Ant- and Ant-Colony-Inspired ALife Visual Art

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Abstract Ant- and ant-colony-inspired ALife art is characterized by the artistic exploration of the emerging collective behavior of computational agents, developed using ants as a metaphor. We present a chronology that documents the emergence and history of such visual art, contextualize ant- and ant-colony-inspired art within generative art practices, and consider how it relates to other ALife art. We survey many of the algorithms that artists have used in this genre, address some of their aims, and explore the relationships between ant- and ant-colony-inspired art and research on ant and ant colony behavior.

Keywords
ALife art, ant painting, ant colony behavior, evolutionary art, generative art, robotic art, swarm art

1 Introduction

Within the past decade a wide range of software-based art projects conducted by artist-scientists grounded in ALife, art, and visualization have emerged under the umbrella heading "ant- and ant-colony-inspired ALife art." In this special issue contribution, we trace the development of this movement in the visual arts, discuss its relevance and stature within both art and ALife, and elaborate on some of the specifics that bind ant behavior research with ant- and ant-colony-inspired ALife art.

For the purpose of this article, we define ant- and ant-colony-inspired ALife art as the set of works where artists use ants as a metaphor for the creation of computational agents for artistic purposes so that they can explore the collective behavior that emerges through the interaction of such agents, independent of their biological plausibility. Thus we focus on the development, relevance, importance, and impact of artwork based on ant and ant colony *behavior*. The astounding variety and complexity of this behavior has captured the attention of artists and public alike, thanks in no small measure to popular surveys such as those by Hölldobler and Wilson [30] and Gordon [17].

Although this article deals exclusively with the visual arts, we note that our definition of ant- and ant-colony-inspired ALife art excludes many familiar examples of ant-*themed* visual artwork, including numerous examples found in Australian aboriginal art (see [7]) and the cast sculptures of ant tunnels by Tschinkel [52] or Forti [14], as well as kitsch art or craft art such as "fire ant art" (see www.extension.org/pages/32528/fire-ant-art).

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In the next section we review the seminal research that created the conditions for the emergence of ant- and ant-colony-inspired ALife art. In the third section we present a chronological overview of relevant work in this genre. In the fourth section we discuss ant- and ant-colony-inspired ALife art within the context of algorithmic art practices, artistic motivation, and the relationship of such art to other forms of ALife art. In the fifth section we provide technical details of some of the algorithms ant- and ant-colony-inspired artists use and explore their connections to ant and ant colony behavioral research. In the final section we draw our conclusions.

2 Prehistory

In this section we recall some of the key research developments that preceded and helped foment the emergence of ant- and ant-colony-inspired ALife art.

1986 Langton's ants [35] were mobile cellular automata maneuvering on a rectangular grid of black and white cells following two rules: At a white square, turn 90° right, flip the color of the square, move forward one unit; at a black square, turn 90° left, flip the color of the square, move forward one unit. There is a well-known 1991 video by Langton (see http://www.youtube.com/watch?v=w6XQQhCgq5c) showing various experiments demonstrating the self-organization and emergent structures that resulted when two (or more) virtual ants, or *Vants*, interact starting from various initial configurations.

1989 A. K. Dewdney [8] popularized Greg Turk's *Turmites*, which extended Langton's idea to multicolored grids. This endeavor has continued to flourish (e.g., http://www.youtube.com/watch?v=1X-gtr4pEBU).

2000 Ramos et al. [44, 45] described ant colony simulation experiments where virtual ants roaming over grayscale images produced "cognitive maps" (i.e., pheromone fields) to represent the images. As an application of this pattern recognition research, they considered image and document retrieval.

3 History

This section provides a chronology of the ant- and ant-colony-inspired artworks we are aware of.

2000 Tzafestas [54] developed a drawing tool, called *Ant Brush*, based on a behavioral model where members of an artificial ant society collect crumbs, in order to pick up and distribute color on a drawing canvas.

2001 Barrass [5] exhibited at the Melbourne University Student Union's George Paton Gallery under the title "Laying Down a Path in Walking" and also gave an artist's presentation at the Second Iteration Conference. His objective was "to make (moving) images that integrate structure and change, showing the perpetual overhaul of structures in a process of continuous change" (refer to online supplementary materials at www.mitpressjournals.org/doi/suppl/10.1162/ARTL_a_00170).

2003 Monmarché et al. [2] used four to six virtual ants roaming over a toroidal grid, which painted by depositing *scent* in the form of one color, while searching for scent of a different color. The abstract images that resulted were interactively evolved. Although the ants were still essentially mobile cellular automata, the genome was considerably more sophisticated than the simple lookup tables of Langton's *Vants* or Turk's *Turmites*. Monmarché's intent was to find a more expressive way to understand and explain some of the ant algorithms that were then being developed by ant colony optimization researchers. Monmarché was the first to use the term "ant painting" for the static images that he created.

2004 Barrass [3] began exploring the artistic potential for modeling ant behavior using neural nets. One example of the videos he produced was included in the 2006 EvoMUSART art show and has also been published online [4].

2004 Semet, Durand, and O'Reilly [48] combined image processing techniques with ant colony simulation methods to develop nonphotorealistic rendering methods. What distinguishes their work is the use of swarms of ants to yield representational, as opposed to abstract, imagery derived from photographs.

2005 Greenfield [18] evolved ant paintings using a model with 8 to 12 ants, similar to that of Monmarché. However, the fitness measures were based on ant behavior statistics. To the best of our knowledge, this was the first evolutionary approach to ant paintings that performed autonomous evaluation of the paintings, that is, did not rely on the user for fitness evaluation.

2005 Urbano [56, 57] considered an ant painting model where individual cells in the environment exuded virtual scent to attract ants. Because the cells ceased to exude scent when they were first visited by an ant, once all cells were visited and painted according to colors assigned to the ants, the ant painting was finished.

2006 Greenfield [19, 20] further developed Urbano's model by having the ants also deposit virtual scents in the environment that could act as either attractants or repellents. Therefore, the approach introduced a more plausible biological model that combined the use of multiple pheromones with evolutionary algorithms.

2009 Greenfield and Machado [29] used a grayscale version of an ant painting model as a software component in a broader "artists and critics" simulation. Greenfield [21] then developed a colorized version to further investigate the artistic potential of such ant paintings.

2010 Fernandes [11], adapting a technique used previously in image processing whereby artificial ants developed pheromone patterns by roaming over grayscale images [41, 13], developed a nonphotorealistic system similar in spirit to that of Semet et al., which he called *Pherographia* [10].

2011 Urbano [58] became the first to execute ant paintings faithful to a biological model. Appealing to research of Franks et al. [15, 16] on nest construction by the ant species *T. albipennis*, Urbano's virtual ants used a stochastic sand grain foraging, collecting, and depositing algorithm in order to construct circular walls defining their nest's outermost boundary.

2011 Greenfield [22] modified an ant colony model proposed by Jones [32], originally used for visualizing the evolution and formation of plasma transport networks of the slime mold *Physarum*, to develop ant paintings, which he called "network transport overlays."

2012 Greenfield [24, 28] used the same nest building algorithm as Urbano [58], but with carefully chosen radii, centers, and sand grain color preferences, in order to create ant paintings consisting of symmetric patterns of circles.

2012 Machado and Pereira [37] introduced *Photogrowth*, which, similarly to Semet et al. [48], created abstract nonphotorealistic ant paintings from color photographs, producing artworks characterized by the intertwinement of lines of varying width and transparency. The evolution of sets of "sense vectors" for the ants and the production of scalable vector graphics as output are two of the novel aspects of their approach.

2013 Machado et al. [36, 38] modified their *Photogrowth* system by allowing its users to design fitness functions, which were then used to guide evolution. Following the work of Greenfield and Machado [29], the fitness functions were based on both behavioral and image features.

2013 Fernandes et al. [12] further enhanced their *Pherographia* system so that it created *abstract* images from color photographs.

2013 Greenfield [25, 26] developed an ant painting technique based on the seed foraging behavior of the ant species *P. barbatus*. It drew from a biological model derived from primary sources [17].

2014 Greenfield [27] extended the Urbano nest building model used for artistic purposes so that nest "boundaries" could be specified using polar or Cartesian curves.

4 Art Theory Perspective

In reflecting upon the history of art and algorithmic procedures, Roman Verostko, one of the founding figures of the algorithmic art movement (see http://www.algorists.org) that emerged in the 1960s, recently noted, "The period from 1980 to the end of the century remains an extremely rich period yet to be reviewed and understood better" (Roman Verostko, pers. comm.). To elaborate further, when paraphrasing the artist Peter Weibel's thoughts on the algorithmic movement, in 2004 Verostko observed:

> The algorithmic revolution lies behind us and nobody noticed it. That has made it all the more effective—there is no longer any area of social life that has not been touched by algorithms. Over the past 50 years, algorithmic decision-making processes have come very much to the fore as a result of the universal use of computers in all fields of cultural literacy—from architecture to music, from literature to the fine arts and from transport to management. The algorithmic revolution continues the sequencing technology that began with the development of the alphabet and has reached its temporary conclusion with the human genome project. No matter how imperceptible they may be, the changes this revolution has wrought are immense [59].

Verostko and, by extension, Weibel speak eloquently of the difficulty of assessing the significance, importance, or impact of art movements. The lesson learned is that due to the limited time frame involved, it is difficult to be definitive about the status and impact of any ALife art genre.

4.1 Artist Motivation

Despite this state of affairs, the use of agent-based simulation in ant- and ant-colony-inspired ALife art establishes that it is firmly embedded in the traditions and practices of algorithmic, computational, and generative art. The effect of incorporating the ALife challenge of synthesizing ant and ant colony behavior into artworks builds upon the art tradition of capturing and emphasizing performance and process over time. To expand upon this point, kinetic art notwithstanding, just as Duchamps captured the passage of time with his *Nude Descending a Staircase* and Pollock focused upon artistic processes in his drip paintings, (static) ant paintings capture ant and ant colony behavior over time while, perforce, ant-inspired videos and installations do the same. The swarm robotic paintings of Moura, which resulted from a collaboration with Ramos that built upon the ant-based projects mentioned above, have been widely exhibited.[1] There is an almost hypnotic attraction to seeing videos of Pollock executing drip paintings or Moura's robots drawing, which no doubt helps contribute to their success. Such an attraction is also, at least in our minds, present in watching the unfolding work of a colony of virtual ants as they create emergent patterns.

1 At about the same time Ramos was using ants for pattern recognition, he initiated a project, "Machines of Collective Conscience," and began collaborating with Moura. In one relevant project they used drawing robots to "paint" over large photographs of iconic artworks and figures (e.g., Picasso's *Guernica* and Marilyn Monroe); in the other, swarms of robots painted on a blank canvas. These large swarm drawings were exhibited internationally.

We argue in favor of both the effectiveness and the untapped potential of ant- and ant-colony-inspired ALife art on the basis of its increasingly close ties to observational and experimental biological research into animal behavior. Our thesis is that understanding such behavior may well be the emerging theme of the twenty-first century. When coupled with the lure of capturing processes over time as discussed above, for some artists and theorists this becomes compelling [40].

Beyond the initial heralding of ALife art via (interactive) genetic algorithms that was garnered by Sims [49] and Todd and Latham [51] under the banner of evolutionary art, perhaps the greatest impact on the art world associated with ALife art can be attributed to Kac's transgenic GFP Bunny *Alba* (see http://www.ekac.org/gfpbunny.html) [33] and the Vacanti mouse [6]. This attention was in response to societal concerns about research involving genetics, the genetic code, and the ramifications of DNA databases. Thanks to growing scientific interest and public debate about crowd intelligence and distributed computation with (small) mobile devices, coupled with the never ending quest to understand animal behavior, ant- and ant-colony-inspired ALife art hopefully will also eventually merit such attention.

4.2 ALife Art Context

There is no definitive taxonomy of ALife art, and for this reason we will only briefly consider the positioning of ant- and ant-colony-inspired ALife art within the broader context of ALife art. There are several interrelated disciplines that produce art works and artefacts overlapping with the use of ant and ant colony behavior that may confound or confuse the discussion about the significance and status of any one them within contemporary art in general, and ALife-inspired art in particular.

4.2.1 Swarm Art

Certainly ants qualify as swarms, but more often than not "swarm art" refers to art grounded in flocking, herding, or schooling behavior algorithms that build upon Reynolds' seminal set of rules from 1987 [46] that were the basis of his *Boids* simulation (see http://www.red3d.com/cwr/boids/). This leads to an extreme divergence between the ant and ant colony art described in Section 3 and the swarm art inspired by flocking algorithms such as the three-dimensional version used by Jacobs et al. [31].

4.2.2 Agent-based Art

Here, we refer to works that trace their lineage to Annuziato's 2002 agent-based art installation *Relazioni emergenti* [1]. These agent-based works have an ecological flavor, often focusing on niche formation or environment sculpting. For example, in view of its description, in this genre Driessens and Verstappen's 2005 *E-volved Cultures* [9] immediately comes to mind:

> "E-volved Cultures" (2005–2011) is a software presentation in which an artificial landscape grows in real time. Virtual agents that leave visual traces in interaction with their environment generate the dynamic pixel-landscape. The colourful abstract animations arouse associations with landscapes, geological processes, cloud formations, fungal growth, organ tissues or satellite photos, but ultimately they still avoid any definitive identification [9].

Similarly, one might view the 2009 *Niche Constructions* of McCormack [39] as an homage to Annunziato.

4.2.3 Collective Robotic Art

As noted previously, Ramos' 2002 ant colony simulation experiments led directly to the physically embodied collective robotics paintings of Moura [42, 43]. We note that even though his robot controllers were hand-crafted, Moura promoted these paintings as "nonhuman" art. Therefore, from an ALife standpoint, what is of principal interest is the nature and manner of the controllers developed for the drawing robots. No collective behavior was evolved. This is also the case in the work of Greenfield [23], where evolving controllers for drawing robots was reduced to evolving executable programs, and the use of multiple robots was a side issue.

5 Fields Related to ALife Research

This section discusses technical details and implementation issues that have drawn from, or have a direct bearing upon, ALife research.

5.1 Neural Nets

To make videos and sonifications of simulated ant behavior [3], Barrass used one-dimensional Kohonen [34] self-organizing maps (see, e.g., http://www.ai-junkie.com/ann/som/som5.html). Neural mappings were developed by sensing the traces ants left in such a way that ants learned to respond to familiar patterns, influencing each other indirectly through a shared artefact they produce and inhabit. The input to the self-organizing map from the ant's "feeler" was a sampled pattern of ant markings, and the activated output node yielded the turning angle to use for updating the ant's position. Thanks to gradually fading ant trails, several clever and innovative ways of updating the self-organizing map, and judicious choices for drawing attributes, Barrass obtained an impressive and diverse collection of digital prints and videos. Barrass carefully stated:

> I should note that the ant metaphor is only a starting point for the work, and a convenient way to think about the agents in the system. I am not making any serious comparison with the behaviour of living creatures [3, p. 61].

Figure 1a shows an example still from the time series of images he created using his methods. We are unaware of any other artificial ant simulation effort besides that of Barrass [3] that relies on neural nets.

5.2 Pheromones

A model for simulating ant pheromones for visual purposes can already be found in Ramos and Almeida [44]. Let $\sigma = \sigma(r, \theta)$ be the strength of the pheromone perceived by an ant at position r with direction heading θ. Then the pheromone *response* $W = W(\sigma)$, formulated based on experimental research, is given by

$$W(\sigma) = \left(1 + \frac{\sigma}{1 + \delta\sigma}\right)^{\beta},$$

where the parameters β and δ reflect the ant's pheromone *sensitivity* and sensing *capacity* respectively. To use this in a grid-based image processing setting, Ramos and Almeida assume that an ant will move from its current cell to one of the eight other cells (numbered from 1 to 8) in its 3×3 Moore neighborhood on the basis of the rank ordering of the transition probabilities

$$p_i = \frac{W(\sigma_i)w(i)}{\Sigma_j W\left(\sigma_j\right)w(j)},$$

where σ_i is the pheromone strength of the ith cell and $w(i)$ is the weight of the ith cell.

5.2.1 Monmarché, Greenfield, and Urbano—Primitive Pheromones

The ant colony paintings of Monmarché [2] and Greenfield [18] were focused more on genome evolution than on pheromones. They used fixed-length strings of parameters as ant genomes. More precisely, an ant genome took the form

$$\left(C_R, C_G, C_B, F_R, F_G, F_B, P_l, P_r, P_a, D, P_f\right),$$

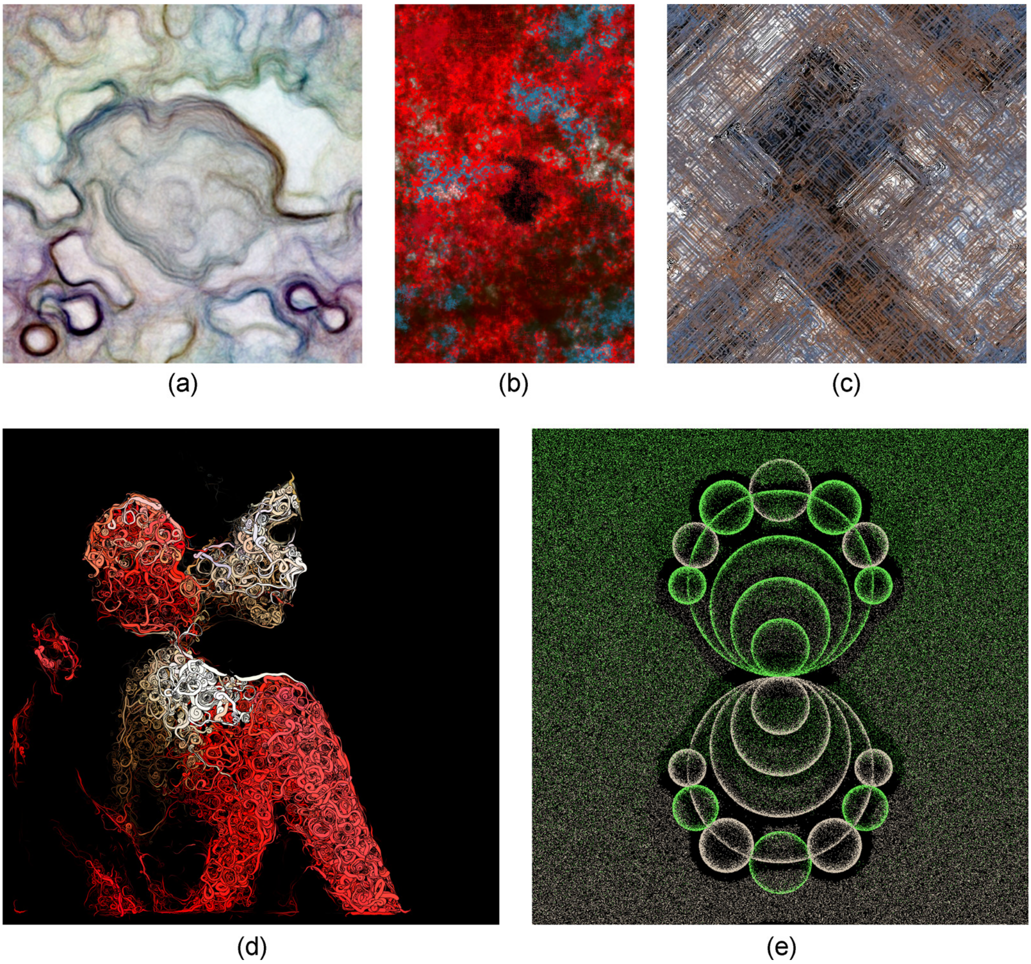

Figure 1. (a) *somant330-60*. A still image from a time series video by Barrass, showing the highly organized system that resulted from disordered behaviors of simulated ants utilizing one-dimensional Kohonen self-organizing maps. Copyright 2004. Tim Barrass. Printed with permission. (b) *AP20121129B*. An ant painting of Monmarché that shows 16 ants interacting for 50,000,000 time steps. It features *blue* and *red* ants competing for territory with the red ant minority dominating due to self-following behavior of the blue ant majority. Copyright 2012. Nicolas Monmarché. Printed with permission. (c) *LLs24031*. An ant painting of Greenfield that shows two colonies with 500 simulated ants interacting for 3,000 time steps. Ants follow an environment-produced pheromone gradient and use pheromones of their own for the purposes of following and avoidance. Copyright 2006. Gary Greenfield. (d) *Dancer*. An antwork produced using the nonphotorealistic rendering system *Photogrowth*, relying on a model where simulated ants roam over an image under the control of a fitness function while depositing "paint" on a separate virtual canvas. Copyright 2014. Tiago Martins and Penousal Machado. (e) *Stigmmetry Print #28235*. The circles in this symmetric design of Greenfield are formed by simulated ants collecting and depositing virtual grains of sand in accordance with the nest building behavior of the ant species *T. albipennis*. Copyright 2012. Gary Greenfield.

where (C_R, C_G, C_B) is the color to deposit; (F_R, F_G, F_B) is the color to follow; the probabilities P_l, P_r, P_a, which sum to one, are the probabilities of moving (l)eft, (r)ight, or (a)head in the absence of scent; and P_f is the probability of following the gradient in the presence of scent. In this model, each ant is a mobile cellular automaton roaming on a toroidal grid whose rule set depends on how the color assigned to each grid cell is interpreted as the artificial scent. The parameter D merely indicates whether left and right will correspond to 45° or 90° turns. For Monmarché the scent is a scalar, the color's luminance, while for Greenfield the scent is a vector, the color's RGB components. In both cases, detecting scent corresponds to sensing its presence above a certain threshold. Somewhat surprisingly, whether scent is determined on the basis of luminance or of color components turns out to have subtle ramifications. Figure 1b shows a recent ant painting of this type by Monmarché.

The genetic algorithms used for evolving ant genomes are straightforward. However, it should be noted that what is evolved in this context is actually a small collection of such genomes, so that the resulting ant "societies" can evolve into *castes* with different color preferences, thus promoting interaction and feedback. Monmarché uses an interactive genetic algorithm with 4–6 ant genomes, while Greenfield uses an automated genetic algorithm with 8–12 ant genomes. Greenfield's fitness functions are simple arithmetic expressions involving the number of time steps ants spent exploring (i.e., seeking their preferred scent) and the number of time steps ants spent exploiting (i.e., following their preferred scent). In this way ant paintings are evolved on the basis of collective ant *behavior*.

Urbano [56, 57] used a different setting. He treated each cell in the toroidal grid as an ant chemical emitter, continually emitting an ant attractant until it was first visited by an ant, at which point the cell was painted a different color than the original background gray and ceased to function as an emitter. The attractant diffused and evaporated. Using this method, an ant painting was finished once all the cells had been visited. The amount of chemical that was emitted and the evaporation and diffusion rates were user modifiable parameters.

5.2.2 Greenfield—Multiple Pheromones

While Urbano did experiment with an ant collision avoidance policy—when an ant senses another occupant in its cell, it jumps to a nearby cell—it was Greenfield [19, 20] who incorporated the use of an invisible evaporating and diffusing pheromone emitted by the ants themselves to first address this problem. When the attractant emitted by the cells was too weak, the ants used the gradient of its pheromone to try and avoid regions of the environment that had already been explored. To leverage this behavior for artistic purposes, when in avoidance mode ants deposited a new color that was blended and diffused into the painting. Figure 1c shows a representative ant painting produced using this technique. An interesting side effect was the rotational patterns of ant movement that emerged as a result. Although it was caused by avoidance rather than attraction, it raises the question of whether ant colony simulations can give rise to the so-called *death circles*, or ant mills, that occur when excessive ant attractant pheromone causes ants to circle endlessly following one another until they die [47]. Another innovation of this work was to initially cluster two colonies of ants (using two different color schemes), as opposed to sprinkling large numbers of ants randomly throughout the environment as was normally done. The rationale for sprinkling is that the randomness will disappear during a transient phase. Greenfield used an evolutionary algorithm to consider how the initial placements of these two colonies could guide the formation of the paintings.

5.2.3 Semet, Fernandes, and Machado—Complex Environments

Ant-inspired models used in nonphotorealistic rendering use the pixels of a source image to serve as the environment; hence they often furnish a rich, complex environment. We consider three nonphotorealistic rendering systems that are based on simulating ant behavior.

Semet et al. [48] use an interactive genetic algorithm to let users control the composition and style of their nonphotorealistic ant paintings. Ants roaming over the environment deposit marks on a separate virtual *output canvas*. Many of the parameters under user control affect ant drawing attributes. In addition to sensing the RGB color of each pixel, ants are also able to sense three preprocessed quantities associated to each pixel: luminance, norm, and orientation of the gradient map derived from the luminance map (computed using 3×3 Sobel filters), and from the *salience* of the pixels, which indicates they are part of key features or regions of interest. Because ants sense the local environment without changing it, and their actions depend only on what they encounter, a colony of several hundred ants is simulated by having one ant at a time roam over the environment for a fixed number of time steps. Ants shift among executing a small number of hand-crafted sensing and drawing algorithms designed for mark making purposes.

In the system *Photogrowth* by Machado and Pereira [37], ants also sense an image environment while creating a nonphotorealistic rendering by laying down "ink" on an output canvas. They adopt a metaphor where brightness is perceived as food. The luminance of an area of the image environment determines the amount of food available at that point. Each ant has an initial *energy*, which decays over time, but ants can gain energy by traveling through illuminated areas of the image environment. Energy governs the birth-and-death cycle. The energy of an ant also determines the width of the trail drawn on the output canvas. Thus variation in energy results in trails of varying width. The consumption of energy affects the image environment, implying that, unlike those of Semet et al., the ants must be simulated in parallel because the behavior of one ant affects the behavior of others. Each ant uses ten *sense vectors* that determine ten positions relative to the current position of the ant, which in turn determine ten brightness readings obtained from the image. A weighted sum of these readings is scaled according to the ant's velocity to determine how to update the ant's position. Perlin noise is added to this calculation to simulate the uncertainty in the sensory readings and movement.

The parameters governing the behavior of the ant, including the direction and magnitude of the sense vectors as well as the corresponding weights, are encoded in the genotype and subject to evolution. Subsequently, Machado et al. [36, 38] abandoned using the interactive evolutionary algorithm to set *parameters* for their system in favor of having users design their own *fitness functions*, by having them weight a linear combination of components that amalgamated image statistics, image qualities, and ant behaviors. Figure 1d shows art work produced using this system (refer to online supplementary materials for additional examples).

In Fernandes' system *Pherographia* [11] the intent is to have the distribution of a single pheromone left by the ants serve as the art work. Ants lay down pheromone based on the contrast observed in the nine cells constituting the ant's Moore neighborhood and then move in response to that pheromone according to Ramos and Almeida's model described in Section 5.2. An ant lays down T units of an *evaporating* pheromone by calculating

$$T = \eta + \rho\left(\Delta_{gl}/\Delta_{\max}\right),$$

where $\Delta_{\max}$ is the difference between the darkest and the lightest pixel in the entire image, Δ_{gl} is the contrast in the current neighborhood, and η and ρ are constants. Because the environment stimulates the worker ants to modify the pheromone distribution and the pheromone distribution affects how the ants will exploit the environment, Fernandes associates his ant behavior with the study of stigmergy.

We wish to point out that there are two options for implementing agents, thought of as ants, roaming on a two-dimensional gridded environment of cells and that these options may result in significant visual differences among outcomes. Either agents can jump from cell to cell, thus effectively acting as mobile automata, or they can move more smoothly through the environment by maintaining position, orientation, and velocity and then relying on rounding to sense and modify grid cells. In the discrete case the environment is realized as a lattice, while in the continuous case it is realized as a surface. Greenfield [19, 20], Fernandes [11], and Semet et al. [48] are examples of the discrete method, while Greenfield [25, 24] and Machado et al. [36, 38] use the continuous approach.

5.3 Remote Sensing

Jones [32] modeled the evolution and formation of plasma transport networks of the slime mold *Physarum* using an agent-based simulation whose agents, thought of as virtual ants, use remote sensing, that is, sense the environment several units distant from their current position. Here, a plasma transport network refers to the flow of protoplasmic sol through a gel matrix of fibers. Although the patterned images Jones obtained often resemble the reaction-diffusion patterns obtained using the well-known algorithmic methods of Turk [53], Witkin and Kass [60], or Young [61], they are, in fact, visualizations of the pheromone distributions of evaporating and diffusing pheromone trails laid down by virtual ants. Greenfield [22] composited colorized versions of these transport networks to create ant paintings that he called "abstract overlays."

5.4 Foraging Behavior

The most recent use of ant behavior for ant- and ant-colony-inspired ALife art draws its inspiration directly from research biology. As it turns out, both examples involve ant foraging behavior.

5.4.1 Urbano—Sand Grain Foraging

Urbano based a method for ant painting on a model of the nest building behavior of the ant species *Temnothorax albipennis*. Ants of this species collect and deposit sand grains to form an approximately circular outer nest wall. Let R be the nest radius, and let r be the ant's current distance from the nest center. Biological literature [15, 16] suggests that the probability of an ant dropping a sand grain it is carrying is

$$P_d = \frac{\kappa_d}{1 + \tau (r - R)^2},$$

while the probability of picking up a sand grain if one is encountered is

$$P_u = \kappa_u \left(1 - \frac{1}{1 + \tau (r - R)^2} \right),$$

where κ_d, κ_u, and τ are constants between zero and one. The constant τ affects the width of the nest wall.

For simulation purposes, the algorithm executed by the ants is:

if ant is carrying grain **then**
    if current cell does not have grain **then**
        with probability P_d drop grain
    end if
else
    if current cell has grain **then**
        with probability P_u pick-up grain
    end if
end if

Interestingly, this algorithm is remarkably similar to a "crumb laying" algorithm for artificial ants that was analyzed by Tzafestas [55] while investigating a robot foraging task. When ants are assigned different preferences for sand grain colors, Urbano called ants executing the algorithm given above "sand artists". Both Urbano [58] and Greenfield [24, 28] have used variants of this sand grain foraging model to create ant paintings. Figure 1e shows a circle pattern design of Greenfield that was rendered using this method.

5.4.2 Greenfield—Seed Foraging

The desert ant species *Pogonomyrmex barbatus* does not use pheromone trails when foraging for seeds. It is understood, however, that the nest mound of these ants has a hydrocarbon profile that helps returning ants find the nest entrance [50], and it is known that in order to initiate seed foraging, each morning a number of *patroller* ants lay down several short pheromone trails on the nest mound to indicate directions foragers should use for that day's foraging. For their first foraging trip of the day, foragers proceed in one of the directions indicated by the patrollers for a considerable distance away from the nest, at which point they begin searching for a seed. When one is found (nearly all trips are successful), the forager returns directly to the nest, and then, for each subsequent trip, the forager returns to approximately the same location where the first seed was found to resume the search for seeds. Based on experimental evidence obtained by Gordon [17] that seed foraging is sustained on the basis of a high enough rate of ant-ant interactions occurring between successful returning foragers and queued idle foragers waiting at the nest entrance, and working from parameter values estimated from primary source materials, Greenfield [26] simulated the foraging behavior of a colony of these ants over a five-hour period. He then followed up by creating ant paintings based on the simulation of all the first foraging trips of the day [25].

6 Conclusion

We have endeavored to document the emergence and history of ant- and ant-colony-inspired ALife art and to understand how such art works relate to other ALife art genres. By examining the technical aspects of artists' projects, we have demonstrated how biological research and ant and ant colony simulation efforts have informed ant- and ant-colony-inspired ALife art.

The recent works of Urbano [58] and Greenfield [26] draw their inspiration from biological models of nest construction and seed foraging behavior. As such, their work can be seen, simultaneously, as artistic endeavors, as information visualization projects, and as model validation efforts contributing to a better understanding of ant behavior.

Along with such efforts grounded in biological models, we observe works where ant and ant colony behaviors are used as a powerful metaphor for the construction of a complex system. This departure from biological plausibility is openly and explicitly acknowledged by the artists, as evidenced from the early works of Barrass [3]—which focuses on the visualization of simulated ant behavior—through the recent works of Machado et al. [36, 38], where an evolutionary computation system evolves the behavior of virtual ants, yielding nonphotorealistic renderings of input images in accordance to fitness functions designed by end users.

The body of work surveyed in this article reveals one of the most valuable characteristics of ant and ant colony research: the ability to provoke and inspire, making researchers push boundaries in an endless quest to understand, mimic, or match the untamed beauty of nature by all means available.

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References

1. Annunziato, M., & Pierucci, P. (2002). Relazioni emergenti: Experiments with the art of emergence. *Leonardo*, *35*(2), 147–152.
2. Aupetit, S., Bordeau, V., Monmarché, N., Slimane, M., & Venturini, G. (2003). Interactive evolution of ant paintings. In B. McKay et al. (Eds.), *2003 Congress on Evolutionary Computation Proceedings vol. 2* (pp. 1376–1383). IEEE Press.
3. Barrass, T. (2005). *Neural networks in new media art*. Unpublished master thesis. Melbourne University.
4. Barrass, T. (2004). *Soma (self-organizing ant maps) tests: August 2003–August 2004*. http://www.youtube.com/watch?v=U0yqQashnQw (accessed January 2015).
5. Barrass, T. (2001). Visualising the emergence of shared behavioural pathways in a crowd. Artist's Presentation. In A. Dorin (Ed.), *Proceedings of Second Iteration* (pp. 22–23). Melbourne: CEMA.
6. Cao, Y., Vacanti, J., Paige, K., Upton, J., & Vacanti, C. (1997). Transplantation of chondrocytes utilizing a polymer-cell construct to produce tissue-engineered cartilage in the shape of a human ear. *Plastic Reconstructive Surgery*, *100*(2), 297–302.

7. Cherry, R. (1991). Use of insects by Australian aborigines. *American Entomologist*, *37*(1), 8–13.

8. Dewdney, A. (1989). Two-dimensional Turing machines and Turmites make tracks on a plane. *Scientific American*, *September*, 180–183.

9. Driessens, E., & Verstappen, M. (2006). *E-volver / E-volved Cultures*. Amsterdam: Stichting Kunst en Openbare Ruimte / Foundation Art and Public Space (SKOR).

10. Fernandes, C., Isidoro, C., Barata, F., Rosa, A., & Merelo, J. (2011). From Pherographia to Color Pherographia: Color sketching with artificial ants. In *Proceedings of the 2011 IEEE Congress on Evolutionary Computation* (pp. 1124–1131). IEEE Press.

11. Fernandes, C. (2010). Pherographia: Drawing by ants. *Leonardo*, *43*(2), 107–112.

12. Fernandes, C., Mora, A., Merelo, J., Cotta, C., & Rosa, A. (2013). Photo rendering with swarms: From figurative to abstract pherogenic imaging. In *2013 IEEE Symposium on Computational Intelligence for Creativity and Affective Computing* (pp. 32–39). IEEE Press.

13. Fernandes, C., Ramos, V., & Rosa, A. (2005). Self-regulated artificial ant colonies on digital image habitats. *International Journal of Lateral Computing*, *2*(1), 1–8.

14. Forti, L., Camargo, R., Fujihara, R., & Lopes, J. (2007). The nest architecture of the ant, *Pheidole oxyops* Forel, 1908 (Hymenoptera: Formicidae). *Insect Science*, *14*(5), 437–442.

15. Franks, N., Wilby, A., Silverman, V., & Tofts, C. (1992). Self-organizing nest construction in ants: Sophisticated building by blind bulldozing. *Animal Behavior*, *44*, 109–375.

16. Franks, N., & Deneubourg, J. (1997). Self-organizing nest construction in ants: Individual worker behavior and nest's dynamics. *Animal Behavior*, *54*, 779–796.

17. Gordon, D. (2010). *Ant encounters: Interaction networks and colony behavior*. Princeton, NJ: Princeton University Press.

18. Greenfield, G. (2005). Evolutionary methods for ant colony paintings. In F. Rothlauf et al. (Eds.), *Applications of evolutionary computing, EvoWorkshops 2005 Proceedings* (pp. 478–487). New York: Springer.

19. Greenfield, G. (2006). Ant paintings using a multiple pheromone model. In R. Sarhangi & J. Sharp (Eds.), *BRIDGES 2006 Conference Proceedings* (pp. 319–326).

20. Greenfield, G. (2006). On evolving multi-pheromone ant paintings. In *2006 IEEE World Congress on Computational Intelligence*. Vancouver: IEEE Press. WCCI06 Conference Proceedings (DVD-ROM ISBN: 0-7803-9489-5), 7425–7431.

21. Greenfield, G. (2009). On variation within swarm paintings. In E. Akleman & N. Friedman (Eds.), *Proceedings of ISAMA 2009, Eighth Interdisciplinary Conference of the International Society of the Arts, Mathematics, and Architecture* (pp. 5–12), *Hyperseeing*, Spring.

22. Greenfield, G. (2011). Abstract overlays using a transport network model. In C. Sequin & R. Sarhangi (Eds.), *BRIDGES 2011 Conference Proceedings* (pp. 45–50).

23. Greenfield, G. (2012). A platform for evolving controllers for simulated drawing robots. In P. Machado, J. Romero, & A. Carballal (Eds.), *EvoMUSART 2012 Conference Proceedings* (pp. 108–116).

24. Greenfield, G. (2012). Stigmmetry prints from patterns of circles. In R. Bosch, D. McKenna, & R. Sarhangi (Eds.), *Bridges 2012 Conference Proceedings* (pp. 291–298).

25. Greenfield, G. (2013). Ant paintings based on the seed foraging behavior of *P. barbatus*. In G. Hart & R. Sarhangi (Eds.), *BRIDGES 2013 Conference Proceedings* (pp. 43–48).

26. Greenfield, G. (2013). On simulating seed foraging by red harvester ants. In *2013 IEEE Symposium on Artificial Life* (pp. 105–112). IEEE Press.

27. Greenfield, G. (2014). Target curves for pick-up, carry and drop mobile automata. In G. Greenfield & R. Sarhangi (Eds.), *Bridges 2014 Conference Proceedings* (pp. 381–384).

28. Greenfield, G. (2014). The computer art of Manuel Quejido revisited. *Journal of Mathematics and Design*, *2013*, 59–66.

29. Greenfield, G., & Machado, P. (2009). Simulating artist and critic dynamics—an agent-based application of an evolutionary art system. In A. Dourado, A. Rosa, & K. Madani (Eds.), *Proceedings of the International Joint Conference on Computational Intelligence, Funchal, Portugal, 5–7 October 2009* (pp. 190–197).

30. Hölldobler, B., & Wilson, E. (1994). *Journey to the ants: A story of scientific exploration*. Cambridge, MA: Belknap Press.

31. Jacob, C., Hushlak, G., Boyd, J., Sayles, M., Nuytten, P., & Pilat, M. (2007). Swarmart: Interactive art from swarm intelligence. *Leonardo*, *40*(3), 248–254.

32. Jones, J. (2010). Characteristics of pattern formation and evolution approximations of *Physarum* transport networks. *Artificial Life*, *16*, 127–153.

33. Kac, E. (1998). Transgenic art. *Leonardo Electronic Almanac*, *Vol. 6*, No. 11. Republished in G. Stocker & C. Schopf (Eds.), *Ars Electronica '99—Life Science* (pp. 289–296), Vienna, New York: Springer, 1999.

34. Kohonen, T. (1995). *Self-organizing maps*. New York: Springer.

35. Langton, C. (1986). Studying artificial life with cellular automata. *Physica D: Nonlinear Phenomena*, *22*(1–3), 120–149.

36. Machado, P., & Amaro, H. (2013). Fitness functions for ant colony paintings. In *International Conference on Computational Creativity, ICCC 2013* (pp. 32–39).

37. Machado, P., & Pereira, L. (2012). Photogrowth: Non-photorealistic renderings through ant paintings. In T. Soule (Ed.), *Proceedings of the Fourteenth International Conference on Genetic and Evolutionary Computation: Conference companion—GECCO 2012* (pp. 233–240).

38. Machado, P., Martins, T., Amaro, H., & Abreu, P. H. (2013). An interface for fitness function design. In J. Romero, J. McDermott, & A. Carballal (Eds.), *3rd International Conference on Evolutionary and Biologically Inspired Music, Sound, Art and Design—EvoMUSART 2014* (pp. 13–25).

39. McCormack, J. (2012). Creative ecosystems. In J. McCormack & M. d'Inverno (Eds.), *Computers and creativity* (pp. 39–60). Heidelberg: Springer.

40. McCormack, J., Bown, O., Dorin, A., McCabe, J., Monro, G., & Whitelaw, M. (2014). Ten questions concerning generative computer art. *Leonardo*, *47*(2), 135–141.

41. Mora, A., Fernandes, C., Merelo, J., Ramos, V., & J. L. J., Laredo (2008). KohonAnts: A self-organizing ant algorithm for clustering and pattern classification. In *Proceedings of the XI Artificial Life Conference* (pp. 428–435).

42. Moura, L., & Pereira, H. (2004). *Man + robots: Symbiotic art*. Lyon/Villeurbanne, France: Institut d'Art Contemporain.

43. Moura, L., & Ramos, V. (2002). Swarm paintings—nonhuman art. In J. Maubant et al. (Eds.), *Architopia: Book, art, architecture, and science* (pp. 5–24). Lyon/Villeurbanne, France: Institut d'Art Contemporain.

44. Ramos, V., & Almeida, F. (2000). Artificial ant colonies in digital image habitats—a mass behaviour effect study on pattern recognition. In M. Dorigo et al. (Eds.), *Proceedings of ANTS'2000—2nd International Workshop on Ant Algorithms: From ant colonies to artificial ants* (pp. 113–116).

45. Ramos, V., Muge, F., & Pina, P. (2002). Self-organized data and image retrieval as a consequence of inter-dynamic synergistic relationships in artificial ant colonies. In A. Abraham et al. (Eds.), *Soft computing systems—design, management and applications* (pp. 500–509). Amsterdam: IOS Press.

46. Reynolds, C. (1987). Flocks, herds, and schools: A distributed behavioral model. *Computer Graphics*, *21*(4) (SIGGRAPH '87 Conference Proceedings), 25–34.

47. Schneirla, T. (1944). A unique case of circular milling in ants, considered in relation to trail following and the general problem of orientation. *American Museum Novitates*, *1253*, 1–26.

48. Semet, Y., O'Reilly, U., & Durand, F. (2004). An interactive artificial ant approach to nonphotorealistic rendering, genetic and evolutionary computation. In K. Deb et al. (Eds.), *GECCO 2004* (pp. 188–200). London: Springer.

49. Sims, K. (1991). Artificial evolution for computer graphics. In *Computer graphics (SIGGRAPH '91 Conference Proceedings)* (pp. 319–328).

50. Sturgis, S., Greene, M., & Gordon, D. (2011). Hydrocarbons on harvester ant (*Pogonomyrmex barbatus*) middens guide foragers to the nest. *Journal of Chemical Ecology*, DOI 10.1007/s10886-011-9947-y.

51. Todd, S., & Latham, W. (1992). *Evolutionary art and computers*. Waltham, MA: Academic Press.

52. Tschinkel, W. (2010). Methods for casting subterranean ant nests. *Journal of Insect Science*, *10*:88. (Available online at http://www.ncbi.nlm.nih.gov/pubmed/20673073.)

53. Turk, G. (1991). Generating textures on arbitrary surfaces using reaction-diffusion. *Computer Graphics*, *25*(4), 289–297.

54. Tzafestas, E. (2000). Integrating drawing tools with behavioral modeling in digital painting. In S. Ghandeharizadeh, S. Chang, S. Fischer, J. Konstan, & K. Nahrstedt (Eds.), *ACM multimedia workshops* (pp. 39–42). ACM Press.

55. Tzafestas, E. (1998). Tom Thumb robots revisited: Self-regulation as the basis of behavior. In C. Adami, R. Belew, H. Kitano, & C. Taylor (Eds.), *Proceedings of the Artificial Life VI Conference* (pp. 457–461). Cambridge, MA: Massachusetts Institute of Technology.

56. Urbano, P. (2006). Consensual paintings. In F. Rothlauf et al. (Eds.), *EvoWorkshops 2006* (pp. 622–632). Heidelberg: Springer.

57. Urbano, P. (2005). Playing in the pheromone playground: Experiences in swarm painting. In F. Rothlauf et al. (Eds.), *Applications of evolutionary computing, EvoWorkshops 2005 proceedings* (pp. 478–487). Heidelberg: Springer.

58. Urbano, P. (2011). The *T. albipennis* sand painting artists. In *Applications of evolutionary computation. EvoWorkshops 2011 Proceedings* (pp. 414–423). Heidelberg: Springer.

59. Verostko, R. (2004). *Pearl Park scriptures*. Berlin: Digital Art Museum (DAM).

60. Witkin, A., & Kass, M. (1991). Reaction-diffusion textures. *Computer Graphics*, *25*(4), 299–308.

61. Young, D. (1984). A local activator-inhibitor model of vertebrate skin patterns. *Mathematical Biosciences*, *72*(1), 51–58.