ALife Models as Epistemic Artefacts

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Abstract

Both the irreducible complexity of biological phenomena and the aim of a universalized biology (life-as-it-could-be) have lead to a deep methodological shift in the study of life; represented by the appearance of ALife, with its claim that computational modelling is the main tool for studying the general principles of biological phenomenology. However this methodological shift implies important questions concerning the aesthetic, engineering and specially the epistemological status of computational models in scientific research: halfway between the well established categories of theory and experiment. ALife models become powerful epistemic artefacts allowing the simulation of emergent phenomena, the interaction between different levels of organization and the integration of different causal factors in the very same manipulable object. The use of computational models in ALife can be classified in four main categories depending on their position between theoretical and empirical practices: generic, conceptual, functional and mechanistic. For each of these categories we analyse their epistemic value and select paradigmatic examples that illustrate how ALife models can be fruitfully inserted in the study of life.

Introduction

Modern Biology shows living systems as highly complex networks of many interrelated elements structured in different levels, which in turn interact among them at different time-scales and hierarchies, where local contingencies and universal self-organizing properties merge to produce a particular phenomena. Unlike other natural phenomena such complex organizations are not describable as the action of few simple laws because many local rules appearing at different levels constrain the dynamical processes in intricate ways. For this kind of systems traditional analytic and experimental research strategies are highly limited. On the analytic side decomposition of a system into functionally complete structures is often impossible since functionality and global structural patterns emerge out of non-linear interactions between lower level components and system-environment recursive interactions. On the experimental side intensive control and manipulation of the studied system is not always possible.

In order to study such systems a synthetic approach is required in which biological patterns can be reproduced according to abstraction of the underlying mechanisms that produce them. As E. Fox Keller (2005) has pointed out the complexity of biological systems can only be modelled through vast systems of differential equations, statistical analysis, larger sets of algorithms and simulations whose partial results require an intimate back and forth relation with empirical experiments. Given this, the study of living systems requires special techniques many of which have being made possible due to the development of computers. Unlike the limitations of traditional mathematical models of theoretical biology, where models must be simplified to accommodate analytic tractability, computer models permit a much wider range of formal treatment by means of numerical methods. At the same time automatized experimentation in the computer allows a systematic study of the effect of different parameter values, perturbations on the system, change of initial and boundary conditions, and a host of intensive explorations in the model, which are not amenable to its natural counterpart.

Hand by hand with a quantitative and systematic study of different biological organizations (ecosystems, metabolic, genetic, neural networks, etc.) it appears also the possibility to go further than the empirical instances corresponding to the historical contingencies of terrestrial evolution. Based on the computational "experimentation" it would be possible to formulate the organizational principles of all possible life, including unknown natural forms of life and even new artificially created ones. In other words these new methodological tools have opened the possibility to universalize Biology. This picture of biological organization and its computational synthetic and universalizable investigation is what ALife brings forth through a set of simulation techniques and artefacts that have been developed over the years, constituting a new kind of science: the study of life-as-it-could-be.

However, since the aim of ALife is the study of living systems as they could be, ALife models have not often a direct reference to any explicit empirical domain. Thus, an adequate interpretation of the functional meaning of the different processes and patterns obtained when running the model becomes much more problematic than what traditional epistemology of scientific methodology has established. ALife simulations acquire a hybrid status: they are, as Sismondo has pointed out, at the same time tools, representations, objects and ideas. “These models and simulations easily cross categories, such as “theory” and “experiment”, the bounds of which are otherwise well established. And modelling and simulation sit uncomfortably in science both socially and epistemically, because the boundaries they cross” (Sismondo 1999, p. 247).

Unlike other disciplines or fields, within the ALife community simulation models sit particularly comfortable. They are not perceived as threatening the methodological identity of the field. On the contrary simulation models constitute, rather, a unifying factor of the community, which is, itself a transdisciplinary field whose fuzzy boundaries are defined by an umbrella of techniques; transcending itself into a philosophy of biology, cognition and complex systems in general. The experimental side of the ALife community does not only lie on the results of its simulation models but on a continuous exploration of new modelling techniques. As a consequence traditional paradigms of epistemology, methodology and even ontology are always being challenged and although socially accepted, the epistemic status of simulation models has long being a controversial issue within the community itself (Wheeler et al. 2002, Webb 2001, Di Paolo et al 2000, Moreno 2000, Bonabeau & Theraulaz 1994, Pattee 1989).

Although most of the major contributions within the field somehow reinvents its epistemological status, some general considerations can be made about the epistemic use and value of ALife models (ALM hereafter). In this paper we distinguish three main modalities of ALMs: aesthetic, engineering and epistemic. Then, we classify ALM in four levels of abstraction specifying an epistemic evaluative framework for each of them.

Simulations, realizations, theories and models in ALife

Although in this paper we will focus on the study of computer simulations in ALife, it is important to clarify previously the relations that theories and models have with simulations and also realizations.

A theory is a structure of concepts in the human mind aimed to explain a given domain of reality. This structure of concepts gives rise to simulations and/or realizations, through the articulation of these concepts in a model. Simulations are formal rate-independent unfolding of mathematical models in computer media. As Pattee (1989) has pointed out, in a simulation a set of formal rules try to reproduce the laws and material constraints that govern the dynamics of certain physical systems, or even, the simulation may generate a virtual universe of objects following alternative laws[1]. A realization, on the contrary, is a physical construction of a system to be used as a model for the study of a given phenomenon. A realization is an example of the synthetic methodology of ALife, since it seeks the understanding by a literal reproduction of those elements supposedly fundamental in the generation of a given phenomenon. When the model gives rise to a realization the processes that unfold the consequences of the basic conceptual assumptions are (at least in part) real rate-dependent dynamical processes, so that the system literally obeys the physical laws[2].

An important proviso is worth taking in mind: in a certain sense, a model is more than the simulation or implementation of a formal system, a model includes auxiliary assumptions to interpret the computational system as a relevant tool. Note that the same artificial system can be used at these four different levels of abstraction, so that it is not the system itself what specifies its level of abstraction but the use and interpretation of it. For instance CTRNNs (Continous Time Recurrent Neural Networks) can be used at different levels: to explore abstract systemic properties of dynamic systems at an abstract generic level, to explore the concepts of learning and memory at a conceptual level, to achieve a desired functionality found in ant behaviour at a funtional level or to model the pattern generator circuit of Aplysia at a more realistic mechanical level. In each case there is a host of auxiliary knowledge, information, assumptions or transformations, which are never explicit in the artificial system itself but become essential components of the model. Failure on making an artificial system productive is very often due to failure on this auxiliary framework that makes the artificial system a valuable or non-valuable instrument. While computational systems have standard methods of testing, debugging and evaluation the auxiliary framework is not always easy to evaluate itself, it depends on a set of not always explicit assumptions. In fact, as we shall see, many ALMs' epistemic value (especially of those

[1] In the so-called “strong” ALife the artificial systems (provided they achieve a lifelike behaviour) are conceived not as good models of biological systems, but literally as artificial creations of the same type of systems. Whereas “weak” ALife considers that models represent certain aspects of living phenomena, strong AL would be ready to defend that the phenomenology that takes place in the actual computational environment is life in a proper sense.

[2] H. Pattee (1989) has criticized the confusion (within stron ALife supporters) between computational simulations and realizations of material biological systems, arguing that the former are symbolic systems operating ultimately on inert sets of symbols, whereas in the latter the symbols (DNA strings) operate constraining active matter, and conversely, in a causally closed process, some of these constrained materials (certain proteins) permit the physical expression of the symbol strings. In other words, the emergence of functions in real, material biological systems is autonomous, whereas the functionality of simulated ALife systems depends ultimately of the designer.

we shall call conceptual) lies on their capacity to make explicit, dissonant or inconsistent some of the components of these auxiliary framework thus leading to reorganization of some theoretical issues.

Aesthetic, Engineering and Epistemic goals for ALife Models

One of the main characteristic of ALife modelling techniques is their capacity to produce emergent patterns or behaviour out of a set of a local rules or equations. These emergent patterns can be used for different purposes. For instance models can be used as epistemic tools to understand how natural systems work, to explain life and living phenomena making explicit and tractable the underlying universal principles of biological organization by exploring properties of complex systems, simulating some specific natural behaviour. The emergent order that natural systems show can also be seen as the unfolding of a functional evolutionary design that turns out to be attractive for engineering goals. In fact evolution is an extremely accurate blind engineer that can teach us weird and new ways of achieving solutions for a wide range of problems; both the organization of individual living systems and their collective behaviour (e.g. colonies) also give rise to intriguing designs and functional behaviours. Nature is not constrained by any theoretical assumption, design principles or industrial tradition and thus becomes an attractive pool in which original and sophisticated, simple but powerful engineering techniques can be found. Finally under aesthetic purposes biologically inspired artefacts can also be used to produce aesthetically pleasant and original visual or musical patterns.

In each case the aesthetic, engineering or epistemic use of ALMs requires that the model be evaluated, interpreted and designed in different (although often overlapping) terms, i.e. the modelling framework of the artificial system will depend on these three main kind of goals. For instance artists will evaluate ALMs against the aesthetic quality of the patterns they produce, their resemblance with some natural aesthetic principles, or the models' capacity to generate visual or musical patterns for an artist to select and combine in a performance. When used for engineering purposes ALMs and artefacts are tested or evaluated against a desired functional outcome and adapted to a set of material or computational resources; independently of the aesthetic result, its final resemblance with the natural system on which it had being inspired or the adequacy with the scientific theories supporting model as far as the system works producing the desired result. Epistemic purposes involve a much more complex evaluation framework ranging from a realistic correspondence with a particular organism or biological process to the exploration of highly abstract properties of complex systems. It is this final purpose what shall concern us the most throughout the rest of this paper. We want to understand how an artificial system becomes an epistemic artefact, what kind of knowledge it can produce and how these artefacts interact with theoretical and empirical objects. But we shall first emphasize the importance (and difficulty) of selecting what is the main purpose of a model.

Often, in ALife, the temptation of building artificial worlds capable to generate some aesthetically pleasant pattern, presenting a vague biological resemblance and based on a partially new computational technique, is too high; but the resulting model might easyly end up being equally useless for any of the previously mentioned purposes. That is why it is important to define an specific purpose for the model in order to adequately establish a framework for its evaluation and, hence, for its design, interpretation and experimentation. In some cases, though, the boundaries between the proposed three categories might not be very clear. For instance engineering and epistemic purposes might be intertwined when the level of abstraction of the model is so high and generalist that it covers both the actual (a wide range of existing natural phenomena) and the possible (and thus useful for engineering purposes). In fact, the universalist aspiration of ALife research, its foundational focus on life-as-it-could-be rather than life-as-we-know-it (Langton 1989) and the functional nature of living system threatens the boundary between science and engineering. In addition, most ALife research feeds back to itself, ALife is certainly a technocientific field where technological artefact and objects of study merge. For example an ALife paper on the study of language evolution might include a contribution to engineering on the techniques used to design or optimize a model of cultural transmission or the GA design to optimize a minimally cognitive behaviour model. But even in such limit cases the boundaries are worth keeping. Within ALife there are still significant differences between engineering and epistemic purposes that make a difference on the construction, testing and interpretation of models. On the one hand, when talking about the naturally possible and the artificially possible, different constraints apply. Lets take the example of an artificial system where some kind of self-assembly occurs. If this system is used as a model of natural self-assembly it will have to satisfy completely different constraints than if used as a model for artificial self-assembly. For instance in the first case the model should accommodate natural thermodynamic constraints. Whereas the engineering use of the system could lead to a model where the self-assembling components have access to global information obtained from a panoramic camera or where energy requirements are solved using batteries. What would be misleading in this case would be to generalize claims on natural self-assembly on the basis of the engineering model or claiming engineering limits based on a number of assumptions derived from spontaneous natural processes. On the other hand, the experiments carried out with the model might be very different if we are to highlight one or the other purpose. Finally the way to contextualize and show the experimental results will depend on the chosen framework. For instance for engineering purposes we might want to compare the proposed model with other existing techniques to solve a class of problems, while in the epistemic case we might want to highlight the plausibility of the model with, lets say, what the chances are that the modelled phenomena could appear under the environmental conditions we can expect to happen in other planets.

From idealism to empiricism: 4 epistemic uses of ALMs

The main interest and methodological novelty of ALMs from the point of view of science and epistemology lies in its capacity to develop an experimental research program in the computational domain. But once we fix an epistemic purpose for a model there are still many different frameworks for its evaluation, in fact the epistemic status of this computational domain does not fit within traditional concepts of philosophy of science. Each model in this domain requires that we understand and assume a methodological framework for its evaluation. We can distinguish four different classes of such frameworks according to the level of abstraction the model shall adjust to or, in other words, the position models are made to occupy between theories and empirical data. This classification in four levels is certainly not exhaustive but reflects somehow a clustering of existing models and their underlying epistemic logic.

We distinguish those models whose object of modelling is theoretical (whose evaluation is done against theoretical principles or formalisms), and those whose object is empirical (which are evaluated against empirical data coming from specific natural phenomena). In the first class we distinguish on the one hand those generic systems that serve to discover or classify generic properties of complex systems, we call these models *generic models*. On the other side of the theoretical realm we find what we call *conceptual models* whose framework of evaluation is given by the dissonance or adequacy with the relationships established among concepts of a given theory; abstract conceptual models are used to formalize or compare definitions of generic concepts (such as emergence, complexity or hierarchy) while domain specific conceptual models are used to explore the role and interaction between more specific concepts (such as learning, autopoiesis, cognitive agent, evolvability, etc.). The third and fourth class of epistemic models directly involve their matching or interaction with empirical data. On the one hand *functional models* are defined as those that must adjust to the particular behaviour or functionality exhibited by certain natural system. *Mechanistic models* , on the other hand, are those which act as functional *and* structural models of a particular phenomena, the model is meant to be realistic: variables of the computational system represent observables of the empirical system including the internal mechanisms producing the phenomena under study.

We shall now explore one by one the particularities, evaluation framework and examples of these four class of epistemic use of ALMs.

Generic Models

At the most abstract level we find certain computational constructions with no particular reference to any specific object of study but whose formal structure has been selected in virtue of its resemblance with a wide range of natural phenomena, i.e. its generality is very high and exploration of these artificial systems leads to the discovery of generic abstract properties of complex systems. Such is the case of explorations in Random Boolean Networks, Cellular Automata (CA), Scale-free networks, some research in Neural Networks, Dynamical Systems, etc. Often generic models evolve out of empirical or functional models when a particular structure is found to have properties which might be generalizable to other domains; then particular and domain specific details of the model are abstracted and the empirical model is transformed into a generic one.

A very common methodology to extract valuable knowledge from these models is the exhaustive statistical analysis of different configurations of the system and measurements and operations performed on the resulting patterns. As a consequence the space of resulting patterns might be classified and a set of internal relationships between parameters and resulting patterns are discovered (e.g. the relationship between the rate of connectivity of a network and the resulting complexity, stability, evolvability, etc.). This knowledge of the properties of generic models can feed back to the empirical domain both at predictive and constructive levels, given the appropriate adaptation of the abstract system to the real one. For example the resulting values might be used to initialize a functional model at the highest complexity region in order to achieve a wide range of adaptive capacities. Alternatively the same results can be used (with the required adaptations) to hypothesize the number of connections in an area of high complexity of the brain.

A paradigmatic example of generic systems is provided by scale-free networks. Although the theory of scale-free networks was originally developed by physicist analysing the structure of the WWW (Barabasi and Reka 1999, Barabasi 2002) it has gained increasing attention in ALife. Research in scale-free networks has discovered a number of properties of the structure of non-random networks found in nature: small-world phenomena (any two nodes are separated by a very small number of connections), robustness to random node failures, etc. The same properties and structure apply to social networks, protein-interaction networks, computer networks, economic networks, etc. Stuart Kauffman's explorations into generic properties of Random Boolean Networks (Kauffmann

1974, 1993)[3] are another instance of generic models aiming to discover some universal principles of self-organization in complex systems (independently of the social, genetic, metabolic, immune or neural nature of these systems).

Conceptual models

The early enthusiasm within ALife of the genuine instantiation of living phenomena in the computer gave rise to a whole a set of artificial worlds. Discussion about the plausibility, similarity, and adequacy of these models with existing theories of life produced both a fruitful debate about the underlying assumptions in theoretical biology and the status of such models as instances of living beings. As a result models moved to be used as a tool to question and reorganized theoretical assumptions and concepts rather than to the creation of so claimed artificial living systems without a clear epistemic purpose. Some of these models became conceptual ones which are, probably, ALife's most specific and original use of models.

What we call a conceptual model involves the simulation of processes which are, in virtue of some dynamic or structural analogy with theoretical notions, *conceptualized* under a certain theory of the living, cognitive, social or, in general, complex systems. Conceptual models can be very abstract or very specific depending on the theory under which they are interpreted/constructed. For instance, at the abstract level, the model could work to illustrate, formalize or compare one or more theories of emergence using, lets say, CA patterns. On the other hand a domain specific conceptual model can be exemplified by a simulation of active perception in situated agents.

Unlike generic models (whose applicability to the empirical realm is more straightforward and related to abstract mathematical research) conceptual models have a more heterodox epistemic status, their relation to theories and empirical data is more complex and intricate. As C. Emmeche (1994) has pointed out these models (which he calls "second-order simulacra") are not elaborated as abstractions of the biological empirical domain, but from the biological theories themselves. Maynard Smith has called AL in question since it is a "science without facts", referring to the problem of how to assess a set of computational models whose (potential) empirical references are imprecise and generic (quoted in Horgan, 95). However, it will is an error to evaluate conceptual ALM based research in these terms. The main interest (and methodological novelty) of conceptual ALM lies probably in its capacity to develop experimental research (in the computational domain) on the internal conceptual relationships within theories of biological organization. This computational research allows what Dennett (1994) calls the realization of highly rigorous and far-reaching thought experiments, which the naked human mind never could perform. Bedau (1998) and, particularly, Di Paolo and colleagues (Di Paolo et al 2000) have elaborated a more detailed account of the role and methodology of ALMs as "opaque thought experiments". The opacity of the thought experiment lies on the complexity of the model. The unfolding of properties and patterns from a set of premises (local rules or differential equations) are not always predictable in the absence of a computer simulation that performs recursive calculations, integrates random perturbations, visualizes the results and so on. As it happens with traditional though experiments the epistemic value of conceptual ALMs does not lie on their adequacy with some empirical phenomena (since the thought experiment involves hypothetical and idealised situations). On the contrary the model operates on the hidden assumptions of the theories used to design and interpret the model and on the conceptual relationships between these assumptions. When concepts of a theory are related to each other through relationships which cannot always be derived on logical grounds computer simulations become cognitive tools for theoretical development (Casti 1997). For instance learning and ontogenetic plasticity has intricate effects on evolution. The interaction between these two concepts (learning and evolution) is difficult to generalize and study through natural fossil records or other empirical means. An alternative is to develop artificial worlds (whose local rules are abstractions of the generic mechanisms that evolutionary theory takes to be essential for natural evolution) where simplified forms of evolution and learning can be studied. The Baldwin effect (for example) was nicely illustrated by a computer model (Hinton and Nowlan 1987), subsequent research has made explicit many other properties and dynamic relationships between learning and evolution (Ackley and Littman 1992, Suzuki and Arita 2004). The conceptual relationships that the model uncovers, illustrates or denies are not always the result of just running the simulation. Most of these models require a careful exploration and experimentation under different conditions in order to generalize results and find intermediate explanatory patterns to extract conceptually useful knowledge from the dynamics of the simulation model. The resulting conceptual achievement shall later be used to configure explanatory patterns of specific cognitive, evolutionary, metabolic or collective systems and models subject to empirical manipulation and introduced on the traditional scientific hypothetico-deductive method.

Conceptual ALMs are used in a number of stereotyped ways. Proofs of concept are a use of these models in which the possibility to produce a particular behaviour is demonstrated in the model given a set of mechanisms previously considered incapable to produce such behaviour or functionality (Seth 1996, Beer 2003). On the other hand models are often used to illustrate, formalize or quantify a previously ill-defined concept (such as

[3] And the set of investigations that followed this pioneer approach, for instance on the effect of the asynchronous update of nodes (Harvey and Bossomaier 1997, Di Paolo 2001, Gershenson 2004)

emergence, hierarchy). Here the model acts as a simplified environment in which (given that the competing theoreticians accept the assumptions on which the model is based) disputes over a conceptual definition can be solved in virtue of their viability, accuracy, correlation with expected classification, etc. Conceptual models are also often used to study interactions happening between different levels of organization or different scales, which are often studied by different disciplines, with different theories and tools. Examples of this levels that appear merged in the same simulation are neural mechanism and behaviour, genotype and phenotype, ontogenetic development and evolution, individual and collective behaviour, etc.

Functional models

Traditional explanatory strategies are based on functional/task decomposition and structural localization of such function so that the functioning of a system can be understood by the aggregation of such component functional parts (Bechtel & Richardson, 1993). Complex systems, on the contrary are not amenable to this cognitive strategy, they are integrated systems where the overall functionality of the system emerges out of internal recursive interactions between components and system-environment interactions. That is why functional models become necessary tools to study a complex integrated behaviour. These models are tested against a particular behaviour or functionality exhibited by some natural system but where the mechanisms that produce this functionality in the natural process are unknown, controversial or incompletely understood. Unlike conceptual models empirical functional models must include constraints which are specific of the phenomena under investigation (a particular metabolic reaction, collective behaviour, etc.). These models are used to discover candidate mechanisms or local rules that produce or contribute to the observed and simulated global pattern or behaviour, to asses the performance of existing hypothesized candidate mechanisms, to asses which enviornmental factors participate in the causal structure of the behaviour, etc.

A paradigmatic example of functional models is found among research on swarm-intelligence (Deneubourg et al 1991, Liviu and Luke 2004), where colonies' foraging capacities are reproduced and studied as a result of stigmergic and cooperative interactions. Particularly interesting instances of functional models are given by the use of CTRNNs (and its variants) as universal smooth dynamical system approximators (independently of any attributed resemblance with real neuronal architectures). Artificial evolution is applied to a CTRNN control system to achieve a particular embodied behaviour on a simulated robot (Beer 2003, Vickerstaff and Di Paolo 2005). The dynamic causal structure of the resulting behaviour can then be analysed independently of the natural mechanism that could support it. Halfway between conceptual and functional modelling this research strategy leads to a kind of emergent functionalism in which it is the dynamic organization of behaviour what captures the essential features of cognitive processes as oppossed to the representational properties of propositional rules (as in cognitivist or computational functionalism).

Mechanistic models

In complete mechanistic models there is a correspondence between the variables in the model and a set of observables of the modelled natural system (synaptic connections, metabolic pathways, number of genes, etc.); the model is meant to be realistic, at least to a particular level of mechanistic accuracy. This mechanistic correspondence with the modelled object is exploited to discover which variables and parameter values are crucial to achieve a particular behaviour or functionality, to manipulate the model in ways not accessible to the manipulation of the modelled system and, once the model is adjusted to its object, it might even be used for predictive purposes. Realistic mechanistic models need integrate many different contingencies and parallel mechanisms that altogether contribute to the production of the phenomena under study. Most of these models are generally incorporated to existing scientific fields and research programs (microbiology, ethology, neuroscience, etc.) and, although inspired in previous ALife models and modelling techniques, they are not commonly seen in ALife meetings or publications due to their high specificity. Some of these models represent the most complete understanding of a given natural systems we can nowadays hope to achieve: maximally simplified (but still complex), manipulable and predictive artefacts that unfold the causal structure of a particular living phenomena. Examples of realistic and mechanistic models can be found at Webb and colleagues' detailed model of a crickets phonotaxis (Horchler et al 2004) or Shimizu et al's (2004) model of bacterial chemotaxis.

Conclusions

Almost 20 years after its birth back in 1987s foundational meeting in Los Alamos, Alife is still alive. Its contributions have been many and have spread over different fields (cognitive science, origin of life, evolutionary thinking, linguistics, robot engineering, etc.) the most important of which has been the toolkit of simulation and modeling techniques that Alife has brought forth; accompanied by the conceptual and theoretical transformations that these tools have permitted. The Alife research program has produced a new way to do science, where computers are used to explore the implications of conceptual theories and models, largely in the absence of any direct empirical evaluation. In order to avoid a dissapointing itineracy within a playground of virtual-toy-worlds ALife Models need to be carefully designed, contextualized and manipulated within an epistemic framework that explicitly addresess how and with which purpose the model should be evaluated.

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Acknowledgments

Xabier Barandiaran holds a doctoral fellowship from the Basque Government BFI03371-AE. Funding was also provided by the Comisión Interministerial de Ciencia y Tecnología (CICYT) of Spain, Grant BFF 2002-03294, and BMC2003-06957, and by the University of the Basque Country (UPV/EHU) Grant 9/upv 00003.230-15840/2004.