On Plasticity, Complexity, and Sapient Systems

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1 Introduction

In the context of Artificial Intelligence (AI), an intelligent agent (Franklin and Graesser 1997; Russell and Norvig 1995; Wooldridge and Jennings 1995) is usually defined as a temporal persistent autonomous system situated within an environment, sensing and acting in pursuit of its own agenda to achieve its goals, possibly influencing the environment. (Russell and Subramanian 1995) argue that an advantage of such definition is that it allows room to consider different kinds of agents, including rational agents and even those that are not supposed to have such cognitive faculties.

Because of the generality of this definition covering a variety of agents with quite different properties, sapient agents has been characterized as a subclass of intelligent agents with "insight" and the ability of "sound judgment". From an engineering perspective, (Skolicki and Arciszewski 2003) propose seven approaches to distinguish sapient agents from the entire class of intelligent agents. Considering knowledge representation, it is assumed that sapient agents are defined as knowledge systems. They must be capable of: abstracting knowledge and adapting its behavior to drive further knowledge acquisition; making long-term decisions; performing exploitation of the representation space, but also of conducting exploration; making strategic decisions which may not be entirely justified by local results; recognizing emergent patterns and avoiding undesired attractors in the representation space, while, if necessary, using various search methods to reach a given attractor.

Even when the mentioned issues are useful to differentiate the subclass of sapient agents, we argue that both biological and social referents are also required to do that. Biological inspiration has been always present in AI, although not always explicitly, with the aim to emulate complex cognitive behaviors. Particularly, behavior based AI (Brooks 1990; Smithers 1992; Steels and Brooks 1995) emphasizes the necessity to work with autonomous, embodied and situated systems, always arguing biological referents. (Brooks, Brazeal, Marjanovic, Scassellati and Williamson 1998) considers embodiment, development, social interaction and sensorial integration, as a methodology to construct humanoids. (Zlatev and Balkenius 2001) identifies embodiment, situatedness, and development as the main issues to built epigenetic robots. (Prince 2002) considers the ability to construct potential complex skills based on developmental architectures, sensory motor integration, and imitation. (Mcintyre, Kapland and Steels 2002) consider the necessity to hold structural issues, but also other external factors to achieve an adequate dynamics and then an appropriated development, e.g., social, individual and environmental stability; and group size, among others. All these approaches consider development as an important issue. Some of them do it from the point of view of developmental psychology, following Piaget like (Drescher 1991; Stojanov 2001). Some others add social interactions, mainly in language research as (Steels 1996, 1997); or neurobiological modeling (Montague and Dayan 2000).

However, a better conceptualization is required. Some of these issues are not well defined or even have different connotations, as embodiment (Ziemke 2001), autonomy (Collier 2000), or even the epigenetic concept (Lederberg 2001; Levenson and Sweatt 2005). Also, there is a lack of global measures mainly because, being biological inspired models, their validation involves comparisons with the functionality of observed systems; but also because only recently a kind of universal way of organization in connectivity has been found, the so called complex networks: Small World and Scale Free Networks.

Properties explained by complex networks include: fault tolerance, attack vulnerability, redundancy in transmission of information, integration and segregation. More importantly, they explain that complex functionality, e,g., cognitive functionality, requires complex physical connectivity. In this paper we claim that sapient agents require an epigenetic development displaying complex network topology, in order to perform complex cognitive functionality.

The paper is organized as follows: Section 2 introduces the concept of networks and their properties. The study of complex networks is proposed as a way to approach the complex cognitive functionality resulting from brain connectivity, emphasizing that the understanding of the mechanisms giving place to complex connectivity are not well-known. Section 3 introduces the concept of epigenetics, and propose some requirements for sapient agents in order to develop a mechanism equivalent to epigenetic organizations. Section 4 introduces the methodology of pragmatic games, a model in which an artificial situated agent develops knowledge networks exhibiting complex properties based on the epigenetic mechanism proposed in the previous section. Results,presented in section 5, support explanations about the required conditions to obtain networks with the expected properties, relating degree distribution and sensing: clustering coefficient and biological motivations; goals, acquired knowledge, and attentional focus. Conclusions are offered in section 6.

2 Networks

Networks are invaluable mathematical objects able to represent a wide variety of phenomena and processes (Barabási and Bonabeau 2003), which makes this mathematical abstraction an appropriate formalism to characterize and analyze many real life problems, both in a static and in a dynamic way. For example:

- Social networks are defined as sets of people showing a specific pattern of contacts or interactions between them, e.g., friendship, business, marriage, and scientific collaboration. (Newman 2003) referred early papers on social networks of friendship patterns in small groups, social circles of women, and social circles in factory workers. However, social networks were difficult to establish, inaccurate and sometimes subjective. Nowadays, digital files made easier to establish relationships in a reliable way, as in collaboration networks, e.g., scientists or actors. These networks are well documented in Internet. Other reliable social relationships are established by e-mail or telephone calls.
- Information networks, also called knowledge networks. One of the first studies of this kind of networks was made by Alfred Lotks, who in 1929 discovered the so-called Law of Scientific Productivity, establishing that the distribution of the number of papers written by individual scientists follows a power-law. This result was extended to arts and humanities. Another example of information networks is the World Wide Web (WWW), obtained joining web pages through hyperlinks. This network shows very interesting properties, as a Power-Law degree distribution. Other examples include the network citation between US patents, peer-to-peer networks, and word classes in a thesaurus.
- Technological networks are designed for distribution of some commodity or resource, such as electricity or information. Examples include the electric power grid, airline routes, roads, railways, pedestrian traffic, telephone, and delivery. A widely studied network of this kind is Internet, joining computers through physical connections.
- Biological networks include the metabolic pathways representing metabolic substrates and products, where directed edges appear if a metabolic reaction relates substrates and products. Another example is the protein interaction network. Since we are interested in the development of systems displaying complex cognitive functionality, e.g., sapient agents, brain functional connectivity is a network in this class of special interest. Brain functional connectivity will be approached in this paper with the tools provided by the study of complex networks.

Despite the nature of a network, they can be defined in terms of graphs. A graph is a pair of sets $G = \{P, E\}$, where P is a set of n nodes $p_1, \ldots, p_n$ and E is a set of edges that connect two elements of P. Graphs are directed if for all of the links, the direction is specified. If relationships between nodes runs in both senses, the graph is called indirected. Directed edges are also called arcs or arrows. Degree is the number of edges connected to a vertex. In a directed graph, is necessary specify the in, out, or all-degree, considering respectively the arcs in-coming, out-going, or the addition of both. Component is the set of vertices that can be reached between them along the edges. In a directed graph, the component to which a vertex belongs is that set of vertices that can be reached from it by paths running along edges of the graph. Geodesic path or minimal path is the shortest path through the network from one vertex to another. It is possible the existence of more than one Geodesic Path. The diameter of a network is the length of the longest geodesic path. The evolution of a graph is understood as the historical process of construction of the graph.

2.1 Complex Networks

(Erdös and Rényi 1960) starts a new way of characterizing networks, considering graphs with a large number of elements, studying the probabilistic space of all the graphs having n nodes and n edges. They use macro variables to statistically analyze the growth of these networks as the result of stochastic processes. Such random networks were considered appropriate to describe many real problems having many nodes and links, including road maps.

Very recently it was discovered that many interesting phenomena and processes also involving huge number of nodes, does not hold random topology, but a different one called complex network topology (Watts 1999; Barabási 2002; Albert and Barabási 2002; Newman 2003). The parameters characterizing such topologies are like macro variables describing the whole network and representing a fingerprint of its complexity. Complex Networks were not considered so important until 1998, when a relation between networks as different as the collaboration graph of film actors, the power grid of the western United States, and the neural network of the worm *Caenorhabditis elegans* were found, showing that they are not completely random, neither completely regular, but somewhere in the middle. Such networks were called small-world networks by (Watts and Strogatz 1998; Watts 1999), who introduced two measures to determine how far of randomness or near to order a network is. Interesting networks were found in the middle between randomness and complete order.

(Barabási and Albert 1999) show that a Power-Law could be obtained from the degree distribution of complex networks, and that this property is rooted in their growth mechanism. Such networks are called scale-free networks. Observe that in random networks, the degree distribution follows a bell. This random departure makes the difference between random and complex networks.

Phenomena holding small-world and scale-free properties include: the WWW (Albert, Jeong and Barabási 1999), metabolic networks (Jeong et al. 2000), human language (Ferrer-i-Cancho and Sole 2001), scientific collaboration networks (Barabási 2002), brain networks in mammalians (Sporns and Chialvo 2004), and functional brain networks in humans (Eguiluz 2005).

The study of complex networks is an active field to understand complex phenomena, focusing in three aspects: Finding statistical properties to characterize the structure and behavior of complex networks; trying to create models of networks to explain the meaning of such parameters; and predicting network behavior, based on their topological properties and local rules for nodes and links.

2.2 Complex networks and brain connectivity

Brains have evolved as efficient networks whose structural connectivity allows a large repertoire of functional states. Recently, it has been shown that functional connectivity in human cerebral cortex present topological properties both of small-world and scale-free networks (Eguiluz 2005). Although this was known for other animals (Sporns et al. 2004), it is the first time in which statistically significant results shown that this happens in a variety of individuals performing different tasks.

(Sporns et al. 2004) ask on the relevance of a research on structure and dynamics of such networks, to contribute to our understanding of brain and cognitive functionality. They establish three major modalities of brain networks:

- Anatomical connectivity is the set of physical or structural (synaptic) connections linking neuronal units at a given time. Anatomical connectivity data can range over multiple spatial scales, from local circuits to large-scale networks of inter-regional pathways. Anatomical connection patterns are relatively static at shorter time scales (second to minutes), but can be dynamic at longer time scales (hours to days), e.g., during learning or development.
- Functional connectivity captures patterns of deviations from statistical independence between distributed and often spatially remote neuronal units, measuring their correlation/covariance, spectral coherence or phase–locking. Functional connectivity is time dependent (hundreds of milliseconds) and 'model free', that is, it measures statistical interdependence (mutual information) without explicit reference to causal effects. Different methodologies for measuring brain activity will generally result in different statistical estimates of functional connectivity.
- Effective connectivity describes the set of causal effects of one neural system over another. Thus, unlike functional connectivity, effective connectivity is not 'model-free', but requires the specification of causal model, including structural parameters. Experimentally, effective connectivity can be inferred through perturbations, or through the observation of the temporal ordering of neural events. Other measures, estimating causal interactions can also be used.

Functional and effective connectivity are time dependent. Statistical interactions between brain regions change rapidly reflecting the participation of varying subsets of brain regions and pathways in different cognitive conditions and tasks.

Structural, functional, and effective connectivity are mutually interrelated. Clearly, structural connectivity is a major constraint on the kinds of patterns of functional or effective connectivity that can be generated in a network.

Structural inputs and outputs of a given cortical region, its connectional fingerprint, are major determinants of its functional properties. Conversely, functional interactions can contribute to the shaping of the underlying anatomical substrate, either directly through activity (covariance)-dependent synaptic modification; or, over longer time scales, through affecting perceptual, cognitive, or behavioral capabilities, and thus its adaptation and survival.

The scale-free properties in brains explain the coexistence of functional segregation and integration; redundancy and efficiency in information transmission. The Power-Law in degree distribution affects the functional impact of brain lesions, being vulnerable to damage on few highly connected nodes, and explains the small impact on damage of random lesions. Cortical areas in mammalian brains exhibit attributes of complex networks. The distribution of functional connections and the probability of finding a link versus distance are both scale-free. Additionally, the characteristic path length is small and the clustering coefficient is high, when compared with random graphs. Short path length captures potential functional proximity between regions. High clustering measures the degree of which a particular area is part of local collective dynamics. Frequent connectivity in all shortest paths linking areas, explains structural stability and efficient working of cortical networks.

2.3 Complex networks and complex cognitive functionality

Human language is an important example of complex cognitive functionality with complex networks properties, mounted on complex connectivity (the brain itself). This connectivity allows the fast and robust construction of a huge variety of sentences from limited number of discrete units (words). (Sole et al. 2006) enumerate and compare three kinds of language networks:

- Co-ocurrence networks can be built relating words that co-occur using directed graphs, capturing syntactic relations useful on speech production processes;
- Syntactic networks are built of pieces forming part of higher structures and joining them due to syntax dependence, as taking arcs beginning in complements and ending in the nucleus of a phrase (verbs). This networks are related to grammar structure.
- Semantic networks try to capture the meaning carried in linguistic productions. Meaning relations between words can be established in several ways: antonymy, homonym, hypernymy, meronymy and polisemy. “Links can be defined by free meaning association, opening the window to psycho-linguistic processes”.

All of these networks are shown to hold complex connectivity, having Power-Law degree distributions ($\gamma \sim 2.2 - -3.0$), high clustering coefficient ($C/C_{rand} \sim 10^3$), and small path-length. Hub deletion have the effect of loosing optimal navigation in co-occurrence networks; articulation loss in the case of syntactic networks; and conceptual loss plasticity in the case of semantic networks.

Graphs of word interactions show small-world properties (high clustering coefficient) and scale-free distributions ($\gamma \sim 1.5 - -2.0$) (Ferrer-i-Cancho 2001). Based on the significance profile of small sub-graphs from different languages, common local structure in word adjacency networks is also observed (Milo et al. 2004). This allows the definition of universal classes of networks by local motif statistics (Milo et al. 2002).

A dynamics within an appropriate connectivity enable approaching some particular brain functionalities. For example, short-term memory, can be envisaged dynamically when bursts are sustained in a small-world network. (Cohen 2004). This is possible because the probability of percolation of loops in such networks is higher than in random networks.

2.4 Complex networks growth and evolution

However, the kind of mechanisms giving place to complex connectivity is not well understood. Growth algorithms have been proposed for the emergence of small-world and scale-free networks. Unfortunately such algorithms are not biologically realistic. (Chialvo 2004) remarks that they do not represent good models for the development of cortical networks.

Specially intriguing is the role that experience might play in network growth. From a biological perspective, we know that this development in brain is the result of an epigenetic mechanism. On the other hand, "the ontogeny of language is strongly tied to underlying cognitive potentials and also is a product of the exposure of individuals to normal language use. What it is clear is that unless a minimal (scale-free) neural substrate is present, consensus between individuals might not be enough to trigger the emergence of a fully developed grammar" (Sole et al. 2006).

Sapient agents are expected to display complex cognitive functionality. It is clear that complex functionality is mounted in complex connectivity. Our claim is that we need to understand how complex connectivity can emerge on situated agents and how experience affects this connectivity. In what follows, we propose an epigenetic mechanism useful to understand some basic considerations on how this processes can be achieved by sapient agents.

3 Epigenetic mechanism and plasticity

Plasticity refers to the ability of the nervous system to change (Gazzaniga et al. 2002). These changes refers mainly to modifications in connectivity that allows learning to contend with novel situations. Such changes results from an epigenetic mechanism or, more specifically, a sinaptogenesis. In order to develop a mechanism equivalent of epigenetic organization, a sapient agent requires:

1. An innate process emulating epigenesis, triggered in function of the experience of the agent. We call this process closure mechanism.
2. A set of biological innate distinguishable states, called biological motivations as in (Batali and Grundy 1996) sense), are required to start the closure mechanism. These biological motivations are inborn affective states as those considered by (Scheutz and Sloman 2001; Scheutz 2001).
3. A kind of distinguishability to discriminate the degree of epigenetic formation. It is used to resemble the natural process which requires definite steps in order to recruit memory: identification, consolidation and eventual long-term storing (Levenson et al. 2005). Making a coarse abstraction, we can talk about states of incorporation of experiences in the epigenetic organization or closure states.
4. Multi-modality is required in order to allow integration and segregation, as shown later by the results of our experiments.
5. To interact with an environment as a situated system.
6. To incorporate new sensorial states by making them distinguishable after experience.
7. A maximum degree of relationship between two nodes. Each one of them corresponds to a kind of rule of the form $State_1 \rightarrow action \rightarrow State_2$, being schemes for (Drescher 1991), or facts for (Foner and Maes 1994); here we will use the last

term. The set of all of the obtained facts constitute the knowledge acquired by the agent.

The acquired knowledge is represented as an evolving network processed by the closure mechanism emulating epigenesis, when the agent performs complex learning of a complex network of relationships.

It is thought that epigenetic mechanisms have an important role in synaptic plasticity and memory formation. If this is true, episodes in our daily life can be stored 'permanently' in a step by step process. Acquisition, consolidation, and long-term memory registering, are carried out by epigenetic development. These mechanisms are very general, observed also in systems as far from humans as plants (vernalization), having to 'remember' the whole winter to do not flowering. Or when mother cells are marked to transmit specificity to her daughters (Levenson et al. 2005).

4 Pragmatic Games

Pragmatic games (Mora-Basáñez, Gesherson and García-Vega 2004), inspired in language games (Steels 1996), are used to explore the ideas expressed in the previous section. They offer a methodology by which a situated agent is immersed in similar but not identical repetitive situations to perform complex spatial learning. Although these games resemble subsets of Drescher's experiments (Drescher 1991), they have different objectives, dynamics, and results are analyzed differently. Using this games we are able to control, test, and make measurements of the epigenetic development. We pretend to isolate learning of complex relationships, excluding any appetitive or aversive reinforcement and any conditioning. The experiments were designed to involve memory use, acquisition, consolidation and long-term establishment, but still not in an integrated way. Three pragmatic games (Fig. 1) have been defined:

- Focusing game. One agent having only one eye and its visual field. The game starts setting an object within an environment in a random place. The eye moves randomly, once the fovea "sees" the object, the game is restarted.
- Grasping game. One agent having one eye, as in the focusing game, and also one hand. The game restarts when the hand reaches the object.
- Feeding game. One agent having one eye, one hand, and a mouth. When the hand passes over the object, the agent closes its hand and the object is attached to it. The random movements continue until the hand (with the object) reaches the mouth. At this moment, the game restarts.

The knowledge acquired by the agents while performing complex learning is represented as an evolving network of affective states, processed by the mechanism emulating epigenesis. The proposed closure mechanism, together with the morphology of the agent, and the specific interrelation within the environment (games), represents the minimal conditions discriminating the games producing complex networks and those that do not. In what follows, the elements of these games are explained in detail.

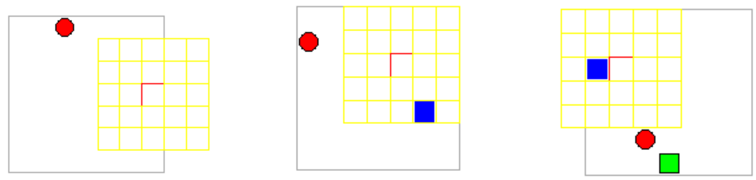

Fig. 1. Pragmatic Games: from left to right Focusing (visual field), Grasping (hand and visual field) and Feeding (mouth, hand, and visual field) Games. In all games the object is the circle.

4.1 Environment

The environment or "world" consists in a simple 7×7 grid (big square in Fig. 1), including one agent and one 1×1 object (red circle).

4.2 Agent

Our agent has 77 bit sensors: 75 for a 5×5 (the grid in Fig. 1) red (R), green(G), and blue (B) sensitive visual field; one for a 1×1 blue "hand"; and one for a 1×1 green "mouth".

The agent has four actuators: two for the eye and two for the hand. Each actuator has three possible states: do nothing, up/right, and down/left. The mouth is always fixed. An agent's actuation is then specified by a set of four values ($e_x, e_y, h_x, h_y \in \{-1, 0, 1\}$). The agent moves randomly choosing one of the three possible states of each one of the actuators, considering these states random variable under uniform distribution. Eventually, the agent can "redo" the last movement, by performing the opposite movement performed by each actuator.

The agent has a set of distinguishable innate affective states (Scheutz 2001), called biological motivations. These biological motivations are mapped to a 5-bit vector: Three bits for detecting RGB in the fovea; one for the hand holding an object, and other for the presence of the object in the mouth. Therefore, there are 32 possible biological motivations, although in our simulations less than ten are experienced. These biological motivations do not have any appetitive or aversive character, they are only distinguishable. At the beginning they are not related with any sensorial state, this relation must be established by the closure mechanism which makes the network grow up.

4.3 Closure mechanism

Every time the agent experiences a particular biological motivation, this motivation and the sensing state (77 bit string) is saved. Thus, every biological motivation has associated a record of sensing vectors. This process does not affect the network. Any biological motivation can give place to an affective state or to a potential affective state and which are then incorporated to the network by two mechanisms:

1. Detecting affective states from biological motivations. After a certain number of iterations (500 in our simulations), the system tries to determine if biological motivations have an specific associated sensing state. The affective state represents the set of sensing bits always present in the associated record, every time the biological motivation has been experienced.
2. Detecting potential affective states. If the sensing state at time t corresponds to an affective state, then a node corresponding to the sensing state at time $t-1$ is incorporated, as well as the directed arc between the nodes (representing the actuation). The new node has the possibility to evoke an affective state.

A potential affective state could become affective if its frequency exceeds some value. If the values are too small, noise can be learned. If the values are too big, then it takes more time to learn. This also happens for other parameters of the model.

The arcs joining nodes can be incorporated in the network in two ways:

1. When a potential affective state is reached, it is linked to the previous state. If the previous state has not an associated node, it is created.
2. When the agent experiences two consecutive sensing states and their associated nodes exist (affective states or potential affective states) then a link between them is created.

Arcs are labeled as frequent or codified. Once an arc exists between two nodes, some statistics (frequency and actuation) are updated if it is traversed. Its label is then computed in the following way:

1. If the frequency of occurrence for an arc is higher than a given value, it is labeled as a frequent arc. The distribution of probabilities for the the actuators is computed from the history and saved in the arc in the form: { $p(e_x = -1)$, $p(e_x = 0)$, $p(e_x = 1)$ }, { $p(e_y = -1)$, $p(e_y = 0)$, $p(e_y = 1)$ }, { $p(h_x = -1)$, $p(h_x = 0)$, $p(h_x = 1)$ }, { $p(h_y = -1)$, $p(h_y = 0)$, $p(h_y = 1)$ }. The distributions for each actuator are normalized.
2. If one of the three probabilities in each one of the four triplets of a frequent arc is higher than a threshold, all the triplet is replaced with one code, representing the associated winning movement for the correspondent actuator. For example, if the distribution of probabilities for the eye in the x direction is { $p(e_x = -1)$, $p(e_x = 0)$, $p(e_x = 1)$ } = { 0.1, 0.3, 0.7 }, then the triplet is replaced by a 1, meaning that the associated movement for this actuator is considered as being 1 unit in the x direction. This is why the arcs holding this condition are named codified arcs, since the nodes joining the arc have more than a random probability to be joined by performing the codified movement.

4.4 Closure states

Given two consecutive iterations, the agent experiences two sensing states: S_{t-1} and S_t, verifying if there are related nodes in the network. More precisely, the agent checks if each sensing state have not an associated node in the network; have associated potential affective states in the network; or have associated affective states in the network. In the same way, it checks if the performed act has not an associated arc in the network; has an associated arc in the network, but not frequent; has an associated frequent arc in the network; or has an associated arc suitable to be codified. So, there are $2^3 \times 2^4 \times 2^3$ possible closure states.

If a labeled arc has affective states as source and target nodes, it will be called a fact. This is considered the most refined state for the closure mechanism. This contrasts with the Drescher's perspective (Drescher 1991), which considers reliability as the way to verify the arc's functionality.

4.5 Attentional Focus

Attentional focus is a number between $[0, 1]$, representing the probability to undo the last performed movement. Thus, a 0.5 attentional focus means that the agent has a 50% of probability of revisit the last sensorial state. Each one of the pragmatic games is performed using different attentional focus values: 0.0, 0.25, 0.50, and 0.75. The 0.0 value is equivalent to a random movement, while 1.0 was not used, because it means an infinite loop between two sensing states. These attentional focus values are fixed during all the experiments.

5 Results

Experiments on plasticity showed that the networks evolved by the situated agents – and then its properties– depends on the played game and the epigenetic mechanism. They also showed that wiring is made in terms of experiences. First, the complexity of interactions between the agent and its environment was found relevant to evolve complex networks, relating degree distribution and sensing. Second, biological motivations affect the clustering coefficient of the obtained networks. And third, attentional focus affects the number of goals achieved and the amount of knowledge acquired by the agent.

5.1 Degree Distribution and Sensing

The possibility to obtain a Power-Law for the degree distribution is the fingerprint to distinguish if a network is complex or not. This property reflects the character of having few highly connected nodes (hubs), and a lot of them few connected. This allows tolerance to random fails, but vulnerability if the failure affects a hub.

A substantial difference exists between unimodal and multimodal games. In the unimodal game (focusing) the resulting network is by no means complex. But in multimodal games (grasping and feeding games) a Power-Law emerges (Fig. 2).

This is not a result of the implemented epigenetic mechanism, but of the richness of the interaction. The only difference between grasping and focusing games is the 1×1 moving hand around the world, absent in the focusing game. It is not only the complexity of the environment what matters, but the complexity of the interactions. To have enough rich networks, multi-modality is required.

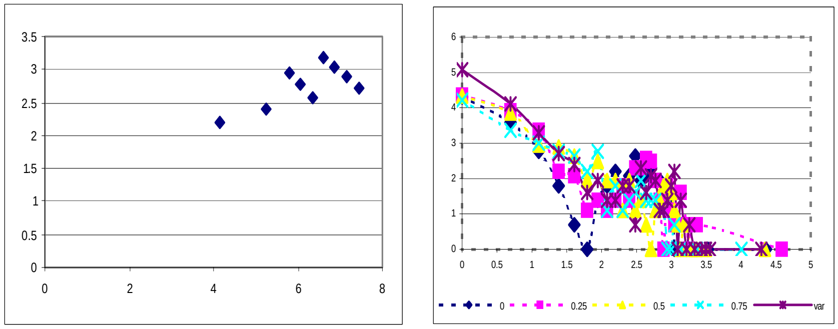

Fig. 2. Degree distribution for focusing game at left ($degree \times frec$) and grasping game at right ($\ln degree \times \ln frec$). The unimodal–multimodal character of the game affects the complexity of the resulting network

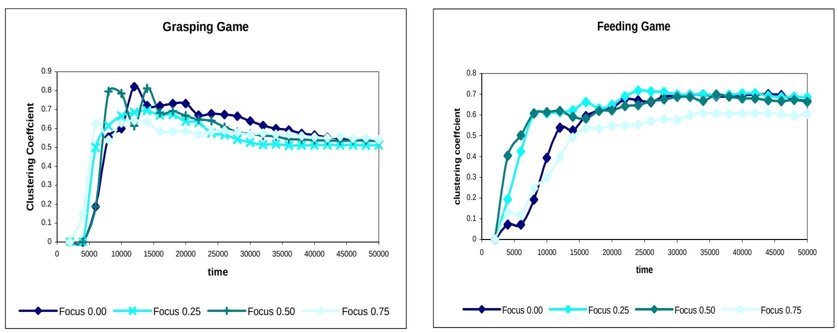

Fig. 3. Clustering coefficient in focusing game (left) and feeding game (right) is high when compared with an equivalent random graph

5.2 Clustering Coefficient and Biological Motivations

Clustering coefficient gives a measure of the possibility of being part of a local collective dynamics. In some way, it measures the integration of elements in a network. It is shown that clustering coefficient in multimodal is high when compared with a random graph (Fig. 3).

It is also shown that this measure depends on the mechanisms itself, and in particular on the consideration of biological motivations (Fig. 4).

5.3 Goals, acquired knowledge and Attentional Focus

The number of games played can be understood as the number of goals achieved by the agents. The experiments show that the rate of growth of the number of goals in time is similar for all the games. A lower focus, as expected, is associated with a higher probability to advance, resulting in more games played (Fig. 5).

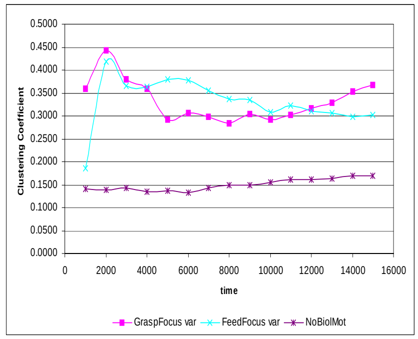

Fig. 4. Clustering coefficient and biological motivations. When biological motivations are not considered (NoBioMot) in the epigenetic mechanism to evolve the network, the clustering coefficient is very low.

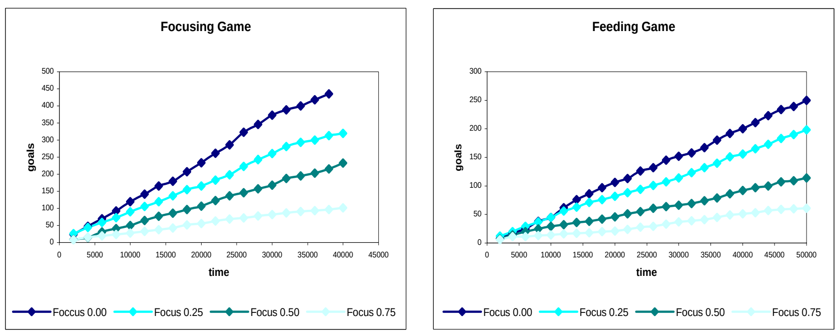

Fig. 5. The number of pragmatic games played (goals) by the agent in time has similar behavior when focus is changed, both for focusing and feeding games.

However, this tendency is different when the amount of knowledge acquired is considered. As mentioned, a fact is identified as two affective states connected by a labeled arc. The number of facts is a measure of the quantity of knowledge acquired. It depends on the focus value, but its effect varies with the played game.

In the unimodal game more goals and knowledge are attained by the agent for lower focus values. In the multimodal games the opposite effect is observed. This seems to be the source of the exploration/exploitation trade–off in learning agents. If the game is multimodal, the agent requires different behavior to achieve goals and to acquire knowledge. In the unimodal game, this situation does not hold (Fig. 6).

6 Conclusions

We used pragmatic games as a methodology to study knowledge development in agents. The acquired knowledge is represented as an evolving network, processed by

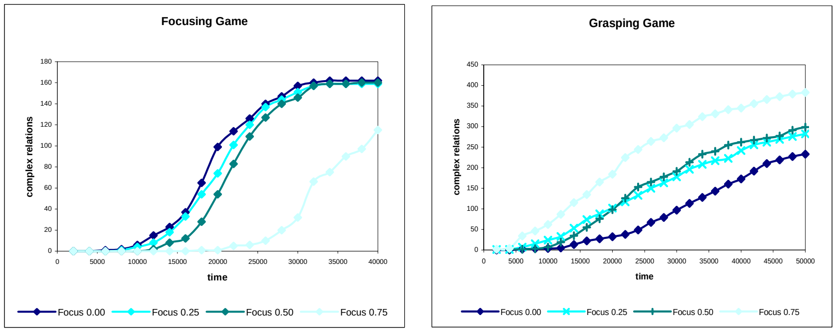

Fig. 6. The knowledge acquired depends on the game played and the focus value.

a mechanism emulating epigenesis, which is enacted by experiences. The acquired knowledge is complex in the sense that it relates spatial rules in the appropriate way. Nodes represent affective states (related with sensing states) and links are actuations relating affective states. The proposed epigenetic mechanism includes innate biological motivations and the incorporation of nodes and links in steps. Network analysis and measures are applied on the corpus of acquired knowledge.

In our experiments, clustering coefficient is large (a Small World property) when compared with random graphs. This result is due to the proposed epigenetic mechanism. Particularly, because the innate biological motivations starting the process, give place to initial hubs to evolve the network.

Knowledge networks in games involving multimodal agents exhibit power-law distributions (a Scale Free property), whereas the games played by our unimodal agents do not. This means that in our experiments complex learning arises independently of the complexity of the environment, but depending on the interactions the agent has with it. Connectivity distribution in our unimodal game is finite and well defined, no matter the size of the eye. If the hand is introduced, the number of states increases significantly, emerging a complex network.

In order to observe how might the agent behavior affect the acquired knowledge, a behavior modulator, called attentional focus, was introduced. If we consider the number of played games as the number of goals achieved by the agent, we observe that the focus value have the same impact for both unimodal and multimodal games, i.e., lower focus value results in more achieved games. However, the number of facts incorporated in the network depends on the modality of the game. For the unimodal game, lower focus value results in higher number of facts; but for the multimodal games, the inverse relation was observed. Thus, the modality of the game seems to be the source of the exploitation-exploration trade-off in learning agents.

The proposed epigenetic mechanism is suitable, in the sense that the topology of the generated networks representing the acquired knowledge, evolves showing complex network properties. These results suggest that sapient agents must consider biological motivations in their epigenetic mechanisms, and must be multimodal. The properties that characterize artificial agents emerge naturally from complex connectivity. For an artificial agent, complex topology represents the potential to exhibit complex functionality, i.e., the dynamics that becomes exploitation of the acquired knowledge.

Future work will consider cognitive autonomy which enables the agent to adapt its behavior to maximize knowledge acquisition, so that the amount of acquired knowledge becomes a behavior modulator. The effect of the relations between knowledge and behavior will be quantified and analyzed in terms of complex networks properties.

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