ESANN'2005 proceedings - European Symposium on Artificial Neural Networks
Bruges (Belgium), 27-29 April 2005, d-side publi., ISBN 2-930307-05-6.

Organization properties of open networks of cooperative neuro-agents

J.P. Mano, P.Glize*

Institut de Recherche en Informatique deToulouse, Université Paul Sabatier
118 route de Narbonne 31062 Toulouse cedex, France

Abstract. Our researches on adaptive systems are inspired by their ability of building by themselves a representation of their surrounding world. Using cooperation as a local criterion of self-organization, we study in a network of neuro-agents the evolution of the system and in the same way, the emergence of a functioning coherent with the environmental feed-back. In this paper we expose the abilities of the neuro-agents that give them the autonomy required to build an *ab nihilo* topology. And finally we want to emphasize the dynamic of the network organization that is basically its best property of adaptation to a changing environment.

1 Introduction

The work presented here concerns our approach to self-organization in a dynamic neural network. We present some experiments of emergent learning based on our knowledge of complex systems through multi-agent systems technology and cellular biology. In fact we are most interested in the mechanisms involved in the construction of a network able to stabilize its structure in a given environment, than in the efficiency of the learning supported by this structure. Obviously those two ontogenetic processes are strongly coupled and appear simultaneously as mutual consequences.

Under those conditions, we conceive artificial systems presenting an inherent complexity close to biological systems as they are open and as their structure evolves from nothing (at least an empty shell) up to an organized, stable and functional network of neuro-agents. Our working hypothesis tells minimal entities of such a system can be built and given with sufficient behavioral potentialities in order to organize themselves to satisfy the whole system activity.

In this study, we want to show that a coherent and useful system can emerge without any global model for its functioning, solely from activity and organizational rules of its sub-parts; only agents are designed, not the topology of the network they will belong to. Our thought process supposes four distinct steps that description will be formerly extended. Firstly the neuro-agent unit has to be designed, their properties, their abilities (calculus, communication) and their knowledge. Secondly, initial system is constituted of a minimal number of unlinked neuro-agents. Those pre-built neuro-agents are only receptors (inputs) and actuators (outputs) of the network. Thirdly the global system has to be plunged in a dynamic and open environment in which it will have to adapt to; regarding neuromimetic systems, this phase suppose

* {mano ; glize}@irit.fr

autonomous behaviors of neurons like proliferation and apoptosis. Fourthly, through an a posteriori study, the internal organization of the global system has to be analyzed in order to understand its functioning and its development.

In a first part we discuss of the adaptive multi-agent system (AMAS) background of this work. In a second part, some properties of neuro-agents are presented, and finally the third part shows some macro-level results of network construction.

2 From Biology and AMAS…

"Essentially, ontogeny is the process that maps the genotype to the phenotype. This mapping is quite simple in most current evolutionary algorithms, though some more complex (ontogenetic) ones have been proposed."[1]. It is not yet possible integrating the complexity of the dynamic that occurs during the self-structuring ontogeny of a biological system [2]. Biological neural structures may be considered as the combined result of self-organizing cellular activities and of the following of many strong planned processes. Such a system is the result of the permanent reorganization of its parts upon among others, the pressure of its environment.

Designing multi-agent systems (MAS) as adequately adapted complex systems, the requirements are a coherent local activity of its parts, and a sufficient feedback between system activity in the environment and related perceptions of the system.

The first aim of the Adaptive Multi-Agent System theory [3] is to realize MAS having the "classical" characteristics to build a society of situated agents [4]. But, from our point of view, a MAS is mainly plunged into an environment and must reach a behavioral or a functional adequacy. This property of "functional adequacy" associated with the following theorem [5] "For any functionally adequate system, there is at least a cooperative internal medium system which fulfils an equivalent function in the same environment" allow us to be focused on the design of systems with cooperative internal medium, in which agents aim at developing exclusively cooperative interactions.

The specificity of the theory lay in that the global function of the system is not coded within the agents, but emerges from their collective behavior. Each agent possesses the capacity to locally rearrange its interactions with others depending on its individual task. Changing the interactions between agents can indeed lead to a global level change that induces the modification of the global function. Cooperation-driven self-organization implying local treatment of non cooperative situations is a mean to optimize system's functioning when a difficulty is encountered.

Our theory of cooperative self-organization has already been validated in several fields†: the tileworld game [6], cooperative information systems in e-commerce [7], behavioral simulation about natural and artificial collective intelligence [8], traffic management of a telephonic network [9], and real-time system for flood forecast [10]. In all these applications, systems have coarse-grained or middle-grained agents. The goal of current project is twofold: first, to give results when having fine-grained agents and second, to develop tools in order to observe and analyze a self-organizing complex network of agents.

† *Home page of Cooperative Multi-Agent Systems:* http://www.irit.fr/SMAC

3 To cooperative neuro-agents

In the domain of artificial learning, we can compare the neuro-agents presented here with the neurons of ontogenic artificial networks [11]. The concept of cooperative neuro-agent (CNA) can be detailed in three functional subsets that justify the "neuro-agent" term. CNAs have the usual transfer function of an artificial neuron [12], have also a vegetative behavior and have moreover a set of cooperative social behaviors according to the laws of the AMAS theory. The role of vegetative and social behaviors accounts mainly for balancing the lack of an initial topology in the network.

3.1 Regulation of CNA function

At a functioning level a CNA realizes a positive integration of the information carried through incoming links, and then this weighted sum is transformed using a transfer function in a positive integer value. The transfer function is in fact a composed with a three adjustable segments curve. A CNA can only receive a single inhibitory link that nullifies the transferred value, but a CNA can produce several inhibitory links.

In order to keep in a cooperative way, each neuro-agent will adapt itself to deal with whatever disturbing event. From an egocentric point of view, it adjusts the weights of its inputs, and its transfer function. This regulation seems hebbian reinforcement learning [13], but the originality presented here consists in the criteria taken into account to quantify weights and other parameters adjustments. This kind of unsupervised and self-organized learning is often used [14] and different mechanisms of neuron adjustments are proposed.

CNA objective is to be useful to the others by having a coherent activity and furnishing to the other relevant information. So, learning consists in reinforcing weights according to correlated temporal activities of inputs. A CNA estimate the rightness of its activation by interpreting messages from its outputs. Following the mean error, the CNA adjust the weights of concerned inputs and if necessary the transfer function. As in a back propagation mechanism, a CNA informs in turn its inputs of the error it has detected.

Explicitly that means a CNA modifies its functioning to fulfill others CNAs it works with. So at a given time the behavior of a CNA is the result of its code expression under the regulation of its local environment. This on-line adaptation process should give the system a robustness advantage in comparison with neural network using genetic algorithm to adapt the neurons behavior [15].

If despite those adjustments, a CNA keeps on receiving error messages that it cannot satisfy, then the CNA triggers a second process of adaptation at the level of network structure. We call this process vegetative behavior, as the CNA can determine by itself if it has to proliferate or if it has to search for new inputs, or if finally it has to disappear in an apoptosis-like mechanism.

This vegetative behavior of the CNA grants the dynamic and the self-organization of the network. That's why the learning stage begins with an unconnected network where only inputs and outputs of the future network are created. The mother CNA provides all the required instances, which are an exact copy. Nevertheless, the basic transfer function of the mother cell is slightly adjusted in each individual CNA in order to find the better cooperative behavior in accordance with its neighborhood.

3.2 Cooperative behaviors and communication

At a social level, we study relations between CNAs of the network. Those relations are realized through two kinds of links. First real links or synapses connect two CNAs on a activating or inhibiting mode. Those links are characterized by a weight‡, a confidence as a kind of inertia relative to weight adjustments, and some counter of non-cooperative situations (NCS). The second type of links concern virtual links; they don't transmit any signal between CNA and only contain NCS counters, so they improve CNA knowledge of its neighborhood; they are an interesting mean to balance the lack of topology and reduce noise during learning phases. Both real and virtual links transmit messages between CNAs.

Cooperative behavior when addressing to CNAs, mean that CNAs help each others to find not only their right place in the network but also their right function in the network. Back propagation is cooperative as it helps CNAs to find their function but is not sufficient to position them in the network [16]. So we can distinguish two other sets of cooperative behaviors. The first includes pro-cooperation, for example when a CNA inform one of its neighbors that is searching accountancies, with the rest of its neighborhood (including virtual links). The last set regroups the behaviors appearing to resolve some particular potential and well defined troubles: the NCS [12].

4 Experimental results

The study of the network is an a posteriori process that needs specific tools to understand the reasons why the system behaves as it behave. A succession of snapshots of the network organization is used to analyze the mechanisms of emergence of system's functions.

4.1 Entropy measurement

As an online interpretation of global connectivity and network stability, we have used an index of entropy (1). This index is computed from global mean connectivity, which represents the number of connection combined with their weight and stability.

$$I = \sum_{i=1}^{N} \frac{a_i + b_i}{C_i^{CNA}\left(\sum_{j=1}^{a} C_j^{Link} \times \omega_j + \sum_{k=1}^{b} C_k^{Link} \times \omega_k\right)} \tag{1}$$

I so represent the entropy of a network containing N CNAs, each CNA presenting *a* inputs and *b* outputs. C_i^{CNA} and C_k^{Link} define respectively a CNA confidence and a link confidence. By confidence we define a parameter of resistance to adjustment.

The graph (fig. 1) presents the average entropy in a network initially composed by 3 inputs and 3 outputs, each output having to learn an AND logical function upon two randomized inputs. The simulation was repeated 60 times; mean and standard deviation are reported. A stabilization of the global entropy of the system is noticeable after 1400 cycles.

‡ Both weight and confidence are integers between 1 and 10^3

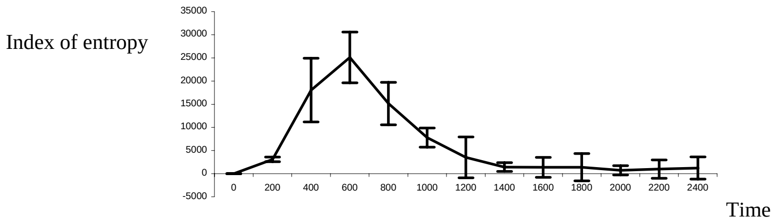

Fig. 1: Evolution of the entropy index.

4.2 CNA proliferation

The figure 2 explores the number of CNAs in two series of learning stages. The MAS has to learn logical AND and XOR function; each function was test 40 times. The XOR learning appears effectively harder to do in a temporal dimension where a late in XOR learning of about 300 cycles, and in a second dimension that deals with accuracy of learning. Seeing standard deviation, current CNAs do not perform well each time in XOR learning whereas AND function is sharply and regularly learnt.

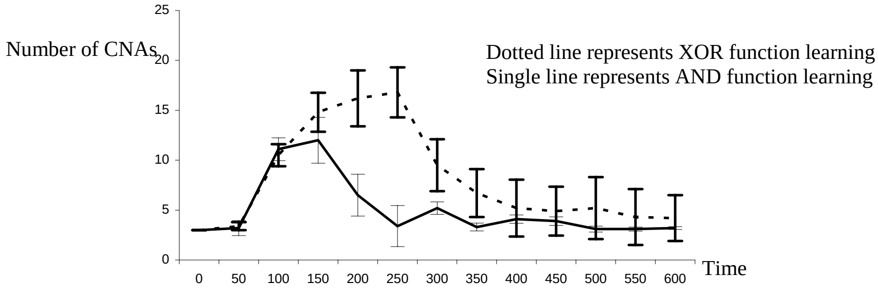

Fig. 2: Evolution of CNA's population.

5 Conclusion

In each sub part of the network, the assembling of CNAs is a self-organizing process. The network is initialized with only unconnected CNAs situated at the interfaces. The behavior of CNAs only depends upon their local perception of the system, and finally there isn't any imposed pattern which leads the organization of the system.

During a learning period, the system adjusts its function by reorganizing its parts. So the learning of the system globally results of population growth and of neuro-agents adaptation (weight adjustments, transfer function regulation, research and disappearance of connections). Self-organization is a mean of leading an open system to an organized one, by the way of emergence [17]. A primordial condition of emergence is the absence of any pattern that predefines the global organization of the system [18]. That's why neuro-agents only have a local view, and by the way of cooperation, they can share a part of the information they perceives.

The analysis of the system organization implies a static point of view upon the final system that will permit a comparison with biological even known systems, and a dynamical observation that should explore the emergence of a function. The training phase allows modifying the strengths between nodes in order to reduce the error between the actual and desired output's signals. In order to overcome their limitations (sub-optimal solutions, off-line training, convergence speed…), lot of works try to add plasticity in the basic neural network architecture. In the same vein, the self-adaptive network of CNA presented here, is able to define criteria for adapting the genotypic transfer function, node strengths, connectivity between nodes, neuron proliferation, and even neuron deaths.

References

[1] Sipper M., “Notes on the Origin of Evolutionary Computation”, 1999, John Wiley & Sons, Inc., Complexity Vol. 4, No. 5.

[2] Maturana H.R., & Varela F.J., L'arbre de la connaissance, 1994, Addison Wesley.

[3] Camps V., Gleizes M.P., & Glize P., “Une théorie des phénomènes globaux fondée sur des interactions locales”, 1998, Actes des 6ème journées francophones IAD&SMA Pont-à-Mousson - Editions Hermès

[4] Wooldridge M., An introduction to multi-agent systems, 2002, John Wiley & Sons.

[5] Gleizes M.P., Camps V., Glize P., “A theory of emergent computation based on cooperative self-organization for adaptive artificial systems”, 1999, Fourth european congress on systemic,Valence.

[6] Piquemal-Baluard C., Camps V., Gleizes M.P., Glize P. Cooperative agents to improve adaptivity of multi-agent systems, 1995, Intelligent Agent Workshop of the British Computer Society in Specialist Interest Group on Expert Systems & Representation and Reasoning, Oxford.

[7] Gleizes M.P., Léger A., Athanassiou E., Glize P., Abrose : Self-Organisation and Learning in Multi-Agent Based Brokerage Services, 1999, 6th International Conference on Intelligence and Services in Networks, Lecture Notes in Computer Science 1597, Springer.

[8] Topin X., Fourcassié V, Gleizes M.P., Théraulaz G., Régis C. Glize P., Theories and experiments on emergent behaviour : From natural to artificial systems and back, 1999, Proceedings on European Conference on Cognitive Science, Siena.

[9] Dotto F., Travé-Massuyès L., Glize P., Acheminement du trafic d'un réseau téléphonique commuté par une approche multi-agent adaptative, 1999, CCIA Conférence, Girona.

[10] Gleizes M.P., Régis C., Georgé J.P., Glize P.- Real-time simulation for Flood Forecast, 2003, Third international conference on Autonomous agents and Multi-Agent Systems.

[11] Fiesler E., “Comparative Bibliography of Ontogenic Neural Networks”, 1994, Proceeding of the International Conference on Artificial Neural Networks – ICANN, 1994

[12] Mano J.P., Glize P., Property analysis of open networks of cooperative neuro-agents using AMAS Theory, Proceedings of TAPOCS WETICE, 2004, Modena

[13] Floreano D., Urzelai J., Evolution of plastic control networks, 2001 Kluwer academic publishers.

[14] Forrest S., “Emergent computation : Self-organizing, collective, and cooperative phenomena in natural and artificial computing network”, 1990, Physica D42 Vol1 N°11 - Norh-Holland.

[15] Moriarty D.E., & Miikkulainen, R., “Forming neural networks trough efficient and adaptive co-evolution”, 1997, Evolutionary Computation.

[16] Kaelbling L.P., Littman M.L. & Moore A.W., “Reinforcement Learning: A Survey”, 1996, Journal of Artificial Intelligence Research.

[17] Holland J.H., Emergence: from Order to Chaos, 1997, Addison-Wesley

[18] Goldstein, J., “Emergence as a Construct: History and issues”, 1999, Emergence Volume 1, Issue 1.