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Genetic Learning for Biologically Inspired Aesthetic Processes

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We investigate the use of the non-interactive genetic algorithm as a tool in evolutionary art for evolving aesthetic images. We consider two problem domains. Our first uses a modification of a model for differential gene expression in order to simulate cell morphology and evolve images consisting of matrices of cells meeting our subjective aesthetic criteria. Our second uses a modification of a model for simulating ants that can deposit and follow scent (in the guise of color trails) in order to evolve ant paintings meeting out subjective aesthetic criteria. In both cases, we focus upon the design of fitness functions that are particularly well suited for ensuring that genetic learning can effectively guide the evolution of cellular or behavioral processes to yield aesthetic results.

Keywords: Simulated evolution; aesthetic fitness; genetic learning.

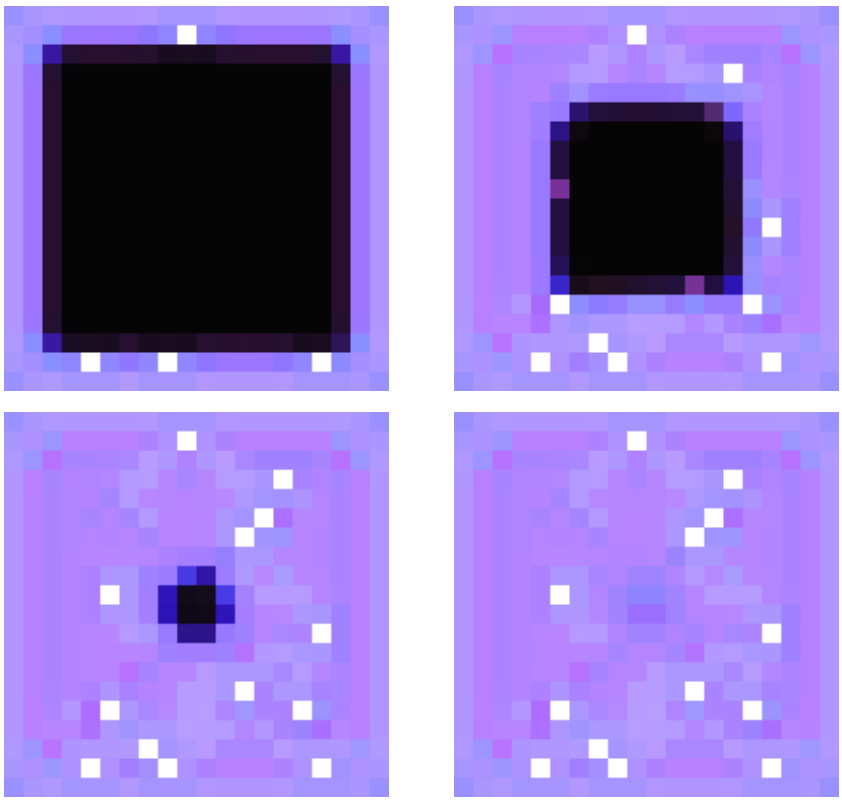

Fig. 1. An example showing the outside-in development of a 20×20 cell pattern obtained after (left-to-right, top-to-bottom) 50, 150, 250, and 350 time steps.

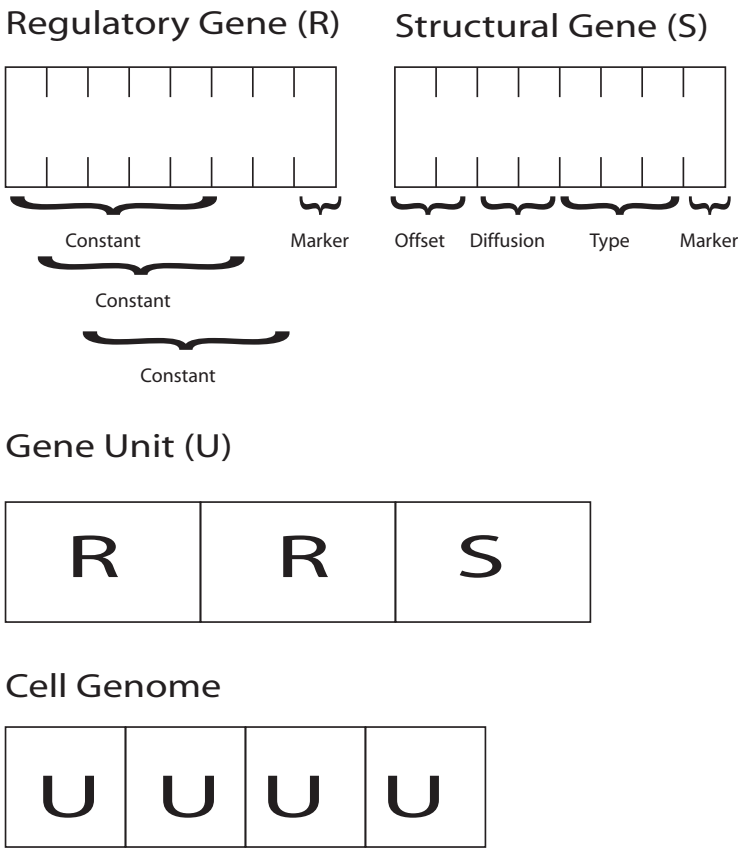

Fig. 2. A schematic of our cell genome. The cell genome consists of four gene units. A gene unit consists of two regulatory genes and a structural gene. Different functional elements are extracted from structural and regulatory genes.

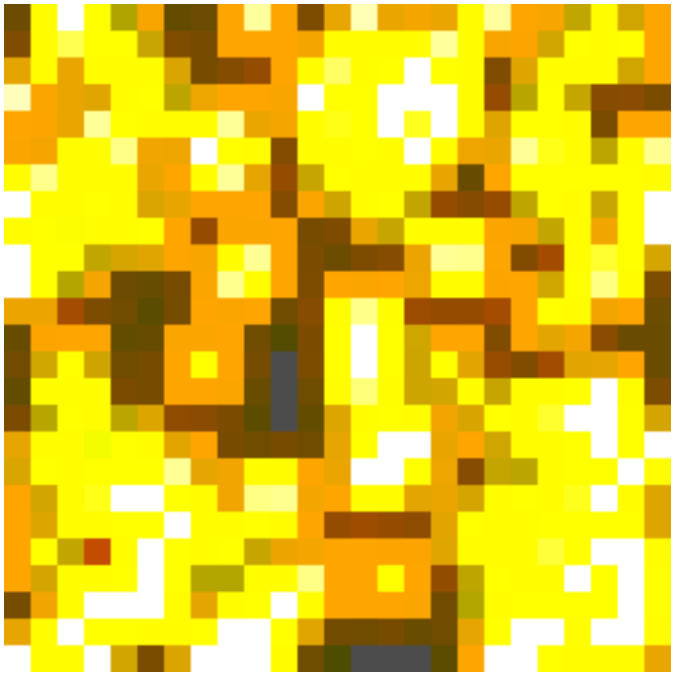

Fig. 3. An example using fitness function F_1, rewarding patterns where there are varying communication behaviors among cells and high variability within all color channels.

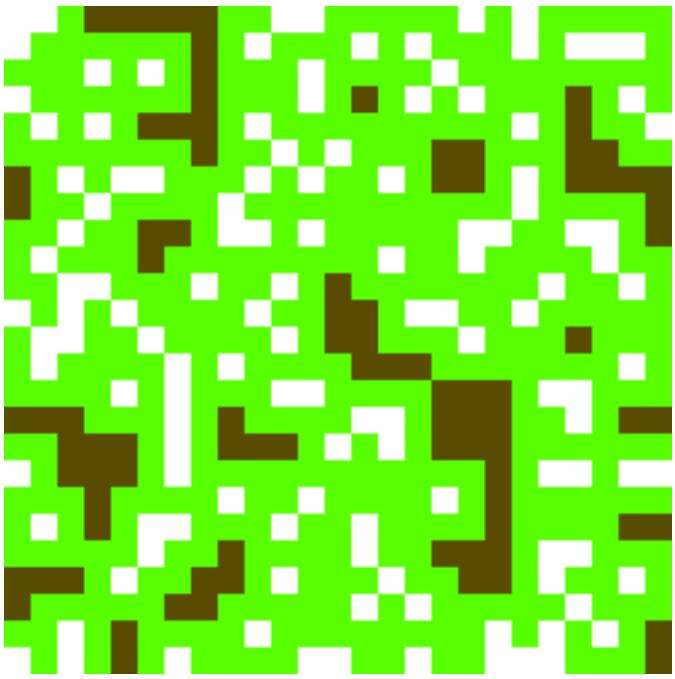

Fig. 4. An example using fitness function F_2, rewarding *only* high variability within all color channels.

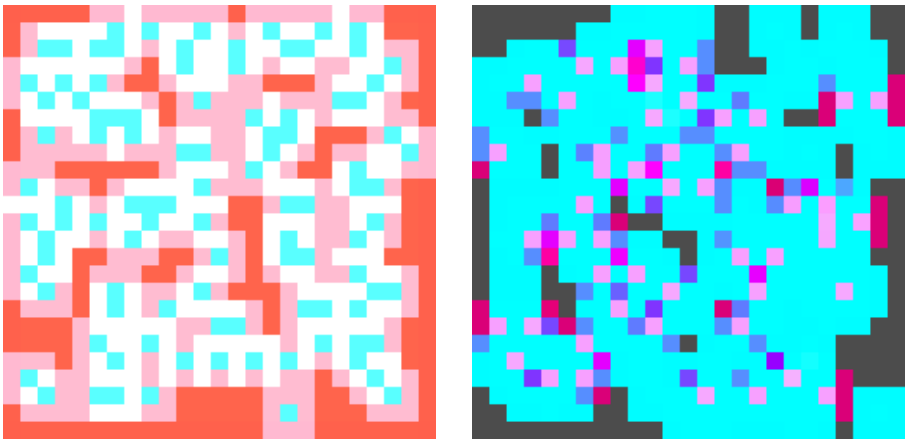

Fig. 5. Two examples using fitness function F_3, rewarding high variability within at least one color channel.

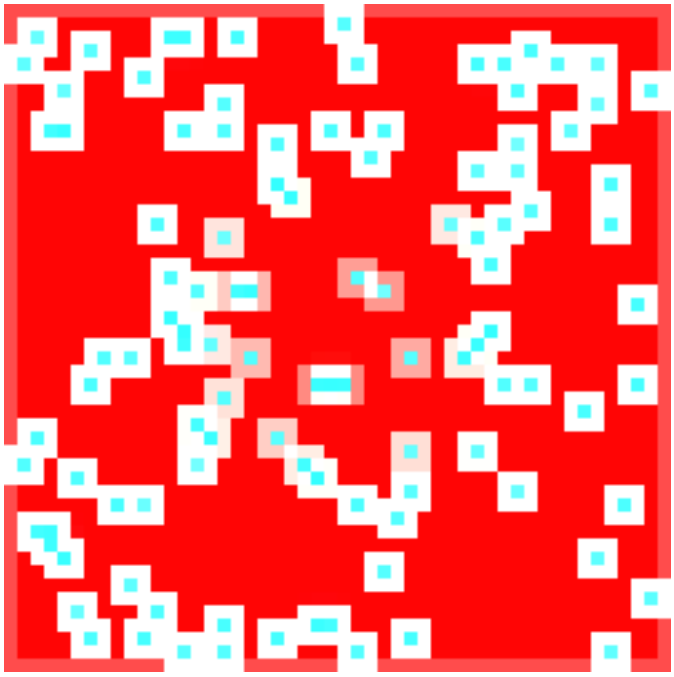

Fig. 6. A 40×40 cell pattern evolved using fitness function F_4 that incorporates a penalty term for dormant, black cells.

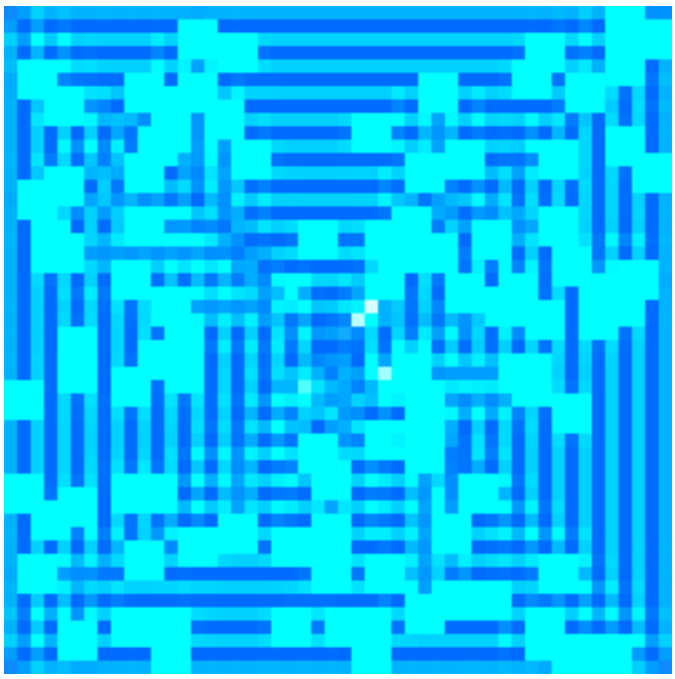

Fig. 7. A 50×50 cell pattern using fitness function F_5 which also incorporates a penalty term for dormant, black cells.

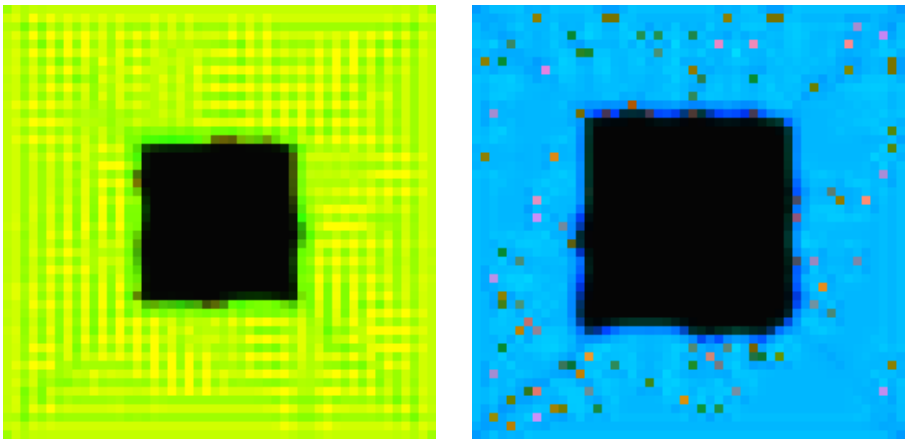

Fig. 8. Two images using fitness function F_4 from *The Void Series*.

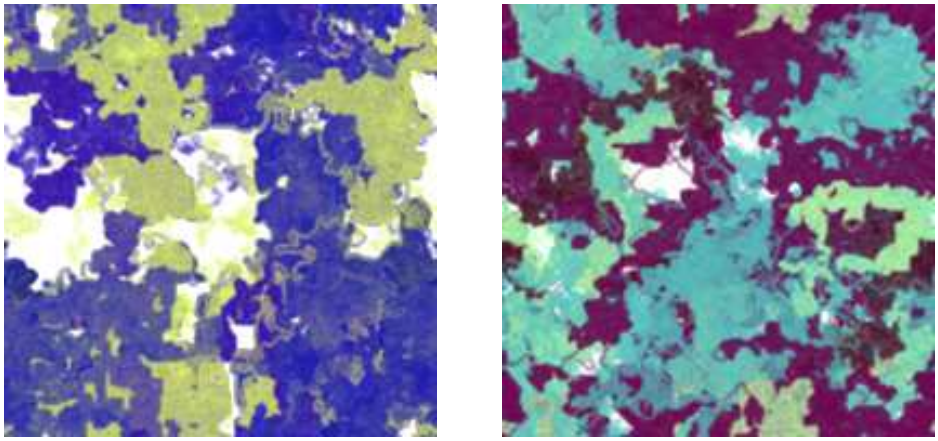

Fig. 9. Two examples from separate runs of blotchy style ant paintings where ant fitness was determined solely by the ability to detect and follow scent. Image on the left preserved from the eighth generation and the one on the right from the tenth.

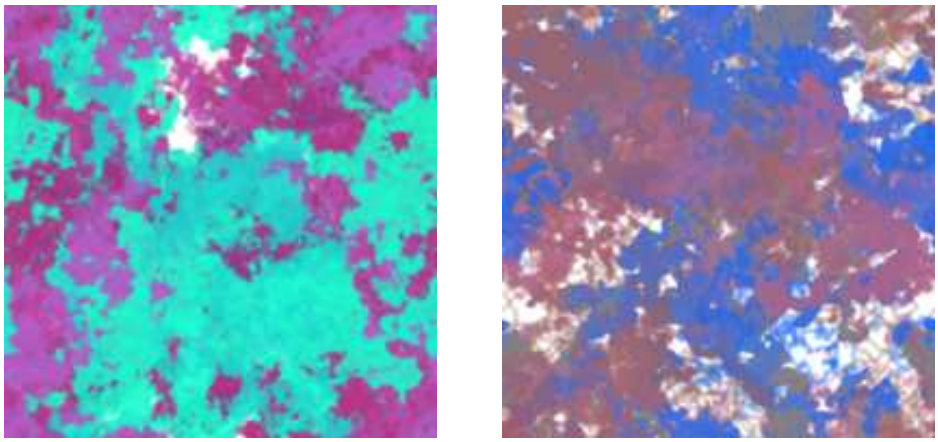

Fig. 10. Examples of a bi-level style where ant fitness was determined solely by the ratio of the ability to follow scent and the ability to explore. Both images are from generation sixteen of their respective runs.

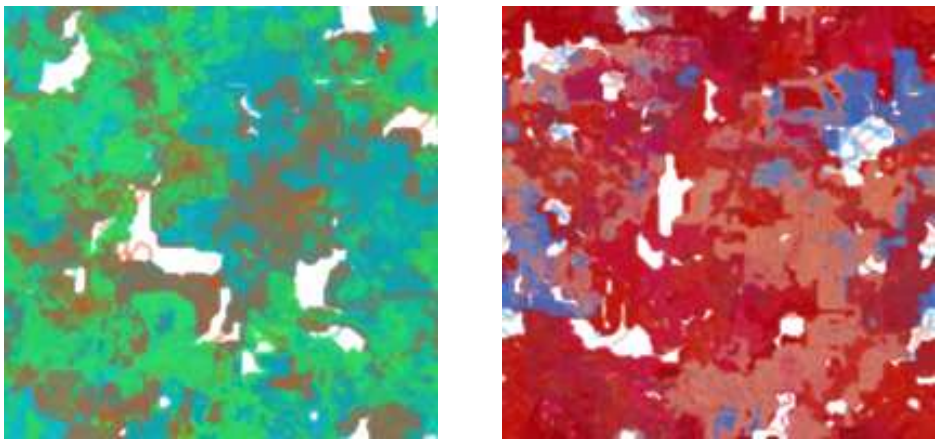

Fig. 11. Two examples of what we describe as a dramatic, organic style obtained using a fitness function proportional to a linear combination of the two terms measuring the ability to follow scent and the ability to explore the environment. Both images are from generation twenty of their respective runs.

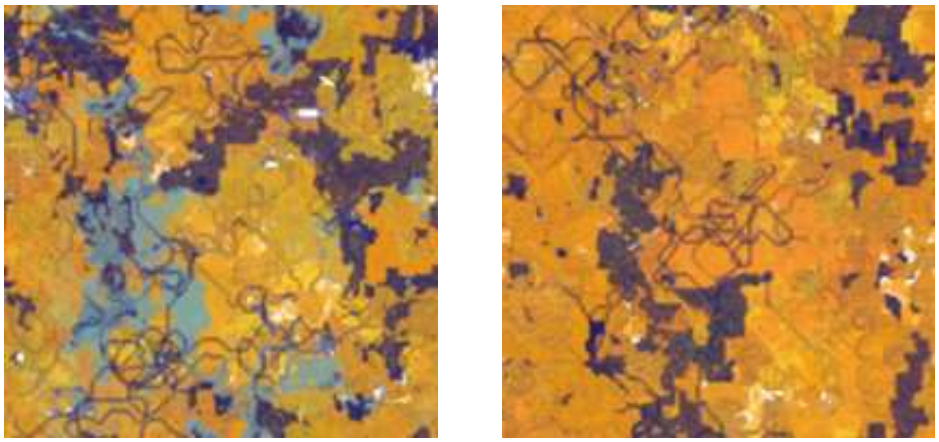

Fig. 12. Examples of the image style obtained using a fitness function that is the product of two terms measuring the ability to follow scent and the ability to explore. Both images are from the same run, the left image is from generation twelve and right image is from generation fourteen.