Ecosystem Dynamics for Creative Image Generation

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Abstract

Generative artists are constantly searching for new methods which innovate or enhance the esthetic value of their works. Over the last years, there has been a growing interest in using the swarm paradigm, i.e. in designing decentralized systems with mobile agents that collaborate on the creation of an emerging piece of art. In particular, "creative ecosystems" are conceived based on characteristic features of natural ecosystems, where organisms not only interact with one another and with their environment, but also complete an entire life cycle. The present paper [... bla bla... to be written as soon as we have the conlusion section].

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 feature in this approach is a generative system providing an automated method for artistic output. The output exhibits stylistic invariants, but also diverse and unpredictable facets, due to complex interactions between the system components and a number of involved parameters. The artistic value of the generated pieces can subsequently be assessed by the user. While the present paper focuses on the creation of images, generative art applies to many other forms including music, 3D sculpture or animation.

The artist typically guides the generative system via interactive evolution (Takagi, 2001), assigning fitness values to the pieces, and selecting which ones will survive and reproduce. Offspring is created using mutation and recombination rules, which give birth to a new generation of individuals. This process forms a cooperation between the human sense of esthetics and the technological means of the computer, allowing man and machine to conjointly work on art that "neither could easily produce alone" (Sims, 1991). Typical examples for this approach are images created by fractal algorithms (Lutton et al., 2003; Draves, 2005), cellular automata (Ashlock and Tsang, 2009) and L-systems (McCormack, 2004; Bornhofen and Lattaud, 2006).

The use of swarm models has also been studied in this context (Aupetit et al., 2003; Greenfield, 2005). Inspired by the behavior of ants, artificial agents deposit colors on a canvas and follow simple rules of motion and reaction to the colors they encounter, just like natural ants move and react to pheromones, collaboratively working on an emerging piece of art. However, these agents do not possess other life-like features such as growth, metabolism or reproduction.

More recently, it has been suggested to explore the application of ecosystem dynamics for the creation of works of generative art (McCormack, 2007; Dorin, 2008). In these models, termed "creative ecosystems", the agents not only interact with one another and with their environment, but also complete a life cycle, reproduce and potentially evolve. The approach raises a number of interesting questions about which ecosystem mechanisms are most useful for creative design, how they can be adapted to generative art, and what their contribution on the work of art can be. As one of the pioneering results in this field, it has been shown that niche construction can considerably increase the diversity and the heterogeneity of artistic output (McCormack, 2010).

The present paper extends this approach by modeling a generative ecosystem with resource consumption and predator-prey relationships, and by evaluating their impact on the produced images. We argue that the introduction of an energy budget to the agent model not only allows the user to partially control the creation process, but also to enrich the overall visual experience, by mapping the energy level of the agents to artistic dimensions such as line width or color.

The rest of the paper is organized as follows. In the next section, the ecosystem model is briefly presented. Several experiments of image generation are described in section three. Section four concludes the paper and discusses the perspectives on the approach.

Model description

The presented model is inspired from existing studies on swarm based generative art: artificial agents move, reproduce and evolve in a two-dimensional continuous environment, leaving a trail as they roam around. The environment can be considered as a canvas, and the trails are lines that progressively compose an image. The image is complete when there are no more agents in the environment (McCormack, 2010).

As a complement to the previous work, we introduce a simplified energy management and explore its potential for esthetic image generation. In particular, we focus on the following dynamics: food ingestion, predatory behavior and agent coloration. In the two above cited works, an agent dies when it crosses an existing trail. This constraint has been lifted and replaced by death through predation and starvation, i.e. total energy loss.

Phenotype

The current state of an agent is described by

- *location*, *speed*, *orientation*: spatial information. In the scope of this paper, *speed* is a constant value;
- *energy*: a positive real number denoting the energy budget which is cunsumed by movements. The energy level can be increased by absorbing resources from the environment. If it falls below zero, the agent dies;
- *covColor*: a covering color which changes according to the colors of the ingested ressources. The overall agent color is a blend between the covering color and the (genotypic) priming color (see below).

Genotype

In addition to the phenotypic information which varies over time, the agent behavior is ruled by a set of constant genetic characteristics. At reproduction, the offspring inherits these values some of which, depending on the simulation setup, may be affetced by random mutations.

- *curvature*: the basic rate of curvature of the agent movement. A curvature of zero signifies a straight line;
- *irrationality*: the degree of variation superposed to the basic 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;
- *mortality*: the probability of dying per time step;
- *offset*: the offset angle of the children that separate form the parent agent;
- *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 and other agents 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 when grazing, hunting or fleeing. The higher this value, the smaller the executed turning radius;
- *prColor*: the underlying priming color of the agent;
- *prStrength*: the relative strength of the priming color versus the covering color.

Hunting and feeding

We defined two types of agents: grazers and predators. Both exhibit the same basic moving behavior as long as no objects exist within their perception range. Grazing agents are attracted by static food bits which are placed in the environment. These food bits possess a certain amount of energy (*resEnergy*) as well as a color (*resColor*) which acts on the agent covering color. Predators hunt grazers but not static resources. When grazers sense predators, they start to flee in the opposite direction even if they have previously been heading for food bits. As soon as a chased entity enters the ingestion range, the agent increases its energy level by that of the target.

Coloration

When an agent feeds from the environment, its covering color updates according to the color and energy of the ingested resource:

$$covColor = \frac{covColor * energy + resColor * resEnergy}{energy + resEnergy}$$

The trails are colored after the current overall color of the agents, called ”complexion”, which is a weighted mean of primary and covering color: the higher the energy level, the higher the influence of the covering color.

$$complexion = \frac{prColor * prStrength + covColor * energy}{prStrength + energy}$$

Experiments

Basic studies

The first series of simulations is intended to explore the basic dynamics of energy and color, the only two phenotypic traits beyond spatial information, and to point out their major impact on image generation.

Figure 1 shows a series of outputs where initial agents are seeded with different energy levels. Note that in these

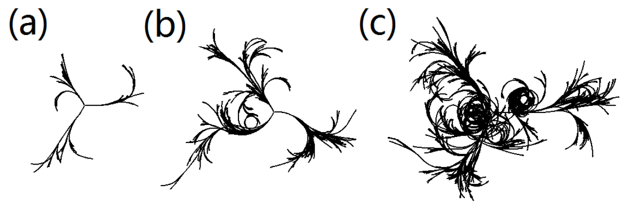

Figure 1: Patterns created with an initial energy of (a) 1000, (b) 5000 and (c) 15000.

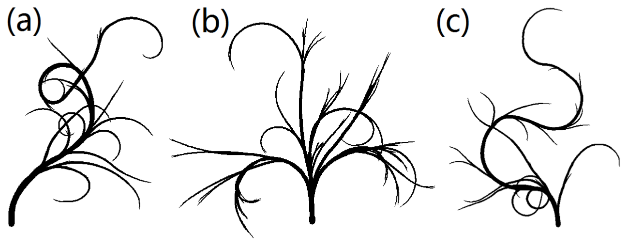

Figure 2: Patterns created with a division ratio of (a) 0.1, (b) 0.5 and (c) 0.9

simulations prStrength=0 and beta=0, meaning that neither color nor line width depend on the agent's energy. It can be observed how increasing values lead to more complex patterns. As a matter of fact, all agents coming into existence during the creation process inherit a fraction of the amount of energy which has originally been supplied to the environment. The primary energy constitutes an ultimate limit for the overall length of lines drawn on the canvas. As a consequence, the user may act on this limiting parameter to control the density of the final image.

The second series of simulations focuses on the visual effect of mapping the agent's energy level to the line width, by defining beta>0. Just as in the previous simulations, no resources are added to the environment, so that all agents rapidly die of starvation. The images of Figure 2 show that the progressive energy loss of the agents causes thinning lines. Moreover, 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 third example highlights the possibilties of mapping the agent's energy level to line color. Figure 3 presents an image generated by a swarm of agents with white priming color, black covering color and positive prStrength. As a result, lower energy levels are visualized by lighter grey shadings. Since the agents constantly lose energy as they roam around, their trails fade into the canvas.

Conclusion

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