From biological to artificial complex systems

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1. Introduction: 25 years of research on biological complex systems

In this short statement article, that is not intended as a review or a research paper, we would like to present to other disciplines (engineering, computer science, etc.) a very brief summary of the body of knowledge that we have accumulated in our research on complex system and emergent behaviour in biological populations like cells, insects and other animals and that could be useful in the design of some specific artificial systems presenting the same type of flexibility, adaptability and autonomous organisation.

We start by a very brief historical perspective of our research activities to give the scientific background on which we base our propositions and outline, by way of definition, the main properties of the biological complex systems that we have studied. We emphasize the fact that the results presented here are not new and are considered, to some extent, as basic “textbook” science in physical chemistry and related fields.

1.1 Physicochemical background the notion of dissipative structure

In a historical paper entited “Structure, Dissipation and Life”, Ilya Prigogine proposed the framework of “dissipative structure” to explain why open physicochemical systems can self-organise. It is suggested that this type of structure is at work in biological systems (1969). It is beyond the scope of this paper to summarise the results obtained from the thermodynamics of irreversible processes and other related physical chemistry fields. However we will emphasize the following important concepts: nonlinearity, structure, bifurcation and the role of fluctuations (Nicolis & Prigogine 1977; Haken 1977; Meinhardt, 1982).

In order to produce such structures the systems must present some nonlinear properties coupled with positive or negative feedback mechanisms. For instance, one of the main roles of a positive feedback is to amplify random fluctuations to obtain a fast, nonlinear response of the system.

Structure means that those physicochemical complex systems are able to self-organise in spatial and temporal organised and regular structures like, for example, Turing’s structures or chemical oscillators. These structures are remarkable because they involve a number of molecules of the order of the Avogadro number (i.e. \( \sim 10^{23} \)) that through their local interactions produce global macroscopic structures. In that sense, those structures are an emergent property of matter. These macroscopic structures are not explicitly “programmed” in each individual molecule but emerge from the numerous interactions between the molecules in specific well defined conditions.

The notion of bifurcation means that upon variation of some control parameter, e.g. temperature, chemical concentration, etc., the systems present new solutions i.e. new type of structures. It also means that the appearance of these structures depends on the correct tuning of the relevant control parameters.

Finally, the formation of these structures demonstrates the important role played by fluctuations due to the molecular noise produce by the thermal random movement of molecules. At the bifurcation point, these fluctuations allow the system to “choose” among the new appearing solutions. For example, if one state becomes unstable and two new equivalent states appear then the choice between these two states is random (50% of occurring chance) but the fact that the system will “choose” is certain. Today, such physicochemical complex systems can be prepared routinely in the laboratory. For instance, chemical oscillators or Turing structures are produced and controlled and the period of oscillation in time or space can be tuned by changing specific control parameters.
1.2 Complex system and emergent behaviour in animal population

Our group demonstrated theoretically (Deneubourg, 1977) and experimentally (Deneubourg et al., 1987), that certain behaviours of insect population are self-organised in the same sense as in physicochemical systems. It is a remarkable fact because animals are not molecules: they present cognitive capabilities and are characterized by a body massively endowed with sensors and actuators.

The group also demonstrated experimentally that collective self-organised behaviours can find optimal solutions and that randomness (fluctuations, noise) helps in finding them (Deneubourg et al., 1983).

The group, for the first time, proved experimentally and demonstrated the algorithms that ants use to perform collective self-organised tasks. The notion of emergent behaviour is demonstrated in real biological societies (Pasteels et al, 1987). Later, these results have inspired the related field in computer science called “ant algorithms” or “ant colony optimisation” (Bonabeau, Dorigo & Theraulaz, 1999).

It is also demonstrated that emergent behaviour as in animal populations can be implemented not only in computer simulations but in simple robots. Small groups of very crude robots working collectively were built to prove the concept (Beckers et al, 1994).

Among other topics (Detrain et al, 1999a,b; Camazine et al. 2001), the group is now involved in demonstrating experimentally that mixed societies of insects and robots can cooperate and self-organise. Moreover, through the use of robots it should be possible to trigger and control the patterns arising (IST-FET project Leurre http://leurre.ulb.ac.be).

Besides building artificial-natural interaction in complex system, our group still continue to study emergent behaviours in animal populations because our knowledge of the organisation of such populations is still limited (Dussutour et al, 2004).

2. Brief presentation of concepts and definitions

Complex systems sciences are rather young and present a great variety of approaches. For the moment, there is no unique theory or framework giving a global view of the phenomena involved. Nevertheless, complex systems present common features that can be modelled by different methods which often are complementary. To avoid the confusion that still surrounds complex systems we list below the definitions of the main concepts which play a key role in our studies on complex systems. Besides, the word “complexity” used in a specific scientific background does not mean the same thing as in everyday life. “Complex” in science is not a synonym of “complicated” or used to qualify systems controlled by too many parameters or variables. Unfortunately, the word “complexity” carries this dual meaning, the first one referring to “complicated” the second one to the scientific notion of “complex system”.

* Emergent behaviour and self-organisation

By emergent behaviour we mean a collective behaviour that is not explicitly programmed in each individual but emerge at the level of the group from the numerous interactions between these individuals that only follow local rules (no global map, no global representation). It does not necessarily always mean a large number of individuals but rather a large number of interactions and actions between the individuals and the environment.
**Randomness**

Individual actions include a level of **intrinsic** randomness. Like moving randomly or behaving in a probabilistic way, an action is never certain but has an intrinsic probability of occurring. The behaviour of each individual becomes then less predictable. The predictability of a system depends also on the level of description and the type of measures done. Randomness and fluctuations (also called noise) play an important role in allowing the system to find optimal solutions. In some cases, there is even an **optimal level of noise** that contributes to the discovery of optimal solutions. This noise is either at the level of the individuals or the interactions. It can be controlled in artificial systems and modulated in living systems.

**Predictability**

The global outcome of population presenting emergent behaviour is **certain** in well characterised systems and in a normal context i.e. in the absence of catastrophe like unexpected rapid and dramatic change in the environment. For instance, the result of emergent collective foraging in ant colonies is certain and efficient. Ants do bring food home or they simply die! Because often the system present multiple possible states coexisting for the same conditions, the **specific solutions** that accomplish the global behaviour at the level of the group are **statistically predictable**. For instance the optimal solution to solve a problem is chosen in 85% of the cases while a less optimal solution is selected in 15% of the cases. Nevertheless, the problem is solved in 100% of the cases! The discussion is then shifted towards knowing if 15% of suboptimal behaviour is **acceptable** and not if the global outcome is predictable.

**Evolution and emergent behaviour**

We think that emergent behaviour is **not** an equivalent of evolution or even a necessity for evolution to take place. Emergent behaviour does not produce, in itself, new and unexpected behaviour. There is no contradiction or even competition between self-organisation and natural selection in evolution. On the contrary, evolution makes use of the properties of emergent behaviour by evolving the **local rules** that will produce new behaviours at the level of the population.

The time scales of emergent behaviour and evolution are completely different: the first takes place in a short time (hours) while the latter require a much longer time. In other words, ants use emergent behaviour, for example to bring food home today, while evolution, is changing these **local rules** of this emergent behaviour to produce new strategies at the time scale of centuries or millennia.

Below, we list important features of animal populations presenting emergent behaviour.

- **Dynamical systems with a large number of events.**
- **Descriptions and predictions based on models with a limited number of parameters are possible.**
  Models make use of different tools like differential or difference equations, cellular or Boolean automata, stochastic equations and simulations, agent based computer simulations, etc.
- **The size of the population plays an important role.**
For the same set of behavioural rules different responses are observed as a function of the population size. In living systems, the organisation plan or the behavioural rules may change as a function of the population size. It implies that in artificial complex systems, scalability is an issue that has to be included into the design so that appropriate, scalable rules are selected.

* The characteristics of communication play an important role.
  The range of communication (i.e. all to all, next neighbours, etc.) change the pattern. Privileged linked between some agents (network of interactions) are important features. The life time of the communication signals is also an important factor.

* The possibility to suppress resources may play an important role.
  Usually it results from a negative feedback produce by the activity. It can be a valuable ingredient that helps in finding optimal solutions.

* Randomness is a positive ingredient to find optimal solutions.
  This noise is an intrinsic component of the system. It is modulated in living systems and should be tuned in artificial systems according to the task and related performance metrics.

* Biological systems are not fully self-organised complex systems, they present a mix between centralised and distributed “management”.
  There is a balance between treatment of information at the individual and at the global level. Specialisation may pre-exist in the systems and affect the emergent behaviour.

* Well known experimental and theoretical examples are found in animal societies which are conceptually closer to artificial systems than to their bio-molecular counterpart.

Actually, a limited number of simple generic rules are at work in self-organising biological systems (from the cellular level to animal societies) and produce efficient emergent collective patterns for resources and work allocation, social differentiation, synchronisation or de-synchronisation without external pacemaker, clustering and sorting. These simple rules become building blocks for higher collective complexity.

What is remarkable is the simplicity and parsimony of these rules that allows solving a great variety of the problems encountered by populations that cannot resort only to a centralised organisation (Detrain & Deneubourg, 2002).

Nevertheless, the implementations of these rules are a real challenge. In biological systems, animals are not simple machines and the physiologies that produce such building block behaviours are highly sophisticated and remain a scientific challenge to analyse.

In artificial systems, even if the level of sophistication of animals is absolutely not necessary to obtain similar results, implementation of these rules still represents a technological challenge. Once the set of rules to be used have been identified and their consequences on the requirements outlined, it still remains the technological problem to correctly and efficiently fulfil these requirements. Members of the engineering community are tackling these “reverse” engineering complex systems tasks and are building new methods or theoretical tools to address them (W. Agassounon, A. Martinoli & K. Easton, 2004; A. Martinoli, K. Easton & W. Agassounon, 2004).
3. When do animal population use emergent behaviour?

The first point is rather evident, emergent behaviours appear most useful in real persistent populations of individuals that have to cooperate in real time. Although this point seems obvious, some applications of the so-called “ant algorithms” do not really fall into this category. Indeed, the population is just momentarily and artificially created to solve the problem like when solving an optimisation problem with an “ant algorithm”. The problem is solved a priori and then the solution is implemented in a centralised manner. Even if this approach might be interesting, we think that it is somehow diverging from the core logic of emergent behaviour in animal populations. To illustrate this point, below, we list some of the characteristics of the populations presenting autonomous organisation.

* Actions and decisions are simultaneous and mixed, actions and decisions are concomitant.
* Only limited “cognitive” capabilities of agents are needed to collect and treat information.
* Tasks, resources, etc., allocation between agents are flexible and autonomous.
* Agents may be unpredictable because they need to be stochastic in some behaviour.
* There is no need for a perfect global knowledge of the system by the agents.
* It is an alternative to predict all the needs of an agent population at anytime.

We would like to stress the first point. Emergent behaviour is very useful when the decision has to be taken while action takes place. It means for example, that there is no possibility to stop the system, to perform an optimisation off-line and to start it again. When ants are looking for the best source of food with the shortest path they find the optimal solution by working out, by walking the computation (in the literal meaning of the word “walk”!) and not by stopping solving an optimisation problem in a centralized way and then implementing it. This implies that it takes some time before an optimal solution is found, during this time the colony explore and make use of available possibilities.

Moreover, in many situations, populations are influenced by the environment that becomes a kind of particular agent in the system. Nevertheless, the global properties of the environment do not need to be encoded explicitly in the individuals neither do the agents need a global view.

4. From natural to artificial complex systems

4.1 Why are we interested in artificial systems?

First, from a scientific point of view, simple artificial complex systems presenting emerging behaviour and self-organisation are used as a proof of concept of the use of simple rules by the animals even if they have higher cognitive capabilities compared to machines. What is remarkable in animal populations is that the individuals, in specific conditions, use such simple local rules to achieve desired global behaviour at the level of the group. Yet, because animals are not molecules and have extended cognitive, sensorial, and actuatorial capabilities a doubt subsists that we may be missing something in our understanding of their behaviour. The fact that simpler machines are able to produce the same type of results with much more limited “cognitive” capabilities is a demonstration of the logic at work.
Second, we are convinced that, in given well defined situation, the same framework can be useful in the design of artificial systems presenting some of the characteristics of complex systems like emergent behaviour, autonomous organisation and adaptability. The preferred contexts of use should be when (i) a centralised organisation is not available or possible; (ii) in a fluctuating environment where events are difficult or impossible to forecast; (iii) when a persistent group of machines or software have to cooperate to offer a service or solve a problem in real time.

4.2 Natural vs. artificial complex systems

We can divide artificial complex systems roughly in two different classes namely; first, systems that have been designed with the use of complexity sciences and, second, artificial systems that already exist and are, or will soon become, complex systems but which have not been designed with the tools of complexity sciences.

This latter category is probably the most problematic. The first question to address is the identification of complex systems behaviours. To answer this question research and analysis have to be undertaken and it can be a tedious and difficult task because it requires experimental tests. This may also be a factor explaining some confusion about artificial complex systems that are supposed to be “very unpredictable” and present “unexpected” behaviours. Moreover, systems that are “complicated” are too often easily classified as complex systems without well founded scientific bases. This confusion is most probably due to the lack of knowledge about the system.

The second question to address is how to design some “plug-in” software or devices to cope with their complex system behaviours or to have a better control on them. Analysing such systems and addressing this latter issue are in themselves scientific and technological challenges. In biology, we are facing closely related issues because we have to analyse and understand natural complex systems with the tools from complex system sciences. Moreover, in close collaboration with engineers, we are designing artificial agents that we would like to “plug in” these natural systems to have some control on them (IST-FET Leurre http://leurre.ulb.ac.be).

On the other hand, artificial systems can be designed taking into account specifically the properties of complex systems. Hence, in parallel to “classical” engineering approaches, this design should involve the methods and frameworks developed in complexity sciences including the various modelling and experimental approaches. In such case, the predictability, scalability and reliability of the systems are known because they must be fully engineered and tested.

Considering the elements we have summarised above, we make a non exhaustive list of what could be useful in the context of designing artificial autonomous systems.

* We need to identify artificial systems (groups of machines and software) where the known rules from natural systems can be applied to produce robust, optimal and autonomous behaviours.
* We need to pinpoint where the balance between fully distributed and centralized control lies as a function of the task the system is accomplishing or the artificial system has to be designed for.
* We need to translate, mutatis mutandis, those rules into practical algorithms. It also corresponds to the transition from different level of description like for example, from physiology to behaviour or from hardware to software.
* We need to close the strong “cultural gap” in methodologies between complex systems science and engineering: frameworks, model building, computer simulations, but also experimental procedures, etc. (“Engineering complex systems.
The emergent properties of complex systems are far removed from the traditional preoccupation of engineers with design and purpose”, Ottino, 2004).

4.3 Putting artificial complex systems at work

To our knowledge, real IT industrial applications of complex systems are rare or non-existent. Of course, the knowledge of complex systems and the related scientific fields is recent but, often, we feel that expectations are too high with technologies derived from complex system sciences. Applications should start from relatively well defined systems and obtain clear and measurable results. Moreover, well defined applications should be implemented with complex system technologies and compared to alternative or classical engineering methods. More complicated situations could always be built on simple but nevertheless useful technological implementations of complex systems.

We list below examples of fields where potentially artificial complex systems could be useful and where research into practical implementation could be done.

* Networks of collaborative computers

The first field that comes to our mind is peer to peer systems (P2P) and GRID computing. These two related fields are examples where persistent populations of computers have to cooperate in real time to collectively offer services. These systems are difficult or impossible to manage in a centralised manner if the demand for services is fluctuating and difficult or impossible to forecast. Clearly, these are domains where autonomous organisation and adaptability could be put effectively at work.

An important problem in these systems is to control the emergence of differentiation between the computers. What are the rules governing the computer decisions that lead to their specialisation when the network needs to perform different services at the same time? Inspiration from emergent behaviour in biological societies may help in identifying the rules that, in real time, “regulate” the number of specialists and their level of specialisation for every task in order to reach an efficient and robust collective behaviour without resorting to an elusive centralised management. Indeed, we know from our studies of biological animal populations that a limited number of rules govern the self-organised emergence of division of labour, task allocations and specialisation through individual differentiation. Such flexible autonomous organisation of a network of computers is one of the technological challenges where biologically inspired complex system science could proof to be efficient and robust.

* Networks of collaborative sensors

The second field is the networks of sensors. Whenever sensors have to be distributed in relatively large populations, the question of centralised management becomes problematic. Again emergent behaviour seems a good way of implementing such networks from a hardware and software point of view. There is a growing interest and need for large populations of sensors, mobile or not, dispersed in an environment that must be monitored.

For these type of networks, it is important to synchronise (or desynchronise) their sampling activity or to allocate the various and concomitant measuring tasks. Following the situations, different synchronization processes are desired such as the simultaneous measurement of a parameter on the whole environment or travelling waves of measurement throughout the environment that have to be produced by the population of sensors. Lessons from complex systems suggest that the modulation of the local rules of
interaction between units is enough to produce this diversity of responses without resorting to a centralised management or to, somehow, build a global view of the system in each and every sensor. Another problem to be addressed in the design of such intelligent network of sensors is the modulation (or not) of the interactions between sensors by the results of their measures.

* Populations of collaborative robots

The third field, collective robotics has yet to prove real application. Nevertheless research in this field should be sustained to provide practical useful implementation of population of robots that have to face a variable environment and accomplish task through cooperation. For example, applications should favour emergent behaviour when the cartography of space is not available or changing too rapidly; when the system should keep functioning if several units present failure; when, for security reason, a centralised management is not desirable.

* Network of collaborative transport

The fourth field of application of complex sciences is the management of large transportation fleet (including robots fleet) that includes phenomena similar to clustering, sorting and synchronisation. If the demand is fluctuating and difficult to forecast, if the population of transport units becomes large, if interactions and cooperation need to be realised, then rules similar to those found in biological self-organised population may be implemented into computers and communication devices to lead to autonomous flexible management. In urban public network, where the vehicles are submitted to many source of noise, quality of the service is largely related to the synchronization between vehicles. Local interactions between vehicles (or drivers) moving in the same neighbourhood seems largely enough to improve the quality of the service at the level of the network. Many activities in transportation systems are clustering processes (Deneubourg et al, 1979, 1994). However, these problems often are not solved in real time. Clustering is a classical question in complex systems. Research and development should identify the rules leading, in real time, to efficient and flexible clustering that govern the decisions of each transportation unit. Results from complex systems show that these desired features do not even need to centralise first and then eventually to broadcast all available information. For both examples, studies should address the question of knowing when a self-organised procedure will be more efficient (or more cost efficient) than a classical centralised procedure. This emergent organisational behaviour must then be combined with classical centralisation and management methods.

* Network of collaborative “computerised” human beings

The fifth field of application is the coordination, in real time, of distributed human individuals that have to cooperate and obtain results at the level of the group. In a similar sense as in collective robotics, humans can carry communication, computer devices, or be embedded in an intelligent, communicating vehicle that could help them to collaborate and accomplish work at the level of the group in a distributed environment. It is an opportunity to combine the simplicity of emergent behaviour with the high cognitive capabilities of the human brain. Large teams of (specialized) workers may be a good example of such systems. New type of computerised communication may help to produce small cooperative teams when it is needed and flexibly reorganize the population when new demand appears.
Another question to be addressed is the influence of new communications properties on the pattern formation. A population of individuals with local interactions and information may adopt some type of efficient pattern. In many modern information systems that make use of broadcasting, a large fraction of the population received the same but often simple information (e.g., a bottleneck on a certain road). Every individual may react by adopting a new behaviour leading to new collective patterns sometimes less efficient than those observed without these “global” information systems.

What must be the characteristics of new information systems that allow teams of individuals to produce efficient collective responses? Inspired by biological complex systems, computerized decisions may help to produce efficient decision. For example, introducing randomness in the individual response may prevent the emergence of undesired patterns. This example is a remarkable counterintuitive lesson learned from biological complex systems. Another example of application of emergent behaviour is to self-organise an exploratory activity at the level of the population without even resorting to a global view like cartography.

These self-organised networks of devices will probably introduce new communication methods that are not necessarily based on oral or other type of symbolic languages. For example, one method used by insect societies to handle the complexity of their environment is by using some “intelligent” variables at the individual level that (i) do not require making some sophisticated and precise appraisal of many environmental parameters and (ii) do not need communicating them directly to every member of the group. Instead, they rely on such local “intelligent” variables that automatically integrate several other variables and will influence the behaviour of the population by inducing collective intelligent decisions. For instance, these local intelligent decision criteria are able to bring about the emergent, robust, autonomous and flexible achievement of recruiting an optimum number of agents involved in a specific activity.

This field of research and development is also a good opportunity, in well defined conditions, to study, from a sociological and psychological point of view, the level of acceptance by human beings of such complex systems based technologies that may present counterintuitive features. Moreover, this type of research allows also analysing the impact of artificial agents on the behavioural pattern of a group of human beings. In the reverse direction, it also a good opportunity to study the influence that groups of humans can exert on such ambient intelligence or ubiquitous computing systems. Research should also focus on the way such systems should be designed to cope with the fluctuating, maybe contradictory and numerous requests humans may exert on them. Again, lessons from biological complex systems may help in the design of the local rules embedded in the devices that will produce efficient and robust behaviour at the level of the network.

This field of application is closely related to animal populations where the system relies not only on simple rules that produce optimal emergent behaviour at the colony level but also on the local cognitive capabilities of the individuals.

5. Conclusions

Complex systems sciences are still young and do not present clearly defined borders. Even in the academic world, complex systems sciences are still surrounded by some confusion and sometimes look like a box where everything that is “complicated” is thrown without sound scientific reasons. Notice that we write complex systems sciences in the plural form because there is no unique global theory but rather a collection of tools and frameworks that helps in studying and understanding the common features
presented by the so called complex systems. Among other factors, this can induced more confusion and misunderstanding from the practitioners or other scientific communities. Nevertheless remarkable scientific results have being obtained in a great variety of scientific domains.

The experimental study and modelling of complex systems is often a tedious task. Our knowledge of emergent behaviour and self-organised populations is only about 25 years old. This knowledge is still limited because experiments on living systems are difficult and are time consuming. Nevertheless, the few results that have being obtained have already had an important impact on other non-related scientific or technological fields like information technology, artificial intelligence or robotics. It is a remarkable fact because the field of self-organisation in biological populations was not (and is still not to a large extent) a main stream field of biology. Sometimes it is even perceived, by biologists themselves, as a highly exotic academic field because they do not grasp what complex system sciences can bring to their own field. Hence, even if the number of biological laboratories involved in such type of research is growing, for the moment, this number remains quite small compared to other fields in biology or even complex systems sciences.

We think that the knowledge acquired in biological complex systems is not a candidate to solve all problems in engineering in a better way. In many cases, if not the majority, “classical” or new methods developed by engineers are more appropriate or even much better than what may be found in natural systems. That is why the first issue we suggest is to identify specific technological domains where inspiration or solutions found in natural complex systems can be useful or efficient. Eventually, the results obtained by methods or knowledge coming from biological complex systems have to be compared or put into competition with other engineering approaches.

We are convinced that such body of knowledge could be put to work in the design of more useful and applied artificial complex systems. In our laboratory we already do real experiments with artificial complex systems, although on a limited number of quite simple case studies. We feel that this type of approach is promising and could lead to new useful concepts and frameworks in the design of some specific information technology systems.

After briefly presenting the concepts on which we base our statements, we have identified a non-exhaustive list of topics where research and development of real application could be done. To take up this challenge, we have still to overcome the cultural differences between the different scientific domains including engineering.

These are just examples, largely inspired by our experience in European projects in the IST Programme of the 5th and 6th European Framework Programme, where laboratories like ours, in collaboration with other scientific domains and with engineers, could transfer their knowledge about biological complex systems to the community of engineering and applied scientists.

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6. References