Adaptive Multi-agent System: Cooperation and Structures Emergence

Imane BOUSSEBOUGH[1], Ramdane MAAMRI[2], Zaïdi SAHNOUN[3]
Laboratory LIRE
Department of Computer Science Faculty of Science of the engineer
University Mentouri of Constantine.
25000. Algeria
Email: 1 Iboussebough@yahoo.fr, 2 rmaamri@yahoo.fr , 3 sahnounz@yahoo.fr

***Abstract*—Nowadays, development of adaptive multi-agent systems has attracted recent attention. Adaptive systems are capable of adapting themselves to unforeseen changes of their environment in autonomous manner. We are interested, in this paper, to adaptation in cooperative systems where agents share a same goal. We propose an adaptive approach based on interaction evaluation and genetic algorithms. Agents, in this approach, have the ability to reorganize themselves in order to bring closer agents capable of cooperating in problem solving. The adaptation task is accomplished at both local and global levels. We present here details of this approach and we show some preliminary experimentation results.**

***Index Terms*—adaptation, multi-agent, genetic algorithm, cooperation, interaction evaluation**

I. Introduction

Multi-agent systems can be seen as societies of interacting agents. Interaction allows agents to find each other and then to exchange information. In such systems, each agent is capable of some useful activities, but being plunged in an artificial society communicating and cooperating with others it is able to enhance its performance and the society's one. Thus, the main issues and the foundations of distributed artificial intelligence are the organisation, coordination and cooperation [21].

However, applications are becoming more and more open and complex such as e-learning, information retrieving and filtering, market place, e-commerce, e-business. Development of adaptive multi-agent systems, to deal with this complexity, has attracted recent attention. Adaptive multi-agent systems must be capable to adapt themselves to unforeseen situations in an autonomous manner. An adaptive system is one in which the structure is capable of changing dynamically [12], [1], [7].

We are interested, in this paper, to cooperative multi-agent systems immersed in dynamic environment. We propose an adaptive approach based on interaction evaluation and genetic algorithms. The system, in our approach, is composed of a set of Task Agents (TAi) that must fulfil the system function and a Mediator Agent responsible of reorganizing the system if this last is in disturbances. The system adapts itself in order to have a cooperative organizational structure; it means that the good agent will be at the good place. For that, task agents have cooperative beliefs about each other; perceive system's disturbances (at local level) from their interactions with each other, then correct cooperative beliefs and, if necessary, send disturbance signal to Mediator Agent. This last is responsible of reorganizing the system when it is judged in disturbances (at global level); the Mediator Agent uses genetic algorithm to enhance system cooperation.

We present in the section 2 problematic of adaptation in our approach, section 3 presents our approach of adaptive system GAMuS, section 4 shows experimentation and preliminary results and finally we give conclusion and perspectives.

II. Problematic

Multi-agent systems have become popular over the last few years for building complex and adaptive software systems. Such systems should have the capability of dynamically adapting themselves according to environment changes, they must be capable of:

- identifying circumstances that require adaptation,
- and accordingly improve their performance in an autonomous manner [8].

Adaptation can take different forms such as change of structure, of content, of relations, of localization of programs or data; and can be at local level or at global one.

We believe that, in adaptive multi-agent systems, adaptability must be a characteristic of agents themselves, they must be able to perceive unforeseen changes of the environment, and act in consequence. In multi agent systems, adaptation can be closely related to evolution of the system structure [3]. At the other hand, to solve complex problems, agents must work cooperatively with other agents in a heterogeneous environment.

Moreover, genetic approach, can harness the power of natural selection to produce communities of agents well suited to their niches, even in environments that are too complex or dynamic for detailed human analysis. In a genetic based system, solutions emerge from a continuous process of adaptive engagement with the

doi:10.4304/jsw.5.10.1170-1177

environment; in some cases this can produce solutions where other methods fail [20], [18].

In multi-agent systems, genetic algorithms can be used globally or locally in the system evolution. In the first case genetic algorithms can act locally on birth, death or evolution of agents themselves, or globally act on organizational structure of the system, considering social character of agents [16], [17], [2].

Proposed approach:

In this context, we propose a model based on genetic evolution of multi-agents organizations. Adaptation, in our approach, consists of reorganizing agents in order to bring closer agents that can cooperate in problem solving. When the system observes disturbances, its organizational structure evolves toward a cooperative one.

Our approach is very interesting in the case of cooperative systems where agents have common goals, such as:

❖ societies where agents have common interests as e-learning systems, information collaborative filtering, recommender systems, systems based on user profiles…

❖ societies where agents must complement one another (complementary competences) as production systems, virtual enterprise, cognitive systems for pattern recognition…

III. GAMuS: Genetic Adaptive Multi-agent System approach

GAMuS Genetic Adaptive Multi-agent System approach is an adaptive approach for multi-agent systems based on interaction evaluation and genetic evolution [2]. A system based on (GAMuS) is able to adapt itself in order to have an organizational structure where agents can cooperate in problem solving. We assume that for any multi-agent system, there is at least a *good* structure for which agents are regrouped by affinities [10], [2].

When the system is in disturbances, it must adapt its structure in order to bring closer agents capable of cooperating according either to their competences or to their interests; it tries to put the good agent at the good place.

The system is composed of:

- a set of task agents, which accomplish the system function. We assume that task agents are cooperative and the system is open.
- a mediator agent responsible of reorganizing task agents when all the system is in disturbances
- a table of cooperative beliefs that define the organizational structure of the system

Task agents have cooperative beliefs about each other, which define strength of links between them. This links express the organizational structure of the system. Task agents must accomplish the system function and adapt its structure if necessary. Each Task Agent, during its action in the system, evaluates its interactions with others and corrects the corresponding cooperative beliefs, which is a local adaptation. If interactions become non fruitful for whole the system, a global adaptation is necessary. In fact, Mediator Agent applies genetic algorithm in order to enhance cooperation degree in the system.

A. System description

We present in this section a detailed description of system components.

A.a. Mediator agent:

The mediator agent has three components as shown in figure 1:

1) *Perception component:* looks for system disturbances (from task agents' signals).
2) *Decision component:* evaluate these disturbances.
3) *Execution component:* applies genetic algorithm which act on links between task agents; it improves, with each step of operation, *the cooperation* between them.

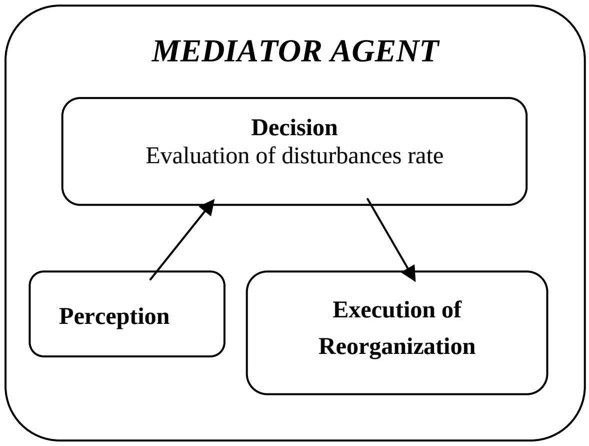

Figure 1. MEDIATOR Agent components

A.b. Task Agent

Each Task Agent is defined by its competences, has a local environment description, an interaction language, environment perception & adaptation component that permits to identify disturbances and adaptation at local level (see figure 2).

1) *Competences component:* defines agent capabilities to solve the problem for which it is designed.
2) *Local environment description component:* is local environment representation of the agent. It defines the set of agent accountancies and the corresponding cooperative beliefs.
3) *Interaction language:* is, for each agent, a set of possible interactions with other agents, and their evaluation defined by quality of interaction. An interaction is considered as a query from sender and response from receiver.
4) *Environment perception and adaptation:* It contains results of different interactions. This component permits to the agent to keep trace of disturbances at local level, and to adapt by link reinforcement.

A.c. Cooperative beliefs

We define an organizational structure as set of links between Task Agents [3]. A task agent (TAi) has a set of accountancies. Some of them can be too cooperative; others are less cooperative and so on.
For that, we define **cooperative belief** (CB) of agent TAi about another agent TAj as the degree of possibility of cooperation of TAj when TAi asks him for help.

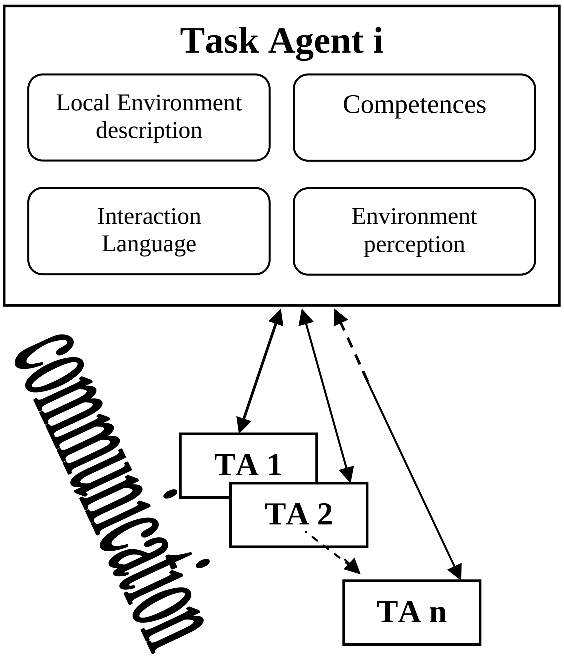

Figure 2. TASK Agent components

This degree depends on TAj competences and/or interests and goals. The set of cooperative beliefs is represented in table I as follows:

TABLE I.
COOPERATIVE BELIEFS OF DIFFERENT TASK AGENTS

	TA_1	**…**	**TA_m**
TA_1	/		CB(TA1,TAm)
TA_2	CB(TA2,TA1)	/	CB(TA2,TAm)
…..			
TA_{m-1}	CB(TAm-1,TA1)		CB(TAm-1,TAm)
TA_m	CB(TA1,TAm)		/

where CB(TAi,TAj) is the cooperative belief of TAi about TAj. TAj can be either cooperative or not according to its judgment to the situation.
In order to facilitate correctness and evolution of CB by genetic algorithm, we represent CB by real numbers as so:

$$\text{CB (TAi, TAj)} \in [0..1] \quad i,j = 1..M \quad \text{where}$$

$0.5 \leq$ CB (TAi, TAj) ≤ 1 means that TAi and TAj are capable of cooperating, and
$0 \leq$ CB (TAi, TAj) < 0.5 means that TAi and TAj can be less cooperative in problem solving.
This structure represents organizational information of the system (see figure3):

1) the network of accountancies from values of cooperative beliefs > 0,
2) strength of agents' links which are values of cooperative beliefs.

	TA1	**TA2**	**TA3**	**TA4**	**TA5**	**TA6**	**TAn**
TA1		**0.32**	**0**	**0.45**	**0.65**	**0.55**	**0**
TA2	**0.25**		**0.87**	**0.43**	**0.87**	**0.29**	**0**
TA3	**0**	**0.75**		**0.69**	**0.33**	**0.45**	**0.42**
TA4	**0.39**	**0.52**	**0.66**		**0.69**	**0.52**	**0.53**
TA5	**0.91**	**0.52**	**0.44**	**0.45**		**0.69**	**0.26**
TA6	**0.45**	**0.52**	**0.72**	**0.53**	**0.45**		**0.44**
TAn	**0**	**0.33**	**0.45**	**0.69**	**0.38**	**0.69**	

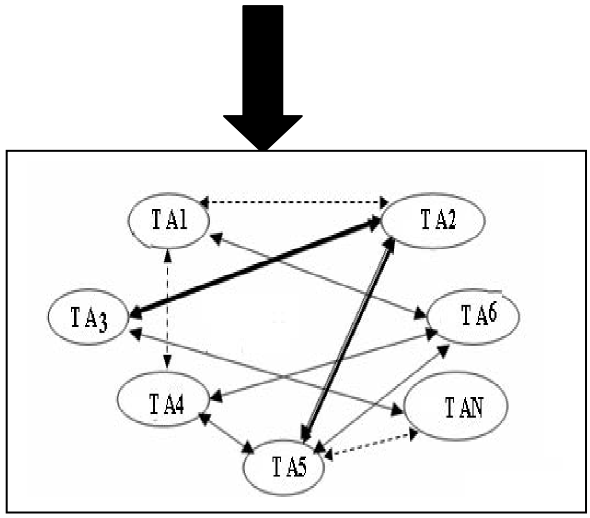

Figure 3. Cooperative beliefs table represents organizational structure

We believe that a cooperative organization is a good one. Generally, cooperation between agents is evaluated by absence of conflicts, comprehension and ability to help each other. So agents' interactions are very important in cooperation evaluation. [4]

B. Adaptation:

We propose adaptation at both local and global levels:
1-/ local adaptation by task agents
2-/ global adaptation by mediator agent using genetic algorithm.

B.a. At local level (Task agent level):

Adaptation is based on interaction evaluation and cooperative beliefs correctness as following:

a. *Interaction evaluation*: Task Agent uses two parameters to evaluate interaction *time of response* (TR) and *quality of interaction* (QuI).

As described above, an interaction language is defined for task agents, where an interaction is described by:

1. message content: a message can be a query or a response
2. evaluation: permits to TA to calculate the quality of interaction according to corresponding response. This evaluation method must be well defined according to problem solving. QuI must be a real number between -1 and 1.

We define a fruitful interaction as:

- Interaction with acceptable time response **TR**:

$$\mathbf{TR} < \mathbf{TRt}$$

where **TRt** is threshold for time response.

- Interaction with acceptable quality according to the problem solving definition, where

QuI is in [-1,+1] ,

We assume that:

$$\text{QuI} \quad = \quad \begin{Bmatrix} +1 & \text{Fruitful interaction} \\ 0 & \text{average} \\ -1 & \text{Not fruitful} \end{Bmatrix}$$

b. *Detection of disturbances at TAi level and CB correctness:*

Each TAi perceives, at local level, non fruitful interactions (when TAj is unable to help TAi), correct the cooperative belief with TAj, and computes **Fi (TAi)**. We define:

- α as correctness parameter, we propose to use α = 0,01.
- **Fi (TAi)** rate of non fruitful interactions of the agent TAi as:

$$Fi\ (TAi) = nFInt(TAi)\ /\ tInt(TAi) \qquad (1)$$

Where
nFInt(TAi) : Number Not fruitful interactions from TAi
and *tInt(TAi): Total number of interactions* from TAi

We define ***Sa*** as *Task Agent threshold of non cooperation*. For each interaction of TAi with TAj, TAi keeps trace represented by *(TAj, (QuI, TR))* and correct the correspondent cooperative belief as following:

$$CB\ (TAi, TAj) = CB\ (TAi, TAj) + \alpha\ .\ QuI \qquad (2)$$

computes then Fi(TAi), if this value exceed *Sa* TAi send disturbances signal to Mediator agent.

B.b. Global level:

Because each task agent has a local view of the system and its disturbances, we propose another level of adaptation if disturbances exceed a rate predefined: it will be at global level. Mediator agent receives disturbances signals from task agents, decide either to reorganize them or not according to the global rate of non cooperation. If this last exceed certain value, mediator agent launches genetic algorithm to improve the system organizational structure.

Genetic algorithms are adaptive heuristic search algorithms; they rely on the analogy with the laws of natural selection and Darwin's most famous principle of survival of the fittest. As such they represent an intelligent exploitation of a random search within a defined search space to solve a problem. The genetic algorithms' strength comes from the implicitly parallel search of the solution space.

They maintain a population of *individuals* that represent potential solutions of the problem. Each solution is evaluated to give some measure of its *fitness*. Genetic operators (crossover and mutation) are then applied to improve the performance of the population of solutions. One cycle is defined as a generation, and is repeated until a good solution is found. The good solution is then applied to the real world. Also because of the nature of genetic algorithm, the initial knowledge does not have to be very good. These algorithms, using simple encodings and reproduction mechanisms, displayed complicated behaviour, and turned out to solve some extremely difficult problems. Like nature they did so without knowledge of the decoded world [11], [18].

In GAMuS approach, mediator agent receives signals of disturbances from task agents, computes then the non cooperation rate of the whole system **F (O)** as:

$$F(O) = \sum_{i=1..N} Fi(TAi)\,/\,N \qquad (3)$$

where N is number of task agents having signal disturbances, and ***So*** is the *organization threshold of non cooperation*. If *F (O) > So* mediator agent launches genetic algorithm to global adaptation until achieving a cooperative organizational structure.

The most important mechanisms that link a genetic algorithm to the problem it is solving are solution encoding and evaluation function. In our case, we propose:

- an individual must represent organizational structure of the multi-agent system, the table of cooperative beliefs is converted to a vector of n*(n-1) real values, each of them is a cooperative belief between a task agent TAi and another TAj, and n is table length.

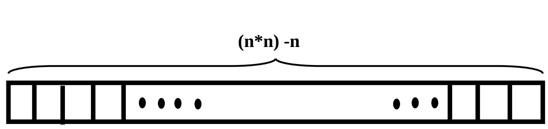

Figure 4. Table of CB converted to a vector

- Evaluation function must be provided from interaction of an individual with its environment. For that, any individual (organizational structure) must be converted to a multi-agent system, and then immersed in the real environment to be evaluated. The system evaluates itself locally and globally as described above.

In figure 5, we show genetic evolution process and evaluation of different individuals. An individual is converted to a multi-agent system, act and evaluates itself, according to this measure the selection mechanism take place, to selected chromosomes are applied recombination and mutation. New chromosomes are created and inserted to the new population. The process is repeated until producing a good individual.

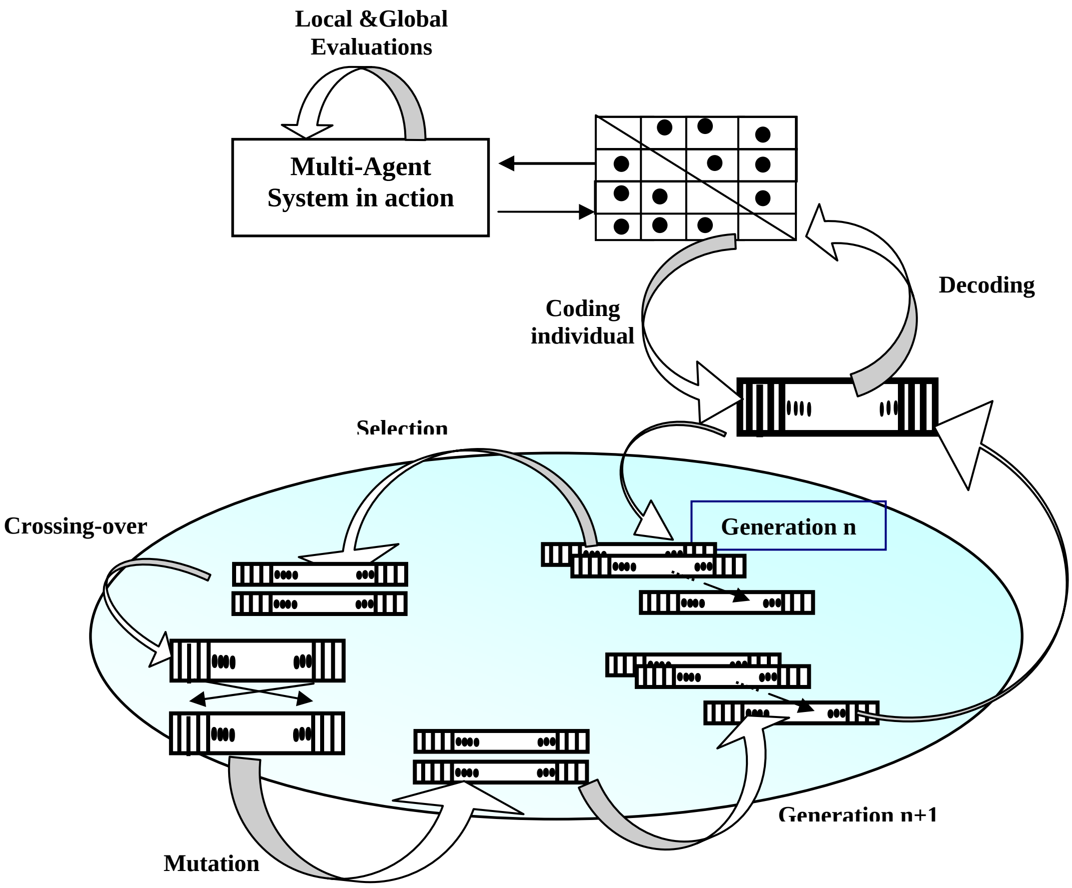

Figure 5. Genetic evolution and evaluation of structures
Each individual is decoded (to give a MAS) and immersed in its environment to be evaluated

C. System design and algorithms:

C.a. System design:

In first time, the system must be defined; designer has to define different task agents: their competences and their neighbours. In order to endow agents of capacity of adaptability, he must define an interaction language that permit to task agent to evaluate their interactions with each other.

Algorithm 1: System design: description of agents and organizational information
1- Define the multi-agent system
*2- **For each** agent define*
a) competences
b) accountancies and cooperative beliefs
c) description interaction language
d) environment perception automatically created
3- Define adaptation parameters: So, Sa, α, TRt
4- Creation of Mediator Agent
5- Action of the system

For each task agent an environment perception component is automatically created; a mediator agent is also automatically created. The system is then immersed in its environment where task agents accomplish their function and adapt themselves to unforeseen changes.

C.b Task agent adaptation:

The system, immersed in the environment, adapt itself to unexpected changes as follows:

Algorithm 2: Local_Adaptation (TAi) ***/* Disturbances perception and CB correctness at TAi level */***
***For each** interaction with TAj*
Save (TAj, (QuI, TR))
CB(TAi, TAj) = α . QuI (TAi, TAj) + CB(TAi, TAj) (1)
***If** non fruitful interaction*
***Then** Fi (TAi) = Fi (TAi) = nFInt(TAi) / tInt(TAi) (2)*
***If** F_1(TAi) > Sa*
***Then** disturbances-signal(TAi, Mediator Agent)*

C.c. Action of mediator agent

Reorganization of task agents is fulfilled by mediator agent as follows:

Algorithm 3 Global_Adaptation (Fi(Ai))
/* Reorganization action of the Mediator Agent */

I-/ $F(O) = \sum_{i=1..N} Fi(TAi)/N$ **(3)**

II-/ *If* $F(O) > So$

then

1. *Initialize algorithm parameters*
   / Population size, mutation rate, crossover rate*/*
2. *Initialize the population;*
   / each individual is a vector of table of cooperative beliefs represented as vector of reals*/*
3. ***For each** individual (organizational structure)*
   a) *Evaluation*
   b) *Selection*
   c) *Reproduction (crossing-over and mutation)*
4. ***GO to** 3- **until** observe a cooperative organizational structure*
   *Where **F(O) < So***

Evaluation of individuals: each individual is decoded to real multi-agent system, the set of cooperative beliefs represent links between agents, and then it is immersed in its environment and evaluated.

Algorithm 4 : Evaluation(Oi)
/*Evaluation of organization i*/

a) *Convert a vector of CB to a MAS*
b) *Action in the environment*
c) *Observe the corresponding system behavior*
d) *Evaluate organization cooperation*

➢ ***for each** TAi /*Local level */*
$Fi(TAi) = nFInt(TAi) / tInt(TAi)$ (1)

➢ *Global level at Mediator Agent*

$$F(O) = \sum_{i=1..N} Fi(TAi)/N \quad (3)$$

IV. EXPERIMENTATION AND RESULTS

We have implemented an adaptive system with JADE platform (Java Agent DEvelopment framework), JADE is a software development framework aimed at developing multi-agent systems and applications conforming to FIPA standards for intelligent agents. JADE is completely written in JAVA. The agent platform can be distributed across machines, it offers possibility to create multiple containers, and each container can be implemented on a machine [14]. Figure 6 shows Jade platform architecture.

A system developed with Jade platform must have at least the main container which contains necessary Directory Facilitator agent (DF) that provides a yellow pages service, Agent Management System agent (AMS) that ensures that each agent in the platform has a unique name.

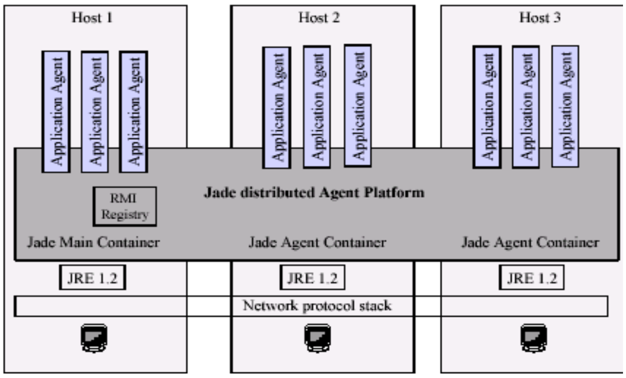

Figure 6. JADE platform architecture

We have implemented a simulation of an adaptive system, composed of mediator agent and 15 task agents. The mediator agent has been created in the main container and the task agents in another one (container1). The figure below shows sniffer agent generated automatically by Jade platform. This agent shows at the right side interactions between system agents and their containers at the left one.

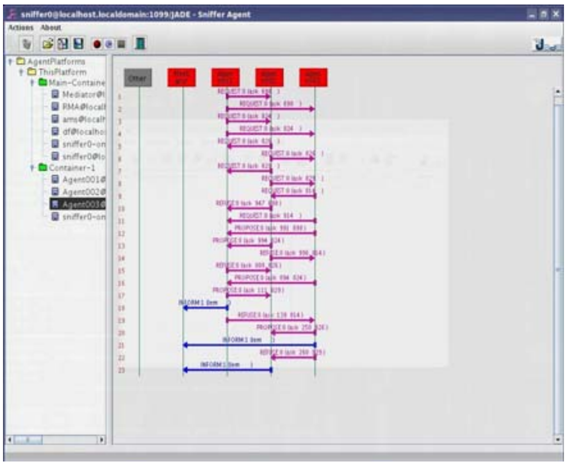

Figure 7. Jade sniffer agent.
This shows a communication between
Mediator Agent(Main Container) and 3 Task Agents (Container 1)

In a first time, we have experimented global adaptation process. Preliminary results that we have obtained are presented in figure 8. Graphs represent evolution of system evaluation according to algorithm 4. Mediator agent must minimize non cooperation rate of the system to a value predefined named So.

Figure 8.a shows system evaluation in the case of population size =500, mutation rate = 0.02 and selection rate = 60% and So = 0.18.

Figure 8.b shows system evaluation in the case of population size =500, mutation rate = 0.02 and selection rate = 60% and So =0.35.

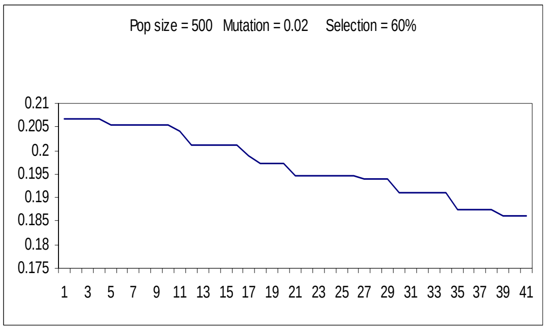

Figure 8.a. Evolution of system evaluation

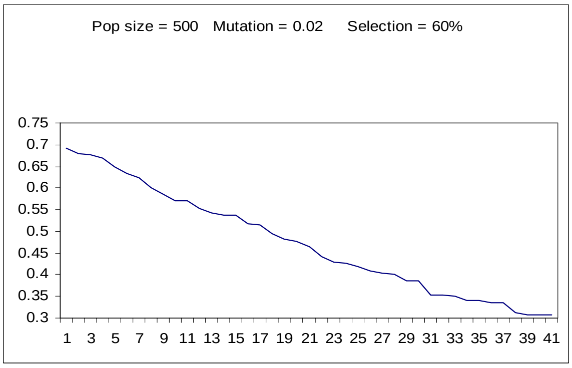

Figure 8.b. Evolution of system evaluation

Figure 8.c shows system evaluation in the case of population size =150, mutation rate = 0.03 and selection rate = 60% and So =0.50.

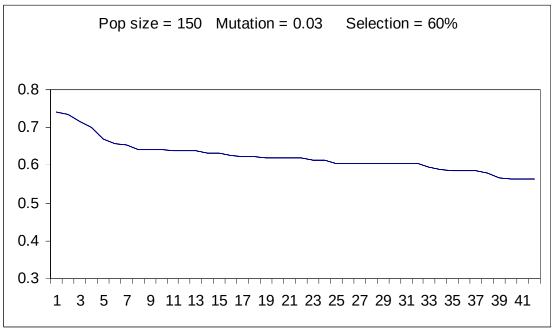

Figure 8.c. Evolution of system evaluation

At global level, communication between task agents and the mediator agent is well implemented, global and local evaluations are exchanged. The genetic algorithm converges towards a cooperative structure. We are actually implementing local adaptation, in which process task agents must correct cooperative beliefs about each other according to quality of interactions as it was shown above.

V CONCLUSION

Currently, agent technology is used in wide variety of applications, particularly, when systems must operate in complex, large, or unpredictable environments.

Multi-agent systems are often considered as collections of agents that interact together to coordinate their behaviour to achieve some individual or collective goal. In fact, cooperation is well suited in collective problem solving. However, before they can cooperate, agents must be able to find each other.

We present in this paper an adaptive approach for multi-agent systems, based on interaction evaluation and genetic algorithm. Agents of the system, called Task Agents, have cooperative beliefs about each other, which represent ability of help one another. Agents interact with each other, and correct cooperative beliefs according to interactions' evaluation; they adapt the system according to their local perception of the environment. When system disturbances exceed a rate of non cooperation, a mediator agent uses genetic algorithm to improve cooperative beliefs at global level. We have implemented the system with Jade platform and we have shown preliminary results of global adaptation. Therefore we have some perspectives to this work:

- Actually, we are studying the different parameters of mediator agent (rates of cooperation, GA parameters) for emerging a good organizational structure;
- In future work we will study metrics of cooperative beliefs and quality of interaction, how to represent qualitatively these parameters.

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Imane Boussebough is a PHd student of computer science in the Department of computer science at university of Mentouri (Constantine, Algeria), received the ingéniorat and MS degrees both in Computer Science from university of Mentouri. She is member of the software engineering and artificial intelligence research team. Her research interests are in the areas of adaptive systems, multi agents systems, Web information research and filtering and complex systems.

Ramdane Maamri is an associate Professor of computer science in the Department of computer science at university of Mentouri (Constantine, Algeria), received his Ingéniorat from university of Mentouri, MS in computer science from the University of Minnesota (USA), and PhD in computer science from university of Mentouri. He is the responsible of mathematics and computer science field at University of Mentouri and he leads the software engineering and artificial intelligence research team. His research interests are in the areas of intelligent agent and multi-agent systems, component based software development and reuse, fuzzy ontologies, Web services, artificial intelligence, and software testing.

Zaidi Sahnoun is a professor of computer science at the Department of Computer Science of the University of Mentouri of Constantine in Algeria. He holds a Ph.D. in information technology from Rensselaer Polytechnic Institute in U.S.A. His main areas of interest include software engineering, formal methods, multi agent systems and complex systems.