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Clustering Behavior of a Bio-inspired Decentralized Aggregation Scheme

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Abstract

This note reviews a bio-inspired scheme for aggregating autonomous agents in the absence of global communication or coordination, a problem that is known as *Decentralized Gathering*. We present results on the clustering behavior of the agents, as we vary the main parameter that controls the agents' aggregation. Our observations show that there exist two phenomenologically different behaviors, characterized by two different evolutions of the number of clusters with time. We relate these different behaviors to the coupling of two factors: a change in the scale of the interaction range of the agents and a change in the significance of the local fluctuations in the model.

Introduction

Assume that a large number of autonomous and *identical* agents are scattered on a plane, and that there is no global authority to coordinate their actions nor any means of global communication. The problem of gathering these agents in a small area is known as the Decentralized Gathering. This problem is known to be difficult in general and is even be impossible to solve exactly in some continuous space frameworks (Prencipe (2007)).

One approach to solving the decentralized gathering problem consists of imitating the behavior of the amoebae species *Dictyostelium discoideum* (Fatès (2010)). The main characteristic of this approach is the existence of an *active* environment that conveys simple messages among the agents, which are called *virtual amoebae*. The agents interact with the environment by either initiating the transmission of a message or by detecting the existence of messages in their local environment. These two types of interaction are the building components for a stigmergic behavior.

The virtual amoebae aggregation scheme has been shown to exhibit a rich dynamical behavior (Fatès (2010); Vlassopoulos and Fatès (2010)) and to be robust. In this note, we focus on a Cellular Automaton-based (CA) instance of the aggregation scheme, as it has been described in (Fatès, 2010), and present a qualitative description of the two contrasting, clustering behaviors that can be observed in the model. As we will describe, these behaviors result from a change of scale on the interactions among the agents, from short-ranged to long-ranged. Interestingly, the aggregation behavior persists despite this change of scale.

Virtual Amoebae Aggregation Scheme

Active Environment

The existence of an active environment simplifies the agent behavior, by delegating parts of its complexity to the environment and allows for "self-sustained" messages, that can travel arbitrary large distances. The active environment is modeled with a two-dimensional Greenberg Hastings reaction-diffusion cellular automaton (GHCA, see Greenberg et al. (1978)). The CA consists of an array of cells of dimensions $L \times L$, a set of cell states, Σ, a set of transition rules for the states and, for each cell, a set of cells that constitute its neighborhood $\mathcal{N}_c$.

In the GHCA, $\Sigma = \{M, \ldots, 0\}$, where M is called the *excited* state, $M-1, \ldots, 1$ are called the *refractory* states and 0 is the *neutral* state. A cell becomes excited only if it is neutral and if at least one of its neighboring cells is excited. An excited cell will become refractory in the next time step and then decrease its state until it reaches the neutral state. The dynamics of the GHCA involve "waves" composed of wavefronts of excited cells followed by refractory cells that extend outwards from an excitation. Most importantly, when two reaction-diffusion wavefronts meet, they annihilate.

Agents

For simplicity, we consider agents as particles that can read the states of the cell on which they reside as well as the state of the neighboring cells. The virtual amoebae behavior is then summarized as follows: If the state of the cell where an agent resides is 0 (neutral), then, at each time step, the agent initiates ("fires") a reaction-diffusion process with probability λ, by setting the state of the cell to M. If the cell is neutral and an excited neighbor is detected, the agent moves towards the excited neighbor, choosing randomly if more than one are excited. Otherwise, if the cell is in a refractory state, do nothing. Here, λ, the *firing rate*, is the most important parameter of the aggregation model. In our study, each cell can hold at most two agents. Increasing the cell capacity affects mainly the spatial dimensions of the clusters and, for high values of λ, the aggregation time. Figure 1 shows the aggregation process for two different values of λ.

One may thus wonder what is causing the agents to aggregate in both cases, where we see a completely different quantitative behavior. A partial answer to this question is: the presence of fluctuations, both in terms of the density and in terms of emission of reaction diffusion waves.

Clustering Behavior

In a previous work (Vlassopoulos and Fatès (2010)) we have shown that there exists an optimal value of λ such that the aggregation time is minimized. The two different clustering behaviors became apparent while studying the aggregation properties of the model (Fig. 1). In both cases, the agents, given a sufficient amount of time, will aggregate to a single cluster, but as we can observe, this is accomplished by exhibiting two completely different sequences of intermediate macroscopic configurations. In the second (bottom) figure, where λ is large enough, we observe that the agents form small clusters that progressively merge into bigger ones. This process continues until there are a few large clusters that persist for a relatively large amount of time before merging into a single one. However, in the first (top) figure we can observe that the agents "collapse" into a single cluster, without going through the formation of intermediate, persisting, clusters.

From our experiments so far, we have observed that this transition, i.e. from (A) the formation of competing clusters and progressive merging into a single one to (B) the "collapse" of the agents into a single cluster, and inversely, appears to be continuous. One important remark is that high values of λ favor small-range interactions among the agents, in the sense that the distance a wave will manage to travel, and consequently, the number of agents it will manage to interact with, before it is annihilated by the presence of other waves in the environment decreases as λ increases. Accordingly, small values of λ will allow a wave to travel larger distances and interact with more agents before it is annihilated, and therefore can be considered as larger-range interactions. To sum up, the aggregation process persists, in spite of the scale changes and the different macroscopic behavior that results from these changes.

Fluctuations as a Source of Order?

What is the "driving force" of aggregation in the different scales we described? The common denominators that "destabilize" persisting clusters and cause agents to collapse in both behaviors are the fluctuations, in terms of density and in terms of emissions. The density fluctuations exist even for very small values of λ, but in this case, where the interaction wavelengths are greater than the grid size, they are not significant and the agents aggregate into one cluster. For

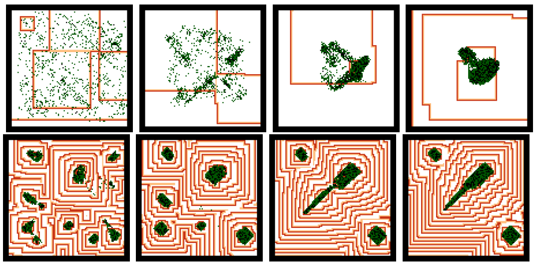

Figure 1: Aggregation instances for different values of λ. Top: $\lambda = 1 \cdot 10^{-5}$ Bottom: $\lambda = 8 \cdot 10^{-2}$. Agents are shown with green and the reaction diffusion wavefronts with orange. The initial number of agents is 400.

high values of λ they become important and are the main reason for the generation of the initial small local clusters that will subsequently merge, until only one cluster remains, but also one of the reasons that cause cluster to merge, since that out of two clusters with (sufficiently) different number of amoebae, we expect that the larger one will emit more waves, in average. The fluctuations in the emission times are the driving force that causes the clusters to merge, for both small and large values of λ. However, it is interesting that we observe the same effective behavior of the system in different scales. More precisely, the same "forces" that cause two amoebae to merge into a cluster, will cause two clusters to merge into a larger one and so on, until only one cluster exists. The merging behavior seems to be similar at different scales, which leaves us with the question: are there quantities that are invariant with respect to rescaling?

To conclude, we described a bio-inspired model that shows how it is possible to exploit the presence of fluctuations in a constructive way, in order to drive a system to a desired final state. The existence of an active environment simplifies the overall model design, but also increases the significance of fluctuations, that constitute a major factor to the operation and robustness of the model.

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