From Swarm Art Toward Ecosystem Art

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ABSTRACT

Swarm intelligence deals with the study of collectively intelligent behavior that emerges from a decentralized system of non-intelligent individual agents. The concept is widely used in the fields of simulation, optimization or robotics, but less known in the domain of generative art. This paper presents the swarm paradigm in the context of artistic creation, and more particularly explores the interest of enhancing swarm models with dynamics inspired from natural ecosystems. The authors introduce an energy budget to the agents of a swarm system, and show how mapping the energy level to visual information such as line width or color, combined with mechanisms such as resource chasing and consumption, enriches the search space of possible images. Moreover, the authors highlight that the approach allows the user to partially control the creation process of the drawings. The authors argue that the exploration of ecosystem dynamics in generative systems may open up novel artistic opportunities and shift the perspective from swarm art toward ecosystem art.

Keywords: *Artificial Life, Ecosystem Art, Generative Art, Line Drawing, Swarm Intelligence*

INTRODUCTION

Generative art is one of the most fascinating blends between art and science. It covers any practice "where the artist uses a system, such as a set of natural language rules, a computer program, a machine, or other procedural invention, which is set into motion with some degree of autonomy contributing to or resulting in a completed work of art" (Galanter, 2003). The key ingredient in this process of artistic creation is a generative system which provides an automated method for producing complex output. The output exhibits stylistic invariants, but also diverse and unpredictable facets, due to interactions between the system components and a number of parameters involved. The artistic quality of each piece remains to be assessed by the user. While generative art is defined as an autonomous realization of the piece of art, the artist takes a high place in the final output. Rules are in the heart of the creation process, but it is the human who defines these rules.

Computers are extensively used in the context of generative art. They allow processing algorithms such as recursive fractal equations or L-Systems and turning them into a visual or audible experience. The present paper focuses

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on the creation of digital images, yet generative art applies to many other forms including music (Eno, 1996), 3D sculpture (Tabuada et al., 1998) or animation (Sommerer & Mignonneau, 2009). During the last decade, the use of swarm intelligence has also been studied in this context. Moura was probably the first to coin the term "Swarm Art," denoting the subset of generative art where a number of agents collaboratively work on an emerging piece (Moura & Ramos, 2002). However, these agents typically do not possess other life-like characteristics such as growth, metabolism or reproduction. More recently, those dynamics have come into focus. It has been suggested to borrow ideas from natural ecosystems for creation in generative art (Dorin, 2004). In these "creative ecosystems," artificial agents not only interact with one another and with their environment, but also complete a life cycle and potentially evolve. The approach raises a number of interesting questions about which ecosystem mechanisms are most useful for creative design and how they can be adapted to generative art.

The present paper extends this line of research and explores the artistic potential of a generative ecosystem with resource chasing and consumption. We focus on the fundamental impacts of these dynamics on the final images and suggest what their contribution for generative art could be. The next section gives an overview of the origins and the concepts of generative art. The ecosystem model is briefly introduced. Several basic experiments of image generation are described and discussed. We highlight the interest of the model by a number of more complex applications. We finally conclude the paper and present the perspectives on the approach.

STATE OF THE ART

Origins and Basic Algorithms

The origins of computer based generative art can be traced back to the 1980s where pioneering artists such as Jean-Pierre Hébert used plotters, i.e., devices that mechanically move a pen to print computer diagrams, for their creations. Since these first explorations, the movement of the "algorists" (algorithmic artists) has inspired many talents like Davis (2012) and Klingemann (2012). Figure 1 is an artwork by Joshua Davis. He used graphical elements based on floral dissections borrowed from the book "Types of Floral Mechanics," which have been processed by a generative algorithm. Figure 2 exhibits a piece of art by Klingemann. He used a computer program analyzing the colors

Figure 1. "Tropism Exhibition," J. Davis

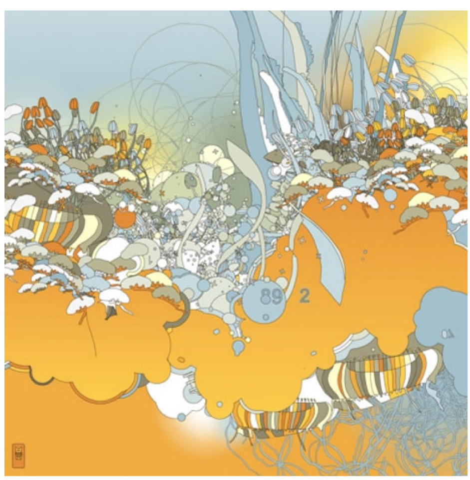


Figure 2. "Starry Night," M. Klingemann

of existing pictures and recreating them in the form of pie charts. Note that these two examples constitute different approaches to generative art: creating a piece by processing an existing source or "from scratch." These two strategies will also be explored with the model presented in this paper.

While some generative algorithms originate from computer graphics research, such as Voronoi diagrams (Kaplan, 1999) or the Perlin noise (Perlin, 2012), many other computational methods adopted by the generative art community are borrowed from the field of Artificial Life (Whitelaw, 2004). "Fractal art" is a form of generative art where fractal objects are represented as still images or animations. Figure 3 recalls the classic Mandelbrot fractal which already possesses much artistic potential. More recently, non-linear Iterated Function Systems have been introduced and turned out to produce spectacular computer art (Draves, 2005; Lutton et al., 2003) (Figure 4).

L-systems are a mathematical formalism proposed in 1968 by the biologist Aristid Lindenmayer (Prusinkiewicz & Lindenmayer, 1990). Their principles are derived from Chomsky's work on formal grammars (Chomsky, 1957). Starting from an initial axiom, a set of

Figure 3. Mandelbrot fractal

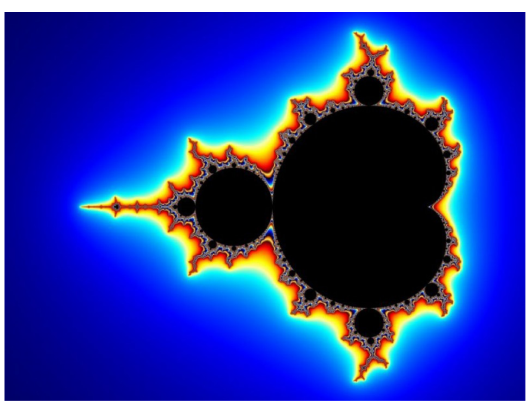
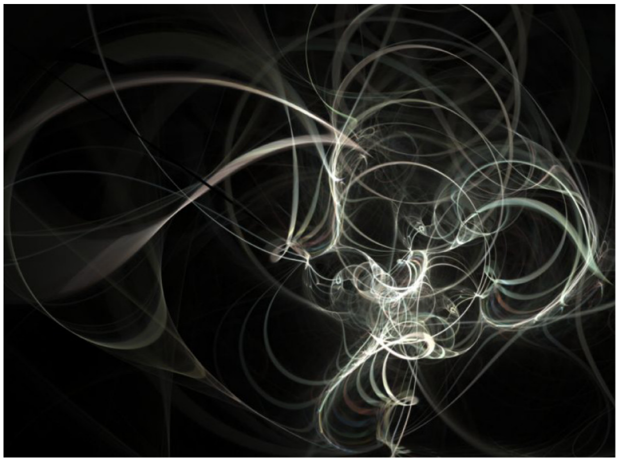


Figure 4. Non-linear IFS



production rules is recursively applied in order to rewrite a symbol string. At each iteration, the string can be mapped to a graphic interpretation, using the principle of the ”turtle geometry,” where a single drawing agent moves on a canvas and plots line segments according to the sequential instructions defined by the L-System string. L-systems are particularly appropriate for modeling growing plant-like structures, each iteration being a growing step of the plant (Figure 5).

SWARM ART

The use of swarm intelligence has also been explored in the field of generative art (Jacob et al., 2007; Kräftner, 2008). This approach defines artificial agents featuring a number of visual characteristics such as color or line style. The agents move and interact on the canvas leaving a trail behind them. It is possible to parameterize their behavior, for example they may move in a straight line, stray at random or change color. The Figures 6 and 7 are samples of patterns that

Figure 5. The first five growth steps of a plant-like L-System

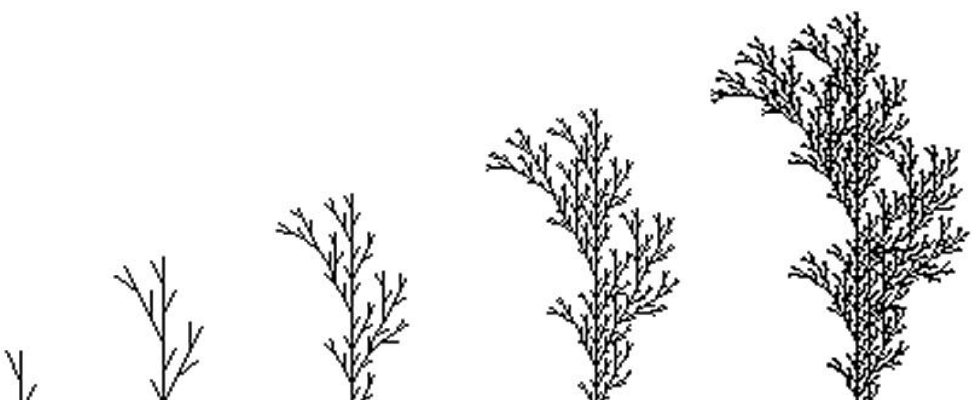


Figure 6. Coded Beauty, T. Kräftner

emerged from this kind of model. Certain swarm systems are inspired by the behavior of ants, where the agents deposit colors on the canvas and follow simple rules of motion and reaction to the colors they encounter, just like real ants move and react to pheromones (Aupetit et al., 2003; Greenfield, 2005; Monmarché et al., 2007) (Figure 8). A remarkable work was done by the artist Stanza who used swarms of real robots following a set of basic movement rules (Stanza, http://www.stanza.co.uk/) (Figure 9).

With a view to modifying or redrawing existing pictures, the "RenderBots" (Schlechtweg et al., 2005) possess different functionalities such that their behavior produces artistic features like stippling or hatching. During the

Figure 7. SwarmArt, C. Jacob

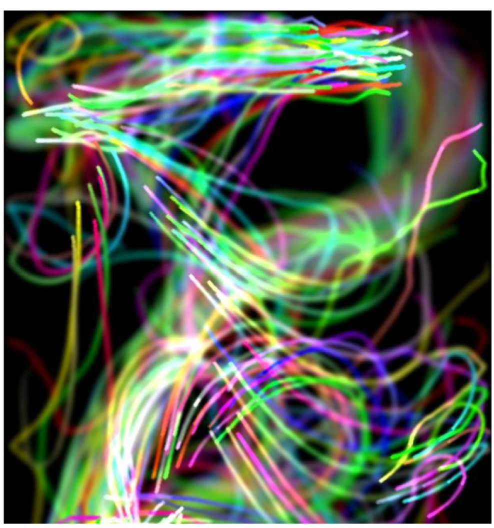
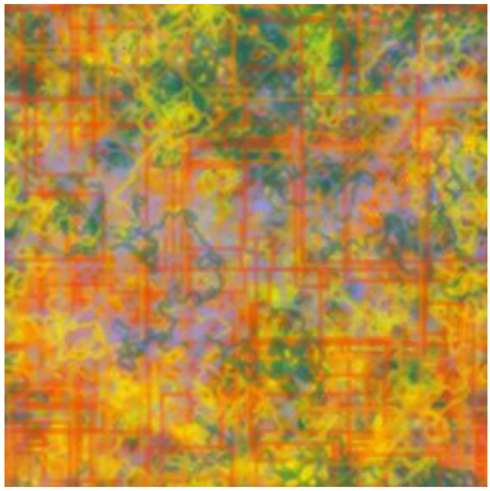


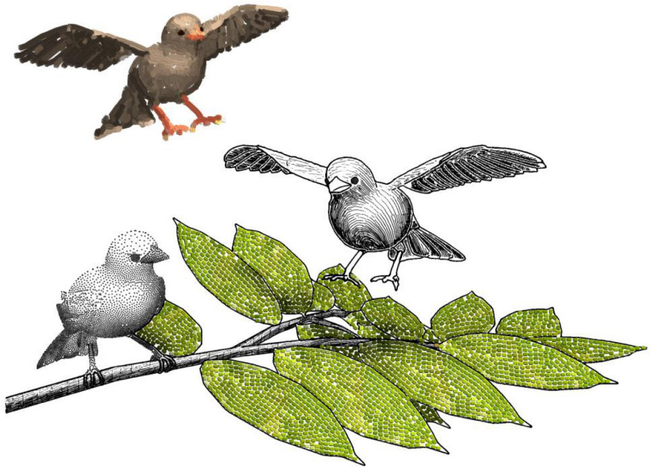
Figure 8. Ant painting, N. Monmarché



simulation, the individual agents deploy in the environment (the source image) and execute their painting function. This multi-agent system can be considered as a toolbox for the user to produce pieces of art in a very flexible way. Figure 10 shows an example of this approach, combining different artistic styles in one image.

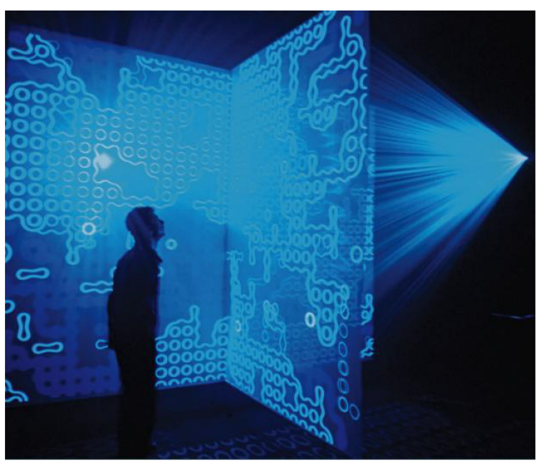
Figure 9. Robotica, Stanza

Figure 10. RenderBots



A few artists have started advocating the use of swarm systems featuring mechanisms inspired from natural ecosystems (Dorin, 2004, 2008; McCormack, 2007). This new perspective goes beyond simple agent-agent interactions and augments the artificial organisms with interactions with their environment as well as biological dynamics such as growth or reproduction. As one of the pioneering projects in this field, "Eden" (McCormack, 2009) was a 2004 installation at the SenseSurround exhibition in the Australian Centre for the Moving Image. In this work, dedicated to generating sonic pieces of art, a virtual world is populated with organisms making and listening to sounds and competing for limited resources. By making beautiful or interesting sounds, the creatures can keep the visitors close to the installation, which increases the resource supply and thereby their chances of survival (Figure 11).

Figure 11. Eden



MODEL DESCRIPTION

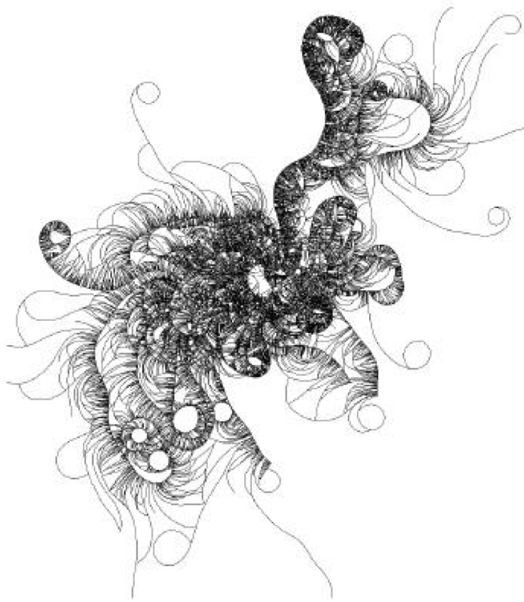
The presented model takes its inspiration from existing studies on swarm based generative art (Annunziato, 1998): artificial organisms move, reproduce and finally die in a two-dimensional continuous environment, leaving a trail as they roam around. The organisms perish when they encounter an already existing trail. The environment can be considered as an initially blank canvas, and the produced trails are lines that progressively compose an image. The image is complete when there are no more line-drawing agents alive. Variation between the drawings is possible by adjusting a number of probability parameters such as the agents' fecundity or the curvature of their trajectories. Using a very similar model, McCormack explored the emergence of machine creativity without user control in artificial ecosystems. It has been shown that niche construction can considerably increase the diversity and the heterogeneity of artistic output (McCormack, 2010). Figure 12 shows a sample picture drawn by the ecosystem.

With a view to extending the dynamics of this promising approach, we add an energy level to the agent model. As a matter of fact, metabolism is one of the most fundamental characteristics of living systems, and since the first seminal studies in the Artificial Life literature, ecosystem models typically comprise a submodel of simplified resource management (Hraber et al., 1997; Ventrella, 1998; Yaeger, 1994). In the scope of this paper, we particularly focus on food chasing and ingestion, as well as on agent size and coloration depending on the agents' energy level, and explore the potential of these concepts for esthetic image generation.

Agent

At the beginning of a drawing, a number of artificial organisms are placed in the environment. Depending on the desired control of the initial configuration, the agents can be positioned by hand, by predefined patterns or at random. The current state of an agent is described by

Figure 12. Creative drawing with niche constructing agents



- ***Location***: the position of the agent in the environment;
- ***Orientation***: the agent's heading direction;
- ***Speed***: the distance covered per time step. In the scope of this paper, speed is constant during an agent's lifetime;
- ***Curvature***: the rate of curvature of the movement. A curvature of zero signifies a straight line;
- ***Energy***: a positive real number denoting the energy budget which is consumed by movements. The energy level can be increased by absorbing resources from the environment. If it falls below zero, the agent dies. In Annunziato (1998) and McCormack (2010), the agents die when they cross an existing trail. This constraint has been lifted and replaced by death through starvation, i.e., total energy loss.
- ***covColor***: a covering color which changes according to the color of the ingested resources. The overall agent color is a blend between the covering color and the genotypic primary color.

Genotype

In addition to the phenotypic information which varies over time, the agent behavior is ruled by a set of constant genetic characteristics. Modeling an artificial genotype allows placing agents with different behavior in the same environment. Moreover, the model can easily be extended to evolutionary dynamics, although these are not implemented for the pictures presented in this paper.

- ***irrationality***: the degree of variation in the curvature. The higher this value, the more chaotic the movement, producing less predictable patterns;
- ***fecundity***: the probability of producing a child agent per time step;
- ***offset***: a positive value indicating the offset angle of the children that separate from the parent agent. The offspring randomly spawn to the left or to the right side;
- ***divRatio***: the proportion of energy an agent allocates to its child at reproduction;
- ***sensorRange***: the range of perception in the environment. An agent senses resources within this distance;
- ***ingRange***: the maximum distance which allows ingesting food from the environment;
- ***consumption***: the amount of consumed energy per covered distance;
- ***agility***: the capacity to rapidly orient towards a target location for food chasing. The higher this value, the smaller the executed turning radius;
- ***prColor***: the underlying primary color of the agent;
- ***prStrength***: the relative strength of the primary color versus the covering color.
- ***linSize***, ***expSize***: a linear and an exponential parameter controlling the size of the agent for a given energy level.

Reproduction

Reproduction is modeled as being asexual, meaning that offspring arise from a single parent and inherit the genes of that parent only. In the scope of this paper, the children always possess an exact copy of the parent genotype. Evolutionary mutation and crossover operators are not enabled for the presented simulations.

In addition to the genotypic data, a reproducing agent passes down to the offspring the following current state values: *location, speed, curvature* and *covColor*. The initial energy and orientation of the descendant are calculated by considering respectively the parental *divRatio* and *offset* gene.

Food Chasing

The agents possess a default moving behavior based on *curvature* and *irrationality*. Resources can be positioned in the same way as the agents. In the scope of this paper, such resources are static and can be considered as food bits placed on the canvas. As soon as a resource enters the agent's perception range, they are attracted to it and adjust their orientation within the limits of the *agility* gene. The presence of food affects the agent trajectory and therefore the produced lines, however the agents do not interact between each other.

The resources hold a certain amount of energy (*fEnergy*) as well as a color (*fColor*) which acts on the agent's covering color. When a chased food bit comes into ingestion range, the agent's energy level is increased by that of the resource, and the resource is deleted from the environment. The color and the size of the agent are updated according to the rules of the next section.

Coloration and Size

The size of the agents, and accordingly the width of the trail they leave behind, follows the equation

$$\text{size} = \text{linSize} * \text{energy}^{\text{expSize}}$$

Note that if *expSize=0*, the line width does not depend on the energy level. When an agent feeds from the environment, its covering color updates according to the color and energy of the resource. The new covering color of an organism having ingested a food bit is computed by

$$\text{covColor} = (\text{covColor} * \text{energy} + \text{fColor} * \text{fEnergy}) / (\text{energy} + \text{fEnergy})$$

The agent trail is colored after the current overall color, which is a weighted mean of primary and covering color: the higher the energy level, the higher the influence of the covering color.

$$\text{color} = (\text{prColor} * \text{prStrength} + \text{covColor} * \text{energy}) / (\text{prStrength} + \text{energy})$$

The described model has been implemented in Java as an experimental platform for exploration and analysis. The next two sections discuss a series of images that emerged from various simulation runs. The generation of each image typically did not take more than a few seconds.

BASIC STUDIES

First, we present the interest of modeling agent energy and color, i.e., the two phenotypic features beyond spatial and motional information. Second, we highlight the implications of placing food resources on the canvas, and point out some major impacts on the artistic output.

Figure 13 shows three simulations where reproducing agents have been seeded with different energy levels. In these runs, *prStrength=expSize=0*, meaning that neither color nor line width depends on the agent's energy. It can be observed how increasing starting values lead to more complex patterns. As a matter of fact, all agents coming into existence during the drawing process inherit a fraction of the primary energy which has originally been supplied to the environment. The user may act

Figure 13. The importance of primary energy. Patterns created with an initial value of (a) 1000, (b) 5000 and (c) 15000.

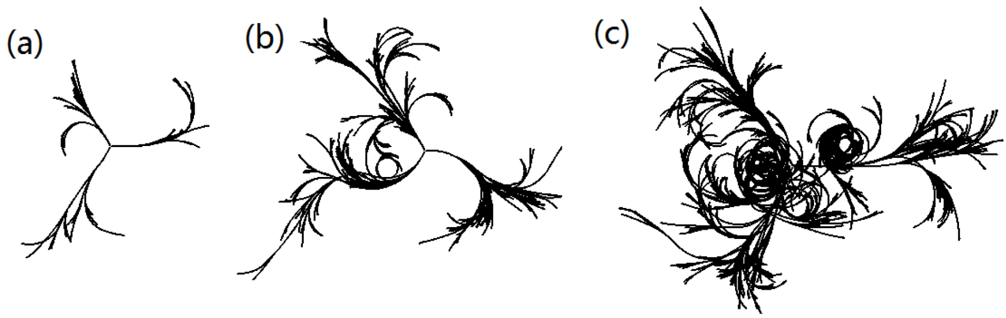
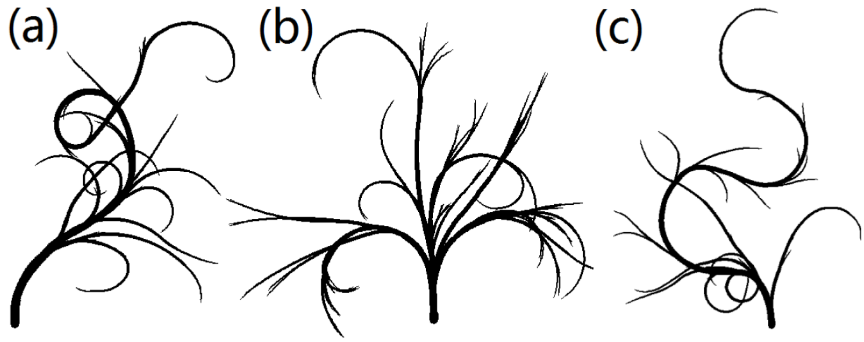


Figure 14. Symmetric and asymmetric duplication. Patterns created with a division ratio of (a) 0.1, (b) 0.5 and (c) 0.9



on this parameter to constrain the overall length of lines drawn on the canvas, and therefore the density of the final image.

By defining *expSize>0*, the agent's energy level is mapped to size and consequently to line width. The second series of images focuses on this visual effect. Just as in the previous runs, no resources are added to the environment, so that all agents rapidly die of starvation. The samples of Figure 14 show how the progressive energy loss of the agents implies a thinning of the lines. Moreover, it can be seen that the proportion of energy ceded to offspring has an influence on the overall appearance of the image. Even splits design rather balanced patterns, whereas uneven divisions lead to the emergence of a master branch with secondary filaments.

The next experiment highlights the interest of mapping the agent's energy to color. Figure 15 displays two images generated by swarms of agents with a positive *prStrength*. In the left image, the agents have a black primary and a white covering color. In the right image, the properties are inverted. Since the agents lose energy as they roam around, their primary color gradually predominates, which produces interesting fade effects. Agent coloring adds a new visual dimension to the generated images and profoundly enriches the artistic possibilities with the ecosystem.

In the previous simulations, the artificial organisms have been conditioned by energy and color parameters, however they were free to move around without constraints other than

Figure 15. Energy loss leading to fade effects

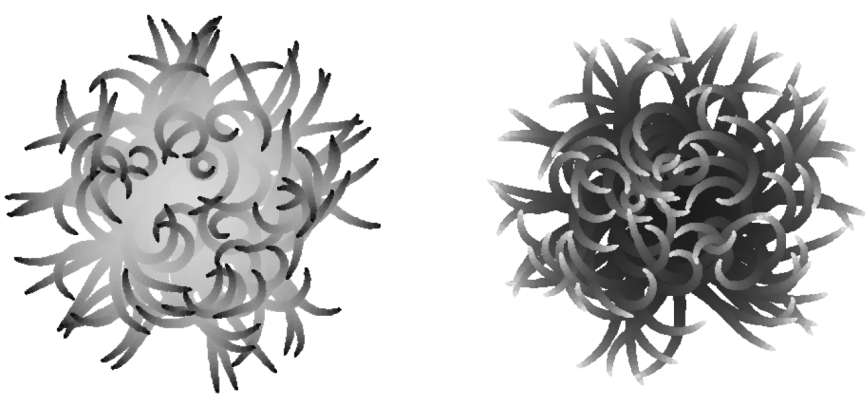
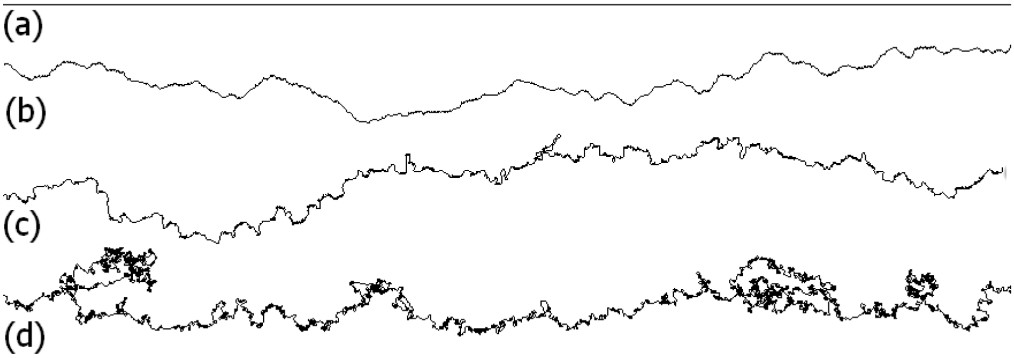


Figure 16. Erratic lines created with an agility of (a) 1.0, (b) 0.6, (c) 0.3 and (d) 0.1



the vicissitudes imposed by *irrationality*. For more artistic control, the concept of food chasing can be used to guide the agent's drive during the image generation. As a matter of fact, a resource can be considered as attractor or destination point the agents tend to reach as soon as it enters the sensor range. The actual trajectory, and therefore the looks of the produced line, varies not only with the values of *irrationality*, but also with *agility*. Figure 16 highlights this effect. For every line of the image, one agent has been placed to the left, and a resource to the right of the canvas. It can be witnessed how the agents with a lower *agility* draw more erratic lines, lacking in the ability to compensate the irrational component of their wandering. Yet, all agents finally meet their destination.

Food chasing in environments with more than one agent produces basins of attraction. The two images of Figure 17 simulate swarms released on a canvas featuring two food bits. As a result the agents are drawn to the targets, but their ingestion range has been set to 0, so that they cannot catch it. Note that some agents in the lower left and the upper right corners are situated in such a way that both food bits are outside their sensor range and adopt their default behavior.

APPLICATIONS

The following examples have been designed to illustrate the artistic potential of the suite of behaviors studied.

Figure 17. Food serving as attractor. Patterns created with an agility of (a) 1 and (b) 0.07.

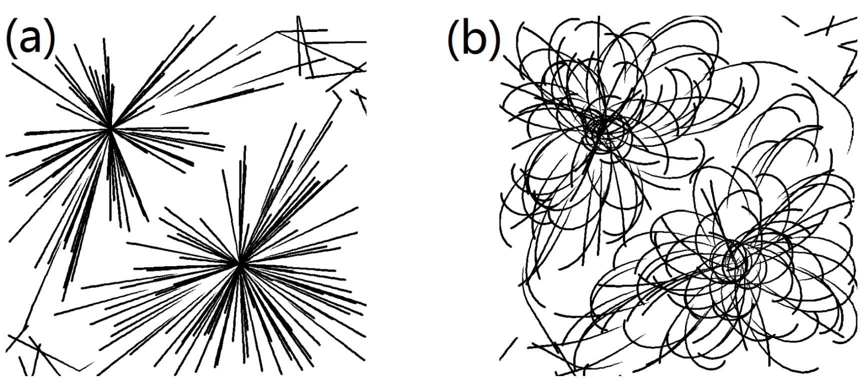


Figure 18. Plant structures

The first example demonstrates the possibility of generating plant-like branching structures with the ecosystem model. The images are closely related to those produced by the L-system algorithm we discussed. In contrast, with the presented model all branches of a plant drawing grow in parallel and without a global control mechanism by means of an agent swarm. The leftmost structure of Figure 18 highlights the visual resemblance to classic L-system graphics which typically feature straight-lined segments. The following three plants point out how increasing values of the agents' *irrationality* leads to more and more surreal sinuous or coiled botanical forms. Note that due to constant energy loss similar to the scenario of Figure 15, the fading of the agent trails allows distinguishing between stem, branches and foliage of the plants.

The next example addresses the idea of controlling the agent coloration which changes according to a user designed initial resource pattern. In Figure 19, a collection of colored food bits has been placed in a predefined pattern representing the letters A-R-T. A number of agents is seeded to the left of each letter, with white primary and covering color. Moreover, they are "blind," i.e., *sensorRange= 0*, so that they cannot perceive resources and only follow their default behavior which is defined to be a fixed rightward run. As soon as the agents meet the deposited food, they start ingesting them and develop colored trails. When they quit the resource-rich region on the right hand side of the letter, they rapidly die of starvation. As an overall visual effect, the swarm redraws but somewhat blurs the original pattern.

Figure 19. Agents running across a predefined resource pattern

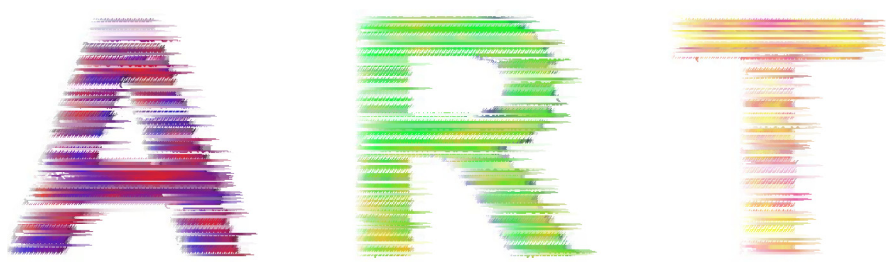


Figure 20. Agents grazing on a predefined resource pattern

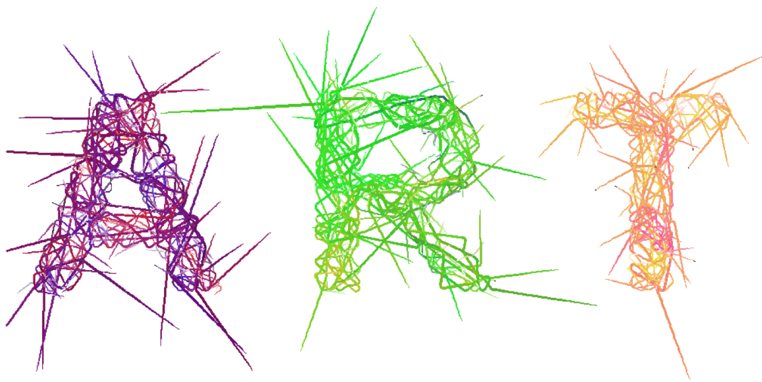
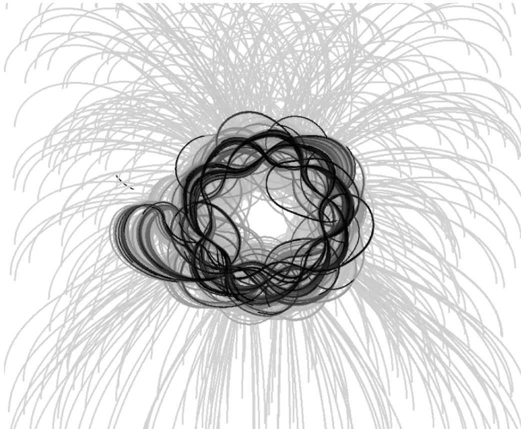


Figure 21. Qun - the Chinese pictogram signifying "swarm"

In the previous section, it has been shown that not only the color but also the moving direction of the agents can be influenced by food patterns. To demonstrate an application of this idea, Figure 20 displays a drawing where food bits have been laid out in a pattern similar to that of the previous simulation. However, this time the agents' sensor range is positive, so that they perceive and actively head for nearby resources. As soon as they start assimilating the deposited food, they produce visible lines. When no more resources are found in the environment, the agents adopt their default strategy, which is a straight forward march. Their trails constantly thin and finally disappear.

Interestingly, the thinning of the lines due to energy loss can be likened to human brush strokes. Figure 21 illustrates this idea by a swarm of agents which, starting from a handcrafted initial configuration resources, collectively draws a Chinese character. The creation of this picture required a considerable amount of trial-and-error, however the endeavor proved that calligraphy is an artistic subspace within the space of all images that can be generated by the ecosystem. The sample painting suggests that, given a sufficiently convenient interface for the exploration process, the system may allow artists to discover imaginary calligraphic patterns or variations of existing ones.

Figure 22. Picture gallery: "Cold fireworks"



CONCLUSION

We presented an artificial swarm system for generative art based on mechanisms observed in natural ecosystems. The key novelty of our approach is the introduction of energy and food chasing to the agent model.

A series of simulation runs allowed identifying the major dynamics of the system. In particular, the agent's energy level is a phenotypic information which can be mapped to artistic dimensions such as line width and color that enrich the visual experience. Despite its simplicity, the system produces output of great variety. The application section suggested ways to leverage the observed properties of the artificial ecosystem. In particular, we demonstrated how a well-directed positioning of resources can harness the agents' drive and allow the user to partially control the creation process.

In the scope of this paper, the agent reproduction did not involve evolutionary dynamics. This restriction was made in order not to blur the basic mechanisms of our model. As a future extension, it would be interesting to introduce genetic mutations, i.e., random variations in the child genotype. Evolutionary change would open new degrees of freedom which could be creatively exploited by the system. Moreover, the definition of distinct agent species would

Figure 23. Picture gallery: "Vortex"

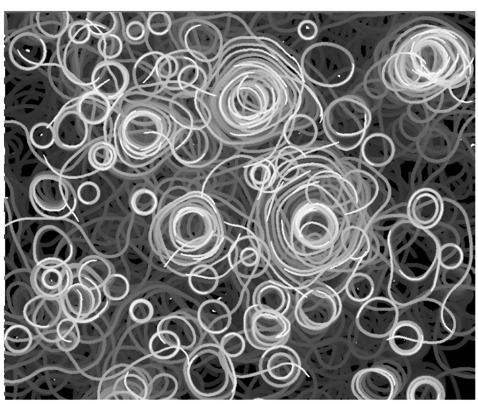


Figure 24. Picture gallery: "Blue energy"

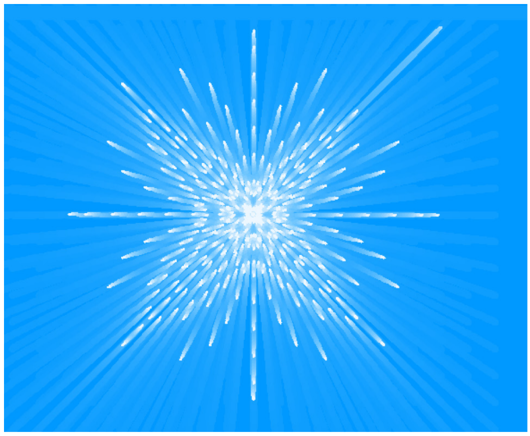
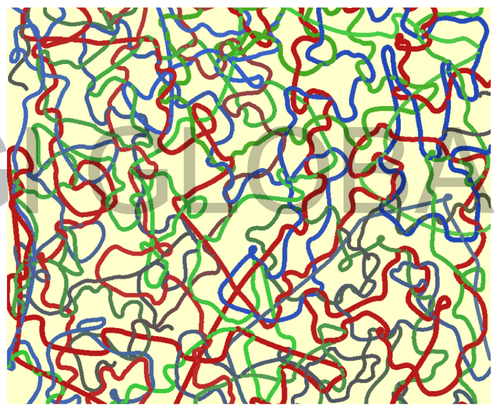


Figure 25. Picture gallery: "I love Stanza"



allow assessing the artistic value of predator-prey relationships, flight behavior and dynamic chase.

Figures 22 through 25 offer a small gallery of our favorite drawings obtained with the model. The presented work contributes to the construction of a toolbox of ecosystem features for creative image generation. "Ecosystem Art" is still in its infancy, and it may still be a long road before its potential is fully understood and exploited. But we participate to the fresh vision of generative art systems featuring "intelligent brushes" (McCormack, 2010) which could be selected by the artist and applied on a canvas in order to produce innovative pieces on the borderline between human inspiration and machine creativity.

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