Complexity, Development, and Evolution in Morphogenetic Collective Systems

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1 Introduction

Various living and nonliving systems are collective systems in the sense that they consist of a large number of smaller components. Those microscopic components interact with each other to show a wide variety of self-organizing macroscopic structures and behaviors, which have been subject to many scientific inquiries (Bar-Yam 1997; Ben-Jacob et al. 1998; Parrish et al. 1999; Solé and Goodwin 2000; Macy and Willer 2002; Camazine et al. 2003; Couzin and Krause 2003; Gershenson 2007; Lämmer and Helbing 2008; Turner and Soar 2008; Turner 2011; Vicsek and Zafeiris 2012; Portugali 2012; Doursat et al. 2012; Fernández et al. 2014; Sayama 2015).

Typical assumptions often made in earlier mathematical/computational models of self-organizing collectives include the homogeneity of individual components' properties and behavioral rules within a collective. Such homogeneity assumptions have merit in simplifying models and allowing for analytical prediction of the models' macroscopic behaviors. However, such homogeneity assumptions would not be adequate to capture more complex nature observed in real-world complex systems, such as multicellular organisms' morphogenesis and physiology (Solé and Goodwin 2000; Camazine et al. 2003), termite colony building and maintenance (Turner and Soar 2008; Turner 2011), and growth and self-organization of human social systems (Macy and Willer 2002; Lämmer and Helbing 2008). Those real-world complex collectives consist of heterogeneous components whose behavioral types can change dynamically via active information exchange among locally

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connected neighbors. These properties of components facilitate self-organization of highly nontrivial morphological structures and behaviors (Sayama 2014).

In this chapter, we present a brief summary of our recent effort in investigating several aspects of complex morphogenetic collective systems that involve (1) heterogeneous components, (2) dynamic differentiation/re-differentiation of the components, and (3) local information sharing among the components. Our objective was to understand the implications of each of those properties for developmental processes of the collectives and to develop effective methodologies to design novel artificial morphogenetic collective systems.

The rest of this chapter is structured roughly following the topics of this proceedings volume—*evolution, development, and complexity*—though we will discuss them in a reversed order. We will first propose a classification scheme of several distinct complexity levels of morphogenetic collective systems based on their components' functionalities. Then we will computationally investigate how the developmental processes, i.e., self-organization of morphological patterns created by interacting components, will be affected by the difference in the complexity levels of those systems. Finally, we will discuss evolutionary methods to design nontrivial self-organization of morphogenetic collective systems, with a brief additional remark on their robustness/sensitivity to spatial dimensional changes.

2 Functional Complexity Levels of Morphogenetic Collective Systems

Our first task is to identify what kind of properties are typically seen in real-world complex collective systems but often omitted for simplicity in the literature on mathematical/computational models of those systems. In Sayama (2014), we selected the following three as the key properties essential for self-organization of morphogenetic collective systems yet often ignored in the literature:

1. Heterogeneity of components
2. Differentiation/re-differentiation of components
3. Local information sharing among components

Heterogeneity of components means that there are multiple, distinct types of components whose behaviors are different from each other. Note that these types are not necessarily a simple rewording of dynamical states. Instead, each type may have multiple dynamical states within itself, while its behavioral rules as a whole (e.g., state-transition rules) should be different from those of other types. Examples include different cell types within an organism, individuals with different phenotypical traits in a colony of social insects, and different professions of individuals in human society. Differentiation/re-differentiation means that each individual component will assume one of those types (differentiation) and potentially switch from one type to another under certain conditions (re-differentiation). Finally, local infor-

mation sharing means that the individual components are actively sending/receiving encoded signals among them for coordination of their collective behaviors, such as cell-cell communication with molecular signals, pheromone-based communication among social insects, and human communication in languages.

Mathematically speaking, distinguishing presence/absence of each of these three properties would define a total of $2^3 = 8$ possible classes of collective systems. However, we claim that there are some hierarchical relationships among those three properties. Specifically, differentiation/re-differentiation of components require, almost tautologically, the multiple possibilities of component types. Furthermore, we assumed that local information sharing would make sense only if the components had an ability to change their types dynamically based on the received information.[1] Taking these requirement relationships into account, we proposed the following four hierarchical classes of complexity levels of morphogenetic collective systems (Sayama 2014) (Fig. 1):

Class A Homogeneous collective
Class B Heterogeneous collective
Class C Heterogeneous collective with dynamic (re-)differentiation
Class D Heterogeneous collective with dynamic (re-)differentiation and local information sharing

The dynamics of components in each of these four classes can be represented mathematically as follows (Sayama 2014):

Class A $a_i^{t+1} = F(o_i^t)$

Class B $a_i^{t+1} = F(s_i, o_i^t)$

Class C $a_i^{t+1} = F(s_i^t, o_i^t), s_i^{t+1} = G(s_i^t, o_i^t)$

Class D $a_i^{t+1} = F(S_i^t, O_i^t), s_i^{t+1} = G(S_i^t, O_i^t),$
$S_i^t = \{s_m^t \mid m \text{ in } N_i^t\}, O_i^t = \{o_m^t \mid m \text{ in } N_i^t\}$

Here a_i^t, o_i^t, and s_i^t are individual component i's behavior, observation, and type at time t, respectively (s_i is a time-invariant type of component i); F and G are model functions; and N_i^t is the set of component i's neighbors at time t. These mathematical formulations help clarify the hierarchical relationships among the four complexity levels. Following these formulations, we will construct a specific computational model of morphogenetic collective systems to facilitate systematic investigation of the proposed four complexity levels and their characteristics.

[1] We note that this assumption is much less obvious than the first one, and if we did not adopt it, we would obtain $3 \times 2 = 6$ different classes. In this chapter, we limit our focus on the four-level classification presented above.

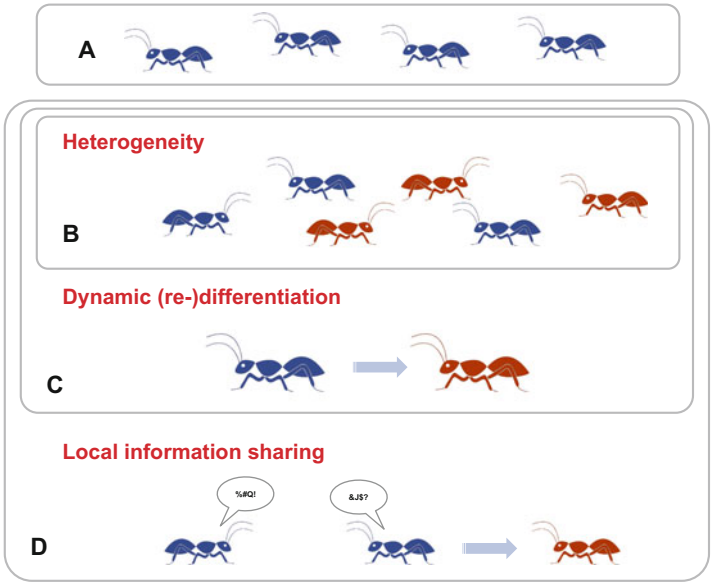

Fig. 1 Proposed four levels of complexity of morphogenetic collective systems. (**a**) Homogeneous collective. (**b**) Heterogeneous collective. (**c**) Heterogeneous collective with dynamic (re-)differentiation. (**d**) Heterogeneous collective with dynamic (re-)differentiation and local information sharing. These four classes form a hierarchical level structure; see text for details

3 Developmental Models: Morphogenetic Swarm Chemistry

We utilized our earlier "Swarm Chemistry" model (Sayama 2009, 2012a) to construct a new computational model of morphogenetic collective systems. Swarm Chemistry is a revised version of Reynolds' well-known self-propelled particle swarm model known as "Boids" (Reynolds 1987). In Swarm Chemistry, multiple types of components with different kinetic behavioral parameters are mixed together. Their behavioral parameters are represented in a "recipe" as shown in Fig. 2. Therefore, the Swarm Chemistry model is already capable of representing both Class A (homogeneous) and Class B (heterogeneous) collective systems. In Swarm Chemistry, components with different types spontaneously segregate from each other even without any sophisticated sensing or control mechanisms, often forming very intricate self-organizing dynamic patterns (Sayama 2009, 2012a).

To make individual components capable of dynamic differentiation/re-differentiation and local information sharing, we made several extensions to Swarm Chemistry (Sayama 2014). First, we made each individual component able to obtain information about its own dynamical type and its local environment in the form of *observation vector o* (Fig. 3) and then utilize this vector to decide which dynamical type it should assume. This allows for dynamic (re-)differentiation required for Class C/D collective systems. This decision-making process was

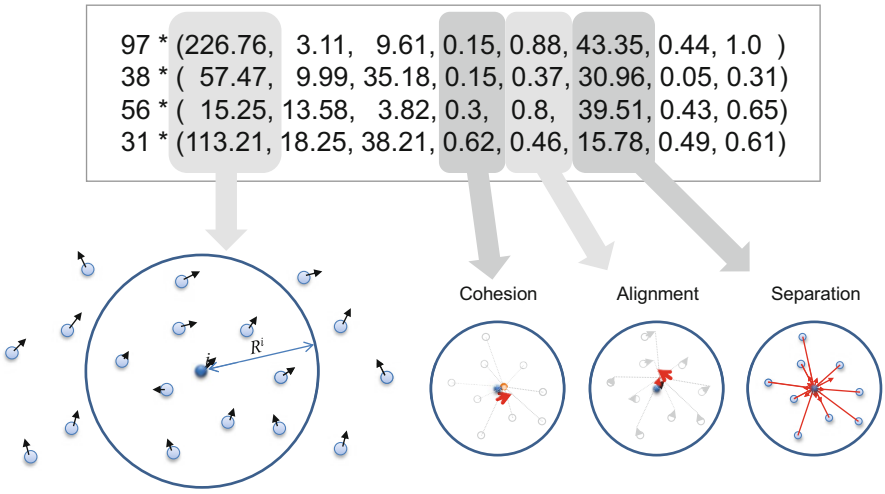

Fig. 2 Encoding of behavioral parameters in a *recipe* in Swarm Chemistry. A recipe is a list of parameter values written in the format "*number of particles* * (*parameter values for behaviors of those particles*)." The parameters include the radius of interaction (bottom left) and the strengths of three primary rules (cohesion, alignment, and separation; bottom right)

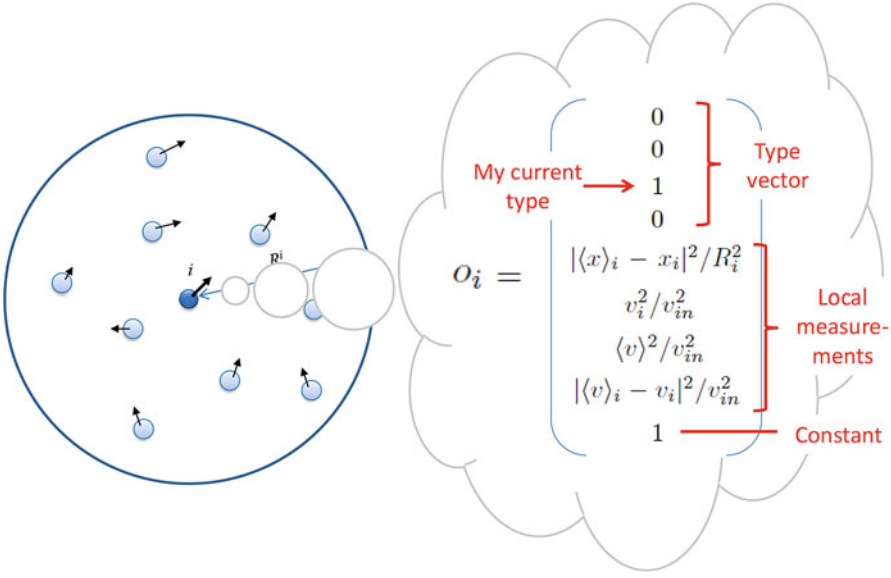

Fig. 3 Observation vector *o* of each particle used in Morphogenetic Swarm Chemistry. The first several values of *o* encode the current type of the particle, while the rest captures the measurements of its local environment. A constant unity is also included at the end of the vector

Table 1 Parameterization of four complexity levels of Morphogenetic Swarm Chemistry models

Class	Recipe	U	w
A	Single-type	0	0
B	Multiple-type	0	0
C	Multiple-type	$\neq 0$	0
D	Multiple-type	$\neq 0$	$\neq 0$

implemented via multiplication of *preference weight matrix* U to the observation vector o, so that letting $U = 0$ represents Class A/B systems as well. The second model extension was to introduce *local information sharing coefficient* w, with which the actual input vector multiplied by U was calculated as the weighted average between the component's own observation vector and the local average of all the observation vectors of neighbor components. Changing the value of w represents switching between Class C and Class D collective systems. With these, the four complexity levels discussed in the previous section were fully parameterized as shown in Table 1. This expanded model is called "Morphogenetic Swarm Chemistry" hereafter. More details can be found in Sayama (2014).

4 Differences of Developmental Processes Across Complexity Levels

We conducted a series of computational experiments using the Morphogenetic Swarm Chemistry model to investigate the differences of their developmental processes across the four complexity levels. This was conducted by detecting statistical differences in topologies and behaviors of self-organizing patterns that were collected via Monte Carlo simulations using randomly sampled parameter values. Topological and behavioral features of self-organizing patterns were measured using several kinetic metrics (average speed, average absolute speed, average angular velocity, average distance from center of mass, average pairwise distance) as well as newly developed network analysis-based metrics (Sayama 2015; Wasserman 1994; Barabási 2016) (number of connected components, average size of connected components, homogeneity of sizes of connected components, size of largest connected component, average size of non-largest connected components, average clustering coefficient, link density) that were measured on a network reconstructed from the individual components' positions in space (Sayama 2014). These new metrics allowed us to capture topological properties of the collectives that would not have been captured by using simple kinetic metrics only.

Results showed significant differences in most of the metrics between the four different classes of morphogenetic collective systems (Sayama 2014). Specifically, heterogeneity of components had a strong impact on the system's structure and behavior, and dynamic differentiation/re-differentiation of components and local information sharing helped the system maintain spatially adjacent, coherent

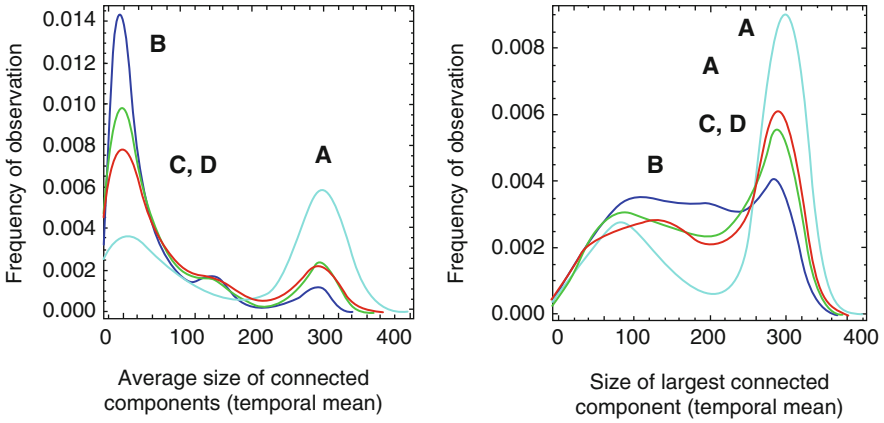

Fig. 4 Examples of experimental results showing clear differences of morphological properties among the four classes. Left: Distributions of the average size of connected components in generated morphologies. Right: Distributions of the size of the largest connected component in generated morphologies. In both plots, Classes C and D show intermediate distributions between those of Class A and Class B

organization. Statistical differences were particularly significant for topological features, demonstrating the effectiveness of our newly developed network analysis-based metrics. It was also observed that the properties of Class C/D collective systems tended to fall in between Class A and Class B in many metrics (Fig. 4). Moreover, it was noted that, as a byproduct, stochastic re-differentiation of components naturally realized a self-repair capability of self-organizing morphologies (Sayama 2012a, 2010).

As described above, straightforward statistical analysis placed the properties of Class C/D systems somewhere in between Class A and Class B, while it did not clarify whether Class C/D systems had any truly unique properties different from Classes A or B. Therefore, we conducted more in-depth, meta-level comparative analysis of *behavioral diversities* between those four classes of morphogenetic collective systems (Sayama 2015a). Behavioral diversities were measured for each class by computing the approximated volume of behavior space coverage, the average pairwise distance of two randomly selected behaviors in the behavioral space, and the differential entropy (Cover 2012) of the smoothed behavior distribution. More details can be found in Sayama (2015a). Results indicated that the dynamic (re-)differentiation of individual components, which was unique to Class C/D systems, played a crucial role in increasing the diversity in possible behaviors of collective systems (Fig. 5). This new finding revealed that our previous interpretation that Class C/D systems would behave more similarly to Class A than to Class B was not quite accurate. Rather, the difference between Classes A/B and Classes C/D helped make more diverse collective structures and behaviors accessible, providing for a larger "design space" for morphogenetic collective systems to explore.

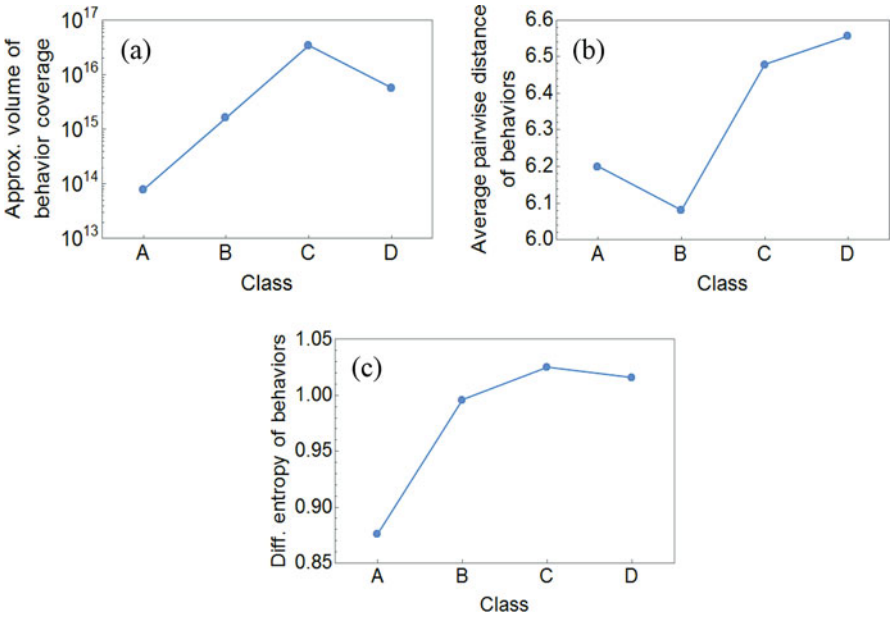

Fig. 5 Behavioral diversities of morphogenetic collective systems measured using three metrics: (**a**) approximated volume of behavioral coverage, (**b**) average pairwise distance of behaviors, and (**c**) differential entropy of behaviors. In all of the three plots, Classes C and D showed greater behavioral diversity than Classes A and B

5 Evolutionary Design of Morphogenetic Collective Systems

The remaining question we want to address is how to design novel self-organizing patterns of morphogenetic collective systems. Unlike conventional engineered systems for which clear design principles and methodologies exist, complex systems show nontrivial emergent macroscopic behaviors that are hard to predict and design from microscopic rules bottom-up (Braha et al. 2006). To design such systems, the evolutionary approach has been demonstrated to be one of the most effective means (Bar-Yam 2003; Sayama 2014b). Here we adopt two different evolutionary approaches: one is interactive evolutionary computation (IEC) (Takagi 2001; Sayama 2009; Bush and Sayama 2011; Sayama and Dionne 2015) and the other is spontaneous evolution within a simulated artificial ecosystem (Conrad and Pattee 1970; Sayama 2011a,b).

In the IEC approach, we developed a novel IEC framework called "Hyper-Interactive Evolutionary Computation (HIEC)" (Bush and Sayama 2011; Sayama and Dionne 2015), in which human users act not only as a fitness evaluator but also as an active initiator of evolutionary changes. HIEC was found to be highly effective in exploring the extremely high-dimensional design space of Swarm Chemistry, discovering a number of nontrivial, lifelike morphological patterns and dynamic

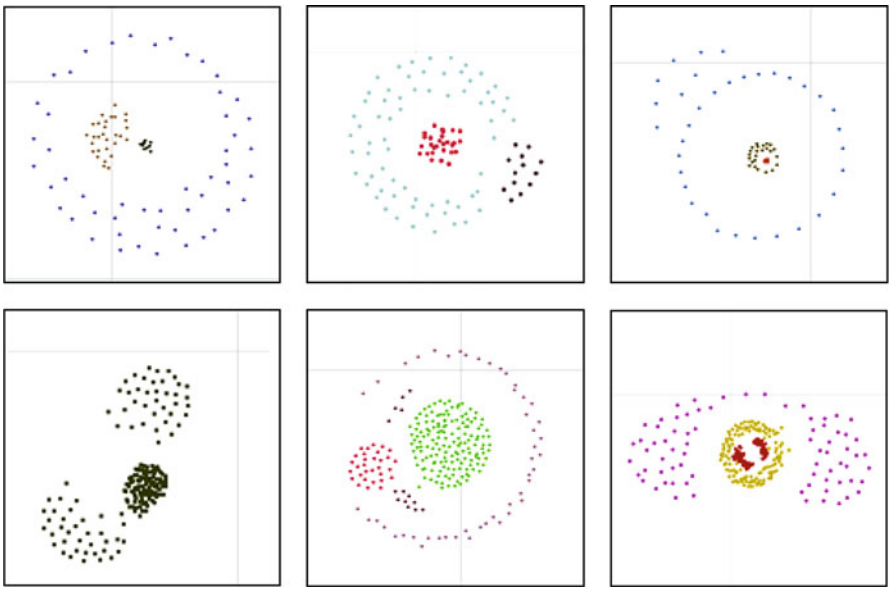

Fig. 6 Several examples of self-organizing lifelike patterns in Swarm Chemistry evolved using the interactive evolutionary computation approach

behaviors (Fig. 6).[2] We also found that these designed self-organizing patterns were remarkably robust against dimensional changes from 2D to 3D (Sayama 2012b) (Fig. 7), which is highly unique given that behaviors of complex systems generally depend heavily on spatial dimensions in which they develop.

Finally, in the spontaneous evolution approach, we replaced the human users in IEC with microscopic "physics laws" that would govern transmission of recipe information among individual components (as evolutionary operators acting at local scales) and macroscopic measurements of "interestingness" (as assessments of evolutionary processes at global scales) (Sayama 2011a,b). Specifically, recipe information was assumed to be transmitted between two colliding particles (with stochastic mutations possible at a small probability). The direction of transmission was determined by specific microscopic laws. These laws were perturbed globally at certain intervals to introduce variations and thus keep the evolutionary processes active and ongoing. The interestingness of evolution was measured by spatial structuredness (i.e., deviation from random homogeneous patterns) and temporal novelty production rates. More details can be found in Sayama (2011a,b). This spontaneous evolution approach was shown to be very powerful in continuously

[2]For more evolved patterns, see the Swarm Chemistry website: http://bingweb.binghamton.edu/~sayama/SwarmChemistry/

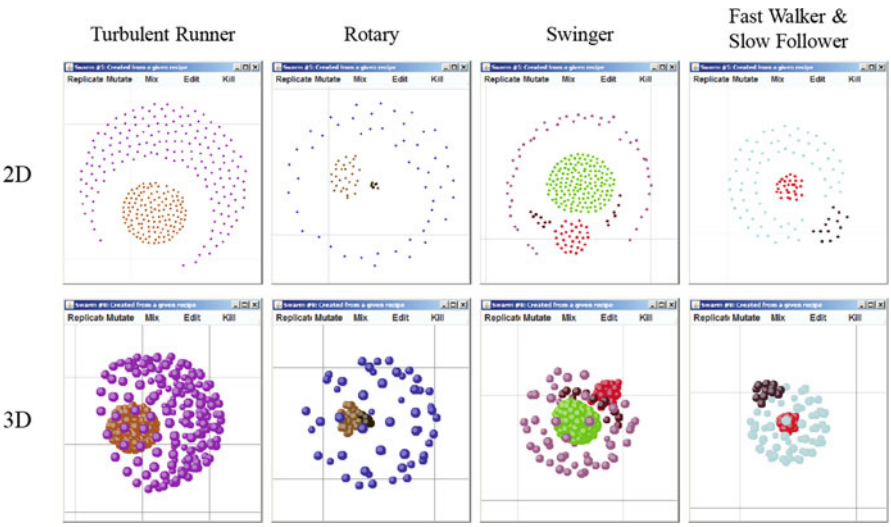

Fig. 7 Comparison of morphologies between 2D and 3D spaces, both developed from identical recipes

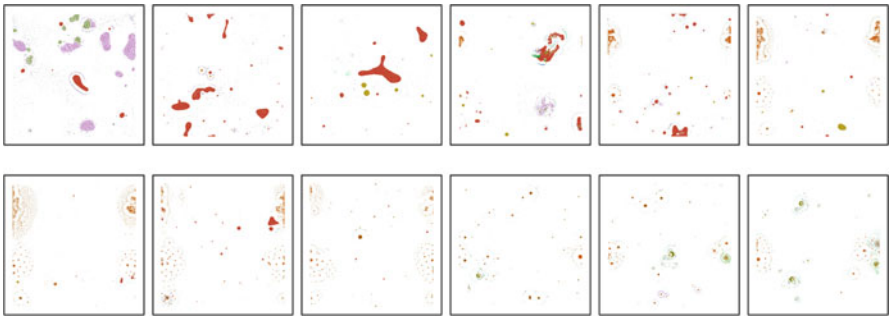

Fig. 8 Sample simulation run of Evolutionary Swarm Chemistry (from Sayama 2014b). Time flows from left to right (the bottom row follows the top one)

producing nontrivial morphologies. An example is given in Fig. 8, and other illustrative evolutionary processes can be found online.[3]

In the meantime, it was also noticed that evolutionary exploration was much less active in three-dimensional space than in two-dimensional one (Sayama 2012c), despite the robustness of self-organization against the same dimensional changes. This sensitivity was considered to be due to the fact that spontaneous evolution heavily relies on collisions between particles, which would become fundamentally less frequent in 3D space (Pólya 1921; Domb 1954).

[3] https://www.youtube.com/user/ComplexSystem/videos

6 Conclusions

In this chapter, we gave a condensed summary of our recent project that explored the complexity, development, and evolution of morphogenetic collective systems. The classification scheme of morphogenetic collective systems we proposed was among the first that focuses on functional and interactive capabilities of microscopic individual components. By orthogonalizing microscopic components' capabilities with macroscopic system behaviors, one can define a design space for various forms of morphogenetic collective systems, which will be useful for both classification of biological collectives and design of self-organizing artificial collectives.

The numerical simulation results obtained by using Morphogenetic Swarm Chemistry demonstrated that each of the characteristic properties of collective systems has unique, distinct effects on the resulting morphogenetic processes. Heterogeneity of components has quite significant effects on various properties of the collective systems, while the ability for individuals to dynamically switch their types contributes to the spatial coherence, the ability to self-repair, and the increase of behavioral diversity of those collective systems. Such behavioral richness would be the necessary ingredient for collective systems to evolve sophisticated structures and/or functions, which was partly demonstrated in the evolutionary approaches also discussed in this chapter.

This short chapter is obviously not sufficient to cover the whole scope of the project, which also produced several more application-oriented contributions that were not discussed here. Interested readers are encouraged to visit our project website.[4]

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