Insects and Agents: Extending the Metaphor

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Abstract. Social insects were an early inspiration for work on multi-agent systems, and continue to provide parsimonious design patterns for models of decentralized coordination. But the original stigmergic pattern has limitations in accommodating intelligent environments and learning agents, including such socially relevant problems as opinion dynamics. This paper describes an insect example, long-range migration, that goes beyond these limitations. We present a simple formalization of the original stigmergic schema, and inspired by migratory insects, show how it can be extended to accommodate systems that the original stigmergic schema could not handle.

Keywords: Stigmergy · Biomimetics · Learning · Evolution · Modeling Technologies.

1 Introduction

In 1959, the French biologist Pierre-Paul Grassé coined the term "stigmergy" to describe how social insects (originally, termites) coordinate their actions by leaving and responding to signs in a shared environment [15].[1] Figure 1 [23] illustrates the basic schema, which is adequate to explain the emergence of the complex architecture of termite hills, as well as path planning and nest sorting by ants: agents coordinate their behavior by making and sensing changes in a shared environment. The canonical example of these changes is the deposit of pheromones (marker-based stigmergy) [29], though changes in the physical structure of the task itself (sematectonic stigmergy [36, 25], as in construction of a honeycomb) is also documented. In this schema, while the agent's actions can change the state of the environment, the agent's state (for example, whether it is carrying something) changes only by actions of the agent, and is not affected by the dynamics of the environment.

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[1] We should clarify the relation between the environment in a stigmergic system and other uses of the term in multiagent systems engineering [35]. In the agents community in the early 2000's, the awareness of the importance of something other than the agents in implementing an MAS was partly inspired by awareness of stigmergic environments. However, an agent environment as developed in [35] is middleware that mediates the access of agents to resources, such as communications. In terms of the classic OSI reference model [39], such an environment is at a lower layer than the agents. In a stigmergic architecture, both agents and environment are generally at the top, or application, layer.

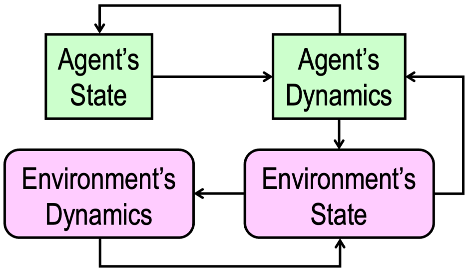

Fig. 1. The classic stigmergic schema

Early AI researchers observed that coordinated insect behavior had many parallels with human behavior. Herb Simon was not controversial when he wrote [31],

> An ant, viewed as a behaving system, is quite simple. The apparent complexity of its behavior over time is largely a reflection of the complexity of the environment in which it finds itself.

But many would pause over his comment a few pages later,

> Human beings, viewed as behaving systems, are quite simple. The apparent complexity of our behavior over time is largely a reflection of the complexity of the environment in which we find ourselves.

Stigmergy has been identified in human coordination [19, 3, 38] and imitated in agent-based software, not only to model insect behavior [6, 29] and control robots [30, 4, 28], but also (drawing more directly on Simon's insight) to generate psychologically realistic human behaviors in a social model, represented as a causal graph that agents stigmergically explore [22]. It also finds application in telecommunications [34] and logistics [12], among other areas.

Previous applications of stigmergy are distinctly asymmetric. Agents change the state of their local environment, but the local environment does not change the state of the agents. The asymmetry of classic stigmergy makes it inappropriate for modeling important phenomena. For example, in classic stigmergy,

- The environment learns from the agents (that is, agents can change the environment's state), but agents do not learn from the environment.
- Information can propagate in the environment (e.g., pheromone propagation), but information propagation among agents (as in social influence models [13]) is not supported.

Closer attention to some interesting insect behaviors (such as long-distance migration) suggests that even insect systems may require modeling the effect of the environment on agent state. Our agenda in this paper is to use these systems to define a symmetric version of stigmergy that can further inspire computational multi-agent architectures, as classic stigmergy did an earlier generation of agent researchers.

Section 2 presents an insect behavior that requires symmetric stigmergy. Then Section 3 sketches formal models of both classic (asymmetric) and symmetric stigmergy, pointing out how the extended model is a useful abstraction not only of migrating insects, but of behaviors of higher-level agents as well. Section 4 outlines directions for further research that build on and extend the concept.

2 The Inspiration: Insect Migration

In the study of social insects, the concept of stigmergy has been a powerful tool in explaining how complex behavior can arise among agents with limited computational resources. Grassé's original application was to cooperative nest building by termites, but simulations have shown that the process can also explain path formation in foraging [14] and inter-nest travel [2], nest sorting [10, 5], and task allocation [32, 33, 7]. Classic stigmergy also offers one of the best known heuristics for the traveling salesperson problem [12]. In spite of these successes, the classic stigmergic schema cannot model some impressive insect behaviors.

Some insect species conduct annual migrations that span thousands of km. Two of the best-known and most studied are the desert locust (*Schistocerca gregaria*), in which as many as 10^{11} insects [27] traverse distances on the order of 5000 km [1] between Africa and the Middle East, and the Monarch butterfly (*Danaus plexippus*), with swarms of 10^8 insects [27] traveling 3600 km [1] between summer grounds in Canada and wintering quarters in Mexico. While path formation is a common stigmergic task, no one imagines that these insects, flying tens or hundreds of meters above the ground, deposit and sense pheromones on the terrain they cross, or that such deposits could reliably persist from one year's migration to the next.

Reviewing this behavior suggests that an extended, symmetric version of the stigmergic schema can in fact explain it. We organize our review around three questions that such migrations present:

1. How can such small creatures find their way and resource their travel over such vast distances?
2. In both of these species (and some other migratory animals as well), no single individual completes the entire journey. Members of the swarm reproduce as they move. How is the navigational knowledge required to make the journey communicated between generations?
3. How does a species develop the navigational knowledge that leads to successful migrations?

The navigational mechanisms used (question 1) have been extensively studied, and though many questions remain [18], several mechanisms have been identified.

The overall trajectory of the migration tends to maintain a consistent compass bearing, suggesting that the insects orient themselves, either magnetically or by sensing the azimuth of the sun (with temporal correction depending on the time of day). Evidence exists for both mechanisms, including neuronal circuits for combining circadian rhythms with vision to provide time-of-day corrected solar information [26], and evidence that the animals (at least Monarchs) carry biologically-synthesized magnetic particles [17].

Two additional factors come into play, at least with some species [8]. First, preference for avoiding mountain ranges (e.g., in the case of Monarch butterflies, the Appalachians) can direct different populations of the same species to different destinations. Second, insect flight differs dramatically below and above the Flight Boundary Layer (FBL). Below this altitude, wind speeds are generally lower than flying speed, so that insects can actively choose their own direction. Above this layer, the insects are carried by the prevailing winds, which can vary by altitude and season. Thus, if an insect knows what direction it wants to go, it can change altitude until it finds winds in the right direction. Studies of swarms with radar show that they do indeed preferentially choose wind streams conducive to their itinerary.

In species such as locusts that require food sources as they travel, we can imagine that terrain features other than mountains (e.g., availability of green plants) may also shape the direction of travel.

In homing in on the final destination, it has been speculated [18] that visual terrain cues, or even olfactory signals left in favorite trees by the previous year's occupants, may play a role.

Except in the last proposal for homing in on favorite trees, classic stigmergy cannot explain these behaviors. We know of no mechanism by which insects can mark the terrain over which they fly or the altitude that they prefer in a way that would be accessible to other individuals. The fact that a single journey may span multiple generations (question 2) suggests that the agents carry a simple genetic recipe for combining local environmental features to guide their behavior. The fully sequenced genome of the Monarch shows DNA sequences that can be clearly associated with migratory mechanisms [37].

With our attention focused on the agents' genomes, the answer to question 3 seems obvious: a given species *evolves* a successful genome for completing the journey. Numerous studies explore the evolutionary drivers for migratory behavior [1, 16]. That is, the agents learn from the environment, through evolution, which combinations of clues lead to a completed journey, and which do not.

In the case of locusts or butterflies, the learning mechanism is binary. If the local environment supports the needs of the organism at that phase of the journey (for forage, reproduction, and shelter, both along the journey and at the final destination), the agent and its genome survive. If the local environment is not supportive, the insect dies. Thus the local environment, through evolutionary dynamics, changes the state of the insect (in this case, of the genome that guides the insect's behavior). Put crudely, the local environment either kills the insect (depleting its genome in the population) or supports its continued movement toward the goal (and thus contributing to the propagation of the successful genome).

More complex organisms support more sophisticated and nuanced mechanisms for learning from experience, and these would also be supported by symmetric stigmergy. For instance, task specialization in leaf-cutter ants can be explained by stigmergy extended with evolutionary learning from the environment [11]. Our point is that it is natural for agents to learn from their interactions with the environment, and that this learning constitutes modification of the agent's state by the environment, an extension beyond the classic asymmetric stigmergic schema. The example of insect migration shows that even without access to sophisticated learning mechanisms, any organism whose behavior is governed by its DNA can learn from its interactions with the local environment, and analyses of behavior that ignore this impact of the environment on the agent are less powerful than they could be.

Figure 2 illustrates the resulting schema, which differs from that in Figure 1 in having an additional arrow from environmental dynamics to agent state. In the classic model, environmental dynamics are restricted to things such as pheromone evaporation and dispersion, but the example of migrating butterflies suggests that it is meaningful to think of the environment as acting directly on agents (by killing them, and thus removing their genomes from the population, or by supporting them, allowing them to survive and pass on their genomes). Of course, more sophisticated learning mechanisms may also alter the agent state in response to environmental dynamics. Whatever the mechanism, it is both reasonable and useful to view learning as a change in agent state stimulated by what happens in the environment.

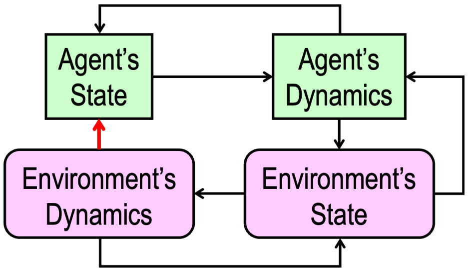

Fig. 2. The symmetric stigmergic schema

3 Architectural Models

A simple formalism may make these ideas more precise.

3.1 Conventional Stigmergy

Classic stigmergy (e.g., ant path planning using pheromones) can be summarized with the following model:

- A set $A : a_0, a_1, \ldots, a_n$ of agents, each with state as_i
- A set $E : e_0, e_1, \ldots, e_m$ of environmental locations, each with state es_i
- An environmental adjacency relation $ea \subseteq E \times E$
- An environment state update function $ESU : as_i \to es_j$, where j indexes the environmental cell where a_i currently resides
- An environment state dynamics function $ESD : es(t) \to es(t+1)$, typically evaporation
- An environment state propagation function $ESP : es_i \to N(es_j)$, where $N(es_j)$ is the neighborhood of es_j (e.g., diffusion of pheromone to adjacent cells)

In geospatial stigmergy (e.g., ant or robotic path planning), the elements of E tile a manifold, and ea is symmetric, each tile being adjacent to the tiles in its Moore or von Neumann neighborhood. But other adjacency relations are possible

- Ref. [24] applies stigmergy to reasoning over a hierarchical task network, in which ea is asymmetric.
- Ref. [23] applies it to a novel causal graph formalism whose nodes are event types rather than variables. A edge from e_i to e_j indicates temporal succession, and so is asymmetric.[2]

As anticipated, this model exhibits several asymmetries.

- While agents can change the state of environmental locations that they visit, these locations cannot change the state of the agents. The examples of migratory insects show that in fact the environment can change the state of even very simple agents, imposing evolutionary pressure on their genomes, and classic learning techniques with more complex agents are central to modern ABS.
- There is no agent adjacency relation or agent state propagation. But social influence models recognize the critical importance of the influence of agents on one another (agent state propagation), drawing on an underlying social network. Even insect level societies exhibit role specialization in which different classes of agents interact differentially with one another [9, 32].
- There are no agent state dynamics. But if agents can learn, they can also forget.

In addition to its asymmetry, the conventional model is static. No provision is made for the addition or removal of agents or environmental locations.

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[2] Actually, it is antisymmetric. Since the nodes are event *types* that may be instantiated at different points in time, this formalism, unlike a hierarchy, does admit cyclical paths, and an agent can repeat an event type several times in a row, following an edge (e_i, e_i). But $(i \neq j) \land ((e_i, e_j) \in ea) \implies (e_j, e_i) \notin ea$.

3.2 Symmetric Stigmergy

It is straightforward to extend the classic model model to make it symmetric (and dynamic).

We retain the elements already defined, and extend A, E, and ea to functions of time, $A(t)$, $E(t)$, and $ea(t)$. (Some applications may require the update, dynamics, and propagation functions to be functions of time as well, but we do not dwell on this natural extension.)

Then we add

- An agent adjacency relation $aa(t) \subseteq A \times A$
- An agent state update function $ASU : es_i \rightarrow as_j$, where i indexes the environmental cell where a_j currently resides
- An agent state dynamics function $ASD : as(t) \rightarrow as(t+1)$, which might model forgetting, or more complex integrative reasoning over learned information
- An agent state propagation function $ASP : as_i \rightarrow N(as_j)$, where $N(as_j)$ is the neighborhood of as_j (e.g., spread of opinion over a social network)

This model supports the evolution of migrating insects in the following way:

- The agent's state is its genome.
- ASU includes mutation, a random change in the genome over time, and health, driven by the environment and possibly resulting in death.
- A changes as agents become isolated from the swarm and die, and as new agents are born.
- aa includes the relation of agents to their offspring.
- ASP passes on the genomes of successful agents from parents to children.

The distinction between agents and environment is justified in many applications by two contrasts. (1) Agents are mobile and the environmental locations are stationary. (2) Many agent behaviors of interest require coordination among agents, but we do not usually think of locations as coordinating with one another. But a large class of interesting social systems are appropriately defined by allowing the same sets of entities to serve both for E and A. How would this work? An agent *qua* agent is located at itself *qua* environment. ASU is null, but ASP allows propagation of information among agents. This approach supports not only models of opinion dynamics [20], but also the task specialization mechanisms mentioned earlier [9, 32].

4 Directions for Future Research

Insect behaviors provided the initial inspiration for stigmergic mechanisms, in which agents coordinate by causing and sensing changes in the state of their local environment. Close examination of insect migration, a behavior that cannot be explained by this asymmetric mechanism, suggests that it is useful to recognize an analogous process, in which the agent learns from locations with which it interacts (or in other words, the local environment modulates the state of the agent). Recognition that stigmergy can be symmetric expands the domain of applicability of this simple but powerful mechanism. Here are some examples.

Symmetric diffusion: One environmental dynamic sometimes modeled in classic stigmergy is the diffusion of pheromone from the point of deposit to nearby locations, generating a gradient that agents can use to find or avoid locations of interest. In social models, agents who encounter one another tend to align their preferences with one another in a process called "social influence" [13]. When agent preferences are modulated by their local environment, the effect is a diffusion of preferences throughout the agent network that strongly resembles the diffusion of presence pheromones through the environment.

The insect analog to *es* is a chemical pheromone deposited by agents on the locations they visit. Many insects use multiple pheromones, yielding a vector-based deposit on each location, and thus establishing a *field* over the entire environment. Artificial stigmergic architectures mimic this behavior with variables on each location that are augmented when agents visit them. Ref. [21] shows that this pheromone field allows a stigmergic system to be viewed as intermediary between a classic agent-based model and an equation-based "mean field" model, and the position of a stigmergic model on this continuum can be adjusted by pheromone parameters .

Our symmetric model establishes a similar field over the set of agents. One implementation that has proven useful is a vector of preferences over the same vector space that defines the field over the environment, so that an agent's choice among alternative environmental options is a simple comparison between its preference vector and the pheromone (or feature) vector of each accessible location. The parallel between the environmental *feature* field and the *preference* field over the agents extends our conceptual resources for exploring the relative benefits of equation-based and agent-based models and developing new designs that combine the strengths of each.

Modeling environmental action: Recent advances in social modeling [23] demonstrate how stigmergy can function in an environment made up of dynamic events rather than only geospatial locations. Events are intrinsically active, and it seems natural, even necessary, to consider their impact on agents. A conceptual framework that recognizes the symmetry of agents and locations can enable us to model and explore such active environments, which are likely to be increasingly important in capturing important social dynamics for analysis and planning.

Between ants and actors: We noted above that the presence of a field allows us to explore the design space between agents and equations. Symmetric stigmergy extends the design space in another direction. At one extreme, classic stigmergy offers an elegant account of very simple agents interacting through a shared environment. In some cases, the most important environment that an agent needs to consider consists of other, peer agents, and in this case BDI architectures have historically been preferred.

Recognizing the potential activity of local regions of the environment (such as event types in an event graph [23]) gives us an intermediate point between these extremes. Consider the two asymmetries we identified at the end of the previous section: unlike agents, environmental locations do not move, and do not coordinate with each other. But as our notion of what constitutes an environmental location shifts from a geospatial tile to an event type, these asymmetries tend to disappear.

1. In an environment made up of event types, an event emerges when one or more agents are concurrently participating in the event type. Each of these agents has a geospatial location. As the system operates, instances of events thus can pop up at different locations. Movement of event types through space emerges from the execution of the system.
2. We do not usually think of environmental locations as coordinating with one another. But as a set of event types modulates the preferences of their participating agents, we would expect to see some correlation across the time and places at which specific events emerge. Discovering this kind of unexpected correlation across events is of great interest to social scientists, and symmetric stigmergy facilitates its study.

The emerging landscape of modeling options is thus changing. Currently, modelers tend to form disparate and incompatible tribes (using, for example, equations, digital ants, or BDI agents). Symmetric stigmergy provides a common abstract model that can support a continuum of modeling techniques (Figure 3), offering the modeler a far richer and better nuanced set of choices. Thinking of agent interactions in terms of fields generated by stigmergy (whether symmetric or asymmetric) helps bridge the gap between equations and agents [21], while symmetric stigmergy helps bridge the gap between ant-like agents and BDI agents. The concept of symmetric stigmergy thus points the way to a Grand Unified Theory of modeling, which can help us derive hybrid techniques that combine the strengths of alternative formalisms.

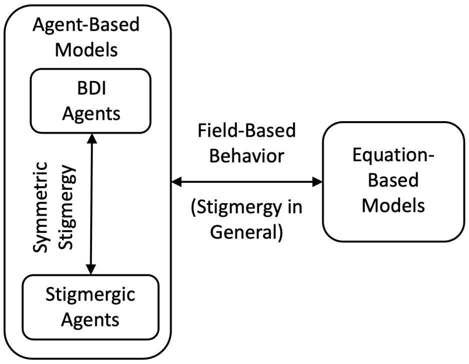

Fig. 3. Stigmergy spans different modeling modalities

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