The Emergence of Social Learning in Artificial Societies

Mauro Annunziato, Piero Pierucci

Plancton
Lung.ere degli artigiani 28, 00153, Rome, Italy
http://www.plancton.com
plancton@plancton.com

Abstract. The most recent advances of artificial life research are opening up a new frontier: the creation of simulated life environments populated by *autonomous agents*. In several cases a new paradigm for learning is emerging: social learning as a form of self-organization of many individual learning. In this paper two different approaches are presented and discussed: genetic competition and partial emulation. Finally an example of application of these concepts.

1 Introduction

The most recent advances of artificial life research are stimulating the creation of environments populated by evolving *autonomous agents*. In these environments artificial beings can interact, reproduce and evolve [5, 7, 10, 17], and the environment itself can be seen as a laboratory where to explore the emergence of social behaviours like competition, cooperation, relationships and communication [6, 8] . It is still not possible to approach a reasonable simulation of the incredible complexity of human or animal societies, but these environments can be used as tools to explore some basic aspects of the evolution [1, 2, 3, 11, 12, 13, 14, 15, 16, 18] including the development of forms of social learning.

The combination of these concepts with robotics technology or with immersive-interactive 3D environments (virtual reality) are changing quickly well known paradigms like *digital life*, *man-machine interface*, *virtual world*. The virtual world metaphor becomes interesting when the artificial beings can develop some form of learning, increasing their performances, adaptation, and developing the ability to exchange information with *human visitors*. In this sense the evolution enhances the creative power and meaningful of these environments, and human visitors experience an emotion of a shift from *a simplified simulation of the reality* to a *real immersion into an imaginary life*. We may think that these realizations are the first sparks of a new form of life: simulated for the *soft-alife* thinkers, real for the *hard-alife* thinkers, or a simple imaginary vision for the artists.

A key aspect distinguishes the learning experiments carried out in the contest of artificial societies in respect to the classic experiments and modelling of the artificial intelligence. This aspect is connected to the contribute of the social sharing and interaction in order to increase the learning process. In this case the knowledge is referred to the society rather than the single agent (*collective knowledge*). The social learning process can be considered as the result of the self-organization of the knowledge of its components. This knowledge can be expressed not only in terms of shared information but also in terms of relationships and inherited or emulated behaviours. For the enormous implication in many different science fields (biology, learning engineering, robotics, sociology, economy, arts, networks, etc…), the mechanisms of social learning represents a fashionable challenge to explore both in science and art.

Some reference experiments can be found in the pioneer works of K. Sims [13] and D. Terzopoulos [17]. They developed interesting models for evolving digital creatures. In those experiments, they fix a specific task (swimming in a marine environment or winning a duel for the food) and trained the individuals through genetics selection or optimisation functions. The goal was to obtain creatures for computer graphics applications. Very interesting experiences are described by the Polyword environment of Yager [18] and the relation between individual and social learning of Parisi and Cecconi [10]. In these works the social component of learning is more enhanced through the interactions of individuals in an environment. The individuals are equipped with neural networks that evolve the weights in the time. In the case of Yager [18] very complex creatures with a Hebbian learning approach are utilized. This study is focused on the same pilot problem utilized in this paper: the food tracking.

The final goal of our work is the development of audio-visual interactive installations embedding new scientific approaches in an artistic frame. Our intention is explore the creative content and suggestions that the artificial life (*alife*) environments have in their potentialities. The suggestion we want to communicate is the evocation of an artificial society able to self-develop in the time and interact with the humans. The idea of the *social development* is very ambiguous and wide. This aspect it could be a drawback by a scientific point of view because of the effort to implement a solution for realistic problem is really huge. By an artistic point of view, the main aspect is not the difficulty of the solved problem but the communication of the paradigm of the - *autonomously evolving society* -. The basic idea is a vision of future digital worlds as a way to better explore the mechanisms which are on the base of the formation of our societies, languages, psyche.

Our long term goal is create continuous learning mechanisms to achieve complex tasks in social contexts. Along this direction, we do fix any specific target except the survival. The digital creatures should be able to derive all the living functions (search for the food, competition/co-operation, communication, language) directly as priorities or intermediate goals to reach a better adaptation in the environment under an evolutionary pressure. In this effort we have built a roadmap for the realization of this context in terms of interactive installations: a) to realize a population of socially evolving creatures, b) establish an hybrid world where digital beings and humans can interact, c) create the conditions for the development of an autonomous language in the artificial society exchanging symbols (i.e. sounds and voice) with the humans.

At the current state of development we are applied several experiments. Similarly to the mentioned case of Yager, in these experiments a community of autonomous agents, equipped with a personal neural network, autonomously develop a behaviour to recognize and search for the food to survive. This task is obtained realizing an evolutionary pressure that pushes the individuals to evolve. In this way, adaptation is not an option for the individuals but a survival need. In this paper we explore two different paradigms for the development of this ability: genetic evolution and social learning.

Finally we will trace a brief synthesis of a first realization of the artificial-human interaction and a performative experience of dance and alife in a theatre. We recommend to see the reference [4] for another aspect of this framework regarding the development of an autonomous language in the artificial society and speaking interaction with the humans.

2 The Alife Environment

The alife environment is a three-dimensional space where the artificial individuals (or *autonomous agents*) can move around. During the single iteration (*life cycle*) the individuals move in the space, interact with other individuals, exchange information, and reproduce generating another individuals. The data structure of the individual is composed by parameters regarding specie, reproduction, interaction, dynamics, life, and the current values of the information coded in the individual neural network. A basic variable of the status is the *energy*. The energy is a sort of probability of surviving for the individual. It is gained through the food eaten by the individual at each life cycle, and is needed to move and reproduce. Low energy values causes the death of the individual.

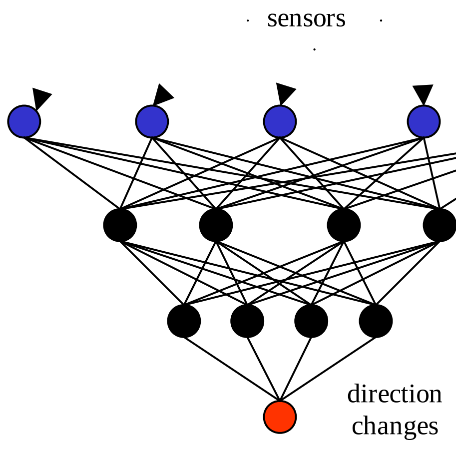

Fig 1: The neural network to control the movement

The central structures of the individual are the sensors and the movement controller. The sensors have the goal to locate substances in the environment surrounding the individual position in term of presence of food and relative direction.

Any individual is endowed with a neural network controlling the movement. This net is composed of four layers of neurons with 4 neurons in the input layer, 4 neurons in two hidden layers and 1 neuron in the output layer (see fig. 1). The net topology is arbitrary and not optimised. The input layer is connected to information coming from the sensors. The output layer defines the change in the movement direction (curvature).

Therefore, the agent movement is the result of the application of the network to the input information in order to decide the new movement direction. Typical reactions are moving towards (or escape from) a substance or show indifference. When the individual enter in a cell with a substance, the individual *eats* the substance that disappears from the environment. The food increases the individual energy.

The reproduction model is aploid: one parent-one child. A probabilistic model for self-reproduction is performed at every life cycle. The *fecundity* probabilistic parameter is recorded in the genotype. Reproduction can occur only if the individual has energy greater than a specific amount. In the reproduction, an amount of energy is transferred from the parent to the child.

In the reproduction, the status of the child-individual is derived from the parent except for random mutations in relation to a *mutation average rate* and *mutation maximum intensity*. In such a way the child will have a similar behaviour but with some little differences in respect to the parent.

Fig 2: Digital creatures living in the artificial life world

When an individual tries to enter in a cell with another individual an interaction occurs. Several kind of interaction have been developed depending on the experiment: competition, co-operation and indifference as described in the following paragraph.

3 Evolution and Social Learning in an Artificial Life World

In these experiments we put a number of individuals in the environment (typically 256) with the neural network initially filled with random numbers. In the environment we random distribute a fixed rate of food bits. Each bit occupies a single cell and it disappears after a fixed number of life cycles (lifetime, typically 10 cycles). The experiment consists in the autonomous development of the ability of the individuals to recognise the presence of food in the neighbourhood, move toward the bit and eat the bit itself. To obtain this knowledge, the population has to modify progressively the neural networks in order to react to the input information in the best way to survive. Any explicit target for food search is a-priori implemented in the individual behaviour.

We have realised three different experiments corresponding three different adaptation mechanisms. Two of these mechanisms are based on genetic evolution: a) direct competition and b) competition for the resources. The third one is based on c) social learning utilizing the behaviour partial emulation model.

Our interest is not the knowledge level reached by the best individual but a global feature of the society. In order to monitor the adaptation progress of the society, we measure the food bits currently present in the environment. When the individuals are not expert in the food tracking, this number is high. The food disappears for accidental eating (an individual passing randomically over a food cell) or for passed lifetime. When the population develop ability to track the food, the food bits decrease rapidly due to intentional passing of the individuals over a food cell.

3.1 Evolution Through Generations: Direct Competition

This first experiment is based on the genetic evolution through the direct competition. The individuals don't change the network weights during their life but only through the genetic mutations in the reproduction. The selection mechanism is a direct competition based on energy. When two individuals meet on the same cell, they fight. The individual with the higher value of energy, wins and survive while the looser dies. For each individual, the energy level is the balance of the energy increased by the food and the one consumed in the life cycle. An increase of the ability to eat food produces an increase of the energy and of the probability to win in the fights.

In the plot of fig. 3 a diagram of the average food density in time is shown for all the experiments. Each time sample corresponds to the average of 100 life cycles. At the beginning, the food presence increases up to reach the maximum corresponding to the equilibrium between the food randomically consumed and the one periodically distributed. After the maximum, a slow decrease of the food presence is exhibited corresponding to the individual learning. After 10000 cycles the curve exhibit a sharp decrease due the a reduction of the amplitude of the mutation on the net weights. Finally a saturation value is reached corresponding to the maximum ability that the individuals can reach trough this mechanism.

The increase of the ability to eat is clearly demonstrated looking to the alife animation. At the beginning the individuals move in a very chaotic pattern. Along the evolution, some individuals succeed to reach the food after some strange trajectories.

At the end, when a food bit compares in the environment, immediately many individuals converge towards the food. The one that has the best ability, succeeds to reach the food increasing its energy. The others don't eat and will be filtered out by some more able competitor.

3.2 Evolution Through Generations: Competition for the Resources

In the second experiment, the adaptation mechanism is based on the genetic evolution through the competition for the resources. Also in this case, the individuals don't change the network weights during their life but only through the genetic mutations in the reproduction.

The situation is quite similar to the previous one but with two differences:

??when two individuals meet, they ignore the meeting and have any interaction;

??the energy consumed in life cycle is quite higher in respect to the previous case.

In this case the individuals are forced to eat in order to avoid the decrease of the energy under the survival threshold. In few words they compete for the resources instead to compete directly each other. The plot of fig. 3 shows a trend similar to the previous case, but the final value is lower. This mechanism is more efficient than the previous one. It recalls an ecosystem where the animals compete mostly for the resources in the context co-evolution of different species.

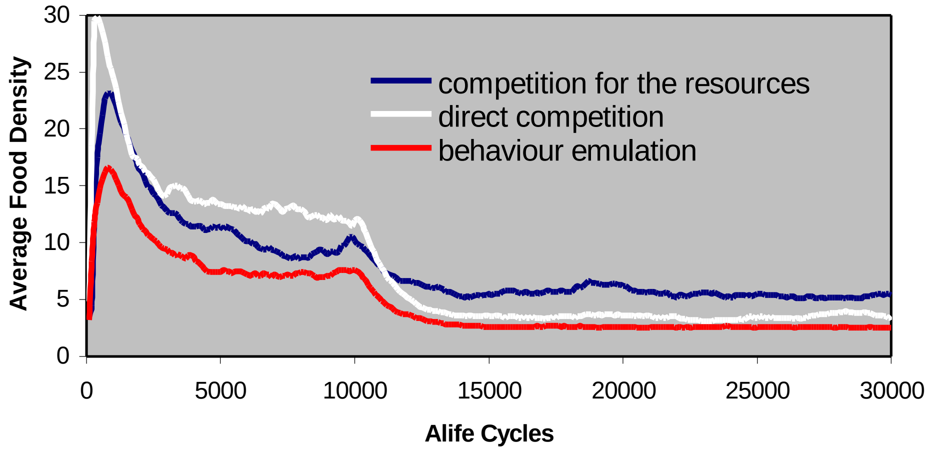

Fig 3: Comparison of the efficiency of the three different strategies of learning: direct competition, competition for the resources, behaviour emulation.

3.3 Learning Through Communication: The Partial Emulation Model

The third mechanism we experimented, is not based on evolution through genetic mutations but it regards the learning during the single individual life and it is connected to the social communication mechanisms. In some sense it is related to the *cultural advancement* of the population: when two individuals meet, they communicate exchanging their information about own developed behaviour.

In this experiment the individuals exchange information about the weights of the neural networks controlling the movement and responding to the presence of food. An emulation mechanism is activated when a meeting between two individuals occurs. In the meeting, the individual with lower energy modifies the weights of its neural networks. In few words, the behaviour could be synthesised by the sentence: *if you have a higher energy respect to me, it could be better for me try to partially emulate your behaviour*. This mechanism represents a sort of translation of the genetic mutation in the cultural domain. In formulas:

$$W_{Ai} = W_{Bi} * ? + W_{Ai} * (1-?)$$

Where W_{Ai} is the i-th weight of the network of the moving individual and W_{Bi} is the i-th weight of the network of the met individual; ? is the emulation factor typically ranging between 0.1 and 0.5.

The individuals do not die, but when the energy goes to zero, they are forced to apply small changes to their behaviour, that means small changes to the neural network weights.

As the previous case, the plot of fig. 3 shows the same trend, but comparing to the other cases, the values reached with this mechanism are lower and faster reached. This means that this mechanism is the most efficient in respect to the others. This comparison has only a reference value because of in the reality these mechanisms are contemporary present and the real living beings are much more complex.

In this case, the competition is similar to the stock market competition. When an individual becomes quite able to eat, it increases its incoming of energy without any competitor. The other individuals try to emulate and learn from him. When the others reach its level and someone becomes better, the first individual starts to have an attenuation of the incoming energy and then a drastic energy reduction up to finish its energy. At this point it is forced to change its behaviour to come back to a positive energy incoming.

This form of learning is the most intriguing because of its feature of dynamics and *volatility*. In fact, the produced knowledge is still a product of the whole society but it is moved dynamically between the various individuals. Although the knowledge is generated during the life of the individuals, it can be transmitted through the generations. In this sense is the one more similar to the *culture*.

3.4 Some Remarks About the Consciousness Dilemma

To have a visualisation of the ability reached autonomously by the digital creatures, in fig. 4 we report two sequences of life with creatures passing close a food bit. In the first sequence the individuals are at the beginning of the training experiment. They exhibit indifference for the food. The second sequence is related to trained individuals. In this case is quite clear a strong finalisation of the creatures movement to catch the food.

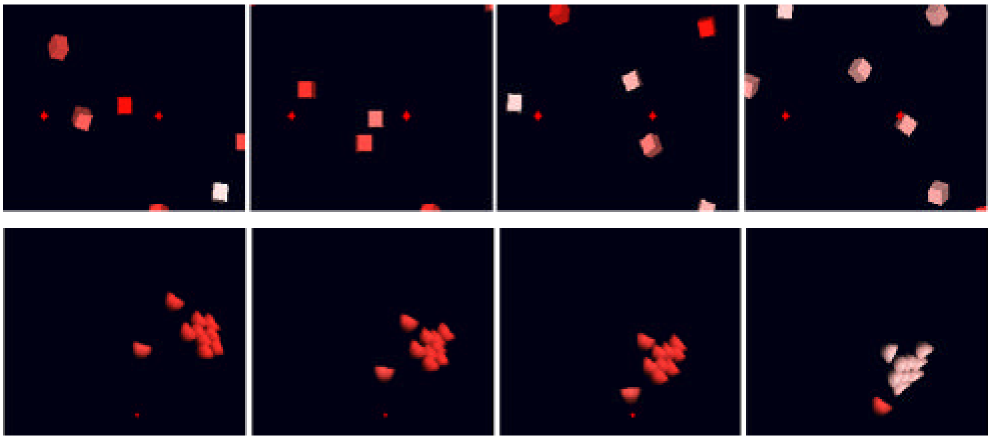

Fig. 4: The creatures at the beginning (top) and end (bottom) at of the training experiment.

It should be noted that in the described mechanism the individuals achieve the ability to eat but they don't develop any form of *consciousness* of eating or *intentional direction* towards the specific target of eating. Simply they establish a relation between some behaviour (the weights of the neural networks) and the satisfaction of some survival needs (the feeding to increase the energy and to longer survive).

We could apply the same procedure to a higher communication level, like sound messages or the development of a language. Probably, we could allow the development of the complex behaviour relating it to an increase of adaptation. When the selection mechanism is extended to the competition between societies and groups also some behaviour like affect, parent care can be revisited as survival needs. In principle a high level of *adaptive behaviour* and *intelligence* could be reached without any form of consciousness.

For the involved implications about relation between individual and social behaviour, we have decided to use the social learning paradigm of the third experiment, as a fertile platform to generate metaphors, open problems and questions that is the natural environment of an artwork. Some questions remain still open: what is really the consciousness ? How could it be developed in a digital being ? Are intelligence and culture possible without consciousness ?

4 Human-Artificial Interaction in the Hybrid Environment

In the previous sections we have shown the realization of an artificial world where the creature can learn and exchange information. So far all the world is confined in the digital domain. A real jump in the potential of these worlds is to establish a contact between this world and humans. The idea is a sort of cross-fertilization between humans and digital beings. There are many approaches to establish this communication which corresponds different communication metaphors. In the following we describe the paradigm we selected among the many possible ones.

The basic idea is to combine two different channels of interaction: biochemical and symbolic. The biochemical interaction is based on the idea that humans emit substances in the digital environment when they move in an interaction area. Depending by the type of substance, the digital creatures are attracted or not by the person. This channel of interaction is more intended for a primitive interaction and it will discussed in the following. The symbolic communication is the exchange of symbols a) in between the creatures and b) between the humans and the creatures. The set of symbols and their meaning emerge as a society feature as a result of a cultural evolution process and interaction with humans. This channel of communication is intended for specific installations based on voice exchange between humans and creatures. It is not discussed in this paper for space reasons but you can find explanations in [4].

The starting point is the place where the interactions occur. So we have to re-define the borders of the environment. In the interactive installation, the image of the artificial world is projected on a 2D screen. The area for the human interaction consists in the area in front of the screen. To interact, a person has to enter in this area in order to produce modification in the artificial world. In such a way we have extended a dimension of the environment in the real world building an hybrid real-digital ecosystem. The interaction area is observed by video-cameras acquired in the computer. A tracking program detects people presence in terms of change detection in the image. This information is mapped as substances emitted by the real people in the digital dimension of the environment. There is a spatial coherence between the location of the human and the digital environment. A program flag is used to decide if the emitted substance is food for the creatures or poison.

Fig 6: Playing with digital entities through a biochemical communication.

If a creature is moving in the same location it reacts to the substance. The creatures have been trained with the procedure illustrated in the third experiment. Furthermore their networks have been trained to track the food and avoid the poison. As results the creatures are attracted by humans emitting fooding substances and repulsed by humans emitting poison substances. See fig. 6 for pictures of the installation.

4.1 Alife and Dance: The *Aurora di Venere* Performance

The described installation was used on an alife-dance performance shown at the Theatre of the *Palais de San Vincent* (Italy), in March 2001. *Aurora di Venere* was presumably the first live performance in Italy including alife interacting with the dancers. The performance (about 30 min.) included 8 dancers, 6 computers (SGI and PCs), 6 video-projectors and 8 sound amplifiers for 3D sound rendering around the theatre. Two video-projectors were focused on two large screens (12x8 m.) located at the background and at the front (semi-transparent) of the theatre's stand. The other 4 projectors covered the entire ceiling of the theatre that has a dome shape.

In the performance, the dancers interact with digital creatures projected on the stand screens (see fig. 7). The performers dance in the middle of the screens, and they seem completely immersed inside the digital creature movements. The dancers play with the images of the artificial individuals which move following their own personality: they attract and repel the creatures through the *biochemical communication* mechanism explained before.

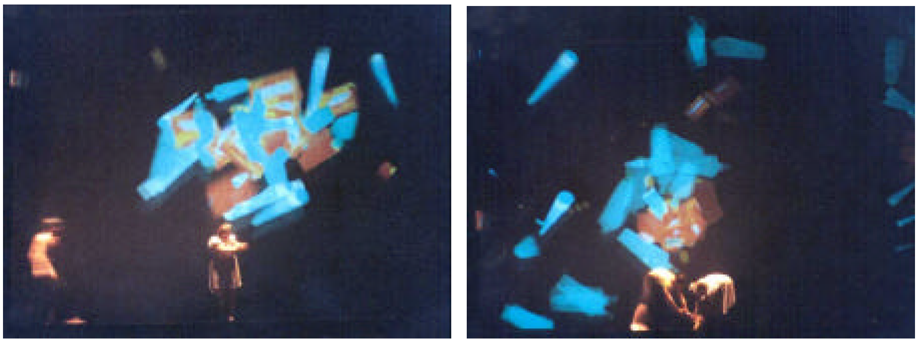

Fig 7: Pictures from the alife-dance performance *Aurora di Venere*: the dancers play with the digital creatures projected over the background and over a semi-transparent screen of the theatre's stand.

During the performance the story grows in intensity when the artificial beings (fig. 8) escape from the front screens invading the public and the theatre ceiling. They search for people movements and produce 3D sounds travelling in the theatre. At the end the whole internal pseudo-spherical surface of the theatre is invaded by digital beings.

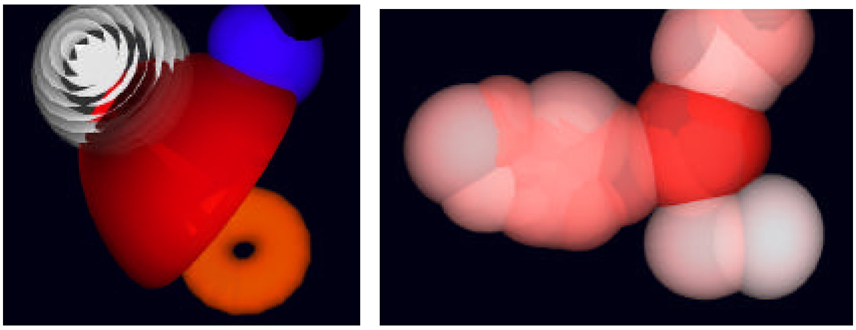

Fig 8: Creatures for the *Aurora di Venere* alife-dance performance.

5 Conclusions

We have explored several ways to build digital creatures living in an artificial world, able to learn from the sensorial experience and through genetics. Several paradigms of evolution and learning has been experimented in order to achieve autonomously simple tasks like search for food. A basic paradigm of the social learning based on a behaviour partial emulation paradigm has been selected as a fertile platform for development of alife-art contexts. These concepts have been applied in an interactive installation where visitors can interact with the artificial creatures through a mechanism of substance emission-reception. This installation has been involved in an alife-dance performance in a theatre.

Rather than conclusions, this experience opens many questions about

What does digital life means ?

Is it really possible to develop an autonomous culture in alife worlds ?

Is it possible to have knowledge without consciousness ?

How far this knowledge could go?

Maybe the only reasonable conclusion today is to raise these questions. Using imagination and art to find some answer.

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