

Measuring Stigmergy: The Case of Foraging Ants

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Abstract. Software today is no longer monolithic, but typically part of a system consisting of many components. As engineers are no longer in control of the entire system, novel methods are sought to design complex software systems that are built from the bottom up and are robust in a dynamically changing environment. The coordination method called stigmergy that is inspired by the collective behavior of social insects is one of the candidates to help solving this problem. In this paper we make a first step in formally understanding the essence of stigmergetic behavior by studying the famous ant foraging model of Deneubourg et al. We explore the relationship between the initial (dis)order in the environment and the performance of the ant foraging behavior. We further study how this configuration of the task to solve governs the behavior of the ant colony, with special focus on the level of coordination that is achieved.

1 Introduction

Software today is not as it used to be. [26] Systems are no longer monolithic, but they are typically part of a larger system consisting of many components, which are partly interconnected and partly co-existing or competing. Software engineers are no longer in control of the entire system; rather, they design solutions that are intended to co-exist with other components, so that the emerging behavior at the system level conforms to the stated goals. As a consequence, novel methods to design ‘complex software systems’ are sought.

Stigmergy is one of the promising concepts to attack the problems of complex software systems. The concept is that of a spatial self-regulatory community of active

components, where the product of the ongoing work motivates the workers and regulates the process. This is underlined by the term itself, which was coined by Pierre-Paul Grassé, a French biologist, in 1959 and originates from the Greek words of *stigma* (sign) and *ergon* (work). [9] Stigmergy is common in insect societies. One of the most known examples is the foraging behavior of any colonies.

In this paper we explore the relationship between the initial (dis)order in the environment and the performance of the ants' foraging behavior. We further study how this configuration of the task to solve governs the behavior of the ant colony, with special focus on the level of coordination that is achieved. Our motivation is best summarized by Parunak and Brueckner, who state that "*The natural tendency of a group of autonomous processes is to disorder, not to organization. (...) We will be successful in engineering agent-based systems just to the degree that we understand the interplay between disorder and order.*" [18] In a sense, we explore formally the phenomena of Herbert Simon's famous ant. [23] According to Simon, an ant crawling on the beach may appear to exhibit complex behavior, even though it is only following simple rules that make it mirror the complexity of the terrain. Applying this metaphor, we seek to understand the relationship between the complexity of the food collecting task at hand, and the complex behavior of the ant colony that solves it. Here we present the preliminary results of a larger project aiming at the understanding of the role of order/disorder in self-organization methods that use the environment of the agents as the primary medium for coordination.

1.1 Foraging Ants

When ants swarm out of their nest they appear to wander randomly at first, but soon they form a well-pronounced trail between the nest and the food source. Surprisingly, the trail found is typically fairly close to the shortest possible path. When there are multiple food sources, the ant colony usually exploits them in the order of their distance.

Individual ants wander out of the nest in random directions, leaving a trail of 'homing pheromone' (a volatile chemical substance) behind. When an ant finds food, it sets out for the nest, this time dropping 'food pheromone' as it goes. Food-seeking ants follow the gradient of 'food pheromone' in their local neighborhood, while homing ants seek places with high amounts of 'homing pheromone'. Below a certain threshold pheromone level and also with a constant probability, the ants move randomly. This latter component controls the balance between 'exploitation' and 'exploration', the essence of optimizing behavior.

Foraging in ant societies is a complex, organized behavior at the colony level, while individual ants apply a simple, probabilistic rule set. It is exactly this agent-level simplicity what makes ant behavior appealing when seeking to tackle complex distributed problems. The key in organizing the colony level behavior is *communication via the environment*, i.e. via pheromones. The communication is always local on the part of the ants (they always leave the pheromone on their actual location), but it is channeled by the physical environment (diffusion and evaporation). Thus, the individual ant has a local communication method using the chemical pheromone, but the

colony itself has no global communication methods. The colony must therefore achieve its macro-goals by coordinating or tuning the individual micro-level ant behavior.

2 A Formal Model of Foraging Ants

In the rest of the paper we will work with the following *model* of the above described behavior, after Deneubourg et. al. [5] Let's consider N ants (indexed by integers from 1 to N) living on a discrete, two-dimensional lattice \mathbf{L} of size S with periodic boundary conditions (i.e., a torus). Let $l_i^t \in \mathbf{L}$ denote the location of ant i at time t , and $f(p) \geq 0$ the amount of food (in discrete units) at position $p \in \mathbf{L}$. Initially, all ants are located in the nest, i.e., $l_i^0 \in \mathbf{K}$, for all $i \in [1..N]$. The nest is defined as a disc of radius R located at an arbitrary position in \mathbf{L} . (Due to the periodic boundary conditions of the lattice, the location of \mathbf{K} may always be interpreted as being in the 'middle'.) The task of the ants is to collect all food units to the nest. For future reference, let F be the amount of food to be collected: $F = \sum_{p \in \mathbf{L}} f(p)$.

The ants leave a trail by depositing pheromone at their current location. The type of the substance depends on whether the ant is homing or seeking food, while the amount A depends on the time T the ant has spent on its current activity: $A = \max(m - (T-1) \cdot d, 0)$, where m and d are model parameters. The emitted pheromone diffuses to neighboring cells and also slowly evaporates. Thus, $\phi_z^t(p)$ gives the amount of pheromone type z at time t at location p .

$$\phi_z^t(p) = \left[\rho \cdot \phi_z^{t-1}(p) + (1 - \rho) \cdot \frac{\sum_{q \in \mathbf{L}, |p-q|=1} \phi_z^{t-1}(q)}{8} \right] \cdot (1 - \delta) + \sum_{i \in [1..N], l_i^t = p} A_i^t$$

where δ is the evaporation rate and ρ is the rate of diffusion, both model parameters. A_i^t stands for the amount of pheromone emitted by ant i at time t .

During their walk, ants follow a simple probabilistic rule: they move to the neighboring cell with the highest pheromone level (depending on their destination, they either seek 'homing pheromone' or 'food pheromone' locations). Below a certain threshold, and with a given probability w , they move randomly. However, the ants prefer not to turn, i.e., their selection of new location is biased by their direction. Let h_i^t be the direction of ant i 's head at time t , given as one of the cells neighboring l_i^t . Moreover, let $left(h)$ and $right(h)$ denote the directions immediately to the left and right from direction h , respectively. The ants' moving rule is then defined as

$$l_i^{t+1} = \begin{cases} random(h_i^t) & \text{with probability } w, \\ pheromone_seeking(h_i^t) & \text{with probability } 1 - w \end{cases}$$

where functions $random(\cdot)$ and $pheromone_seeking(\cdot)$ are defined as follows.

$$\begin{aligned}
\text{random}(h_i^t) &= \begin{cases} h_i^t & \text{with probability } \frac{2}{3} \\ \text{left}(h_i^t) & \text{with probability } \frac{1}{6} \\ \text{right}(h_i^t) & \text{with probability } \frac{1}{6} \end{cases} \\
\text{pheromone_seeking}(h_i^t) &= \begin{cases} \text{random}(h_i^t) & \text{if } \max\{\phi_z^t(D)\} < \alpha \\ \arg \max\{\phi_z^t(D)\} & \text{otherwise} \end{cases}
\end{aligned}$$

where $D = \{h_i^t, \text{left}(h_i^t), \text{right}(h_i^t)\}$ and α is a model parameter.

3 Order in and out of the Ant Colony

The efficiency and flexibility of the above ‘algorithm’ is very appealing, because it is exactly in line with the anticipated needs of modern software systems. However, as Simon observes, an ant crawling on a beach, simply following the erratic surface of sand, will leave an intricately complex pattern of movement. [23] Therefore, it is possible that the efficiency, seen here as a demonstration of complexity, of the foraging ant colony originates from the order present in the initial environment. (Here we use the term ‘order’ to describe the non-randomness of food-placement.)

3.1 Ant Efficiency Depends on Order in the Environment

To test our hypothesis, we have performed computer simulations. During these we have explored various initial configurations of the F units of food. We distributed food equally among G food sources, placed randomly on L . Units of food were placed in the sources with a deviation of σ . We varied G between 1 and 10, and σ between 1 and 50. The other parameters of the model were set according to Table 1. Notice that we kept all parameters directly governing the ‘ant algorithm’ constant. We only varied the *task* to be solved.

In order to quantify the order in a configuration of food, we calculated the *average distance between pairs of food units*. This measure, which clearly depends on S and F , *increases* with decreasing order. Therefore, in the following we will loosely call it the *disorder* of the food configuration. (The dependence on system size can be neglected in case of the experiments reported here, since the two parameters were held constant.)

On the other hand, as a measure of ant colony performance, we used the simulated time that it took to collect $0.9 \cdot F$ units of food in the nest. The reason for the 90% threshold is that the location of the last few remaining food units is essentially random (within the source), and thus they are almost always collected by random walk, since no pheromone trail can prevail that connects them. Accounting for this last random period would add an amount of ‘random noise’ to our measurements. None

theless, our findings hold even if the limit raised to 100%, albeit in a little less strict form.

Table 1. The parameter settings of our experiments

Parameter	Value	Parameter	Value
N	100	W	0.1
S	100	α	1
R	5	δ	0.01
F	800	ρ	0.86
m	100	D	2

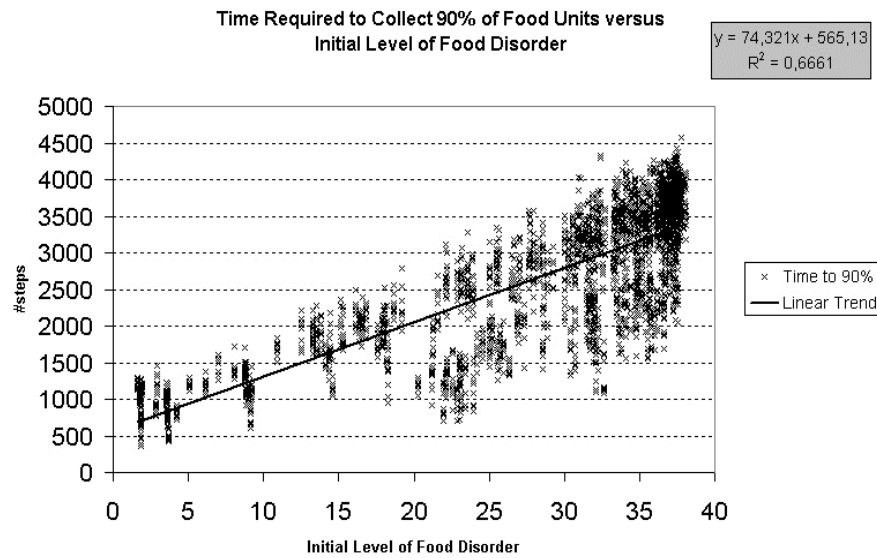


Figure 1. The dependence of the ant colony’s performance on the initial order in food placement. The horizontal axis shows the measure of disorder in the initial food configuration, while the vertical axis represents the number of time steps that it took for the ant colony to collect 90% of the food in the nest. Each mark represents the result of a simulation run with the default parameter set. Food placement parameters were varied: G took the values of 1, 2, 5 and 10, while σ varied between 1, 2, 5, 10, 15 and 20. For $G=1$ we also explored 8, 20, 25, 30, 40 and 50 for σ . Each combination was run with 10 different pseudo random number generator (RNG) seeds for food placement, and each initial configuration was tested with 10 different RNG seeds. That is, the figure shows 10x10 marks for each combination of G and σ

Figure 1 summarizes the dependence of ant colony performance on the initial order in food placement. The horizontal axis shows the measure of order in the initial food configuration, while the vertical axis represents the number of time steps that it took for the ant colony to collect 90% of the food in the nest. It is evident that the performance decays (the number of time steps required to collect the food increases) about linearly as the disorder of the initial configuration increases. However, the variance in performance also increases dramatically, which blurs the picture. Therefore, on Figure 2 we separate the two ‘sources of disorder’, i.e., the cases when we increased the

number of food sources and those when the original order was disrupted by increased deviation from the source. The figure shows the results for $G > 1$, and those with $\sigma > 1$ separately. (The cases when both placement parameters were varied are omitted.)

It is clear that the foraging ants favor more ‘pointed’ food sources, even to the extent of being quicker in collecting *several* ‘compact’ food sources than a single, but ‘disordered’ source. The reason for this tendency is that information about a pronounced food source can be ‘communicated’ (even if indirectly) within the ant community, while this is less efficient for dispersed sources. The thus identified food sources can even be exploited in parallel, explaining the better performance for multiple sources.

Time Required to Collect 90% of Food Units versus Initial Level of Food Disorder

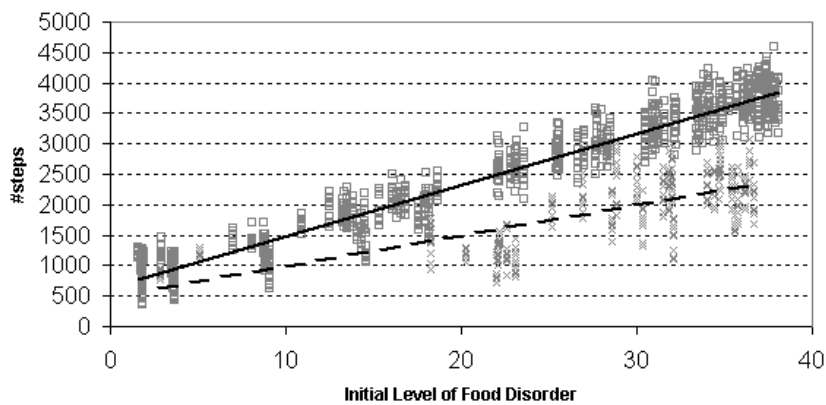


Figure 2. The dependence of the ant colony’s performance on the initial order in food placement, separating single food source cases from ones with multiple sources. The horizontal axis shows the measure of disorder in the initial food configuration, while the vertical axis represents the number of time steps that it took for the ant colony to collect 90% of the food in the nest. Each mark represents the result of a simulation run with the default parameter set. Food placement parameters were varied. Hollow squares represent runs with $G=1$ and σ taking values of 1, 2, 5, 8, 10, 15, 20, 25, 30, 40 and 50. Crosses stand for runs where $\sigma=1$ and G varies over 2, 5 and 10. Each combination was run with 10 different pseudo random number generator (RNG) seeds for food placement, and each initial configuration was tested with 10 different RNG seeds. That is, the figure shows 10x10 marks for each combination of G and σ

It may appear that these results so far are not much more than saying that the algorithm’s performance depends on the difficulty of the task at hand. While this is evidently true, it is important to see that it is not much known about *what* kind of tasks can be solved efficiently by ant-like systems. Albeit analyzing worst-, best-, and average-case performance is common in studies of algorithms, the efforts dedicated to analyze the capabilities of ant algorithms have been limited. [16] Moreover, the point here is that performance depends on the *level of (dis)order* in the initial food placement and that this dependence is vaguely linear. Figure 3 demonstrates that this kind

of dependence is not trivial, by comparing our findings to the performance of a colony of uncoordinated ants performing random walks. The main message of this figure is not that stigmergetic ants outperform the uncoordinated colony, but the clearly different nature of the dependence between the two societies' performance and the initial level of order in the environment.

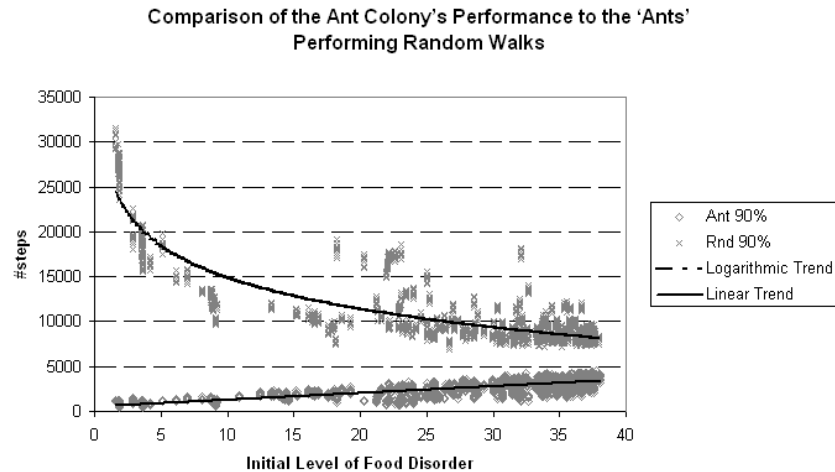


Figure 3. Comparison of the ant colony's performance to the performance of 'ants' performing random walks. The horizontal axis shows the measure of disorder in the initial food configuration, while the vertical axis represents the number of time steps that it took for the colony to collect 90% of the food in the nest. Hollow squares represent the same runs as on Figure 1, while crosses stand for the performance of the 'random ant' colony for the same initial configurations. To implement the 'random ant' colony we used the above ant algorithm with $w=1.0$

3.2 Order in the Ant Colony Corresponds to Order in the Environment

Computer programs solve problems by processing information. That is, they *convert* data from one format to another, changing its information content. In case of the foraging ant society, food units are carried from the source to the nest. That is, the colony changes the configuration of food in the environment. It would be nice to say that the ant colony's task is to reduce the disorder of the food, but this is not always true. Especially, it is often not true in the simplest case, when there is only a single food source. In this case, whether the overall disorder of food decreases or not depends on the size of the food source, compared to that of the nest.

Therefore, we are interested in how the disorder (cf. information content) of the environment changes during the foraging process, and how this change is reflected in the order of the ant colony itself. In the following, we will focus our study on the single food source case.

We measure the (dis)order in food configuration as in the previous section. Similarly, we quantify the ant colony's (dis)order by the *average distance between pairs of ants in the colony*.

Figure 4 and Figure 5 show the development of food and ant colony disorder in case of a single food source. Each panel on the figures shows the change of both food (solid lines) and ant colony disorder (dashed lines) for 10 runs (with different random seeds for ant behavior). Each row contains results for a specific value of food variation (σ) around the randomly selected single food source. The value increases from the top to the bottom. The two figures show two examples of food source placement (values resulting from two different seeds).

The initial value of the ant colony's disorder is the same (low value) on each graph, because the ants start by hiving out from the nest. When the ants start exploring the environment, their disorder rises radically. It reaches its peak when the colony discovers the food source. Then, the ants start forming a trail between the source and the nest, which decreases their disorder. The timing and height of the peak depends on the actual location of the food source. When it is closer to the nest, the random exploration period is shorter and thus the disorder of the ant colony is lower. The peak is also affected by the variation parameter (σ). If the food source is spread out more, this brings its edge closer to the nest.

At the end of the foraging, when most of the food is already in the source, the disorder of the ant colony raises again. This is because there is no more enough food to occupy all the ants, so they start exploring again. However, the persistence of the pheromone trail may delay this phenomenon, as observable on the panels of the first two rows of Figure 4 and Figure 5. In some cases, the disorder of the colony in this last period is even higher than its former peak. This depends on two factors. First, on the time it took for the colony to discover the food source. If they were quick, the peak is likely to be at a lower value. The other factor is a measuring effect: namely, when the recording of the process was stopped. When all food units are in the nest, in the long run, the ant colony's disorder should approach the theoretical maximum value of disorder defined by the parameters of the closed system. This is because the ants move randomly in the absence of food.

On the other hand, the initial disorder of food is the same in each row, as it is governed by the variation around the center of the single food source, but increases with the growth of σ . After the initial random exploration phase of the foraging, a few ants find the food source, and the disorder of the food changes gradually. As the ants' disorder starts to drop, that of the food raises. This is because some of the food units are now taken away from the relatively ordered configuration of the food source, and are now on their way to the nest. Later during the process, the food units are divided in three classes. Some still reside in the source; others are already collected in the nest, while the remaining is in transit. This results in an initial increase in the disorder of food. However, after half of the food units are collected in the nest, each additional unit that leaves the source will bring the disorder down. Even those in transit will, since they are almost certainly traveling *towards* the nest, thus decreasing their distance to more than half of the other food units. (For larger food sources, i.e., when σ is high, the initial disorder of food is so high that the first part of the above described 'hill' in the trajectory partially disappears.)

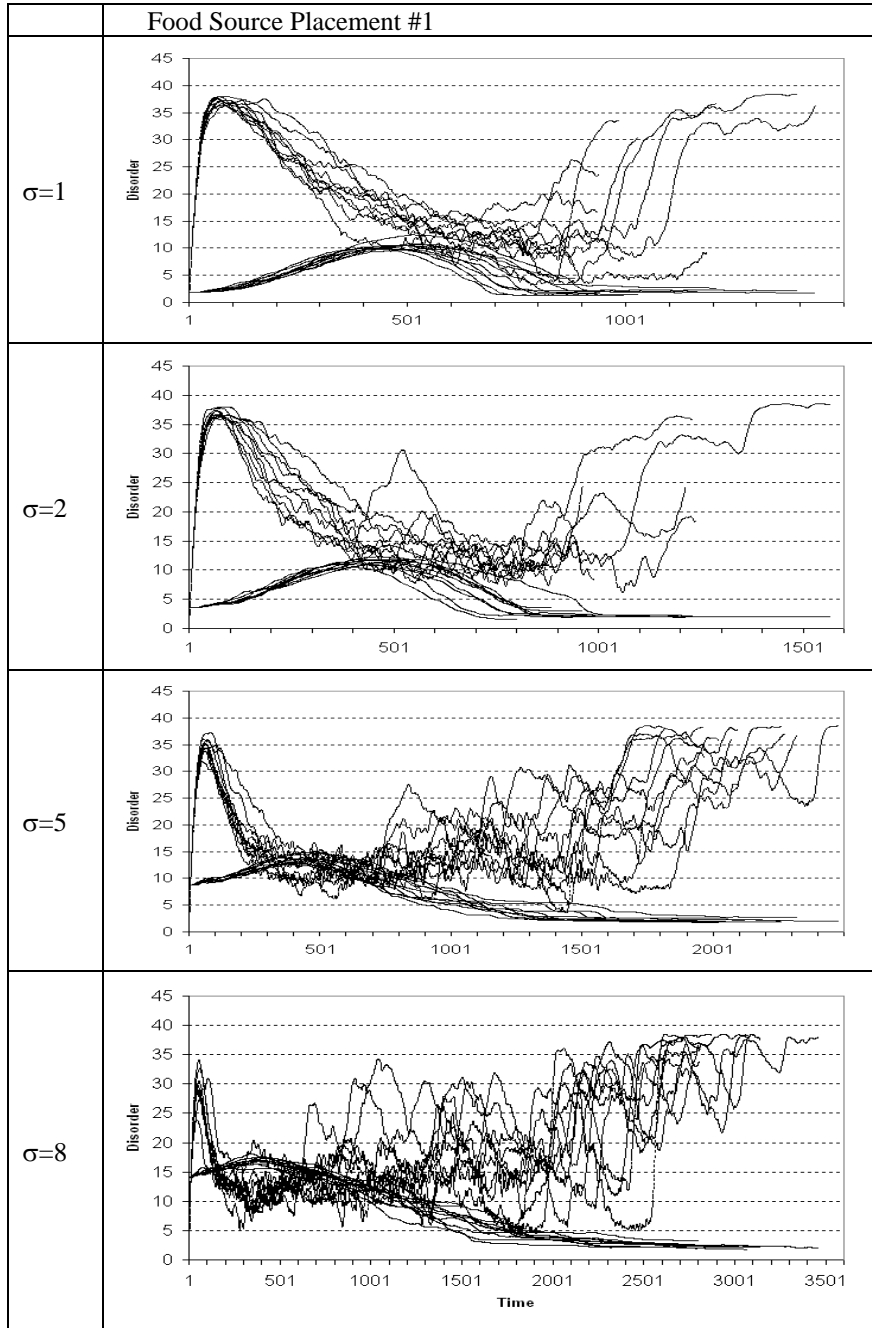


Figure 4. The in-run development of food and ant colony disorder in case of a single food source. Each figure show the time-trajectories of both food (solid lines) and ant colony disorder (dashed lines) for 10 runs (with different random seeds for ant behavior). The rows represent increasing values of food variation (σ) around the randomly selected food source

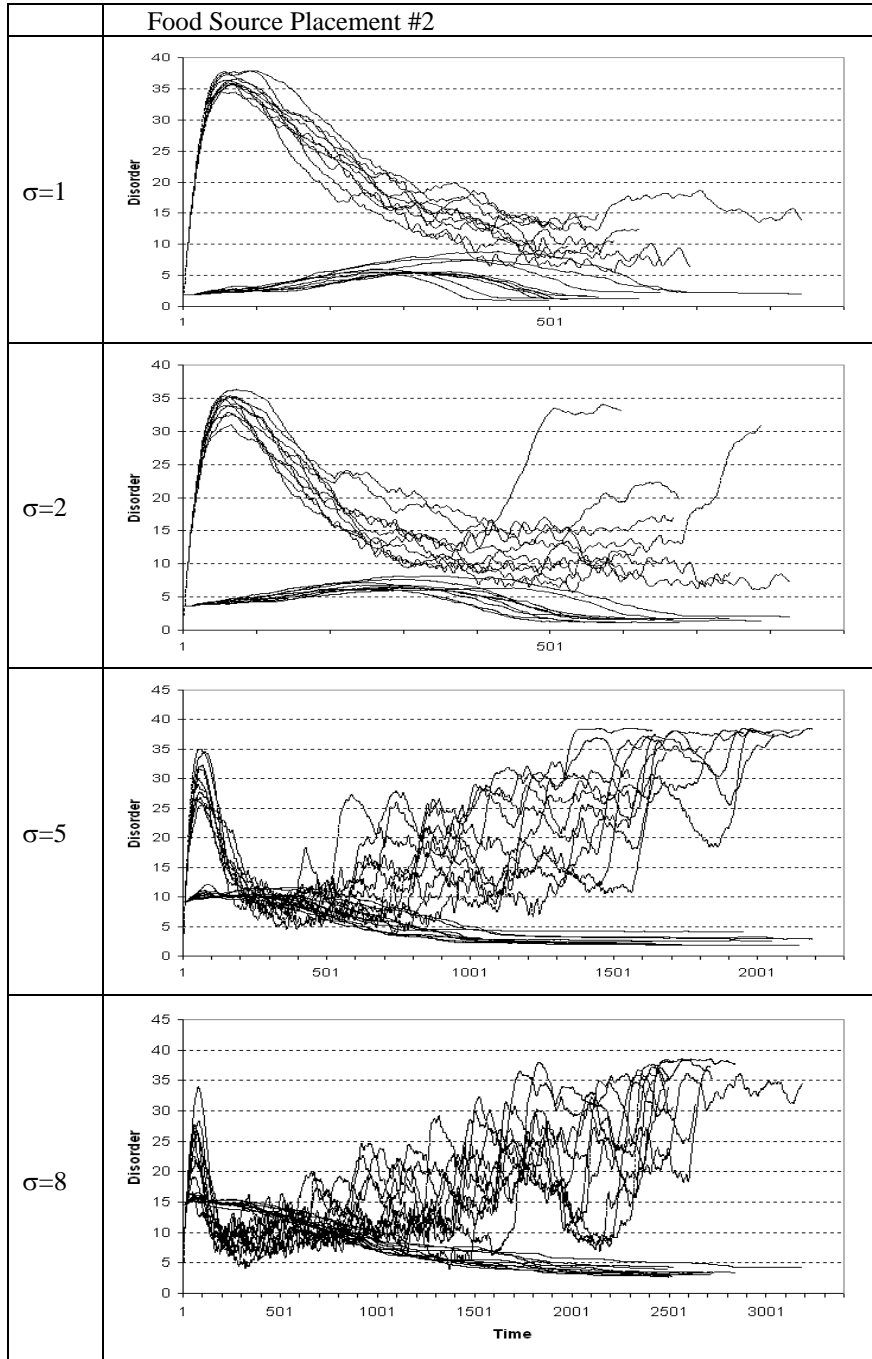


Figure 5. Another example of the in-run development of food and ant colony disorder in case of a single food source (a different seed for food source placement)

A significant observation is that the ant colony reaches its minimum disorder about the same time when the food disorder peaks. This is when the ants found the ‘optimized’ trail between the source and the nest, and most of them are walking this path back and forth, carrying food to the nest. Clearly, this is the most ordered (or coordinated) behavior that the ant colony displays during the whole process. On the other hand, this is when they are most effective in transferring food. Therefore, this is when the highest number of food units are ‘in transit’, i.e., scattered along the ant trail. This explains the peak in food disorder.

The exact values of the ants’ minimum disorder and the maximum disorder value of food placement depend on the distance between the nest and the source. This follows from our earlier explanation of the correspondence. If we assume the ants to be uniformly scattered along the trail at each time, their disorder will clearly be a function of trail length. Similarly, since the food units are carried by the ants, the disorder of food will also be dependent on trail length during this phase.

When the size of the food source is larger (i.e., when σ is higher), the increase in the ant colony’s disorder starts earlier. This is because, as observed in the previous section, the colony is less efficient in case of more dispersed food sources. Technically, this is because the trail is most efficient in connecting two points, i.e., the area of the food source that was found first, and the location in the nest closest to it. If the food source is large, the original end of the trail runs out of food before the entire source would be exploited and thus the ants need to start exploring again. Obviously, they can find other parts of the source easily, since they start exploring from the end of the trail, but still, some ants will wander off from the nest. This explains the tail of the ant disorder curves, and also accounts for the colony’s degraded performance in collecting the last 10% of the food.

When all food is collected in the nest, the disorder of the food reaches its final value. In case of high σ , this value is lower than the initial food disorder. This is because the radius of the initial food source is larger than that of the nest. Also, ants are likely to deposit the food in the nest right at the end of the trail, lowering the food disorder even further, resulting in a value that is slightly lower than the initial disorder of the ant colony.

Figure 4 and Figure 5 show two different random locations for the center of the food source. By comparing the timeline of the different runs it is clear that the ant colony is more efficient in the environments on Figure 5. This is independent of the particular values of σ . However, *within each figure*, increasing initial food placement variation reduces the efficiency of the ant colony, as observed in the previous section.

Another observation is that higher σ values result in higher variance across the runs. That is, the food disorder curve is fairly similar, but the disorder of the ant colony differs more and more with increasing variation in the initial food placement. Especially, this is true for the phase following the minimum disorder value. The previous observation is important, because the ant colony uses a probabilistic algorithm. Yet, in case of ‘point like’ food sources, *the performance appears almost independent of the given random number seed*. On the other hand, for higher σ , the efficiency of the ant colony becomes more dependent on random factors. Notice that this dependence is on probabilistic elements in the foraging algorithm, and not in the ran

dom initial placement of the food units, even though the σ parameter controls the latter.

Above we focused on environments with a single food source. Multiple food sources may be analyzed similarly. When food sources are exploited sequentially, multiple ‘hills’ in food disorder are visible. The later ‘hills’ are often superimposed on a plunge towards the final, very low food disorder value. This is due to the amount of food approaching $0.5 \cdot F$. The ‘hills’ also correlate with the ‘valleys’ of ant colony disorder, albeit parallel explorations may make this less clear. Also, in between two sequential exploitations, the disorder of both the ant colony and food may increase simultaneously. This is caused by the explorative behavior of the ants switching from one source to the other.

4 Discussion and Related Work

The behavior of social insects has inspired a growing body of work in computer science. [19] A fair amount of this work was based on different models of the ant foraging behavior. Dorigo et al. give an extensive overview on various theoretical and practical applications of this approach, which amounts to the traveling salesman and quadratic assignment problems, graph coloring, routing in telecommunications networks, task scheduling, etc. [8] They also describe the original phenomena, as observed in [6], by Deneubourg et al. on the ant species *Linepithema humile*.

The algorithms inspired by ant foraging behavior has been grouped and generalized under the Ant Colony Optimization (ACO) metaheuristic. [5] Although this approach supersedes the ant foraging model of Deneubourg et al. in detail and in practical applicability, we constrained our analysis to the latter in this paper. This is due to our different motivation: we were seeking the underlying reasons why ant foraging works, for which a simpler model seems more appropriate.

The theoretical analysis of the above range of algorithms so far amounted to showing various convergence properties of ACO, to establishing that a colony of ants can approximate the shortest path between the nest and the food source, and to discovering second order phase transitions separating random and ordered behavior. [8][4] However, less effort has been dedicated to analyze *why*, in essence, ant algorithms work; a step of reasonable necessity in order to devise ant-like algorithms not directly mimicking behavior of real colonies.

Ramos et al. analyzes the role the environment and negative or positive feedbacks play in the workings of ant sorting. [20] Yet, the most significant attempt to date to explore the problem is by Parunak and Brueckner. [18] Their key observation is that ant-like systems involve multiple coupled levels and that global (macro) self-organization is fueled by the disorder increase at the local (micro) level. (This issue is analyzed formally by Bar-Yam, who also finds that the sum of the complexity at all scales of a system with a fixed degree of freedom is constant and independent of the particular system. [1]) Parunak et al.’s interpretation of macro-level disorder is based on ant movement, while they consider the configuration of pheromone molecules for micro disorder. Although, according to this approach, our measurements in this paper are all at the global level, the results of our second set of experiments also support

their explanation. Parunak and his colleagues also study the more general problem of achieving global objectives by programming local decisions. [17] Observing that “*much current work on constructing systems of this sort is more art than science*”, they present a simple model of adaptive walk (a minimal version of ant sorting behavior) and illustrate how important properties of three practical applications can be derived from the analysis of this model. Our work is another step in this direction by providing insights into the workings of the ant foraging algorithm.

Another attempt to address similar issues, in the context of ant sorting, is by Gutowitz. [10] His focus is on local criteria (ant behaviors) necessary for global efficiency. He compares ‘basic’ and ‘complexity seeking’ ants, to find that the latter are more suitable for the task. In contrast to Parunak et al., he argues that disorder is ‘pumped’ into the system by the energy consumption of the ants, which balances the increased order-level in the environment. Gutowitz’s focus is thus on energy efficiency, measured as the time dedicated to information processing by the ant prior to moving decisions. This departs from our approach to relate the order-level of the environment to that of ant colony behavior.

The issues addressed in this paper are also related to collective robotics. In their pioneering work Deneubourg et al. suggest that sorting and clustering ants may serve as a behavioral model for mobile robots. [7][2] A series of subsequent works investigate the performance of ant-clustering. Martinoli et al. measure the dynamics of average cluster size depending on the number of cooperating robots. [15] Holland et al. experiment with arena size, probability of retention, and sensor characteristics. [12] In a more general framework, Handl et al. compare the performance of ant-based clustering to traditional clustering methods on specific data sets. [11] Wilson et al. analyze three different annular sorting mechanisms with respect to separation, compactness, shape, and completeness. [25] Contrary to our approach, however, none of these works analyze the dependence of the algorithm’s performance on the aggregate properties of the input. Similarly, Krieger et al. experiment with a group of robots solving an ant foraging-like task, but do not address performance’s dependence on the properties of the task to be solved. [13]

Our work is also motivated by that of Boer, albeit at a more general level. Boer argues that information retrieval and processing of a stochastic system can be captured by measuring its disorder. Applying this idea to the process of operating a machine, Boer discusses the relation between the level of control and the disorder of movements using the machine’s levers. [3]

4.1 Measuring Order and Disorder

Several of the works discussed above consider the disorder, information-level or (dis)order of various systems. However, they use a variety of measures to quantify these properties. Parunak et al. discuss the inherent problem of terminology related to such endeavors: namely, the dichotomy of the term ‘disorder’ in thermodynamics and information theory. [18] While the latter, as defined by Shannon, even has a strong formal similarity to the former, their intrinsic relationship is unclear. [22] Parunak et al. opt for a spatial version of information disorder, and observe problems in its use,

like the dependency on the (artificial) grid's size used to model space. On the other hand, Gutowitz applies two different measures at the micro and macro levels. In the former case, complexity means the density of items at and around a certain location. In the latter, he considers spatial disorder and also discusses the results' dependence on grid resolution.

In preparation for the experiments reported in this paper, we also considered several options to measure the complexity of both the food and the ant society. For theoretical soundness, Shannon's original definition of information disorder was a strong candidate. Ecologists and demographers also use this measure to determine the homogeneity of an area, regarding the diversity of certain species or residential segregation. [21][24] However, as discussed by both Gutowitz and Parunak et al., this measure brings a strong (and artificial) dependency on resolution, which we wanted to avoid. Moreover, we were seeking a measure that would also express the difficulty of the food collection problem.

Another, commonly used option to measure the (dis)order of behavior in higher dimensions is to compare the trajectory of the system to a fixed baseline case. For example, this approach has been used to measure the disorder of saccadic eye movements during the recognition of a face. [14] In our case this option would mean to fix a food or colony configuration and calculate the relative difference between what is actually displayed and this 'ideal case'. However, due to the parallel changes in the configuration of food and that of the ants, as well as to the dependence of the baseline case on the actual location of the food sources, we voted against this option.

5 Conclusions and Future Work

Algorithms inspired by the behavior of social insects became popular over the last decade. This popularity is due to the growing need to 'engineer emergent phenomena' in order to cope with today's and tomorrow's software engineering problems. [26] A growing number of applications have been put forward based on the 'ant colony' approach, as well as a generalized and well-formalized metaheuristic under the name of Ant Colony Optimization (ACO). [5] However, most of these algorithms and applications follow closely one of the well-known and widely discussed insect models, like ant foraging, ant sorting, or task differentiation. ACO generalizes the foraging model, making it applicable to a truly wider set of problems, but tells us nothing about why exactly the heuristic works and under what specific circumstances. As discussed above, a limited number of papers dealt with this issue, but the question still remains essentially open.

In this paper we proposed a disorder measuring approach to analyze this issue. As a first step, we investigated how the foraging ant colony's performance depends on the (dis)order in the initial configuration of food in the environment (as a proxy for the difficulty of the task at hand). We found that execution time depends about linearly on the initial disorder in case of a single food source. We also studied the time-trajectory of food disorder together with the level of coordination in the ant colony. Our main finding is that the ant colony reaches its minimum disorder about the same time when the food disorder peaks. This is when the ants established the 'optimized'

trail between the source and the nest. We also found that, in case of a single food source, increasing the disorder of the initial food configuration makes the colony's performance more sensitive to the stochastic elements governing its behavior.

These preliminary results show that this type of analysis has a potential for success in understanding the 'driving force' of stigmergetic algorithms. Given this understanding one would be in the position to design completely novel 'insect-like' distributed algorithms for complex problems. This is the long term goal of our work, but before getting there we intend to perform a series of further experiments. We would like to extend our study to the analysis of the two pheromone fields. Since these fields convey information about food placement to the ant colony, these measurements are expected to shed light on the correspondence between the order of the ant colony and the order of the environment and on the efficiency of information transmission in this stigmergetic system. Similarly, we will revisit the use of classic spatial disorder to determine our finding's dependence on the particular measure used. Finally, at a later stage, we also plan to extend our approach to other stigmergetic algorithms, e.g., to ant sorting.

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