A Robust Aggregation Method for Quasi-blind Robots in an Active Environment*

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Abstract. The aggregation of a swarm of autonomous agents into compact clusters is often a required behavior of multi-agent systems. In the case where no central control or coordination exists, this problem is known as the *Decentralized Gathering*. This presents a first step in the application of a bio-inspired aggregation scheme to aggregate robots whose abilities are very restricted: the only way they can communicate is through an active environment (stigmergy) and the only information they can receive is the local detection of the waves produced by other robots. The active environment obeys a cellular automaton rule and is simulated with a projection of light on the robots.
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1 Introduction

Let us consider a system constituted of a great number of autonomous robots randomly spread on a plane area, the *environment*. The robots need to gather to realize a given task, for instance to exchange of information about the area or to unite to collectively remove an obstacle. In the case where the agents are not aware of their position, orientation or of the presence other agents in the environment and if furthermore there are no means of centralized coordination, the problem is known as *Decentralized* Gathering.

Similar problems have been studied before, using different assumptions about the agents and the environment. An early work [3] on the subject deals with the distributed coordination of a swarm of robots in order to form geometrical shapes. The work presented in [1,2] studies the emergent aggregation of robots that mimic the behavior of *Blattela germanica*, while [4,14] study the aggregation problem under the assumption of limited visibility. Finally, [13] presents some recent theoretical developments on the problem of decentralized gathering.

One approach to solving the decentralized gathering problem consists of imitating the amoeba species *Dictyostelium discoideum* [6]. The global behavior of this aggregation scheme has been studied in the scope of cellular automata (CA) modeling. However, the scheme is more generic, as it can be considered

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as a generic behavioral description. The key ideas that characterize the scheme is the existence of an *active* environment that conveys simple messages between the agents, here called the *virtual amoebae*. The agents interact with the environment by either initiating the transmission of a message or detecting the existence of messages in their local environment. These two ingredients form the basis for a stigmergic behavior.

Initially, the aggregation scheme involved agents that were modeled either as particles residing on the cells of a CA or as properties of the CA cells [6,7]. The rules that govern the evolution of the cellular automaton mimic reaction-diffusion waves, namely they follow the Greenberg-Hastings CA [8].

The first advantage of this scheme is that both agents behavior rules and the active environment are simple and straightforward to implement. Numerical simulations have further shown that the aggregation scheme is robust under different assumptions and perturbations in the environment, i.e. presence of obstacles and noise in the movement of the agents. In this paper, we present our first results on the application of the aggregation scheme to the case of robotic agents and we examine two different series of experiments that use physically different implementations of the same active environment.

The first approach we will present is based on the ALICE micro-robots [9]. These robots feature a compact design but have a restricted set of abilities: the sensors of the robots we handled were only two sensors that could measure the light intensity of a source located above the robots. The second approach uses the a modified version of the KheperaIII robots, in conjunction with the interactive table ROMEA that has been specifically developed for conducting robotic experiments [10]. These robots have a far more sophisticated design as they interact with the interactive table. Their standard sensors include peripheral infrared transceivers that can be used to measure distance from obstacles and ultrasound distance sensors. Further, they are equipped with color sensors that are capable of measuring the intensity of the (Red, Green, Blue) color components of the surface beneath the robot, which allows them to read the values projected on the interactive table, as well as LEDs that allow the table to track their position. However, as we will describe later, we made a minimalistic use of these features: our goal is indeed to present a simple method for a aggregating the robots, in particular we want the experiment to be set rapidly without having to tune a great range of parameters.

This paper is organized as follows: Section 2 presents the aggregation scheme while Section 3 describes the implementation on the two different types of robot agents. Following, Section 4 presents the advantages and drawbacks that we observed during our experiments, as well as the differences we observed between the two types of robots and environment implementations. Finally, we discuss the results in Section 5.

2 Description of the Aggregation Scheme

The *virtual amoebae* aggregation scheme is based on the interaction of virtual agents with an active environment. To implement the active environment where the robots evolve, we use a CA approach in the form of the Greenberg-Hastings (GHCA) model for reaction-diffusion processes. There are two main advantages that make this type of environment attractive: (a) it is easy to implement and simulate in software and, (b) the reaction-diffusion wavefronts travel over arbitrary large distances in the environment without any attenuation. From a practical viewpoint, making the agents aware of the environment and enabling them to interact with it, i.e. *linking* the agents with the environment, requires a different approach for the two types of robots. We now describe shortly the GHCA and the parameters that govern the environment.

2.1 Description of the CA Environment Layer

Let $\mathcal{L} = \{1,\ldots,L\} \times \{1,\ldots,L\}$ be a two dimensional array of cells where L determines the environment size. Each cell $c = (c_x, c_y)$ is associated with a state σ such that $\sigma \in \{M,\ldots,0\}$ We will call M the excited state, 0 the *neutral* state and states $M-1,\ldots,1$ the refractory states. The state of a cell at time t is denoted by σ_c^t The time evolution of the state of each cell is a function of its current state and the states of the cells in its neighborhood. If we denote by $E_c^t = \{c' \in \mathcal{N}_c : \sigma_{c'}^t = M\}$ the number of excited cells in the neighborhood of c at time t, then the state evolution of a cell, c is described by the following set of equations:

$$\sigma_c^t = \begin{cases} M, & \sigma_c^t = 0 \text{ and } |E_c| > 0 \\ \sigma_c^t - 1, & \sigma_c^t \in \{1,\ldots,M-1\} \\ 0, & \text{otherwise} \end{cases}$$

Our experiments used two types of neighborhood: 4-connected, 8-connected neighborhood and, in the case of the KheperaIII robots, a special circular neighborhood to simulate the diffusion of isotropic waves. Finally, we assumed that the environment boundaries are *free*, i.e. wavefronts that reach the boundaries are simply absorbed. This is a desired behavior, since, as we will see, we want the agents to move towards the direction of the source of a wavefront.

The reaction-diffusion process can be quantitatively described as *waves* that start from single excited points and expand outwards. Figure 1 shows the evolution, after $t = 20$ steps steps of 5 initial wave departures.

2.2 Coupling of the Virtual Amoebae with the environment

The basic model assumptions for the behavior of the virtual amoebae (agents) can be summarized in the following:

- Each agent is independent.

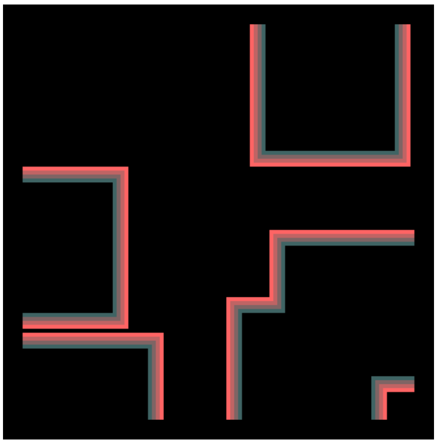

Fig. 1. Reaction-diffusion process with M=4, t=20 and 5 initially excited cells. Excited cell are marked with bright red color, while cells in the neutral state are marked with black.

– There is no direct communication among agents.
– Each agent interacts only with its immediate environment (local interaction).
– Agents are not aware of their position, orientation or relative positions of other agents in the environment (quasi-blindness).

With the above in mind, the behavior of each agent can be described as follows:

1. If a reaction-diffusion wavefront is detected in the immediate neighborhood of an agent, *and* the agent is not on a refractory cell (or in a refractory state) then the agent moves towards the wavefront.
2. If nothing is detected, then the agent initiates a reaction-diffusion wave by modifying the cell of the environment where it resides. This happens with probability p_F so that the average number of waves emitted by an agent are $\lambda \frac{\text{waves}}{\text{sec}}$. The agent then becomes *idle*, which means that becomes insensitive to the environment.

Therefore, quantitatively, each agent either moves towards a wavefront, if is detects one excited cell in its neighborhood, or, initiates a reaction-diffusion process with a certain probability that we will call the *firing rate*. The above rules describe the behavior of agents on a discrete lattice [6]. Naturally, their implementation migration of this behavior to agents operating in a physical environment required some changes. The most important problem is to prevent an agent from detecting and following a wave he has just emitted. In the following section we look into the details of this implementation.

3 From Virtual Amoebae to Robot Agents

The main differences between the original CA-based instance of the aggregation scheme and its robot counterpart concern space and time. In simulations, both the agents and the environment operate in discrete time but in the physical experiments the movements of the robots are continuous. Moreover, in the discrete model, the actual size of the agents is neglected and each agent is simply assigned to one cell as a location. In the physical experiment, the agents have a non-negligible size and they cover many environment cells. As a consequence, the relative length of the environment cells with respect to the agent dimensions, as well the *sampling time*, that is, the time unit which separates consecutive CA steps, become important, since they affect how the agents perceive and interact with the environment.

3.1 Chemotaxic behavior

Before going into further details, we call the reader's attention on the fact that it is the same behavior that is used for the two robots. This behavior was mainly chosen to cope with the limited abilities of the sensors of the ALICE robots. An overview of these robots is shown in Figure 2. The robots are equipped with two wheels, so that controlling their speed and direction can be accomplished by setting the speed of each wheel. The two light sensors are located on the front of the robot. These sensors are connected to analog-to-digital converters, and the intensity of the incident light is measured in a normalized scale from 0 to 100. The wheel motors can be controlled independently by setting their rotation speed. From an agent-based point of view, the behavior of an agent can be described as a control system with two input variables and two output variables: the light sensor measurements and the motor speeds.

Fig. 2. ALICE robot

The main problem to achieve the aggregation is that by using only two sensors, we cannot determine the exact direction of an incoming wave. An example of such ambiguity is shown in Fig. 3: the robot can not distinguish between the two incoming wavefronts. Indeed, from the different time of arrivals of the wavefronts, the agent can only determine if the wave is more or less parallel to the line that connects the two sensors. In other words, in the best case we are able to determine the absolute value of the angle of the incoming waves, but not its sign. One solution to this problem would be to use three or more sensors. Nevertheless, this would require designing a specialized extension module, as well as some extra processing overhead in order to determine both the angle and the sign.

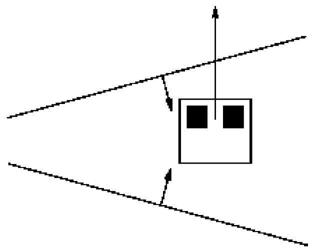

Fig. 3. An example of the directional ambiguity, where the robot cannot distinguish between the two incident wavefronts

The simplest method to overcome the directional ambiguity is, surprisingly, to completely ignore it. As we can observe in Fig. 4 by programming the robots to turn for an angle 90^o towards the direction of the incident wave, i.e. towards the sensor that detects an incoming wave, the robot will eventually turn towards the source of the waves, although this might require more than one waves to reach the robot.

The second major problem is related to the capability of the agents to follow the gradient of the incident reaction-diffusion waves. Imagine that a reaction-diffusion wave, whose intensity gradually varies from a maximum value to zero is detected first from one of the sensors and following from the second one. Assume that the agent eventually turns so that its direction is perpendicular to the incoming wavefronts. The problem that arises is that since there are only two sensors and they are placed perpendicular to the movement direction of the agent, they are both parallel to the wavefronts. As a consequence so they become unable to accurately detect the gradient, since the light intensity varies in the same way on the two sensors. This problem appears both when the robot faces towards or away from the reaction-diffusion waves. To resolve this ambiguity, we used again the simplest possible approach. Instead of trying to follow the gradient of the waves, moving towards the source of the wavefront, we programmed the robots to only react to the presence of wavefronts, that appear as a sudden change in the detected luminosity. When such a change is detected, the robot turns towards the sensor that detected the change. The effect of this approach

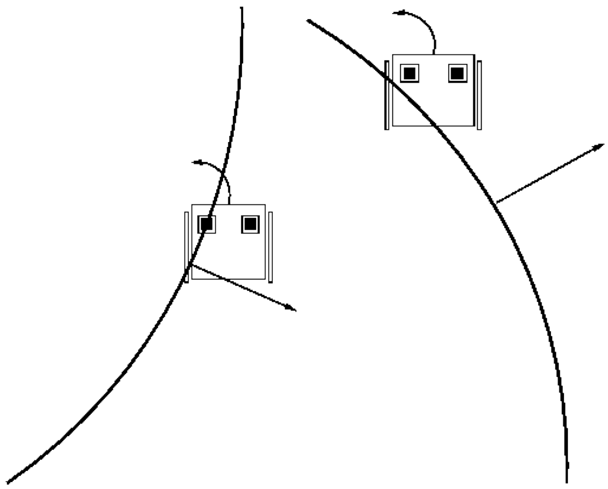

Fig. 4. Elementary chemotaxis movements

is that the agents follow a "zig-zag" track, as it is shown in Fig. 5 towards the source of the waves.

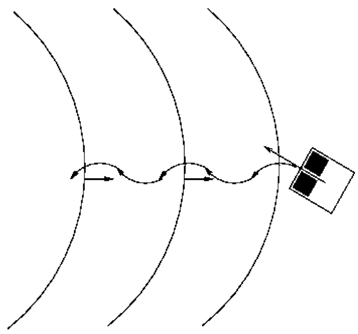

Fig. 5. Zig-zag approach for moving towards the source of reaction-diffusion waves

Note that, contrary to the ALICE robots, the KheperaIII robots have an adequate number of color sensors (7), so that they can properly detect the exact direction of incoming wavefronts as well follow the gradient of the waves. However, in order to be able to compare the two experimental setups, we used the exact same method in both cases. As we will discuss in the following sections, this approach proved to be robust and efficient despite its simplicity.

3.2 Experimental Setup for the ALICE Robots

As we have already seen, ALICE robots are equipped with two light sensors that are located on top of the robot. This arrangement was the basic guideline on the setup of the aggregation experiments, since the reaction-diffusion waves should be projected on the surface where the robots are located from above. We used a setup that was based on a camera and a projector: the images from the camera were processed in real-time in order to identify the positions of the robots on the environment and map them to cell locations in the CA array. By knowing the agent locations and the state of the array, we simulated the environment using FiatLux CA simulator [11] and projected the resulting images back on the surface where the agents were located. Figure 6 shows a snapshot of one experiment, where we can see the agents and the projected waves.

Problems of the experimental setup The main problem of this setup is the fact that although the agents can "read" their environment and detect incoming wavefronts, it is not possible for them to "write" directly on the environment, i.e. to initiate a wave. In order to overcome this problem, we delegated the wave initiation part of the agent logic to the environment. However, since the fire decisions are not taken by the agents, it becomes impossible for them to know whether they should enter a "refractory" state and ignore their own emitted waves. The solution to this problem was again implemented in the environment, and more precisely by generating a "mask" that prevented from painting the first steps of the evolution of the reaction-diffusion process.

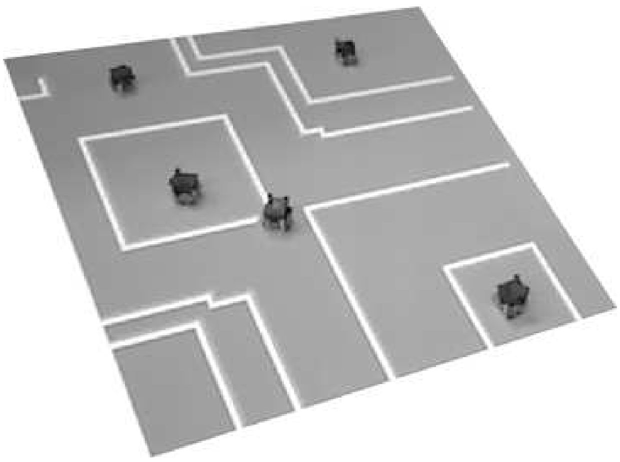

Fig. 6. Snapshot of an experiment with ALICE robots, as taken from the camera that detects the robot positions.

3.3 Experimental Setup for the KheperaIII Robots

In the case of the KheperaIII robots, the experimental setup was eased, since the interactive ROMEA table and the existing programming interfaces provided all the tools required to track the position of the robots and simulate the reaction-diffusion process. In that case, in order to prevent the robots from detecting the waves they emitted, we introduced a refractory delay after each fire event, during which the robot became insensitive to the presence of waves in the environment. That delay was empirically set as a function of the environment simulation step time, which determines the speed of waves and the positions of the sensors on the robot.

Fig. 7. Snapshot of an experiment using the Khepera robots on the interactive ROMEA table. The experiment uses a circular neighborhood with radius 2.5 and M=6

4 Results and Observations

The most important feature that became apparent as soon as we started running the experiments with the ALICE robots is the fact that the aggregation scheme is rather robust with respect to perturbations in the agent movement. More precisely, although the robots that we used for our first experiments were calibrated so as to turn by 90^o, this was not the case during the experiments and as a result, the robots would turn from 0 to sometimes much over 120^o. However, this did not obstruct the aggregation process and in all experiments we performed, the robots managed to form a single cluster. To study this robustness in more details, we implemented a simplified model in software that modeled as closely as possible the ALICE robots, with configurable sensor and wheel positions as well as turning radius. Using this model we ran several experiments while varying the angle a robot turns each time it detects a wave and also trying out some configurations where the angle was a uniformly distributed random number between 0 and 90^o. In all of the above cases, the robots managed to converge, with the fastest average convergence time obtained for a turning angle of 90^o.

One major difference between the ALICE and KheperaIII experiments was that in the first case we did not implement any method for avoiding obstacles. Although this resulted in the ALICE robots blocking and pushing each other, still, this behavior would only delay the aggregation. On the other hand, with the KheperaIII robots, using obstacle avoidance is mandatory since the robots cannot push each other. This does not hinder the aggregation but sometimes produces deadlock configurations in the experiments where the environment contains static obstacles.

One further advantage of the aggregation scheme is that it can be described with a small number of parameters. More precisely, the main parameters to set the agents are the fire rate and the refractory time, if we consider the turn angle and movement time constants. Regarding the environment, the main parameters are the number of states M and the discretization time, that is, the time between two simulation steps. Regarding the latter, it is sufficient to set it such that the final speed of the reaction-diffusion waves are greater than the turn speed of the robots and greater than the ratio of robot dimensions divided by the refractory time. This allows us to ensure that no wavefronts will be detected more than once.

Two basic features of the aggregation scheme is that it works using only local operations and stigmergy, as well as the fact that it delegates most of the communication overhead to the environment. The operations are local both in terms of the agents but also, in the case of a CA based environment, in terms of the environment. Therefore the aggregation is performed without any need for global communication. The second feature makes the greater part of the system complexity hidden in the environment. This significantly simplifies the agent design and agent logic, but also requires the of *active* cells and, so far, we do not how to implement this feature physically.

For the robot control, the behaviour is described with a purely discrete state machine, without having to reside to a "control system" approach. This is an advantage since we have a simple design, but on the other hand, it would be difficult to extend this design to more complex environement types. We thus leave for future work the analysis of other types of obstacle avoidance.

Regarding the disadvantages of our method, the presence of static obstacles, for instance blocked agents, seems to create some deadlock configurations. These configurations appear in the cases where an agent is for example in the corner of an obstacle, either concave or convex. So far we have tested several methods for obstacle avoidance, and although we have some good results, the aggregation times are significantly increased.

One other thing to mention is that the agents seem to destabilize in the cases where we have a robot that would emit waves at a high frequency. In this case, the agents can not separate the consecutive waves, and therefore, turn randomly. This situation was prevented here by the use of idles states for robots. However, it could be an important problem in really noisy environments, in the sense of environments detecting many "false" emissions from agents.

The experiments confirm that the aggregation scheme exhibits good properties of avoidance of obstacles. Further, since the scheme is not based on a gradient method, but only on the detection of wavefronts, that is, abrupt changes on the environment, the number of states of the GHCA can be as low as 3 states ($M = 2$). Our observations indicate that the system's robustness is linked to the fact that it does not depend on the detection of a gradient, but it works more in an "all-or-nothing" fashion. It also appears that the type and size of neighborhood of the GHCA is not so important, as all three neighborhoods that we have tested gave the same or similar results.

A source of improvement of our approach is to improve the aggregation time by minimizing th e number of colliding waves annihilate. Indeed, not all the emitted waves reach all agents and therefore this somehow slows down the aggregation. From a previous research on the aggregation scheme [12], we know that there is an optimal value of the firing rate. A future direction of research is thus to see how this optimal value can be determined for the case of the robotic agents.

5 Conclusions

We have presented some preliminary results on the application of a decentralized aggregation scheme on two different types of agents. This method is based on local interactions of the agents with the environment, and in the case where the environment is modeled through a cellular automaton, the locality is preserved within the environment as well. The main characteristics of the scheme, as we have deduced from our experiments, is that it is robust to perturbations on the movements of agents. The required complexity on the agents is minimal, as well as the required sensor precision. The main difficulty for implementing the aggregation scheme is the design of an active environment. When this environment contains obstacles, one also need to solve some "deadlock" configurations that appear.

Our first results are available through the AMYBIA project webpage[1], where we have included one of the early videos of our ALICE experiments. Several recordings of our KheperaIII experiments are also available on the webpage and are accessible through an applet[2] that "replays" the recorded robot positions and orientation. The list of experiments shown there is by no means final and it will expand as we run more experiments to study and evaluate the properties of the scheme and test new methods for solving the problems that we observe.

[1] http://www.loria.fr/~fates/Amybia/project.html

[2] `http://www.loria.fr/~fates/Amybia/html/showViewer.html`

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