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Evolutionary Multiagent Systems Towards An Emergence Behavior

Yamina Mohamed Ben Ali
Laboratoire de recherche en Intelligence Artificielle, Institut Informatique,
Université Badji Mokhtar, BP 12 Annaba, Algerie

Abstract: The scope of this study is to figure out how to use biological principles to model multiagent systems. However, through many evolutionary concepts already used to model adaptability in genetic algorithms, we try to propose a new multiagent organization to show how the contribution of such architecture improves the cognitive behavior of this resolution trend. The efficiency of this model relies on the conceptual model of a cell agent in addition to the general planning of their cooperative strategies.

Key words: Adaptability, cell agent, evolutionary behavior, multiagent system

INTRODUCTION

A multiagent system consists of entities called *agents,* which interact in order to achieve a goal. An agent, in general terms, is anything that can be viewed as perceiving its environment through sensors and acting upon that environment through effectors. Computational multiagent systems consist entirely of artificial agents realized as software programs running on a computer system. These systems are being studied and engineered in a sub-field of Artificial Intelligence called Distributed AI (DAI)[1-4]. Multi-Agent Systems (MAS) are the subject of research for researchers studying systems made up of multiple heterogeneous intelligent software entities (called agents)[5-8]. The agents in a MAS can compete, cooperate or simply coexist[9-12]. MAS differs from distributed problem solving in the sense that there is no common global goal to be solved which is known at design time[13,14]. Agent-based systems technology has generated lots of excitement in recent years because of its promise as a new paradigm for conceptualizing, designing and implementing software systems.

This study investigates the cognitive plausibility of an agent to mimic a human agent at cell granularity. The relevance of the proposed organization model relies on an evolutionary computational model inspired from Genetic algorithms. In fact, the evolutionary multiagent architecture provides more than concept to show the emergence behavior. Initially, we only emphasize the global scheme of this simulation environment able to capture several comportments belonging to human society. By this mean, we aim an efficient distributed resolution carried out by agents' society.

EVOLUTIONARY MULTI-AGENTS ARCHITECTURE

Social simulation environment characterizes a multiagent system based on evolutionary computation principles[16]. The evolution of this system relies on Learning in agents' society. This Evolutionary Multiagent Cells System introduces many novel concepts in both agent model and cooperative behavior. Basically, the interaction view between agents is explicitly carried out by cooperation. However, a cell agent could communicate (and cooperate to decode messages) with its neighbor agent provided that sex of their transmitted genes (part of message) are opposite. Here, the intent layer, also the highest level of abstraction of the interaction design, consists in three target components:

Planning agent: Also called environment manager, it specifies the domain problem and designs the appropriate specification of the input universe problem.

Agents society: It is the resolution universe, where each cell agent at individual level is self-interested because it is ability to reason and to adapt its behavior through the learning multiagent cycle.

Sexual agent: It handles the individual energy required by each agent which is paramount to modify its internal structure.

What is a cell agent?: In the social simulation environment, an agent cell is an autonomous entity able to survive, to reproduce and to die whether it is unable to satisfy the environment condition. This general view assigns then comportment to an agent since it fulfills the requirements of a life cycle. In fact, a cell agent model pays above all attention to three basic comportments. Besides the obvious resources (domain knowledge)

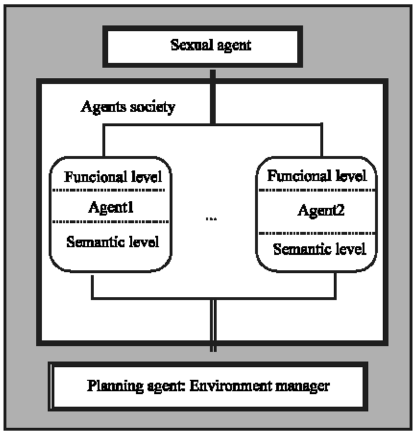

Fig. 1: Evolutionary Social Multiagent Architecture

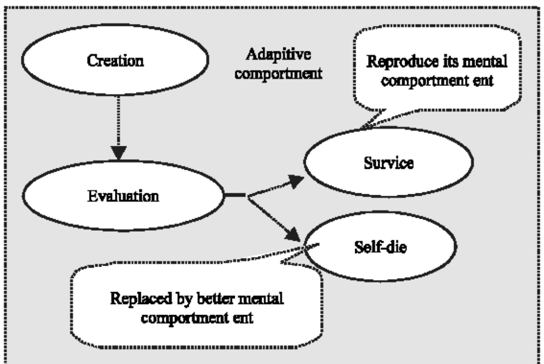

Fig. 2: Cell agent model

inherent from the environment, a cell agent develops other genuine attitudes: Adaptive comportment and social comportment based on a sexual cooperative study.

Mental comportment: This specification level recovers all required resources inherent from the environment well specified by the domain problem.

- Fitness Resource. It defined an agent property needed to decide on how the agent should behave in the society (population).
- Domain Resource. It is knowledge domain specified according to an appropriate reasoning model where a linear representation structure is preferred.
- Society Resource. In fact, it is a validation society parameter that controls the evolution of the multiagent system.

Adaptive comportment: Despite the conceptual specification and representation of domain knowledge, a

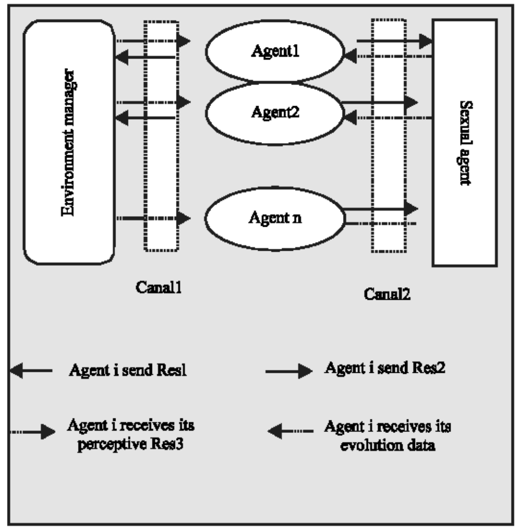

Fig. 3: Communicative Scheme through two Canals Canals

specifies an evolution description inherent to human life at cell granularity. Semantically, an adaptive agent is able to change its functional aspect without any external influence. Indeed, this flexibility enables a cell agent to handle its evolubility and dynamism in the agents' population, from where emerges its cognitive behavior.

Social comportment: Cell agent must evolve in community by cooperating with others agents. Each of its activities, namely learning activities, is undertaken on the basis of atomic knowledge. Therefore, according to combined information, a cell agent uses a defined parameter 'sex' to communicate with the appropriate neighbor via the *sexual agent.*

Cooperative behavior and communication strategies: A cell agent perceives the evolution degree of the multiagent system through two communicative channels. The interaction (channel) between the agents' society and the environment is the important task which systoles the global energy to all the system. Like behavior enables agents to adapt their evolution mechanism in order to select the appropriate decision. Thus, for a given living cycle, cell agents receive environment resource able to modify the internal comportment of the system. However, interactions through channel2, determine the cooperative behavior between pairs of cell agents provided that the sex of their transmitted messages (genes) is more approved. Of course, this assumption is considered by the sexual agent. The synchronization between all transmitted messages is also undertaken by the sexual agent at each cycle.

At this conceptual specification of the social simulation environment, the description of other specific components is not necessary because the aim of this study is to give a general view of a conceptual evolutionary multiagent system.

CONCLUSION

Designing and building agent systems is difficult. They have all the problems associated with building traditional distributed, concurrent systems and have the additional difficulties that arise from having flexible and sophisticated interactions between autonomous problem-solving components. The aim of this study is to present an evolutionary conceptual description based on many biological concepts introduced to give more cognitive and plausible trend to multiagent systems. We believe that the implementation specifications will accord more attention to this system that will give more reality and efficiency to solving-problems methodologies.

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