becomes structured to accomplish a particular function then the systems is said to be organized [4]. Systems exhibiting this dynamical process are considered robust in the sense they autonomously adapt their behavior to the changing dynamic environment where they are immersed into, maintaining in this way and with the aid of a feedback their internal organization.

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Multi-agent systems (MAS) are widely used to model artificial self-organizing systems mainly because agents are autonomous software systems that have the ability to estimate the plausibility of the behavior of real self-organizing entities and their interactions. The consequence of both behavior and interactions is exhibited like dynamic aggregate behaviors or patterns that emerge from individual agents' activities and can be observed through computer simulation. Artificial self-organizing mechanisms have emerge from different disciplines, for example, the *stigmergy* theory from the natural systems studies has inspired a coordination mechanism in MAS under the idea that direct interactions between agents are not necessary and indirect communications through the environment are used to coordinate a collection of agents. Another important approach for engineering self-organizing systems in MAS is a cooperation mechanism proposed in the AMAS theory [3]. It focuses on engineering the microscopic issues, i.e. the agents' cooperative behavior and their local interactions to achieve a *global function* that meets the systems' requirements. This function emerges only from the locally interacting agents without explicit knowledge for engineering the macroscopic behavior.

In this paper we propose a self-organizing approach directed to model self-organizing social systems whose individuals exhibit a remarkable adaptation to changing circumstances in the environment and are endowed with mechanisms to evaluate options and decide which actions to take. In order to model these characteristics we propose an agent architecture based on goal dynamics according to the theory of social action [1]. Under this theory goals are mental constructs which have a life cycle. We use this perspective to include a motivation state to these goals to increase or decrease agents' motivations for pursuing those goals. Depending of these motivations agents will exhibit roles specialization which will guide the agents' behavior. The approach is complemented with a mechanism that allows an agent to adapt its behavior dynamically (playing different roles) in response to a feedback from its own experience. This feedback is provided from an evolving memory of previous adaptations which emerges during agents' interactions. Even though this approach requires the definition of a set of rules or conditions which relate roles and motivations initially, the behavior of the agents adapts dynamically during runtime as a consequence of the emerging memory of social interactions. In this approach we only model micro properties and the self-organizing macro behavior of the system is let to emerge.

The previous proposal requires conceptualizing an individual with mental states. The individual should be modeled like a goal-oriented agent whose actions are internally regulated by goals and whose goals and decisions are based on beliefs [1]. To do this we propose the adoption of INGENIAS methodology [6] which agent model basically supports the preceding conception of individuals.

This paper is structured as follows. Section 2 introduces the self-organizing model we proposed. It consists of the agent architecture model and the definition of the mechanism that encourage a dynamic adaptive behavior. Section 3 presents how the model is instantiated in a specific MAS modeling language. Finally, Section 4 presents the conclusions of this work.

2. SELF-ORGANIZING MODEL

Self-organization proposed by this model is founded on the ability of the agents to change dynamically their behavior according to some reinforcement learning. This reinforcement comes from a positive or negative feedback as a property of self-organizing systems [4]. In [5] feedback is seen as a reward an agent receives from its actions. Alike [5], in our mechanism, rewards are received from agents' interactions (actions involving a relationship with other agents) and agents do learn an action policy but they do not try to maximize a reward, instead this policy guides their future activities. A good experience or previous positive interactions increment a determined agent behavior and negative ones or bad experiences decrement it.

Instead of an action policy (a selection of an action or task depending on the feedback) we propose a behavior policy. This means that agents are able to select dynamically a behavior represented as roles, that is, certain functionality an agent is responsible of, and which could imply more than one task. Thus, the consequence of a learnt reinforcement is that agents adapt their capabilities through roles specialization.

2.1 The agent architecture model

The previous mechanism for the adaptive behavior of individual agents is modeled as part of an agent architecture. This is a deliberative architecture based on the goals an agent wants to achieve, the tasks it can perform to satisfy its goals and the roles it knows to play (this architecture is motivated by the INGENIAS agent model). Under this architecture, the decision to execute a given task or play a given role depends on the actual goal the agent is pursuing. If the agent drops this goal and activates another one, then it could happen to change its behavior dynamically. However, we provide another option here based on goal dynamics as in [1]. A goal as in [1] is a mental representation which has the potential to constrain the behavior of an agent towards its realization, whether or not this constraint is actually activated depends on the agent's beliefs. This is called *belief-based goal processing* and depending of the appropriate belief a goal may be activated, promoted, drop, suspended, etc. In this sense, we propose in this architecture the definition of a particular belief called *motivation*. The purpose of a motivation is that an agent pursues a given goal with a weaker or stronger intensity, and according to this intensity will be the specialized role the agent will play. In this way, the behavior of an agent can be adaptive even when pursuing a unique goal. Finally, the variation of an agent's motivation will be achieved through the feedback of the agent's own past experience. Figure 1 illustrates all the elements of this self-organizing model.

Basically, the mechanism is formed by: 1) a belief called motivation, endowing goals with a dynamic intensity for being pursued (*Mi* in Figure 1) 2) the behavior dynamic selection, achieved through roles specialization and according to a motivation for pursuing a given goal (on the bottom of Figure 1 we can observe how depending on *Mi* an agent plays a specialized role inherited from role *R*) and 3) the update of the motivation's intensity through a reinforcement mechanism that takes into consideration the agent's experience (modeled like a social network of previous adaptations in Figure 1), the state of the perceived environment and the current state of the agent.

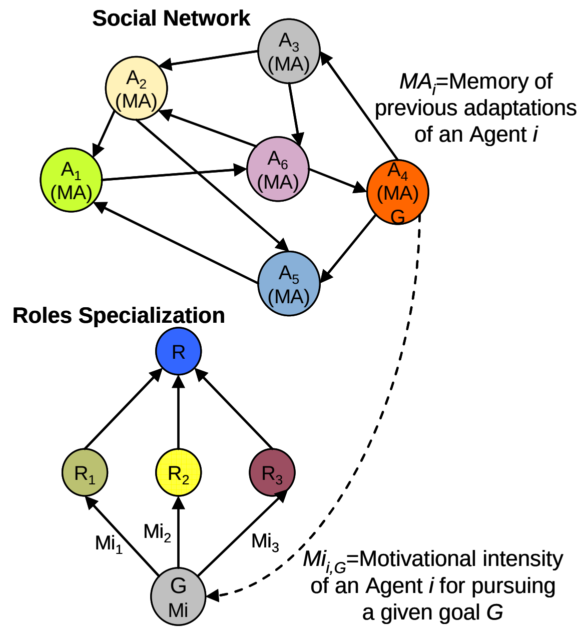

Figure 1. Elements of the self-organizing model.

2.2 The reinforcement learning mechanism

The reinforcement mechanism for dynamic adaptive behavior consists of the positive or negative feedback an agent receives from their own interactions with other agents. In the system, agents act and form an interaction network called *social network*. This network provides agents with a *memory of adaptations* or *MA*. The formation logic of this network will depend on the specific application domain. This network represents the experience of a particular agent or the positive or negative impact an agent can have over another agent during their interaction. Keeping this experience in its memory an agent will be able to reinforce or diminish its future behavior. The formation rules of the network are specified by the designer or domain expert who has knowledge about the system at design time, however, the evolution of the *MA* permits an adaptive behavior over time.

In Figure 1 we can observe that *MA* feedbacks the value of *Mi* associated with the goal an agent is pursuing. This affectation is performed dynamically during runtime. In accordance to *Mi* an agent will choose a strategy or role according to the mapping from different motivation values *Mi* to roles (will see further on how this association is established). As a result, the behavior of the agent is adaptive depending on its motivation for pursuing a given goal. Consequently, the intensity of a motivation *Mi* of an agent *i* for pursuing a goal *G* in a given time *t* is defined as a function of: the agent's memory of its previous adaptations *MA* when pursuing that same goal *G*, the agent's current internal state *S* and the state of the perceived environment S_E in that same time *t*. Thus, given an agent *i* where $i \in 1 \ldots n$, the value of $Mi_{i,G,t}$ is given by the following function *f*:

$$Mi_{i,G,t} = f_i\left(MA_{i,G,t}, S_{i,t}, S_{E,t}\right)$$

This function can be defined with simple rules or with more complex algorithms according to the problem domain we are modeling.

Finally, the adaptability model requires the mapping from different agent's behaviors to its corresponding motivations' intensities. This mapping is established at design time, even though an agent starting from its initial state can adopt those behaviors dynamically during its execution. This fact is thanks to the variation of the intensity of its motivations. The motivation-roles mapping is illustrated in Figure 2.

$$R_i = f_i(Mi_{i,G,t})$$

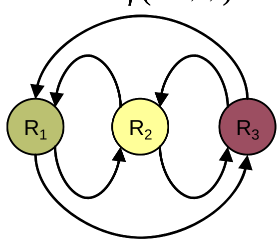

Figure 2. Motivation-based behavior selection graph.

In Figure 2 the roles are represented as nodes and the mappings from motivation to roles as the links of a graph. This graph is called *motivation-based behavior graph*. From this graph an agent can select a new behavior when it needs to adapt its current behavior. Although the mappings could be a simple motivation-role pair association, they are thought to be conditional entities. These entities could have parameters like agents' properties and those of their perceived environment. Since those properties also change during runtime, dynamic role selection is assured not only because motivation change but also as a function of the conditional entities' parameters. Therefore, in Figure 2 we can observe that roles selection is represented as a function of *Mi*. Thus, given an agent *i* where $i \in 1 \ldots n$, the role *R* the agent will play is given by the following function *f*:

$$R_i = f_i(Mi_{i,G,t})$$

This implies that the role selection mechanism can be implemented more adequately for each application domain defining this function to fit the adaptability requirements.

3. IMPLEMENTING THE MODEL

Social systems are highly dynamic and complex. In particular, we are interested in observing the emergent behavior that results from the interactions of social individuals as a way to discover and analyze the construction and evolution of social patterns.

The agent paradigm offers many advantages to express the nature and peculiarities of social phenomena. It assimilates quite well to the individual in a social system. With this perspective, agent-based simulation tools have been developed to explore the complexity of social dynamics. One of these tools is provided by the INGENIAS methodology [6].

The main reasons to choose INGENIAS as the implementation framework of the self-organizing model is that it supports well the specification of organization structure and dynamics, as well as agent intentional behavior, characteristics that are present in self-organizing social systems.

3.1 INGENIAS MAS modeling language

INGENIAS is a methodology for the development of multi-agent systems (MAS). Its development tools rely on its MAS modeling language, which is specified with a meta-modeling language, MOF (Meta-Object Facility), a standard by OMG. The language is structured in five packages that represent the viewpoints from which a MAS can be regarded: Organization, Agent, Goals-Tasks, Interactions, and Environment. The agent viewpoint describes the agent's behavior. It is determined by the agent mental state, a set of goals and beliefs as well as the roles it is able to play. Also, an agent has a mental state processor, which allows the agent to decide which task to perform, and a mental state manager to create, modify and delete mental state entities. The goals-tasks viewpoint describes the relationship between goals and task, since agents are intentional entities; they act as they pursue some goals. Hence, it is possible to identify individual goals for agents, which could be refined into simpler goals up to a level where it is possible to identify specific tasks to satisfy them.

3.2 Extending the language meta-models

The INGENIAS MAS modeling language was extended to introduce new concepts envisaged for the adaptive agent architecture and for the reinforcement learning mechanism.

3.2.1 Goals-Tasks meta-model

This meta-model was modified to include a *motivational intensity* as a property of the goal entity. In this way, goals can be modeled defining a metaphoric intensity property for being pursued; this extension corresponds to the *Mi* belief of the proposed model. Figure 3 illustrates an extract of this meta-model. We can observe that there exits several types of relationships or associations between entities, for example a task can affect (*GTAffects*) the entities of an agent's mental state. Following this same criterion, we extended the meta-model as shown in Figure 3 with three new entities.

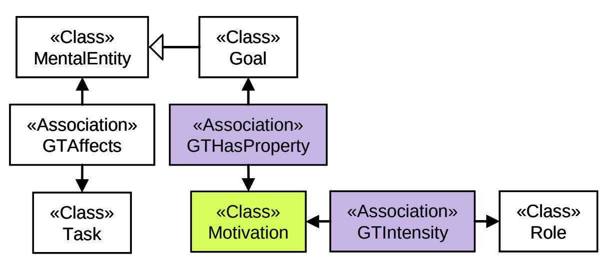

Figure 3. Extended Goals-Tasks meta-model.

We included a class *Motivation* and two types of associations *GTHasProperty* and *GTIntensity*. *GTHasProperty* indicates that a goal has a property called *Motivation* and *GTIntensity* is an association between the class *Motivation* and the existing class *Role* to model the different possible mappings from motivation intensities to roles. Associations in INGENIAS can be decorated with a mental state pattern to indicate under which conditions they can exist. We took advantage of this characteristic to provide the possibility to include and edit association rules between motivations and roles to define the behavior mapping of the self-organizing model.

3.2.2 Organization meta-model

This meta-model was extended to include a *social network* entity. A social network is a social dynamic structure constituted of nodes. These nodes are generally individuals or organizations. The network indicates the way the nodes are connected dynamically through relationships. This entity was included extending the *Group* concept of this meta-model. The fact that an agent belongs to this network group means that it is able to engage in relationships with other agents as well as other agents can create relationships with it. The main purpose of this entity is to allow the designer to represent a network of relationships among the agents and define the formation rules, that is, whether an interaction is considered important for the feedback or not, if so, how to include it in the network. How a specific past experience or *MA* feedbacks positively or negatively an agent's motivation is dependent on the specific application and is described in terms of the agents' interactions. Specifically, those subjectively considered bad or good experiences, and the evolution of their mental states.

Figure 4 shows an extract of the organization meta-model together with the corresponding extensions. In this diagram we can observe that an *organization* class is structured in *organizational group* classes through *OHASGroup* associations. Figure 4 also includes five new extensions to the meta-model. These extensions are: an *OrganizationNetwork* class, a *Link* class, the *LinkFrom* and *LinkTo* properties and the association *ONHasMember*. The *OrganizationNetwork* class inherits from *OrganizationGroup* class, so a network is practically a group where agents belonging to it are provided with a *Node* property. Additionally, an *OrganizationNetwork* class can have *Link* members included through a new association called *ONHasMember*. *Link* entities also contain pointers to the nodes that they are to and from. These pointers are specified with the *LinkTo* and *LinkFrom* properties.

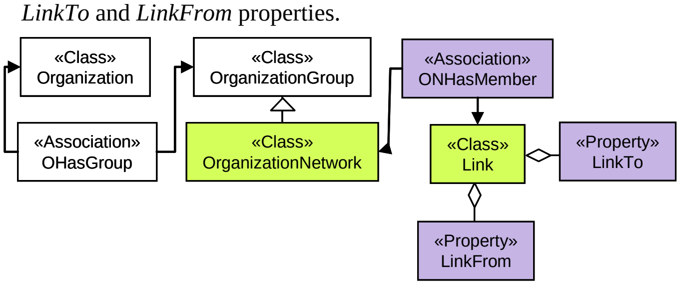

Figure 4 Extended Organization meta-model.

3.2.3 MAS Viewpoints

Finally, once the agents have learnt a behavior policy, they apply it to select dynamically a role to play. For this to happen, it is necessary to define the motivation-roles mapping, either as a simple motivation-role pair or as a function of *Mi*. Since we already have all the elements to model this relationship, it was only necessary to define a new viewpoint called *Goals-Roles viewpoint*. In it we represent how an agent pursues a given goal and how the motivation's intensities are related with the roles an agent is able to play.

4. CONCLUSIONS

In this paper we proposed an adaptive agent model for artificial self-organizing MAS. We tested the viability of implementing this model using a MAS modeling language. Specifically, we discussed how the model was integrated in the INGENIAS modeling language extending the meta-models that specify this language. The flexibility of the language permits to describe the reinforcement mechanism easily as shown in [7]. However, not all the elements or concepts of the mechanism are part of the meta-models, leading to ambiguities at design time. Though the language proved to be especially expressive to allow a designer to specify the adaptive behavior of self-organizing MAS systems, the specification turns tedious when the types of agents and goals are numerous. Then, this approach is best oriented to model small societies.

As future work we envisage to include the whole dynamic adaptive mechanism as part of the INGENIAS meta-models. This means that we could have predefined entities to specify, for example, what is considered a positive or a negative feedback, in a standard way, as well as the formation rule of the network of past experience.

5. ACKNOWLEDGMENTS

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