Cellular Automata Between Life Science and Parametric Design: Examples of Stochastic Models to Simulate Natural Processes and Generate Morphogenetic Artefacts

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Abstract. Cellular automata are models that deal with both nature and artefacts: they can indeed simulate living beings as well as be employed in the creation of objects. After the introduction of this concept by Stanislaw Ulam and John Von Neumann in the late 1940s, many different kinds of cellular automata have been created and have become part of what Christopher Langton called "artificial life" in 1986. The most complex examples among them are based on stochastic development, thus they share their structural properties with morphogenetic models like the one suggested by Alan Turing (1952). This is the reason why some cellular automata are capable of simulating the development of living beings, but also of cities and artefacts. They are indeed widely used in computer graphics related to parametric design, in order to create performative objects at various scales that can be produced according to the principle of mass customisation. The purpose of this study is to analyse the properties of these models with the help of computer simulations and, as a consequence, to explore some of their different fields of application. As a result, it can be observed that these processes, based on a stochastic geometry, can lead not only to simple biomimicry (regarded as the artificial replication of biological features) but also, in a wider sense, to bioinspiration (a more general relation between nature and artefacts based on shared structural properties).

Keywords: Cellular automata · Morphogenesis · Parametric design

1 From Deterministic to Stochastic Cellular Automata

1.1 Introduction

Cellular automata, algorithms that describe the evolution of a system throughout time, can be regarded as models that deal—to some extent—with both nature and artefacts: they are indeed widely employed in computer graphics in order to simulate the growth of living beings and the interaction of different species, as well as to create objects at various scales in the context of parametric design.

Introduced in the late 1940s by Stanislaw Ulam and John Von Neumann, cellular automata are based on a set of simple instructions applied to a group of cells, which, starting from a definite initial arrangement and a predetermined rule depending on their

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neighbours, can take a finite number of states. We can mention, for instance, the "elementary cellular automata" created by Stephen Wolfram in the 1980s [1], to prove that even a simple rule can give rise to a wide range of patterns. Such models have been used to reproduce a large number of phenomena that occur in our world: "Wa-tor" [2], for example, derives from the equations of Lotka and Volterra and is therefore employed to simulate the competition between two species, like sharks and fish.

Another well-known simple case of cellular automaton is the Game of Life by John Conway [3], where the survival of a cell depends upon the occupation of the adjacent ones.

This topic has become part of what Christopher Langton called "artificial life (a-life)" in 1986 [4]: this term gathers together many different models that try to reproduce biological systems in artificial—mainly virtual—environments, such as cellular automata and L-systems, among others. Invented by Aristid Lindenmayer in 1968 [5] in order to study the growth of algae and bacteria, L-systems have been subsequently extended to the study of a huge variety of plants and animals. They are based on a recursive algorithm and this is the reason why they have been used to create fractals as well. Similar models have been also applied to the study of other natural phenomena like the dielectric breakdown model, but also to the analysis of the development of cities (Fig. 1).

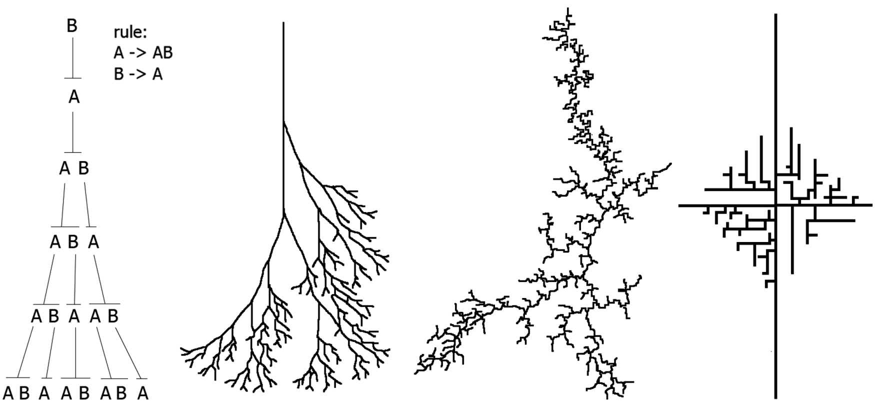

Fig. 1. (From left to right) A scheme of L-system [6], its application to the simulation of algae [7], a dielectric breakdown model (DBM) [8] and a step in the development of a city according to urban morphogenesis principles [9]. The global evolution of these models depends on local interactions: each point is determined in relation to the previous state of the system in the point itself and its surroundings, such as in cellular automata. Reworking and composition by Irene Cazzaro

Cellular automata are sometimes considered the matter that constitutes the entire universe (as an example, we can mention the theories by Konrad Zuse and Edward Fredkin [10, 11]): from this point of view, all the physical processes that occur in nature, even at the most elementary level, would be interpreted as forms of calculation and elaboration of data: as a consequence, everything would be based on computation and immateriality.

Anyway, our approach doesn't consist in applying a model to reality, but in describing some aspects of reality—as far as possible—using models. Thus, instead of dealing with a general theory, we will concentrate on particular examples that can be explained—approximated—through algorithms such as cellular automata.

1.2 From Elementary Cellular Automata to Complexity

All the cases mentioned before are based on simple rules dealing with the initial arrangement of a system and the neighbours of each considered cell.

The fundamental elements in a cellular automaton are indeed:

- A grid, constituted by the totality of cells taken into account, which in the simplest cases is one- or two-dimensional;
- A number of possible states that can be assigned to these cells: generally each cell can be given the value 0 or 1, but in more complex cases there may be a larger number of possibilities;
- A neighbourhood for each cell, which is the set of cells adjacent to it that are capable of influencing its development by means of a rule.

Wolfram's elementary cellular automata constitute the simplest example: they are one-dimensional (a row of cells), the possible states are 0 and 1, the neighbourhood for each cell is composed of the two adjacent ones. Yet, there are 256 possible developments: thus, we can see that even the simplest case of cellular automaton can generate a considerable variety of results, among which we can recognise all the four classes identified by Wolfram in 1984 [1]. According to this classification, the initial pattern can evolve towards a uniform (class 1) or oscillatory (class 2) final state, but it can also become generally random (class 3) or produce simple localised structures whose interaction can give rise to complex patterns (class 4).

We will see that there is something in common between this classification and the one adopted by Alan Turing in 1952 to describe his morphogenetic model.

In order to simulate the development of a cellular automaton, having also the opportunity to change the initial configuration, we can use "Golly" [12], a program that also allows to give rise to the same automaton starting from various points in space and study what happens when the different processes interact (Fig. 2).

This is a method to find complexity even in the simplest conceivable automaton, but the rules are not stochastic yet.

In order to make them stochastic, we need to add a percentage to each event that can take place, as we can see in Fig. 3.

Even though we cannot reduce everything to an algorithm, we can deduce, starting from these premises, that the analogies between different complex systems (such as the growth of a living being, the behaviour of different animal or human groups, the development of cities, the creation of artefacts and the evolution of particular cellular

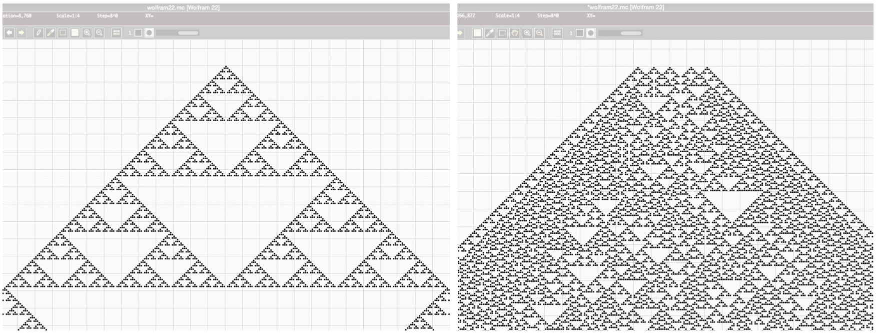

Fig. 2. Simulations created with the program "Golly" [12] and related to rule 22, one of the 256 elementary cellular automata by Stephen Wolfram. Each row corresponds to a different stage of the automaton's evolution and is generated by the previous one following a few rules based on the configuration of a neighbourhood of three cells and on two possible states for each one of them. The automaton on the left shows the development starting from a single point and giving rise to a fractal-like structure. The one on the right shows the development, according to the same rule, starting from five different points. This produces a more complex and sometimes hardly predictable structure. © Irene Cazzaro

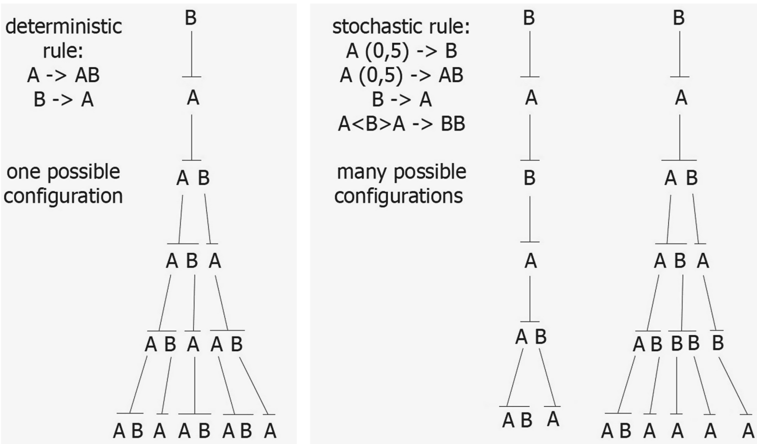

Fig. 3. The basic rule to create L-systems, as seen in Fig. 1, can be transformed from deterministic to stochastic introducing randomness: in the examples on the right, which are only two among the many possible configurations, A has a 50% chance of becoming AB and a 50% chance of becoming B, whereas B is transformed into A except when it is located between two A: in this case, it becomes BB. © Irene Cazzaro

automata) rely on a stochastic geometry based on the possible random arrangements of points in space and on the relations between them, which can lead to the emergence of form through self-organisation. For this reason, these mechanisms seem related to models of reaction-diffusion such as the one proposed by Alan Turing.

2 Applications in the Study of Stochastic Development

2.1 Alan Turing's Morphogenetic Model and Cellular Automata

The most complex examples of cellular automata and, more generally, artificial life, can develop stochastically, thus they have something in common with morphogenetic models like the one conceived by Alan Turing (1952) [13]. However, the evolution of the latter is based not only on the state of the immediate neighbours, but also on two elements (interpreted as chemical substances called "morphogens") that are responsible for processes of reaction (between them) and diffusion (from each cell to the adjacent ones). Thus, the process of differentiation takes place through a mechanism of self-organisation that causes symmetry breaking without the action of any external forces. This happens because of the presence of irregularities like the fluctuations in the number of molecules that undergo the reactions, generating a series of concentration peaks that tend to grow at the expense of the surrounding areas and that can develop various patterns through time, according to a nonlinear dynamic process, which is typical of complex systems.

These two contrasting forces can give rise to different classes of patterns, such as in Wolfram's cellular automata: they can be composed of spots, stripes, maze-like arrangements, or even uniform or oscillatory states.

The number and dimension of the peaks mainly depend on the diffusion rates of the substances: if they are low, the range of the peaks is short and many little spots are formed, whereas, if they are higher, the range is longer and a few bigger spots are formed. Stripes emerge from the connection of spots that reach saturation.

In the simulations that we propose, the reaction rate remains constant and only the diffusion rate changes. Abstracting from chemical and biological considerations, the only thing that influences the development of the system is the state of the neighbours, a local interaction that gives rise to a general behaviour: therefore, from this point of view, there's no considerable difference between this model and cellular automata. Moreover, in computer simulations this similarity becomes clearer because the original equation, representing the continuous variation in the concentration of the morphogens in space and time, is transformed into a discrete case [14].

The evolution of the system remains stochastic (it depends on the initial configuration and a small difference can lead to a considerable variation) and we cannot make predictions about what will emerge after a certain number of iterations. We can only try to describe the pattern at a qualitative level (i.e. try to guess which class it belongs to, even though there are some cases that are difficult to categorise).

Actually, these are pre-patterns of concentration, which can regulate many natural phenomena among which the arrangement of specific organs or the pigmentation patterns on some animals, like the spots in leopards or the stripes in zebras.

The qualitative differences between patterns originated by changing the diffusion rates of the two morphogens can be seen in Fig. 4.

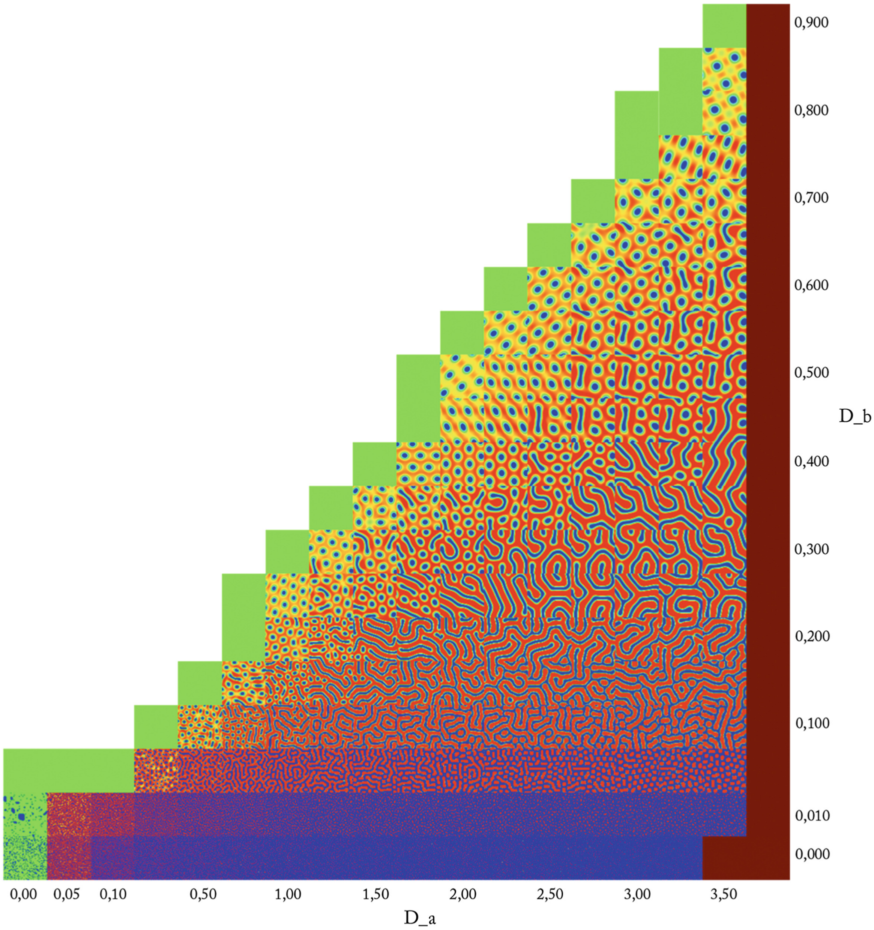

Fig. 4. Turing's patterns obtained with the program "Ready" [15] by changing the diffusion rates while keeping the reaction rate constant. Thus, the original equation, applied to each point of the system, becomes only dependent on the neighbours, such as in cellular automata. In particular, the variation of the diffusion rates allows the creation of patterns that range from stripes to spots of different dimensions. Each one of them can be associated with a step in a process of morphogenesis leading, as an example, to the differentiation of a living being as well as the development of an artefact. © Irene Cazzaro

2.2 Morphogenesis in Nature and Its Digital Replication

Turing had been fascinated by nature and in particular phyllotaxis since he was a child, but this was not so far from his studies, as he considered nature as cryptography, with a code to be deciphered (Hodges 2015, pp. 19–22) [16].

He aimed at accounting for a wide range of natural phenomena that involve the transformation of an initial homogeneous state into a final differentiated one, as he wrote in a letter addressed to the zoologist J. Z. Young in 1950 [17]: he was trying to develop a model capable of explaining gastrulation, phyllotaxis, the formation of animal markings, the configuration of structures with a polygonal symmetry (such as flowers and starfish) or even spherical structures such as Radiolaria.

Many other examples depending on a similar process of reaction-diffusion have been found in nature: we can mention, for instance, the mechanism of aggregation of slime moulds in case of starvation, the organisation of ant colonies, or even the appearance of sand ripples [20]. These processes are similar because they deal with the aggregation of a substance whose quantity grows in some points of space at the expense of the surrounding area.

Furthermore, the patterns found on the surface of particular seashells, made of triangles of various dimensions, have been simulated through both Turing's model and Wolfram's elementary cellular automata [1, 21], giving interesting results that are not so far from reality, even though we do not know how they are formed.

The simulations of natural patterns through Turing's reaction-diffusion model (Fig. 5) have been obtained by using the program "Ready" [15] and varying only the diffusion rates.

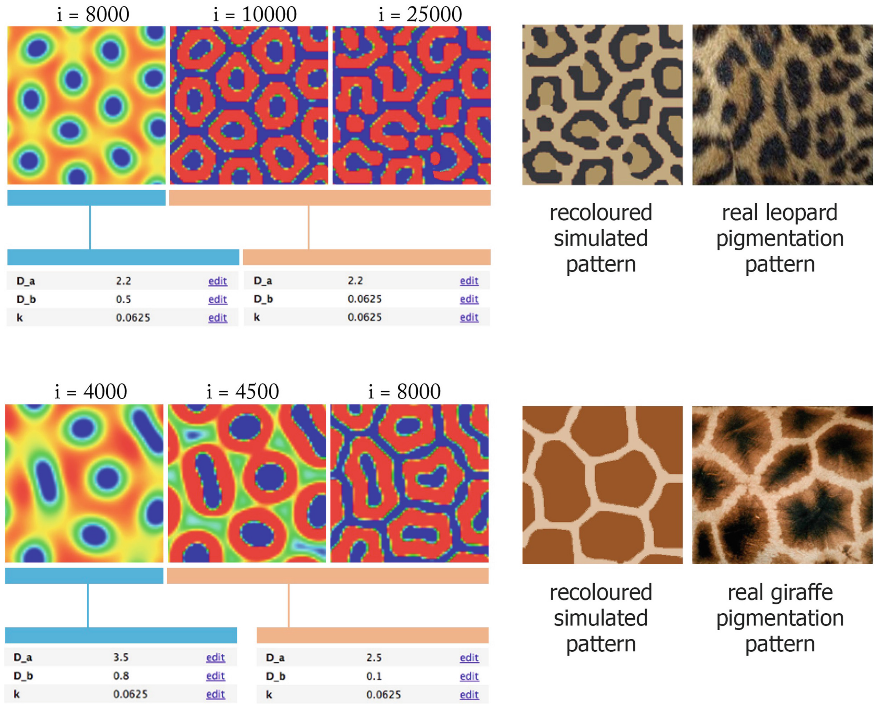

Fig. 5. Although there is no scientific evidence yet, the simulations of processes of reaction-diffusion have led to results that are really close to patterns that can be observed on the furs of some animals like leopards, zebras and giraffes [18], but also on some fish [19]. These simulations have been created with the program "Ready", by changing the diffusion rates (D_a and D_b) after a certain number of iterations (i). The reaction rate (k) remains constant. © Irene Cazzaro

2.3 Parametric Design and Urban Morphogenesis

The same interaction between different, sometimes opposite forces can be seen in other kinds of simulations, like in the study of settlement processes, where the morphogens are replaced by the economic, political, cultural, geographic forces involved, that give rise to forms intended as transient states in a dynamic system. Cities evolve by themselves and can be compared to actual “organisms” because of the relationship between the physical shape of the settlement and the living forms that continuously generate and transform it. For this reason, we can try to apply stochastic cellular automata even in this field: “they can produce qualitative change stemming from small quantitative variations in some parameter values”, even if we must remember that there are limitations to this analogy and the experimental results “should include the creative and cognitive behaviours which characterize the genesis of complexity in spatial systems” (Pumain 1998) [22].

The evolution of cities can be described through cellular automata by assigning a different value (generally 0 or 1) to the presence or absence of a considered force capable of shaping them. The challenge, indeed, is recognising which are the main features of an urban settlement rather than tracing a general geometric scheme: this is the reason why specific eidetic categories, which are not those provided by traditional geometries, are required. In fact, form is not the result of a streamlining towards a clear purpose, but it is generated by complex evolutionary mechanisms that can make a system develop in different directions. Thus, the exploration of more appropriate eidetic categories, which are based on stochastic models such as those seen before, is the aim of many studies related to urban morphogenesis that follow several directions but have also something in common. These approaches range from the comparison between urban expansion, physical models and individual decisions [9] to the analysis of self-organisation systems (Fig. 6) in which local interactions give rise to a global behaviour [23, 24], from models based on fractals, thus on iterations of algorithms [25] to the conception of the city as a network in which streets are the elementary components that shape it [26].

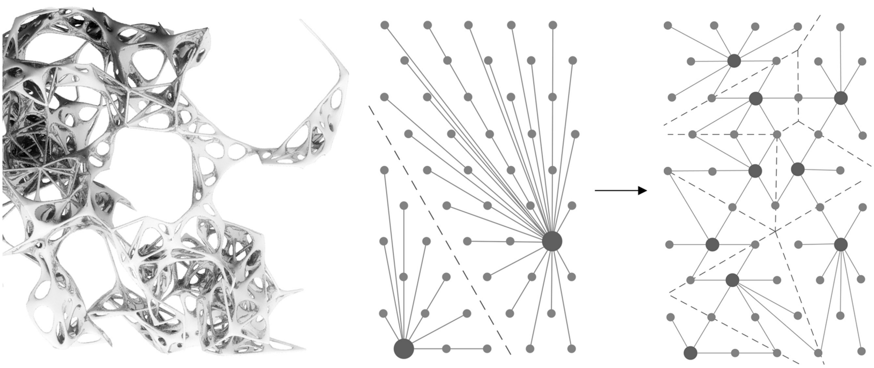

Fig. 6. An example of morphogenetic structure [32] and the two states in the evolution of a group of cities according to Allen and Sanglier [24]. Reworking by Irene Cazzaro

Such models are becoming increasingly important in morphogenetic design too.

Even in this case, shape is generated through self-organisation, allowing the growth of a performative structure, with a constant feedback between computational design, simulation, fabrication and external influences: this leads to mass customisation, a hybrid technique combining mass production and flexibility. This “open-ended design process” (Menges 2012) [27] where materiality is an active generator can also be enhanced through the use of robots in order to customise the manufacturing process as much as possible (Fig. 6).

The nature of the performative element has led to different approaches to morphogenetic architecture and design. Greg Lynn, for instance, conducts research on membrane structures that can create many different and unpredictable equilibrium states by adjusting some parameters (Lynn 1999) [28]. Similar research is developed by Achim Menges and Sean Ahlquist, who work with tension-driven materials as well. Besides, Menges also works with wooden architectural structures, where the performative elements lie in the physical properties of the material, like hygroscopy, anisotropy, elasticity, rather than in advanced technology. Examples of this approach are the ICD/ITKE Pavilion at Stuttgart University and the FAZ Pavilion in Frankfurt. There are also researchers who design the physical outline of natural elements in order to develop specific material characteristics. This is the case of Ferdinand Ludwig, Hannes Schwertfeger and Oliver Storz with the Baubotanik research group at Stuttgart University. Furthermore, some designers have specifically used Alan Turing’s model to create morphogenetic objects: as an example, Jessica Rosenkrantz and Jesse Louis-Rosenberg, founders of the studio “Nervous System” in Massachusetts, have applied it to the production of lamps, jewels and other items, which can become highly customisable.

The principle of aggregation is at the basis of the behaviour of these structures: this feature does not arise from a simple connection between existing objects, but from an interaction between continuously reconfiguring parts (Dierichs and Menges 2012) [29], in an “emergent” complex system (Johnson 2001) [30].

However, one of the most relevant aspects of this approach in architecture is the use of Building Information Modelling (BIM) software, which could provide more comprehensive models of an artefact considered as an “artificial organism”. It deals, indeed, with the properties of building components, such as manufacturers’ details, interconnections, interactions, life-cycle stages and could also be integrated with software for the simulation of their physical behaviour. Thus, they can become tools for shaping, simulating and computing all the different components of a building.

3 Conclusions

By analysing these different processes, it seems clear that they are capable of generating shapes and patterns that evolve progressively starting from a uniform, regular space and reaching different steady states. Yet, we must keep in mind that these are only some of the possible models that can be used to describe reality and, like any other model, they remain “a simplification and an idealization, and consequently a falsification” [13].

However, they seem adequate to account for phenomena like those analysed before: as George Box said, "all models are wrong, but some are useful" [31].

In the most complex cases, we have observed that these processes need to be described by employing computational and stochastic geometry, which can help us understand the principles shared by living beings and human artefacts, considering form as a temporary state originated by the interplay of forces in a dynamic system. Thus, the success of such models in natural and artificial pattern simulations is fundamental because they involve the emergence of forms: this conception is far from the hylomorphic scheme, according to which a demiurge imposes a form to an inert matter. On the contrary, matter becomes an active part of the process.

In this framework, we have seen the applications of cellular automata and morphogenetic models to design and architecture, but we must remember that their importance in these fields resides not only in parametric modelling, but also in the ability to explore new eidetic categories, thus concerning the form of the objects and the living environments that interact with them.

Moreover, these morphogenetic models are significant for their explanatory value, rather than for their predictive one: they can indicate which categories, from the designer's point of view, are more appropriate to account for a given phenomenon and they facilitate the exploration of particular complex structures, which sometimes challenge our individual possibility of calculation and imagination.

In this context, the examples analysed before become important in the constantly expanding field of bioinspiration, which is not simple biomimicry (even though the difference between these two terms sometimes blurs) because it concerns the shared structural properties of different systems rather than superficial and "formal" similarities between them [33]. Thus, it is considered a less direct approach that doesn't simply replicate the processes and techniques applied by nature (see for example the well-known studies on the adhesion of gecko's feet [34] or on the structures created by the mound-building termites [35]). Bioinspiration rather aims at studying the principles underlying natural processes (such as the emergence of form) and replicating those concepts in artificial contexts, remembering that we usually consider just one of the ways in which nature produces its variety of forms [20].

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