Self-adaptive tuning of dynamic changing problem solving: a first step to endogenous control in Multi-Agents Based Problem Solvers.

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***Abstract*—In this paper, we propose a new model, EC4MAS, for endogenous control in self-organizing system for problem solving. We first present the characteristics of exogenous and endogenous control and draw the differences between them. Problem solving methods are often faced with the exploitation/exploration dilemma. We propose in this work an approach that tries to find a good coupling between structural/topological characteristics of a problem and the local associated behaviors that compose the solving method. More precisely we organize the multi-agents based solver into a social organization that represents the organization of the different local behaviors and a spatial organization that represents the different characteristics of the problem. The objective of the system is thus to find a good coupling between these 2 organizations. We illustrate our approach on a graph coloring problem, show that our model can solve the exploitation/exploration dilemma in this case and how it can provide a mean to build a more robust and efficient tuning of the solving process on dynamic changing problems.**

***Keywords*-multi-agent system; self-organization; endogenous control**

I. Introduction

The design of self-organized multi-agent systems (MAS) raises the issues of developing a decentralized control and the fitness of the global (eventually emergent) behavior produced through multiple interactions of various local behaviors. As in these ascendent approaches, the understanding/description of the global behavior is not reducible to the understanding/description of its composing local part, it is also difficult to imagine an easy way to control the global system, by controlling its local components. Much work have been achieved to address this issue, either during design or run time [1][2][3]. They are often designer's knowledge or heuristics based, which makes them often problem specific and hardly adaptable to complex dynamic problems.

In addition, complex problem solving is also subject to the exploitation/exploration dilemma when searching the solution space. When and how to explore is primordial to obtain a good quality of the solving process. A badly tuned exploration process can lead the system into local optima, or can be the source of uncontrolled perturbations [4]. This difficulty is increased in dynamic problems where permanent changes of the solution space occur.

We propose in this paper a new model for endogenous control in self-organizing multi-agents based complex problem solvers. Our model deals with the dynamic of the solving process. More specifically, we propose a process that dynamically couples the problem structural/topological characteristics to the appropriate solving behavior. The global solving behavior is achieved by a society of agents on an environment that represents the problem to solve. Each agent of the society achieves a specific local behavior, on a specific situation of the environment representing a structural characteristic of the problem to solve. The MAS has thus to find a social organization, a non random layout of local behaviors, that best fits a spatial organization, a non random layout of local configurations, representing the structural/topological problem characteristics. The endogenous control is the mechanism that allows the dynamic coupling of these two organizations, as a solution for the problem solving. In this paper, we describe our model based on this dynamic coupling and we show how it deals with the exploitation/exploration dilemma and the associated dynamic parameters tuning for a graph coloring problem.

Section II is a related work section about control in multi-agents systems, distinguishing exogenous and endogenous control and drawing the differences between them. Section III describes the exploitation/exploration dilemma. The proposed model is then defined in Section IV. Section V presents some experiments and their discussed results on a graph coloring problem. Section VI concludes the presented work and draws some perspectives.

II. Related works: Control in self-organized systems

In this section, we distinguish exogenous and endogenous control. In the exogenous case, the control is supported by mechanisms that are outside the system, whereas in the endogenous case, control mechanisms are issued by the inside of the system.

A. Exogenous Control

When the control system is based on external definitions, like fixed rules for example, it is qualified as exogenous

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control. Exogenous control is mainly dependent on the multi-agent system structural characteristics and is often based on the designer or user's knowledge. Using a classification given in [5], we describe in this section some approaches for control in MAS : Design based approaches and Calibration approaches. In Design based approaches, the control is expressed through the process design, by defining the global behavior at macro level and operational rules for its realization at micro level [1]. The relation between macro and micro levels is fully addressed at design time like in AALAADIN [2] or in ADELFE [3]. Calibration based approaches work on reducing the size of the search space, either by using knowledge about the problem to solve [6] or dividing the search space when the parameters are independents [7]. With design approaches the control is relatively static in the sense that once defined it is not easy to make it evolve during computation. In dynamic control approaches, the control is achieved through the guiding of the system's behavior at run time. The control system has a target to achieve/to maintain, means of action on the system and means of observation of the system. Two kind of dynamic control approaches are distinguished: *a priori* control and *a posteriori* control.

In a *priori control*, a set of possible agents's actions are predefined and used to determine the most adapted individual behavior, using tools like Markov Decision Process (MDP) [8]. The relations between global patterns and local behaviors are treated during the learning stage of the MDPs. A global *a posteriori* control approach is presented in [9]. The idea consists to define a system with a correct behavior and then influence this behavior through external control. This global state is captured as a pattern representing the aggregation of all the states of the different agents. If the form is not adequate, it is corrected by acting on the agents local behaviors. The forms definition and their evaluation are determined by preliminary simulations and user's knowledge. Assuming that the observed shape can be reduced to the aggregation of agents' states is too restrictive because it ignores interactions and the system's dynamics. This morphocontrol is an *a posteriori* control because it is applied during the system's computation. Control actions are not totally known at the beginning of system's computation.

B. Endogenous Control

To go further through an endogenous control, the controlling process should guide the agents behavior, but do so in a comprehensive manner. The control system must be built and evolved during the system computation to ensure that it is always consistent with the current situation. An endogenous control needs to be designed as an internal process to the system to control, and in an unsupervised manner. Three important concepts may provide building blocks for a controlling system: learning, observation and dynamics.

- Learning is an important step in a controlling process. The system needs to "understand" its past behavior to know which selected actions have produced success or failures. In endogenous control, the problem structure is learned during computation without any intrusion from outside the system. Learning is strongly related to the systems dynamics including the different configurations encountered. Unlike exogenous control, these configurations are not created artificially, but from real computations. Learning is more restricted but is continuous and provides a greater diversity in the situations addressed. To learn from their actions, agents must have some means to evaluate their environment and means to register the interests (good or bad) of their past actions to update the control system.
- Observation is important as far as it could be used to assess the current situation and then act accordingly. When one looks at the overall behavior of the system, one first seeks to determine the situation in which the system is but also indirectly determines the agents' states. The overall configuration, as we have already stated, is not only dependent of agents local behaviors but also of their interactions. Thus, the process that allows to understand the dynamics that lead to the overall configuration of observation should not be centralized and static. If the system must determine its state, it does not has access to a global observation, unless there is a centralization (or synchronization), which is not acceptable in decentralized autonomous system. The observation should be limited but should not be purely local. It should provide a broader vision about agents local behaviors and their organization.
- Lifelong learning implies a permanent dynamics in the system of control and influence. Modifying the control data influences also its actions. This development is a form of permanent adaptation to control the situation. This dynamics is an important element in the endogenous control. Beside this internal dynamic, the external dynamic has to be considered. The multi-agent system is situated in a permanently evolving environment, so the system is always submitted to perturbations and has to adapt itself. This dynamic does not directly direct the multi-agent system but it influences the control system. The perturbations are captured and interpreted by the control system, then it adapts itself to direct the agents' reactions.

The three previous elements are strongly related to each other. To learn from the computation it is necessary to be able to observe the evolution of the system and to understand its dynamic. In order to create an endogenous control, local observation and evaluation means of the global state, means to share self interpretations and means to update the control system are the elements to study.

III. Exploitation / Exploration dilemma

To illustrate our view of an endogenous control in a multi-agent system, we will use in the next sections, the exploitation/exploration dilemma. Exploration aims to gather as much information on the solution space. Exploitation intensifies the search around selected areas already encountered, based on information collected through exploration.

The exploitation/exploration problem can be divided into two sub-problems, which are *when to explore* and *how to explore*, which we discuss in this section.

The *when to explore* problem means that the system at a given time has to determine whether it is more useful to keep exploring the solution space to collect more details, or to improve already encountered solutions that seem promising. This problem can also be divided into two types, directed and undirected decision. In undirected methods the exploration is chosen randomly at any time of the search. In directed methods, the decision to explore is triggered based on previous knowledge of the problem. This type of methods use recorded past experiences to direct the search. Directed methods are typically used in reinforcement learning [10] to find an adapted exploring rate.

The *how to explore* problem determines the strategy to use to explore when exploration had been selected. The efficiency of a search is very dependent on the exploration process because it introduces some perturbations in the solving process. On the one hand these perturbations can be very useful when the search is stuck in local minima, on the other hand it can be very problematic when the process is close to a solution. The jump due to the exploration has to be adapted to the current search strategy and the solution space. [4] shows the influence of the exploration strategy comparing gentle and strong exploration strategies, which determines the size of the jump done in the solution space.

These two problems are very important to study when we want to build a complex problem solving system like a multi-agents based one. In the case of a self-organized multi-agent system, where control is decentralized and autonomous, it is not easy to memorize and use a big amount of previous information. The local action, evaluation, system dynamics and decentralization characteristics prevent the agent to easily learn from its own action. Exploit/explore strategies in autonomy can be found in [11]. An endogenous control can be a good tool to solve the exploitation/exploration problem, because it is created during the computation and is based on it. In order to illustrate our model for endogenous control, we will focus on the exploitation/exploration problem in a graph coloring problem.

IV. Endogenous control for multi-agent system

We propose in this work, a new model for endogenous control in self-organizing multi-agents based complex problem solvers. Our model deals with the dynamic of the solving process. More specifically, we propose a process that dynamically couples the problem structural/topological characteristics to the appropriate solving behavior. The global solving behavior is achieved by a society of agents on an environment that represents the problem to solve. Each agent of the society achieves a specific local behavior, on a specific situation of the environment representing a structural characteristic of the problem. The multi-agent system has thus to find a social organization, a non random layout of local behaviors, that best fits a spatial organization, a non random layout of local configurations, representing the structural/topological problem characteristics. The endogenous control is the mechanism that allows the dynamic coupling of these organizations, as a solution for the problem solving.

In this section we define the three key elements of the proposed model for endogenous control in multi-agents system (EC4MAS) which are the social organization, the spatial organization and the coupling. The control system has to represent the influence between the main system and its environment. The model is based on the relationship of three elements to construct an emergent control in the MAS to ensure its permanent and continuous adaptation.

A. Social organization

The multi-agent system involving multiple interacting agents, must be addressed in a more extended view than of a single agent. The overall activity is dependent on all individual actions but also on the interactions between agents. The group of agents is a reflection at a given time of the search activity of the system. This activity has to be captured by the system and has to be used to direct and control the research. To implement this perception we use :

- $RSo = \{Rso_1, ..., Rso_n\}$, a set of n social roles
- $Lso = \{Lso_{11}, ..., Lso_{nn}\}$ where $Lso_{ij} = (Rso_i, Rso_j), \forall i, j \in [1, ..., n]$
- $\forall Lso_i \in Lso, Cso = \{Lso_1, ..., Lso_i\}$, a set of social contexts
- a social organization $Oso =< Rso, Lso >$

The roles Rso act as guides for the agent to determine the appropriate strategy and dictate it a predefined behavior. The adoption of a social role by an agent implies that it adopts the guidelines and directives of that role. The action of the agent, so its social role choice, could have been influenced by the other agents social roles, this result in the relation Lso_{ij}. A relation Lso_{ij} exists if an agent with the role Rso_i has encountered an another agent with the role Rso_j. The social organization involves a set of roles Rso and relations Lso between them. The activity of a single agent can not be isolated from other agents and therefore the social roles are linked within the organization. The social organization Oso gives information of the agents situation within the solving process at a given time. The situation of an agent, and more precisely the adequacy of its social role, is directly dependent on its environment. To locate an agent of a social perspective, relations between him and its neighbors define a

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context Cso. The context is a part of the social organization, with a limited size around one particular agent, it provides information on relations between different social roles So in a particular situation of the resolution.

Formally, the social organization is used to represent the solving strategy of the system. Social roles' relations are based on the activity of the system, and more particularly on the agents' actions. This dynamic updates permanently the organization to adapt the search.

B. Spatial organization

The spatial organization is used to model the current situation in the search space, it is based on :

- a set of m spatial roles $Rsp = \{Rsp_1, ..., Rsp_m\}$
- a configuration $Csp = \{a_1, ..., a_j\}$ with $Csp \in SP$ where a_i is an agent state and SP is the search space
- a function $fRsp : SP \rightarrow Rsp$

The spatial role Rsp represents some characteristics of the current solution in the space of solution. It reflects the current position of the agent in the search space and allows it to apprehend the difficulty of its situation. The organization of a group of agents in the environment or physical agents organizations Csp, can highlight basic characteristics of the problem relevant to the resolution. In order to capitalize these informations, it is necessary to allow their identification and use by the system. The spatial organization is based on the $fRsp$ function which associates a spatial role to an agent from the current spatial configuration. This function uses sensors, given to the agents to capture their situation, to determine the Rsp. The sensors could be specific to the problem to solve or more generic as we will see in V-B2.

Unlike social information which models the actions of the agents, spatial roles are about the effect of the solving process in the physical environment. The role is essentially descriptive of the problem and the situation of the system during the resolution. The spatial organization connects particular configurations of the problem. In some cases the problem definition may give access to specified elements to define spatial roles such as topology of the graph for graph coloring. In other cases this information is not identifiable from the outset but may appear during the resolution.

C. Coupling

Social and spatial organizations both provide information of a different nature. The first one is particularly interested in the mechanisms of resolution looking to the fittest agents' behavior. The second one gives information on the status of the system in search space. These two elements are strongly linked because the social role defines how they act in the environment and the spatial role represents the situation of the system in the environment. The coupling of these two organizations is defined by :

- a coupling function $fC : Cso \times Rsp \rightarrow \mathbb{R}$ with $\forall x \in Cso$ and $\forall y \in Rsp$, $0 \leq fC(x, y) \leq 1$
- a fitness function $fT : (Cso \times Rsp) \times Time \rightarrow \mathbb{R}$ where $Time$ is the number of cycles of the resolution

The coupling fC is dynamic and allows the relations between space and social roles to evolve according to the fitness function fT evolution. The determination of the best couple *(Rso, Rsp)* for an agent in a given situation, is the key to success. This coupling is determined by evaluating and storing the pairs created by agents during the search in the previous cycles (a cycle is an amount of time where each agent acts one time). A look back at previous choices with fT allows to update the coupling fC to adapt the control system.

D. EC4MAS principle

Social roles are based on the actions we want the agents to do. They implement the mechanisms used to solve the problem, like explore or exploit strategies for example. Spatial roles are defined in order to give some specific informations on the search space. Spatial sensors have to be able to capture the current situation in the solution space. The fitness function allows the evaluation of the evolution of the search in time.

Algorithm 1 Agent cycle

$UpdateCoupling(fT);$
$Cso \leftarrow GetSocialContext();$
$Rsp \leftarrow GetSpatialRole();$
$Rso \leftarrow GetSocialRole(Cso, Rsp, fC);$
$Act();$

In an agent action cycle, given by algorithm 1, the agent uses the fitness function to update the coupling values then it gets its social and spatial situation to get its new social role according to the coupling function.

V. Results and discussion

In this section, we present an example of the use of EC4MAS to solve a graph coloring problem and we will focus on the exploit/explore problem in graph coloring.

A. Experimental Setup

The agents of the system represent the nodes of the graph to color. A solution is found when all the agents have no conflicts with their neighbors, so each two connected nodes are assigned different colors.

The main solving strategy of the agents is based on the Min Conflict heuristic. Two social roles are used, the first is the exploitation strategy and the second is the exploration strategy. Exploitation tends to decrease the number of conflicts between an agent and its neighbors. Exploration can randomly take a color or apply the exploitation strategy (Min Conflict with exploration). The social organization is modeled with a tree, where one role is represented at a level. The children are based on the representation amount percentage of the role in a situation. The figure V-A-1 illustrates a social organization where relations between roles is divided into two possibilities.

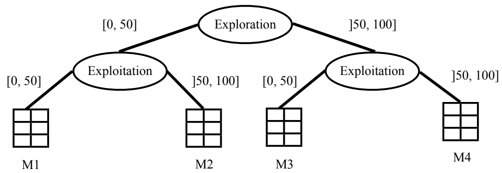

Figure 1. Example of a social organization

The spatial roles are based on the nodes degrees (static). Each role regroups nodes with similar degree. The spatial organization follows the graph topology.

The coupling is done using matrices to link social and spatial organization. The matrices M1, M2, M3, M4 in figure V-A-1 have one column per social role and one row per spatial role, so in this case there is 2 social roles and 3 spatial roles. The values in the matrix are float numbers between 0 and 1 and are normalized on the row. To use the coupling an agent finds its spatial role and its social context, so the associated matrix to use to choose a social role. Higher is the value in a social column, higher is the probability for the social role to be selected.

B. Results and analysis

To test our model we generated 100 different graphs with different seed. We used equi-partite 4-colorable graphs with 300 nodes, that means that the 4 color sets have the same size or can only be different from one node. An edge connectivity (*ec*) of 0,02333 (7/300) is used to get hard problems like seen in [12]. Each resolution is done 1000 times with a maximum of 1000 cycles. The performance is the number of cycles to get a solution, if no solution is found 1001 is used.

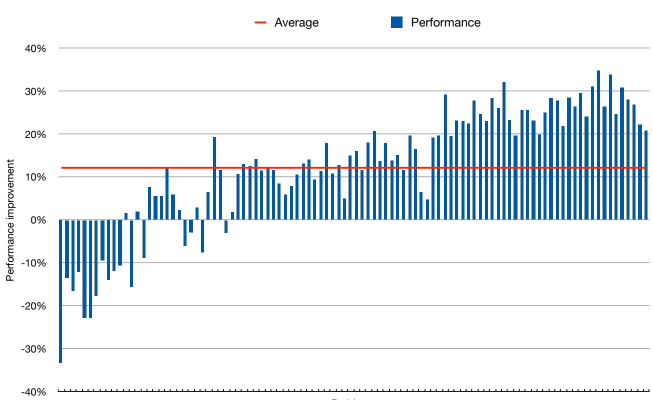

Figure 2. Performance improvement of EC4MAS on 100 problems with 300 nodes, *ec* = 0,02333, 4 colors.

1) Performance: First, we randomly picked a problem (*ref-problem*) among generated graphs, a genetic algorithm is used to get coupling values and to find the best exploring rate for Min Conflict with exploration (17,7% for *ref-problem*). We used this tuning to resolve all the generated problems. The figure V-B1-2 shows the performance improvement on all the 100 problems which consists in the difference between Min Conflict with exploration results and EC4MAS results. The problems are ordered by the number of cycles of the solving process. We can see that EC4MAS can generally improve the resolution on a set of problems with similar characteristics since the average improvement of EC4MAS is about 12,4%. There is a big difference of performance between easier problems (at the beginning) and more difficult ones (at the end). The *ref-problem* number of cycles for resolution with EC4MAS is 234, most of the problems with a negative improvement are under this value. The coupling used for *ref-problem* is a representation of the problem and gives specific informations on it. With problems much easier than that, the resolution is too specialized and instead of guiding the search process it introduces too much perturbations.

Resolution	Perf.	Tuning time	Efficiency
Min Conflict (17,7%)	100%	4	-
Optimal Min Conflict	124,71%	333	29,68%
EC4MAS (17,7%)	112,14%	22	231%

Table I
PERFORMANCE AND EFFICIENCY

In addition to the performance gain, we also focus on the tuning time of the system. Table I presents the performance gain of three different tuning and the efficiency of each method. The Min Conflict with 17,7% of exploration is taken as a reference for the measures. The tuning time is the sum of the time to find the optimal exploring rate for each problem for Optimal Min Conflict, and is the time to find the optimal exploring rate and the coupling values for *ref-problem* for EC4MAS. In the first case the tuning time is dependent on the number of problems and their hardness, in the second case only on the hardness of *ref-problem*. We can see here that the performance is much higher with optimal exploring rate, about 2 times more than EC4MAS, but the tuning time (in minutes) is about 15 times higher. In the end, the global efficiency (performance gain divided by tuning time) of EC4MAS is almost 8 times higher than Optimal Min Conflict. This shows that EC4MAS can learn the characteristics of a particular problem and is able to use this knowledge to really well solve similar problems with a limited tuning cost.

2) Genericity: ECM4AS uses the nodes degree to create spatial roles. EC4MAS has been developed to be as generic as possible. To illustrate the genericity we introduce here a new type of sensor for spatial role, the local clustering coefficient. This coefficient is based on triangles between neighbors of the node and the node itself. This coefficient is very useful to apprehend the difficulty of a graph coloring problem as seen in [13].

Spatial role	Perf. (cycle)	Improvement
Degree	234	11,5%
Clustering coefficient	223	17,04%

Table II
IMPROVEMENT OF DIFFERENT SPATIAL ROLES OVER MIN CONFLICT

Table II shows the performance on *ref-problem* with the Min Conflict with exploration, EC4MAS with degree and clustering coefficient for spatial role. We can see that the most specific sensor which is the clustering coefficient is more efficient than the others, about 17% than Min Conflict while the degrees are only 11,5% better than Min Conflict. EC4MAS could support several types of sensors for spatial roles, from more general one like degree to more specific one like clustering coefficient. EC4MAS is generic but is also dependent to the type of spatial role and sensor it uses.

VI. CONCLUSION AND FUTURE WORK

In this paper, we discuss the control problem in reactive self-organized systems. We distinguished two types of control, exogenous and endogenous. We describe the differences between them and pointed the main elements to address the creation of an endogenous control system, like observation, learning, dynamic and structural coupling. Then to illustrate the possibilities of an endogenous control system for problem solving, we considered the exploitation/exploration dilemma. We proposed a new model to create endogenous control in a self-organized multi-agent system, EC4MAS. This model is based on a social and a spatial organization and their coupling. These two organizations give informations on the current resolution strategy of the system and on its result, and the coupling allows the control system to dynamically adapt the strategy more efficiently.

EC4MAS is a generic model and could be used to solve different type of problems. The spatial organization could be adapted to use specific informations to let EC4MAS be able to solve different kind of problems. On more hard problems EC4MAS gives good improvements since the characteristics of the problem are used to better tackle it. EC4MAS makes the tuning of the system robust face to problem changes, the coupling of social and spatial organization gives pertinent solutions to encountered situations with a specific strategy. The tuning has not been changed when new problems are submitted. This is a great point because individual optimization is very expensive and could not be always used, more particularly when problems are dynamic. The endogenous self-organized characteristic of EC4MAS could efficiently limit the amount of time and resources to solve a problem.

Future work will focus on two main points, the dynamic adaptation of the coupling and a new social organization. The dynamic adaptation of the coupling will let the system find the good parameters during the resolution process. In addition social organization will be upgraded to give more specific informations on the current strategy. Instead of general information on the neighbors strategy, the real specific organization of a local situation should be considered.

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