Evolutionary Methods for Ant Colony Paintings

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Abstract. We investigate evolutionary methods for using an ant colony optimization model to evolve "ant paintings." Our model is inspired by the recent work of Monmarché et al. The two critical differences between our model and that of Monmarché's are: (1) we do not use an interactive genetic algorithm, and (2) we allow the pheromone trail to serve as both a repelling and attracting force. Our results show how different fitness measures induce different artistic "styles" in the evolved paintings. Moreover, we explore the sensitivity of these styles to perturbations of the parameters required by the genetic algorithm. We also discuss the evolution and interaction of various castes within our artificial ant colonies.

1 Introduction

Monmarché et al [1] recently described an interactive genetic algorithm involving ant colony optimization (ACO) methods for the purpose of evolving aesthetic imagery. Although it was never well documented in the literature, it should also be noted that the digital image special effects developed by Michael Tolson using populations of neural nets in order to breed intelligent brushes may be an historical precedent for using a non-interactive approach involving ACO methods for evolving aesthetic imagery [10]. Thanks to the early favorable publicity garnered by Dawkin's *Biomorphs* [3], Sim's *Evolving Expressions* [11], and Latham's *Mutator* [13], *interactive* genetic algorithms have long played a central role in the evolution of aesthetic imagery. The use of more traditional non-interactive genetic algorithms to produce aesthetic imagery — the computational aesthetics approach — has received much less attention, no doubt due in large measure to the inherent difficulty in formulating fitness criteria to assess images on the basis of their aesthetic merits. Research previously published along these lines includes approaches involving neural nets [2], evolving expressions [6] [7] [8], and dynamical systems [12].

It has been suggested that the evolution of images by means of organisms that are evolved for their *aesthetic* potential is less about evolution and more about the search for novelty [4]. In fact, psychologists are only just beginning to understand the neurological underpinnings of visual aesthetics [9] [14]. Be that as it may, the goal of this paper is to consider techniques for evolving ant colony paintings using a non-interactive genetic algorithm. Our objective is to show how

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different fitness criteria used to evaluate the aesthetic contributions of the ants determine different painting styles as well as influence ant colony formation.

2 The Basic Model

The basic framework for our ACO ant painting model follows that of Monmarché et al [1]. In their model individual ants possess *attributes*: an RGB color (C_R, C_G, C_B) for the ant to deposit; an RGB color (F_R, F_G, F_B) for the ant to follow; a vector of probabilities (P_l, P_r, P_a) satisfying $P_l + P_r + P_a = 1$ used to determine the probability that the ant veers left, veers right, or remains on course by moving directly ahead; a movement type D which takes the value o or d according to whether an ant veering off course veers at a $45°$ angle or a $90°$ angle; and a probability P_f for changing direction when "scent" is present. Thus an individual ant genome is simply a vector of the form $(C_R, C_G, C_B, F_R, F_G, F_B, P_l, P_r, P_a, D, P_f)$. Since ant behavior is determined using a simple move-deposit-sense-orient sequence, scent trails form from the colors the ants deposit as they explore a toroidal grid. Deposited colors are allowed to seep throughout the 3×3 neighborhood the ant is currently occupying by invoking a convolution filter defined using a 4:2:1 ratio such that immediately adjacent cells to the one occupied receive half as much color as the occupied one receives, while diagonally adjacent cells receive one-quarter as much color as the occupied one receives. The unusual and surprising feature of the Monmarché model is that the metric used for detecting scent depends on a *luminance* calculation. Specifically, if L_W is the luminance of the neighboring cell W that the ant is sensing, and L_F is the luminance of the color (F_R, F_G, F_B) that the ant is attempting to follow, then the scent value detected by the ant is $\Delta_W = |L_W - L_F|$. Of course the smaller Δ_W is the stronger the scent is.

Using the same sensing constraint as Monmarché, namely that scent following behavior should not be invoked unless Δ_W falls below the threshold value `MAXS` of 40, thanks to the table of genomes accompanying the four hand-crafted examples appearing in Figure 1 of [1], when using a 200×200 toroidal grid where each

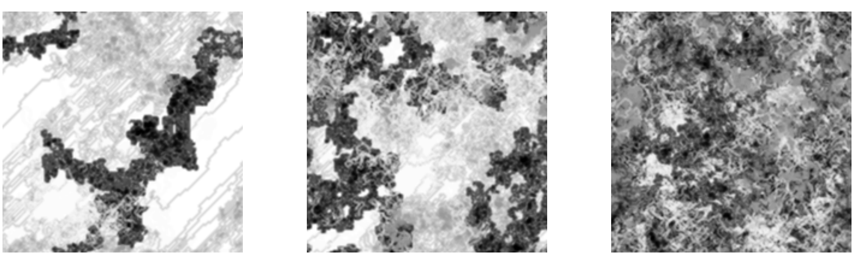

Fig. 1. Images reprising the three-ant, black-and-white Monmarché example that were obtained using randomly generated initial positions and directions. The exploration times were (left to right) 12000, 24000, and 96000 times steps respectively

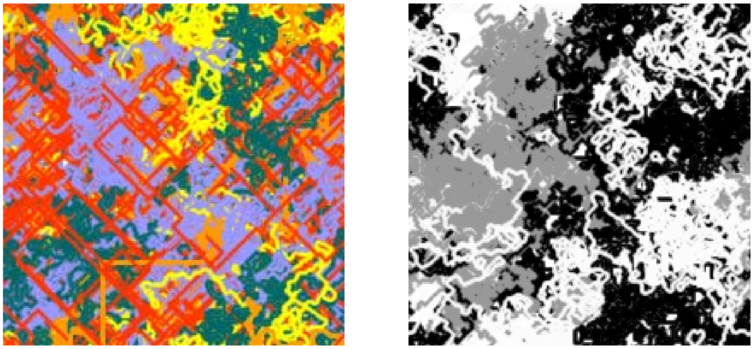

Fig. 2. The effect of replacing, as opposed to blending, using the deposited color. The image on the left uses the five-ant, multi-color Monmarché genomes, and the one on the right the three-ant, black-and-white genomes

ant was allowed to explore for 24000 time steps we were essentially able to duplicate the paintings of that figure. Figure 1 shows the results from a reverse engineering experiment using the three-ant, black-and-white example of [1] in order to estimate an appropriate value for the exploration time parameter.

Based on the description given in [1], it was not initially clear to us whether an ant should *replace* the color of the square it currently occupied with the color it was depositing, or blend (using a 1:4 ratio) the color it was depositing. Figure 2 shows what happened when we tried using the replacement strategy for both the three-ant, black-and-white example and the five-ant, multi-color example given in [1]. Such tests convinced us that replacement was not the method intended and that the following color printed as $(255, 0, 0)$ in Table 1 of [1] for the five-ant, multi-color example was probably meant to be $(255, 153, 0)$. This correction is consistent with the assertion that those examples were hand-crafted so that each ant was seeking a color that another ant was depositing.

3 Scent Modification in the Basic Model

Recall that the luminance L of an RGB color (X_R, X_G, X_B) is defined to be $L = 0.2426X_R + 0.7152X_G + 0.0722X_B$. Determining scent on the basis of luminance has two implications. First, ants become abnormally sensitive to the green component of the color they are following. Second, colors perceived as different RGB colors by humans may be perceived as virtually identical colors by ants. While it is true that in nature a swarming species such as, say, bees may perceive colors differently than humans, for the most part there is still a comparable basis for color *differentiation*. Consider, for example, ultraviolet photographs of flowers compared to photographs of those same flowers made using the "visible" spectrum. Since ant paintings are not *imaged* solely on the basis of the luminance channel, the ant paintings we view are not the same as the ones the ants view. For this reason, henceforth we will measure scent using a supremum norm by defining

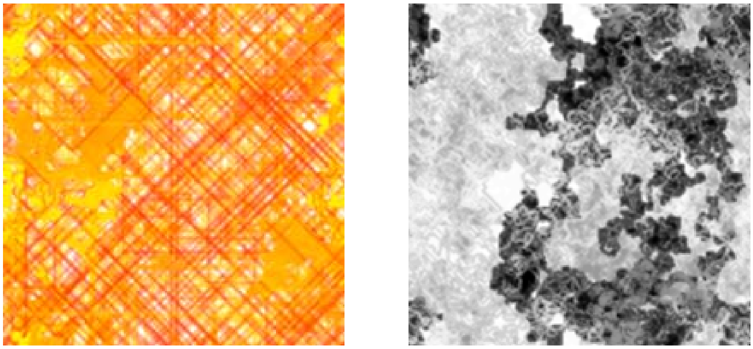

Fig. 3. The effect of redefining the scent metric. On the left the four-ant, red-component Monmarché example and on the right the three-ant, black-and-white example

$$\delta_W = \max(|W_R - F_R|, |W_G - F_G|, W_B - F_B|).$$

Under this metric, with the scent threshold MAXS still set to 40, Figure 3 reprises two of the four examples of [1]. Indeed, when we ran all the examples of [1] using this metric we discovered that most of the following behavior that ants exhibited was due to following their own scent, and nearly half of the ants exhibited no following behavior at all.

To further reduce the opportunity for ants to follow themselves we introduced a repelling force, under the control of the threshold constant MINR, to inhibit ants from following scent in a neighboring cell W whenever

$$\psi_W = \max(|W_R - C_R|, |W_G - C_G|, W_B - C_B|)$$

falls below this threshold. To test the parameters MAXS and MINR using our new metric, we generated several five-ant, multi-color examples for which depositing and following colors were randomly and independently chosen. Figure 4 shows representative results from these tests.

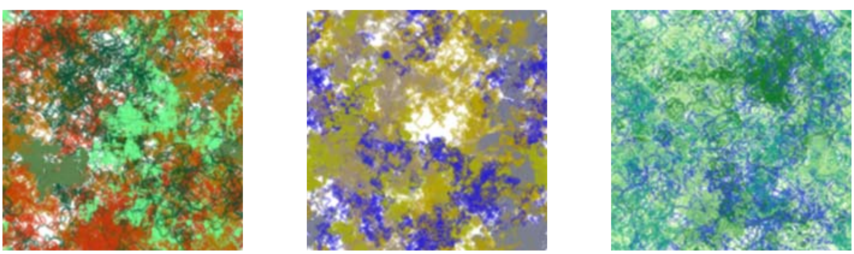

Fig. 4. Sample images from five-ant, multi-color examples testing the attracting and repelling thresholds. Left MAXS $= 40$, MINR $= 60$. Center MAXS $= 60$, MINR $= 120$. Right MAXS $= 60$, MINR $= 40$

4 Adding Non-interactive Fitness to the Model

For consistency, while exploring fitness criteria to use for ants, we fixed MAXS at 80 and MINR at 40. On a 200×200 grid, with ants in motion for 24000 time steps, each ant in the population can hope to visit at most sixty percent of the grid. Ant fitness criteria were based on two measurements recorded during this exploration period, the number of distinct cells visited by an ant, denoted N_v, and the number of times cells were visited by following scent, denoted N_f. Our initial population consisted of twelve randomly generated and randomly positioned ants. We quickly discovered we could not breed replacements for too many ants after each generation because ants became overly sensitive to the background color i.e. evolution quickly evolved monochrome paintings that were dependent wholly on the settings of the scent thresholds MAXS and MINR. This explains why after each generation we chose to replace only the four least fit ants. The replacement scheme invoked uniform crossover coupled with a point mutation scheme. We replaced least fit ants two at a time by randomly mating a pair randomly chosen from the eight ant breeding pool. During some runs we introduced "mortality" by replacing the three least fit ants plus one ant randomly chosen from the remainder of the population. Evolution proceeded for twenty generations. Ant paintings were preserved every other generation.

We discovered that failure to reset the grid to the background color after each generation introduced monochromatic degeneracies. Letting ant fitness depend solely on the number of squares visited, N_v, also caused monochromatic degeneracies. This occurred because ants were rewarded for being able to simulate a random walk by *ignoring* an overpowering scent arising from the *average* blended color — yet another instance of organisms exploiting a flaw in the "physics" used to model the optimization task.

Figure 5 shows two ant paintings from separate runs using ant fitness function $A_1(a) = N_f$. They reveal how rewarding ants solely on the basis of their

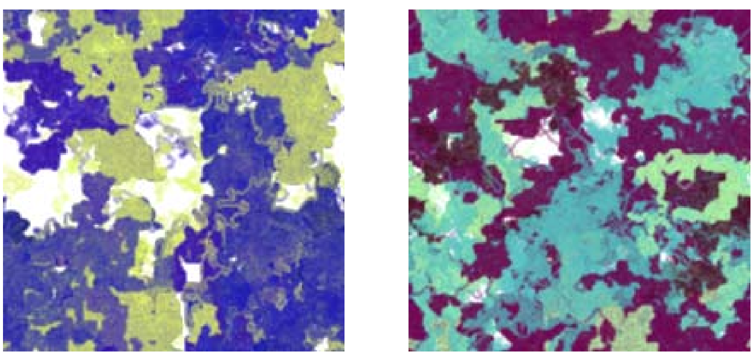

Fig. 5. Examples of the blotchy style using fitness function A_1 where fitness was determined solely by the ability to detect and follow scent. An image from generation #8 is on the left and generation #10 is on the right

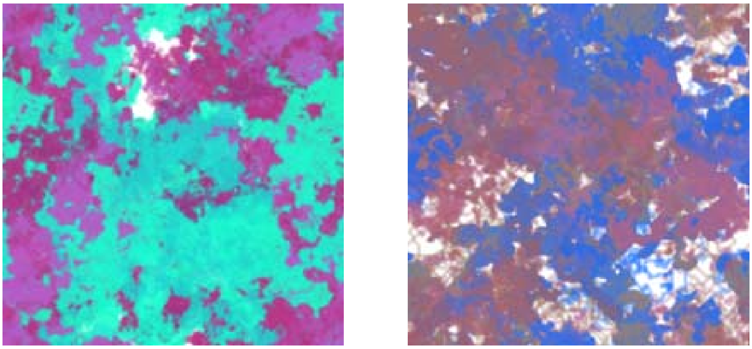

Fig. 6. Examples of a bi-level style using fitness function A_2 where fitness was determined solely by the ratio of the ability to follow scent and the ability to explore. Both images are from generation #16 of their respective runs

ability to follow scent leads to a blotchy style where paintings seem to be dominated by trails of polka-dots. "Convergence" usually occurred quickly, within ten generations.

Figure 6 shows two ant paintings from separate runs using the fitness function $A_2(a) = 100N_f/N_v$. The style that results is a bi-level style. Often, two castes of ants evolved each depositing a different color, but with both seeking essentially the same scent trail. It appears that the `MINR` threshold operating in tandem with the exploration penalty in the fitness function caused ants to evolve a plowing forward behavior so that ants in the two castes could mutually support each other. In some runs more complex behavior emerged due to deposit color "shades" evolving within the two different castes. Unfortunately, no examples of paintings in this style with good color aesthetics were ever evolved.

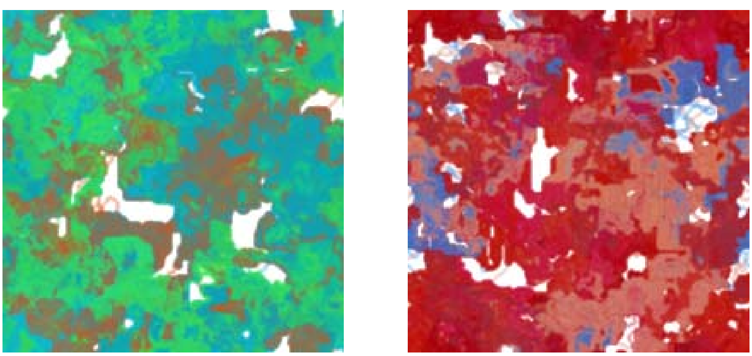

Fig. 7. Examples of a dramatic, organic style obtained using fitness function A_3, a linear combination of terms measuring the ability to follow scent and the ability to explore. Both images are from generation #20

By letting the fitness function be $A_3(a) = N_f + N_v$, we achieved our most dramatic style. The evolved paintings had an organic form and the stark color contrasts gave shading highlights. The key feature of the ant populations that made these paintings is the formation of one dominant caste that made up over half the population and provided the base color for the paintings. Interestingly enough, even though the evolved paintings reveal that significant portions of the background are never visited, the underlying probability vectors reveal that the ants possess more or less random exploration tendencies. This indicates that scent following is tightly coupled with the evolved behavior. Figure 7 gives examples of the evolved paintings we obtained.

Our most impressive ant paintings, from both a composition and color standpoint, were obtained by letting the fitness function be $A_4(a) = N_f \cdot N_v/1000$. As Figure 8 demonstrates, shading and detail received equal emphasis. Figure 8

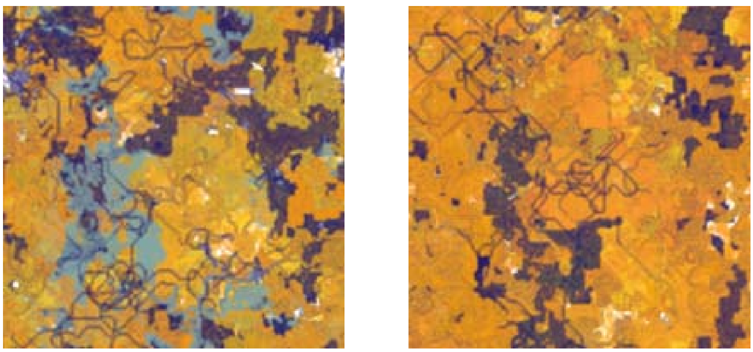

Fig. 8. Examples of the balanced style using fitness function A_4, a product of terms measuring the ability to follow scent and the ability to explore. Left image from generation #12 and right image from generation #14 of the same run

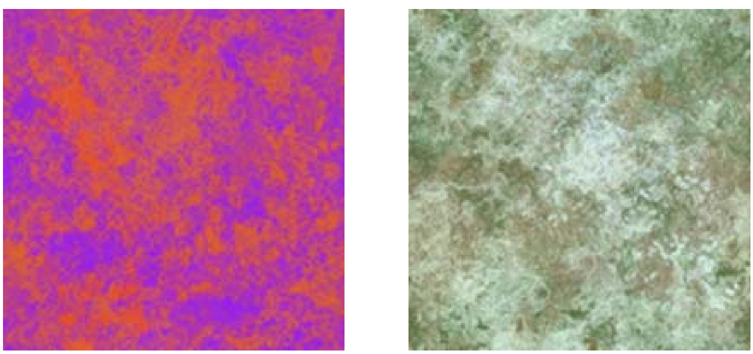

Fig. 9. Using a neutral background color the "degenerate" fitness function $A_5(a) = N_v$ evolved non-degenerate paintings. Both images are from generation #20

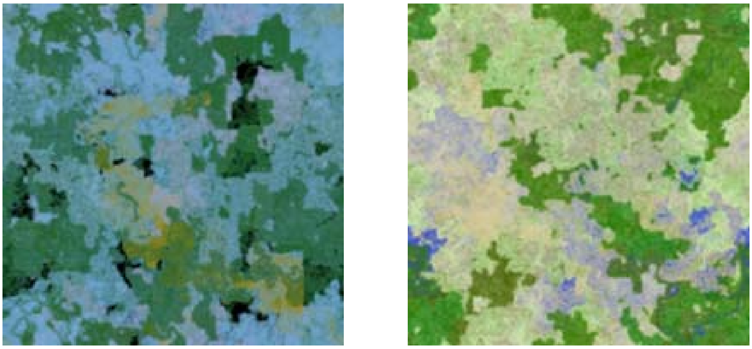

Fig. 10. The fitness function A_4 was the most robust with respect to shifts in background color. Image on the left using a black background and on the right using a neutral gray background. Both images are from generation #20

shows an example where one of three extant castes went extinct while passing from generation #12 to generation #14.

Attempting to change ant behavior in such a way that evolved paintings more closely mimic the style of the images found in Monmarché by raising the value of the repelling threshold `MINR` to 60, 80, 100, or even 120 did indeed reproduce their style for the first few generations, but as evolution progressed the paintings always degenerated to dark, monochromatic paintings.

The effect of using background colors other than white was difficult for us to assess. We remarked earlier that the fitness function $A_5(a) = N_v$ evolved monochrome paintings with either a black or white background. However, Figure 9 shows two examples that we obtained after 20 generations using the neutral gray RGB background color $(128, 128, 128)$. Figure 10 shows why we believe our most consistent fitness function $A_4(a) = N_f \cdot N_v/1000$ was also the most robust in this regard by showing examples evolved using both a black and neutral gray background.

5 Adding Initial Conditions to the Model

All of the ant paintings described above used random positioning of ants at the start of each generation. This meant that it was equiprobable any cell on the grid would be visited and, given the exploration time, highly probable almost all cells would be visited. It seemed plausible that more organized paintings would result if ants explored the grid by always starting from fixed central locations. Therefore we experimented with placing ants at the same fixed locations within a central 20×20 "cluster" and pointing them in the same fixed directions from those locations at the start of each generation. We also allowed longer evolution

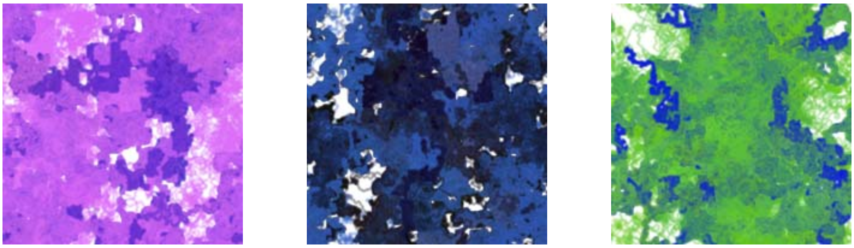

Fig. 11. Ant paintings evolved using fitness function A_4, initial clustering of ants, and longer evolution times. The two on the left are from generation #30 and the one on the right is from generation #35 of their respective runs

times and preserved paintings after every five generations. Figure 11 shows paintings representative of the results we obtained when using our preferred fitness function $A_4(a) = N_f \cdot N_v/1000$.

6 Summary and Conclusion

We have introduced a more carefully reasoned and more sophisticated model for evolving ant paintings while exploring the problem of automating their evolution. We have shown how different styles of ant paintings can be achieved by using different fitness criteria, and we have investigated the effects of varying the simulation parameters controlling evolution. While the resulting paintings are still aesthetically primitive, there is reason to hope that ants possessing additional sensory capabilities and given better guidance for color aesthetics could produce more complex and interesting paintings.

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