Outlines of Artificial Life: A Brief History of Evolutionary Individual Based Models

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Abstract. In the research field of Artificial Life, the concepts of emergence and adaptation form the basis of a class of models which describes reproducing individuals whose characteristics evolve over time. These models allow to investigate the laws of evolution, to observe emergent phenomena at individual and population level, and additionally yield new design techniques for computer animation and robotics industries. This paper presents an introductory non-exhaustive survey of the constitutive work of the last twenty years. When examining the history of development of these models, different periods can be distinguished. Each one incorporated new modeling concepts, however to this day all the models have failed to exhibit long-lasting, let alone open-ended evolution. A particular look at the richness of dynamics of the modeled environments reveals that only little attention has been paid to their design, which could account for the experienced evolutionary barrier.

1 Introduction

Artificial Life, or ALife, is the research field that tries to describe and study natural life by creating artificial systems that possess some of the properties of life. Its final aspiration is “understanding life by attempting to abstract the fundamental dynamical principles underlying biological phenomena, and recreating these dynamics in other physical media, such as computers, making them accessible to new kinds of experimental manipulation and testing.” [1]. Besides the ambition of enriching the knowledge about Nature, Alife helps to find new design techniques. As computer simulations become more and more accurate, game, entertainment and robotics industries are constantly researching for new ideas to animate artificial characters.

The seminal novelty of ALife lies in its synthetic approach. Whereas traditional research is essentially analytic, breaking down complex systems into basic components, ALife attempts to construct complex systems from elemental units. The synthetic approach is based on two concepts, emergence and adaptation. A class of models which particularly applies these concepts describes reproducing individuals whose characteristics evolve over time. This paper refers to these models as “Evolutionary Individual Based Models” (EIBMs).

Considering the history of EIBMs in chronological order, four periods can be distinguished. They are thought of as overlapping stages of development in the art of individual based modeling by progressively incorporating new concepts. The beginnings of the first period reach back to the sixties. It comprises the discovery of new modeling techniques and the implementation of the first individual based models, but at that time extensive computer simulations were not yet feasible. At the end of the eighties, the progressing research culminated in the appearance of ALife as a distinct discipline. With the advent of computational power in the early nineties, allowing computers to run elaborate ALife systems at a tolerable speed, the second period incorporated evolution into individual based models, trying to capture population level phenomena by simple agents without particular morphologies in one ore two dimensional environments. The third period was marked by the adoption of environments with physical dynamics and directed the attention towards more elaborate phenotypic morphologies. Evolution was achieved by modifications of grammar-based genetic encoding schemes. The current fourth period of artificial embryology, since the end of the nineties, applies the discoveries of evolutionary developmental biology and models virtual creatures based on the concept of cell division by genetic regulatory networks. To this day, a great variety of extending or complementary research has been done with respect to each approach, but interestingly no further groundbreaking advances have been reported. It seems as if every model hits on limits of evolutionary complexity which prohibits the kickoff for long-lasting creative evolution in artificial worlds.

This paper serves a double purpose: to structure the history of EIBMs by classifying samples of the most influential works into periods, and to take advantage of this short survey to particularly review the dynamics, i.e. the rules and forces that produce motion or affect change within the environments. It will be suggested that the design of this component lags behind the advances in modeling the evolving individuals.

Section two presents the two important concepts of emergence and adaptation, both of which are present throughout the paper. Section three describes early EIBMs featuring simple evolving agents. Section four inspects models with physical dynamics and grammar-based genetic encoding. Embryological models are described in section five. Section six concludes with the synthesis of all the presented works.

2 ALife concepts in modeling

ALife researchers have been inspired by the creation as observed in Nature and developed the concepts of emergence and adaptation which are opposed to conventional human design techniques. This section describes the two concepts and their implementation in modeling.

2.1 Emergence

Models of complex systems, i. e. systems composed of a large number of interacting elements, are traditionally described by mathematical formulas like differential equations to manipulate some aggregate state variables of the system as a whole. This method allows a general and compendious way to analyze the behavior of a system. However, as aggregate variables always oblige to deal with mean values, they have difficulties with heterogeneity in the system, and their high abstraction level often does not grasp the underlying reasons for the dynamics.

The Alife approach of modeling is "bottom-up engineering", thinking of complex systems as collections of distinct objects or individuals rather than continuous values. Individual based models can include refined representations of the individuals and their behavior. Emergence describes the phenomenon that simple local interactions between the entities of the system lead to a complex high level organization.

One of the earliest examples of emergence is Craig Reynolds' individual based model of boids [2]. Boids are autonomous agents simulating the flocking behavior of birds. Flocking arises as global behavior from the interaction of very few simple local rules. Placed into a virtual environment, the boids are programmed to follow three directives of "steering behavior" (figure 1):

- *Separation*: to maintain minimum distance from other boids in the environment
- *Alignment*: to match velocities with other boids in the neighborhood.
- *Cohesion*: to move toward the perceived center of mass of boids in the neighborhood.

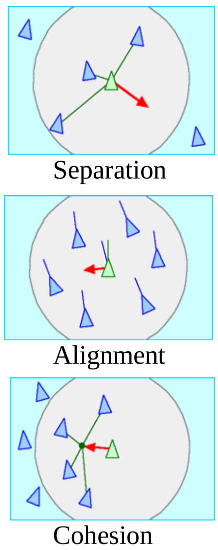

Fig.1. Steering behavior

These rules are entirely local, referring only to information accessible within a boid's own vicinity. Hence, the flock that forms is an emergent phenomenon.

Based on this algorithm, the boids can be enriched by more elaborate behaviors like obstacle avoidance or goal seeking. Obstacle avoidance allows the boids to fly through simulated environments while dodging static objects. Goal seeking behavior causes the flock to follow a scripted path. The boids render such an impressing realism at simulating flocking as well as other coordinated motion like fish schools or human crowds that they have been used in many cinematic animations such as the bat swarms of the motion picture "Batman Returns" [3].

Within Nature, interaction of simple agents can be observed in insect communities like ants, bees or termites, and their cooperation strategies have inspired researchers to devise new optimization algorithms based on the concept of emergence [4].

2.2 Adaptation

The second principle of ALife modeling is adaptation, the capability of developing advantageous traits in response to a changing environment. Adaptation divides into lifetime learning and evolution which operate on different time scales.

Lifetime learning represents an individual's ability to interact and learn from its environment. In contrast, evolution is not defined for individuals, but in the context of entire populations. Evolution works with genetic information, called genotypes. Through a process of development, the "mapping function" translates genotypes into phenotypes which represent the individuals' manifestation within a simulated virtual environment. Subsequently, the phenotype is evaluated by a fitness function which determines if the corresponding genotype is selected for further reproduction (figure 2).

Lifetime learning and evolution are profoundly interwoven. Their interplay leads to new and insufficiently understood phenomena like the "Baldwin effect" [5] which denotes that over time learnable traits of the phenotype are potentially assimilated into the genotype. Hinton and Nowlan clearly demonstrated this effect by a simple evolutionary simulation [6].

One of the most fundamental EIBMs are Richard Dawkins' biomorphs [7]. His purpose was to demonstrate an evolutionary model on the basis of selection and mutation as proclaimed by Darwin [8], and to point out the feasibility of discovering a desired genotype inside a huge genetic space. Biomorphs are two dimensional branching structures used as a graphic representation of a number of simple binary genes, controling features like depth of recursion, angles of branching and length of lines and allowing about 500 billion possible combinations. To produce offsprings, biomorphs use asexual reproduction by copying the parental genes with some probability of random mutation.

To evolve a biomorph, the user starts with a display of an initially given parent individual in the center of the screen and twelve children surrounding it. The user simply clicks on one of the children or the original parent to select it for survival and reproduction. Subsequently, the selected biomorph's genes are used to create a new generation, and the biomorph as well as its children are again displayed. These steps are repeated, and with every generation the biomorphs "adapt" to the given fitness function, that is to say, to the taste of the user. In spite of the simplicity of their genetic encoding, the resulting morphologies of biomorphs are surprisingly manifold. Some biomorphs may look like insects, microorganisms, trees or other familiar objects (figure 3).

The general concept of biomorphs has been extended into models which simulate the process of evolution not only based on user selection, but also on agent interactions within a more complex environment [9].

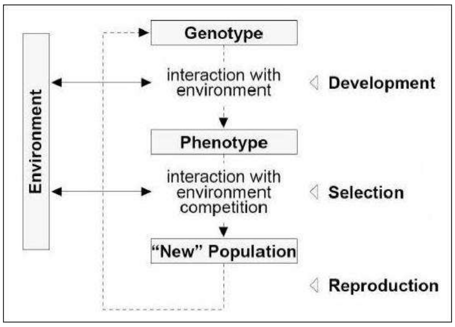

Fig.2. The evolutionary cycle

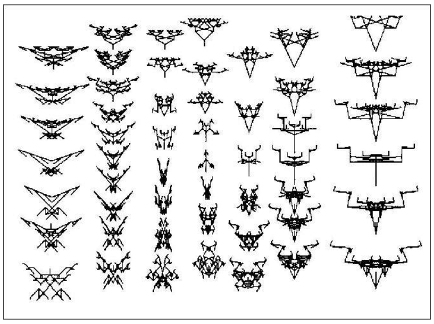

Fig.3. Evolved Biomorphs

3 Simple agent approach

Early implementations of EIBMs tried to capture the processes of evolution by modeling simple reproducing individuals acting on a small set of behavioral routines. Their level of detail was reduced to a one or two dimensional environmental framework and individuals which lacked almost any morphology, but this is sufficient to observe ecological interactions between the organisms and the emergence of population level phenomena: the limitation of resources introduces a competition between the reproducers, and they become engaged in a struggle for existence. According to the principle of the “survival of the fittest”, the organisms either develop successful strategies or die.

3.1 Tierra

In 1992, Tom Ray modeled evolution by the propagation of self-replicating programs running on a virtual machine, called Tierra [10]. These programs can be thought of as digital organisms whose genotype matches the phenotype, and whose physical environment consists of energy, i.e. CPU time, and limited space in memory.

An evolutionary run is started by introducing a hand-written ancestor program into the empty memory. To reproduce, the organism's code is executed. It writes a copy of itself into newly allocated memory space. Mutations introduce differences in the offsprings, and competition for memory causes an evolutionary process to begin.

During a run, organisms shrink by decreasing the length of their genotype, as shorter genes mean less genetic material to be copied more rapidly. Parasites occur, i.e. organisms that execute instructions of other programs, and even hyper-parasites develop which utilize instructions from parasites. At the same time, hosts evolve immunity to parasitism, forcing their parasites to evolve methods to get around the new defenses. These observations illustrate the “Red Queen principle” [11] which states that coevolving populations are due to continuing development in order to maintain their fitness relative to one another.

Tierra has been used to experimentally examine ecological and evolutionary processes such as host-parasite density dependent population regulation. Even if Tierra is modeled in an abstract virtual fashion, it finds many analogies to the real world and its diverse ecological communities.

3.2 Echo

John Holland's Echo system [12] is a simulator of virtual ecologies which is geared to more lifelike notions of space and time. It investigates mechanisms which regulate diversity and information-processing in systems comprised of many interacting adaptive agents, or “complex adaptive systems”.

The surrounding environment is made up of a square toroidal lattice of sites which produces different types of regenerating resources, encoded by a letter. Agents are located at a site and possess a small set of simple interactions with their environment. They can relocate to another site, eat the resources and store them. At the same time, the environment charges a maintenance fee which can be considered as metabolic cost. An agent also features a small range of predefined inter-agent behaviors which are fighting, trading and mating. Fighting and trading allow for resource exchange. If an agent has collected sufficient resources to rewrite its genetic code, it reproduces asexually or, via mating, sexually.

This system exhibits emergent phenomena like the formation of agent communities and trading networks. Echo was used by environmental researchers to show that explicitly deriving differential equations was not necessarily the most accurate method for modeling food web complexity [13]. However, due to the high abstraction level of the Echo model, the degree of fidelity to real systems is uncertain.

3.3 Polyworld

An approach, more faithful to biological systems, was attempted by Larry Yaeger [14]. His virtual ecology, called Polyworld, brings together all the principle components of real living systems into one artificial system. Polyworld consists of a two dimensional plane with growing food bits. Just as in Echo, the agents interact, fight and mate, eat the food and relocate by expressing behavioral primitives. However, an agent's architecture exhibits more complexity. Its behavior is controlled by a neural network, determined from its genetic code. During lifetime, a Hebbian algorithm modulates the synaptic weights, so that the agents are able to learn. Moreover, organisms perceive their world through a sense of vision from their own point of view.

An evolutionary run is started with the introduction of a random population whose evolution is guided by a simple external fitness function rewarding the individuals' activities. If the population is on the verge of dying out, reproduction is regulated by the system. Evolved populations that exhibit behaviors which allow them to perpetuate their number by reproduction on their own are said to exhibit a “Successful Behavior Strategy”.

A variety of species with recognizable behavioral strategies, like fleeing, grazing, foraging, following, and flocking, evolved from this model. These results met Yaeger's primary goal, that is to achieve the emergence of population level behavior from elementary naturalistic building blocks.

3.4 Discussion

In these early models, the multi-agent architecture of EIBMs is already visible. A number of evolving agents is placed in a non-evolving framework. The agents account for the “living” part of the environment, whereas the framework, representing their outside world, can be considered as the “non-living” part. It comprises the space where the agents' phenotypes are inserted and potentially holds accessory objects with simple dynamics, like obstacles or regrowing food bits. Interactions possibly occur among agents and between agents and the non-living component (figure 4).

Tierra's memory is one dimensional and features no explicit resources at all, so that space and CPU time are the only constraints for the individuals. Organisms do not migrate, they are bound to their initial location. Hence, the only significant interaction between organisms and non-living environment is the allocation of memory for offsprings. Echo and Polyworld incorporate the notion of food by modeling ingestion of nearby located resources and subjecting the agents to metabolism. Echo allows the agents to relocate to a discrete neighboring site. Polyworld features a two dimensional continuous flat world, in which agents express locomotion commands like “turn” or “move forward”.

Two major interactions between organisms and non-living environment, i.e. locomotion and ingestion have been incorporated, but they are modeled as primitives and cannot be affected by evolution. The three presented models have proved that a high level of abstraction allows to grasp various population level phenomena. However, they yield little results on an individual scale. One of the main obstacles could be the lack of morphology that limits the agents' degrees of freedom. The models of the following section particularly tackle this problem.

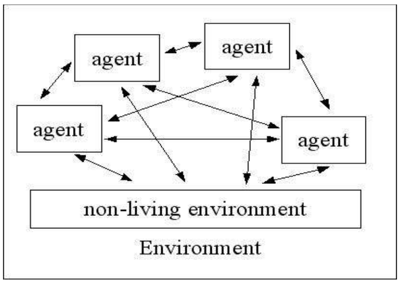

Fig 4. Standard architecture of an EIBM

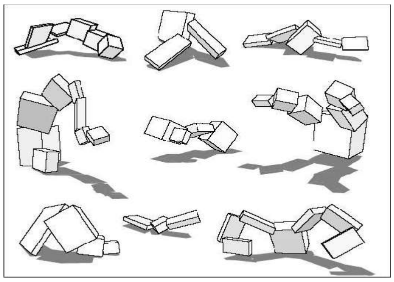

Fig.5. Sims' evolved creatures for walking

4 The grammar-based approach

Then next generation of EIBMs has been augmented with environments of more physical accuracy. This improvement allowed a substantial gain of complexity of the individuals' phenotypes and their interactions with the outside environment. In this kind of models, a creature's morphology is made up of a number of pre-designed elemental units whose assembly is encoded in the genotype by a grammar-like record such as a nested graph or L-system [15]. The presented works still used their own implementations of physical dynamics. However, today a number of available physics engines relieve researchers of programming this component themselves [16].

4.1 Karl Sim's block creatures

In 1994, Karl Sims pioneered a new way of evolving both the morphology and behavior of virtual creatures [17]. Situated in a three dimensional world with realistic physics, these creatures consist of collections of blocks, linked by flexible joints which are controlled by neural circuits. Joint angle sensors and touch sensors allow the creatures to obtain information from their environment. A creature's genotype is written as a nested directed graph which describes both its morphology and neural control architecture. This representation provides modularity to the mapping from genotype to phenotype, and naturally leads to duplication and recursion of body parts.

Sims evolved several locomotion tasks like running and jumping on a flat surface, or swimming in a virtual marine environment. It turned out that different runs of evolution produced different solutions to the same problem. Some creatures were evocative of real existing animals like a swimming snake or a walking crab. Others, equally effective at their tasks, used strange patterns of movement and form (figure 5). In an extending work [18], Sims studied competitive behavior. In a simple game, two opponents had to fight for possession of a cube that was placed halfway between them. The creatures not only evolved ways of reaching the cube quickly, but also of fending off their opponents.

4.2 Sexual Swimmers

Sexual Swimmers [19] is an artificial ecosystem which demonstrates the evolution of morphology and locomotion among a population of stick figures in a virtual two dimensional pond. A simple model of physics enables the agents to propel themselves through simulated water. Swimmers ingest regrowing food bits throughout the pond and reproduce by mating with other swimmers. As there is no explicit fitness function, selection is dictated by the swimmers' locomotion skills which allow them to quickly reach a desired goal, either food or mate. Moreover, the agents have basic perceptions, and the choice of a mate is influenced by preferences for morphological traits like color, length of limbs or degree of agitation.

When length is considered attractive, populations with elongated bodies and only few branching parts emerge. When selecting for color, swimmers of differing colors rarely mate with each other and population often breaks into distinct coloration groups. This work shows how the phenomenon of sexual attractiveness affects the course of evolution in respect of the creatures' body plan as well as locomotion style.

4.3 Framsticks

Framsticks [20] is a three dimensional virtual ecology, i.e. a project modeling creatures seeking food in their environment. Besides energy balls that can be ingested by the creatures, the outside world is enriched with a non-trivial topology and a water level. An agent is made up of connected sticks which can be specialized for various purposes like assimilation, strength, ingestion or sensors (figure 6). A neural brain computes excitations in neural nets, collects data from the sensors and sends signals to effectors that bend and rotate the connection points.

The Framsticks project proves that an increased level of complexity can yield the same results as those obtained in simpler population level simulations, while offering much more possibilities to investigate individual level behavior. Like in Sims' work, a number of locomotion techniques evolved from this model. Moreover, a comparison of different kinds of genotypes was published showing that evolution can be enhanced by the choice of well-designed genetic encodings [21].

4.4 Discussion

The environments of the presented models are characterized by the adoption of realistic physical dynamics. Ventrella's interest in population level phenomena dictated a relatively simple two dimensional pond. Three dimensional flat land and marine environments were modeled by Karl Sims, and the Framsticks project merged land and water worlds into various landscapes.

The design of possible interactions between the agents and their outside world still focuses on ingestion and locomotion. However, whereas ingestion remains to be modeled by behavioral primitives, the articulated morphology of a creature's phenotype allows for a new vision of locomotion. The behavioral building block of previous models is superseded by an emergent result of the agent's morphological activities.

This fact illustrates how, to achieve a given goal, evolution can exploit the dynamics of the environment. In the case of locomotion, evolution discovered that an organized behavior of the agent's morphological elemental units allows to relocate its phenotype. Nature offers a wide range of further demonstrations of this principle. For example, the forces among the molecules of the air lead to properties that allowed to evolve birds that flap their wings to fly, plants which disperse their seeds with the wind, or humans who stimulate their vocal cords to communicate.

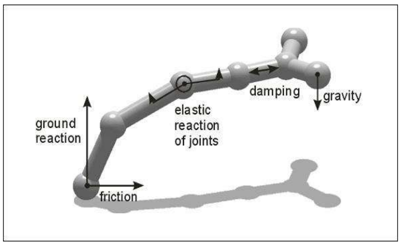

Fig.6. Framsticks creature and its physics

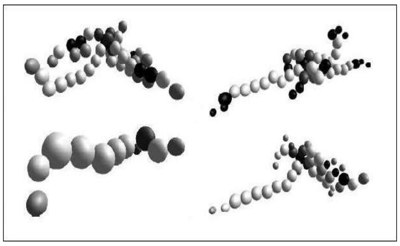

Fig.7. Evolved Blockpushers

5 The embryogenic approach

The grammar-based genotype encoding does not mirror the process of a real creature's biological embryogenesis, since the stage of development corresponding to the molecular chemistry is systematically skipped. The embryogenic approach, inspired by evolutionary developmental biology, attempts to evolve the morphology and neural architecture of virtual agents in a new, biologically more accurate fashion.

The mapping from genotype to phenotype takes place during a developmental phase. The genotype encodes “functional genes” which express the behavior of a cell like division, growth or death, and “regulatory genes” which generate substances that affect the activity of both gene types. The interplay between diffusing genetic information of adjoining cells forms a genetic regulatory network which directs the transformation of an agent from a single structural unit or cell into a multi-cellular organism.

5.1 Eggenberger's evolved morphologies

The constitutive work in this field was achieved by Eggenberger [22] who evolved static morphologies. The environmental framework consists of a discrete three dimensional lattice which constitutes both the diffusion space of various chemicals and the sites for the individual cells of the organisms' compound morphology. The lattice additionally contains substances whose concentration gradients provide a positional information to the cells.

Eggenberger demonstrated how artificial genetic regulatory networks can be modeled, and that it is possible to evolve artificial multicellular organisms in a way that they display high degrees of symmetry. Moreover, his work highlights that differential gene expression dissociates the complexity of information in the genotype from the complexity of the evolved phenotype.

5.2 Blockpushers

Taking up the idea of embryogenesis, Bongard and Pfeifer [23] developed a simulation system, called “Artificial Ontogeny”, to evolve both the morphology and neural control of virtual creatures. Similar to Sims' work, these creatures exist on a flat plane within a three dimensional environment endowed with physical dynamics.

The ontogenetic process transforms a single structural unit in a continuous manner into an articulated agent composed of several units: After a unit splits from its parent unit, the two units are linked by a rigid connector. The new unit is attached to the rigid connector by a one degree of freedom rotational joint. In a similar manner, some or all units develop sensors, actuators and internal neural structure (figure 7). In order to evaluate its fitness, an agent is first grown and then tested against a given fitness function, that is to push a nearby block as far as possible.

The evolved blockpushers were found to solve the problem, showing that a minimal model of embryogenesis suffices to evolve agents that perform a non-trivial task in a virtual environment with physical dynamics. According to the authors, the obtained results “point to the high evolvability of the Artificial Ontogeny system” [23].

5.3 Discussion

The models of this section are characterized by a new approach with respect to the agent's genesis. For this purpose, the environments have been enriched with the capacity of diffusing substances in order to allow the propagation of gene products. In addition to the dynamics of realistic physics, the concept of diffusion is another example of environmental dynamics that allows emergent phenomena which are, in the case of embryogenesis, new ways of phenotypic shaping.

However, the quality of diffusion is only exploited during the process of the agents' developmental phase. Eggenberger abstains from complex physical dynamics as he is only interested in static phenotypes, whereas Bongard and Pfeifer adopt a physics-based three dimensional space in order to study morphological activity. Interactions between full-grown agents and the outside world do not seem to exceed those in the models of the last section.

The recency of the approach does not allow for final conclusions, but it is questionable whether further research will considerably surpass the results of grammar-based encoding schemes, as long as the environment is not endowed with new properties. Two approaches are suggested in the next section.

6 Synthesis and Conclusion

The study of EIBMs is becoming an increasingly important domain in Artificial Life research. EIBMs allow to investigate the laws of the evolution of autonomous agents at individual and population level. They are based on the two concepts of emergence, as the models are based on individuals, and adaptation, as evolution and possibly lifetime learning allow the individuals to enhance their fitness.

A short and non-exhaustive survey of influential EIBMs during the past twenty years has been presented in this paper. The works can be grouped into four periods which reflect a particular state-of-the-art. Successes have been made with respect to evolving both population level and individual level phenomena. Virtual ecologies achieve the formation of simple group behavior such as flocking or trading. As to evolution of individuals, simple locomotion behaviors can be readily bred.

From the view of creative and long-lasting evolution, it has to be recognized that in every model evolution ceases after initial progress. After all, current ALife approaches “do not seem to be as alive as we might hope” [24]. In search of a reason for this phenomenon, the history of EIBMs can teach a lesson: In early models, the main focus was placed on the emergent relationships between the evolving agents, whereas their outside world was somewhat considered as an uninteresting framework whose primary function was the supply of space and, at best, food bits. When the design of the environment switched to physical models, evolution was given the possibility to exploit dynamics not only among agents, but also between agents and environment, which resulted in the emergence of locomotion behaviors. However, after this incisive changeover, most of the attention returned to the agents. Even in more recent models the outside world remains not much more than an inert vacuum space whose sole purpose is to allow the agents to express their morphological activities. It stands to reason that if more care was accorded to the design of the environmental framework, evolution would not fail to discover ways to make use of its dynamics. This idea is indeed not a new one, since early pioneers in Artificial Life like John Holland already stated in 1962 that "the study of adaptation involves the study of both the adaptive systems and its environment" [25].

Starting from the current state-of-the-art, different ways of enriching the environment can be considered. As seen in the discussions of sections 4 and 5, the idea of creatures initiating dynamics in the environment might have been underestimated in current models. In extension to the embryogenic diffusion space, the environments could be enriched with several media whose properties can be exploited by evolution. If the media are able to propagate information, the approach could also provide new ways of communication among the creatures. Furthermore, since ingestion is still modeled as a behavioral primitive, a simple chemical model could complement the physical one and extend the creatures' metabolism to ingestion, digestion and excretion. Phenotypic evolution would occur not only at a functional, but also at a physiological level and affect the creatures' resource management. This approach is based on the idea that a fundamental criterion for Life is the presence of a metabolism. To be considered as “alive”, any being, natural or artificial, should convert matter or energy of the environment into suitable forms for its organism [26].

These few ideas are only suggestions of how to reconsider the significance of all the components of a model in the research about life-at-it-is and life-as-it-could-be.

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