Exploring Aesthetic Pattern Formation

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Abstract

This paper is an exploration of an interdisciplinary nature. Through studies in fine art, pattern formation in nature, and artificial life, a mechanism for the artistic process is presented. Asynchronous updating schemes implemented in cellular automata and pheromonal agent swarms were evolved to produce aesthetic patterns and compared favourably to non-evolved synchronous production methods. The curious adaptive properties of the resulting patterns were investigated.

1. Introduction

"When we stand before great churches, temples, pyramids, and other works of architecture built hundreds, if not thousands of years ago, our minds are filled with awe and admiration. Yet there have been architects millions of years before that. Their work, it is true, owes its existence not to the inspired genius of great artists, but to the unconscious, unremitting activity of the force of life itself." [1] Pp 2.

There remains a great deal of mystery surrounding the processes involved in the generation of aesthetic and functional forms, as they occur in nature and as generated by humans. Many would still like to believe that both human and natural generation of aesthetic form, at some level at least, a conscious creative plan, some central idea, meaning or goal. Artificial life offers an alternative paradigm of thought, and it is the point of this paper to explore how the seemingly disparate domains of pattern formation, social insect communication and artistic processes can be linked.

The aim of this paper is to show that the processes involved in the formation and generation of shapes and patterns, aesthetic or functional, are best viewed as evolved adaptive systems. Formation relies on distributed local rules and sensorimotor interactions rather than any global ideals or representations. There is reasonable evidence to suggest that asynchronous updating in adaptive systems is more biologically plausible [2][3], and it will be shown that this can also be considered the case for human artistic 'updating' of paintings.

The following section contains a brief overview of background material. An analysis of the processes involved in the production of my own artistic works was carried out and is detailed in section 3. Section 4 outlines the Cellular Automata model, the Pheromonal Agent System and the Genetic Algorithm implemented. The adaptive properties of the resulting patterns were investigated and three such experiments with their results are detailed in section 5. Section 6 contains conclusions drawn from this work.

2. Background

There are many areas of nature where ordered patterns occur. It is interesting to note that the idea of formation as a result of *local interactive signals producing adaptations in movement* can be used as a model of growth of patterns in both animate and inanimate forms, for example snowflakes, animalcules, nests and mammalian coat patterns [1].

Pattern formation is concerned with how the spatial arrangement of cells occurs. It would appear that pattern is generally laid down early on providing good evidence for the autonomy of development as a separate process [4]. However, there is as yet no experimental evidence to support any of the proposed pattern formation theories offered by theoretical biology.

Pattern formation was originally dominated by theories in terms of *prepatterns*, the idea that developmental fields have a non-uniform spatial arrangement of substances in a tissue whose local peaks induce the formation of pattern elements, i.e. pattern is preprogrammed, laid out globally [5]. *Positional information* was an alternative approach that replaced this outdated theory and paved the way for a number of interesting theories all incorporating local cell to cell interactions as a method for pattern formation, rather than a predefined arrangement of pattern elements [4][5].

Cellular Automata have been used to model pattern formation as it occurs in many domains e.g. mammalian coat patterns, seashell patterns and embryological pattern formation. This is mainly because of the general property of local interactions to produce global phenomenon, meaning that they provide a good generic model of other models of pattern formation, for example the Turing system [6].

There are many species that construct complex architectures, social insects can be seen to generate hugely intricate patterns and structures when nest building, the possible organisational mechanism put forward in [7] to explain how this can occur is *stigmergy,* a form of self organisation. The basic idea is that the coordination of individuals' tasks depends not on any communication between them but on the nest structure itself [6]. A termite picks up a soil pellet, impregnates it with a 'cement pheromone', which diffuses away, attracting other termites to drop their pellets near by.

Aesthetic evolution selection by a human observer has been much utilised for the generation of, often stunning, visual images, [9][10][11]. However, as pointed out by Dorin [11] the images evolved not only reflect the users desires but more importantly the restrictions of the program. Dorin notes that the user selection process is a top down method for generation of form, in a 'choose your own adventure book' way, that is, no matter how creative the user tries to be, the image cannot stray out of the ones available in the book. This 'explorer' rather than 'artist' generative method seems far removed from the bottom up procedures implemented in my own art. The process of globally assessing the aesthetic merit of an image should not be confused with the local updating of a canvas with aesthetic intention; art appreciation is not synonymous with art production.

Design by distributed systems reflects the processes observed within many fields and also the current trend to explore the computational possibilities for exploiting design theories, such as computer aided design packages for Architecture, robot morphologies and furniture design [6][12][13]. Computer simulations have been put forward as works of art themselves, artist Paul Brown used cellular automata to produce very attractive and distinct images, however, they were aesthetically biased by the use of patterned tiles and randomness rather than relying only on the cellular Automata rules[1].

3. The Artistic Process

Generally, in work done using distributed models of pattern and structure formation in nature the method is contrasted with the centralised, plan based methods assumed to be invoked by humans, particularly artists and architects [1]. This assumption is just as short sighted as the prepattern approach was to pattern formation and it is hoped that highlighting this in this paper could spark further, more realistic models of aesthetic production that are all encompassing, as positional information did for pattern formation.

There are certain principles, techniques and medium specific methodologies that contribute to the attractiveness and quality of a piece of painting. Artistic talent is far from a magic, indefinable essence, possessed by the few and jinxed by deconstruction. Rather it can be thought of as the conscious or unwitting implementation of an adaptive system, consisting of a particular updating scheme and low level local rules or techniques, which have been arrived at through an evolutionary process.

“I first thought that making a portrait consisted of looking at the model and drawing the portrait, and that this entailed artistic creativity and was quite a mysterious process.” [14] Pp 24.

Using eye tracker tests, which record precisely where the eye was looking and motion trackers which tracked the movements of the hands in space, Tchalenko et al tried to find out what the ‘magical’ process involved in the drawing of a portrait is. Their results back up my own experience and method of portrait painting. To begin with the painter makes very quick precise eye movements on the paper and the sitter followed by very small markings on the paper. As the picture progresses longer and longer periods are spent looking at larger and larger sections of the paper, and not the sitter, and producing bigger bolder sweeping movements. Tchalenko concluded from these observations that “portrait painting, at least for this painter, was a complex combination of a fading memory image and an increasing presence of the emerging picture” [14] Pp 24.

It is crucial to the development of the picture how each local area to be assessed and altered is selected. This is based on the idea that the *global* image is not assessed at each paint stroke and that the small area viewed is important to the type of stroke made. It is clear, from the fact that there is generally only one hand making any movements on the canvas at any one time, that the updating of each section of the painting can not happen at once, the areas of the painting are updated *asynchronously*.

There are many different methodologies employed for the development of a picture. For example, it is not generally advised to make one tiny area of the painting perfect and polished before painting any other areas. Interestingly enough this discouraged method is the most prolific among untrained artists and school age children. A more refined approach, which is medium specific, is to move about the painting in a systematic or random way (but generally hitting every area of the canvas) and, for example with oils and acrylics only put down dark

[1] Insight from Paul Brown at Blip sci-art discussion group Brighton 22/07/02

paint where it is needed and then move on. Only once an area is encountered that needs no more dark are the next lightest shades applied, this process continues until the white highlights are added, then, in theory, the painting is finished. This was the updating scheme used in fig 1.

Figure 1: *Adaptive Cubist* K A Bentley 2002

There are some general rules that are taught and can be observed in aesthetic works. For example the rule of complementary colours and that shade supports light, that is, light should always be next to dark [15][16]. It is not suggested that all aesthetic pieces are, or can all be, produced using the *same* rules but just that an interactive rule based system can be a good generic model of aesthetic production.

All established artists have a distinct style. They will have experimented with and learnt from other styles and it is through the discovery of new rules and the effect of the interaction of that new rule with others that arts creativity and novelty perpetuates. As with evolutionary models, children's paintings are in general not aesthetically pleasing, they are the beginning of a very long learning and refining process, picking out the good tricks and the bad ones and repeating pleasing structures but within new environments and with different rules. This process has also been noted in the drawings of apes [17]. Recurrent themes and paint application techniques along with updating schemes and implementation of particular aesthetic rule systems like those already described can define an artist's unique style [15].

4. The Models

To investigate the aesthetic potential of the evolutionary, adaptive methodology put forward in this paper, two self-organising systems were experimented with. Cellular Automata (CA) and Pheromonal Agent Systems (PAS) were used because of their ability to model other adaptive distributed systems and due to their connection with natural pattern and structure formation models.

The Genetic Algorithms (GA) employed for the evolution of the CA and PAS were of the same generic structure. However it became necessary to alter the various parameters given the different situations as it became clear that the updating systems greatly affected the size of the search space, given that asynchronous updating meant that the same rule set genotype could map to several, albeit similar, phenotypes. It was not known if there would be patterns that could form independently of this random updating and even if they could cope with the asynchronous nature of updating within the CA or PAS, although the results obtained in the preliminary experiments suggested that there would [18].

4.1 Cellular Automata

A two dimensional ($M \times N$) toroidal CA was used. Each cell p represented the pixel in the (m, n) co ordinate position, where $m \in M$, $n \in N$. Each cell could be in one of four states representing four colours. In most experiments the radius r of the CA, specifying the range of the update rule, was 1. In all experiments the initial CA cells were randomly set.

Three types of updating were investigated: *synchronous* (Synch), *asynchronous set* (Asynch Set) and *asynchronous random* (Asynch Rand). Asynch set updating meant that at each stage only one cell was updated, and that cell was set. The first cell to be updated was cell (0,0) then cell (0,1), then (0,2) all the way through the rows and columns in order. A time step corresponded to one complete run through all the cells being updated. Although this is asynchronous it is still a deterministic form of updating. In Asynch Rand updating one cell was picked at random to be updated at each stage, with replacement. Unlike Asynch Set updating, after $M \times N$ stages not all cells had necessarily been updated. This was a non-deterministic form of updating. One time step corresponded to $M \times N$ updating stages. So for all types of updating, in a time step, on average, all cells would have been updated.

4.2 CA Genotypes

The CA genotypes were split into eight blocks, one for each rule. The position of a block in the genotype was crucial as the first two were the rules to implement if the pixel was of the first colour, the next two blocks if it was the second colour and so on, for each of the four colours. Each block contained four genes. The first gene in a block chose the counter to assess, the second related to the operation to use in the rule. Five operations were possible, =, <, >, ≥, ≤. The third gene was the condition, and the fourth was the action. There was a probability of 0.5 that no action would be taken.

For example if the four genes of the first block were 1,2,3,2 then the rule would expand to be: if p=0 and $C1 > 3$, then $p \rightarrow 2$. Where $C1$ denotes the number of neighbours whose state = 1. The rules expanded in a hierarchical format. This resulted in a lot of the genotype essentially being *junk DNA*, as earlier rules took priority.

4.3 Pheromonal Agent System

The PAS was an extension to the Basic Agent Model that was experimented with in [18]. Agents were placed in N randomly chosen, with replacement, cells of the CA array. $r = 1$ which might or might not have been inclusive of the agents cell. The agents all updated the particular cells they 'inhabited' synchronously by assessing the states of the cells in the given radius, they then moved to one of their eight neighbouring cells. Each agent was capable of leaving and reacting to plumes of a 'pheromone' that diffused over time. The movement of agents was governed either by pheromone reaction rules or neighbour states or a hierarchical combination of both. The CA cells initial states, in all experiments, were set to 0.

The pheromone diffusion was based on random walk diffusion [19]. After a pheromone plume was dropped at cell (m,n), the amount of pheromone A at any given cell in the array, of Euclidean distance x from (m,n) at time t from when the plume was dropped was given by equation (1) where D is the diffusivity constant (how much the chemical diffuses at each time step) and Q is the amount of pheromone dropped.

$$A = \frac{Qe^{-x^2/4Dt}}{2\sqrt{\pi Dt}} \quad (1)$$

4.4 PAS Genotypes

The PAS genotypes were split into eight blocks with six genes each. Unlike the CA GA the state of the cell that the agent inhabited was not assessed. However the position of a block was just as important as a hierarchical rule system was again implemented. The first four of the six genes related to the same rule specifications as in the CA genotypes, the fifth specified whether to move to or away from pheromone detected and the sixth specified whether a plume of pheromone was to be dropped or not. Thus the movement system was simple, but was enough to create complexity in the resulting image. The PAS genotypes then had an extra four genes that specified Q, D, t and the optimum number of agents (*AGENTS*). Unfortunately, due to the effect large numbers of agents and plume diffusion time had on evolutionary run time a limit of 20 for each had to be enforced, this was found to be small enough to allow a pattern to develop and run time to be realistic.

4.5 Evolution

A population of 100 genotypes were evolved for 100 generations. The system was elitist. The top scoring genotype would be replaced into the next population. The top 10 fittest genotypes would become the parents of the next generation, and from this parent pool random parents, with replacement, were chosen to be crossed over at some random starting point of a rule block in their gene string. The resulting genes were then subject to mutation. Each one had a probability of 0.05 of being mutated, so on average 1.6 genes were mutated.

5. Experiments and Results

In this section two of the evolved asynchronous CA patterns generated and one PAS pattern will be analysed. For details of other experiments and patterns obtained see [18].

Fig 2 shows some of the images that were attained without the use of evolution. Various rule sets were experimented with, *smudged ink* shows the effect of involving variable paint trail width into the rule sets. *Game of Life* is simply an Asynch Set updated version of Conway's game of life rules [20]. *Reticulation* was a style of pattern that occurred within many of the arrangements of rule sets, as well as being highly prolific in nature [18], the piece shown in fig 2 is an enhanced section of the *game of life* when updated with Asynch Rand. Without evolution it was highly time consuming to create aesthetically pleasing rule sets, and the act of doing so began to resemble the evolutionary process described in section 3.

For all evolutionary CA experiments a grid size of 40 × 40 was used and for the PAS 30 × 30 was used. This is because it was necessary to minimise run time whilst retaining complexity in the patterns.

5.1 Fitness Function

As it was not the intention to obtain a specific global image but for the pattern to self organise into an aesthetic state local fitness functions were experimented with, with the general aim of achieving mosaic like or clustered patterns.

The fitness function was of the following general form, where there are *n* conditions (*RC*) that must be satisfied to be rewarded and *m* conditions (PC) that if satisfied, the function is penalised and reset to 0. The amount of the sixteen neighbours, outside of $r = 1$ but within $r = 2$, of a certain state *s* will be denoted by *R2Cs*. *One, two* and *three* refer to the number of cells in the entire CA grid that are of the respective state. See equation (2).

$$fitness = \begin{cases} 0 & if\ PC1\ is\ true \\ \vdots & \\ 0 & if\ PCm\ is\ true \\ \sum_{p=0}^{N\times M} f(p) & otherwise \end{cases} \qquad f(p) = \begin{cases} 1 & if\ RC1\ is\ true \\ \vdots & \\ 1 & if\ RCn\ is\ true \\ 0 & otherwise \end{cases} \tag{2}$$

Every member of the population was subjected to 5 trials to eliminate patterns that were dependent on the initial conditions. The fitness was judged on each of these trials and the total score for a genotype was the sum of these. In general the fitness was judged at the 40th time step allowing the pattern to develop into its stable state. For Asynch Rand updating 100 steps for development were used, also functions for agents that didn't reward for *C0* surrounds, i.e. the canvas colour, also needed around 100 time steps for the canvas to be covered in other colours in development.

The occurrence of blanket grid, where all cells were the same colour, became an issue when evolving both the CA rules and the PAS rules. This was due to certain fitness functions, originally designed to reward for clustering, actually being optimised by a blanket grid. This was an uninteresting state for the CA to be in, thus every experiment had a harsh penalty (fitness set to zero) if, at the time step where fitness was evaluated, a blanket grid was detected. However, one problem was that the rule set may be on course to converge to a blanket, but *after* the evaluation time step, meaning that it optimised the fitness function, avoided the penalty *and* remained an uninteresting pattern. Harsher penalties ensued, where fitness would be set to zero if more than half the cells were of the same colour, with this, it was rarely seen, but blankets, with extra long times before convergence, still sneaked in.

5.2 Evolved Asynch Set CA Pattern: *Red Tiles*

The pattern evolved with the fitness function in fig 4 is shown in fig 3 and tentatively titled *Red Tiles*. The fitness function used was a competitive one, meaning that if one pixel satisfied the function then its eight neighbours necessarily could not. It was also a forgiving fitness function in that the fitness for a pattern would accumulate as more of the pixels satisfied it, rather than being dependent on a specific outcome globally. This forgiving fitness was found to be necessary when the desired outcome required that the radius 2 neighbours be of a specific colour as no patterns early on in evolution would be able to satisfy this outright. The desired image was a mosaic like tile pattern where tiles would comprise of a central colour and two outer rings of different colours. What emerged were tiles with only one, red, outer ring floating in a sea of another colour. This is due to the forgiving nature of the fitness function.

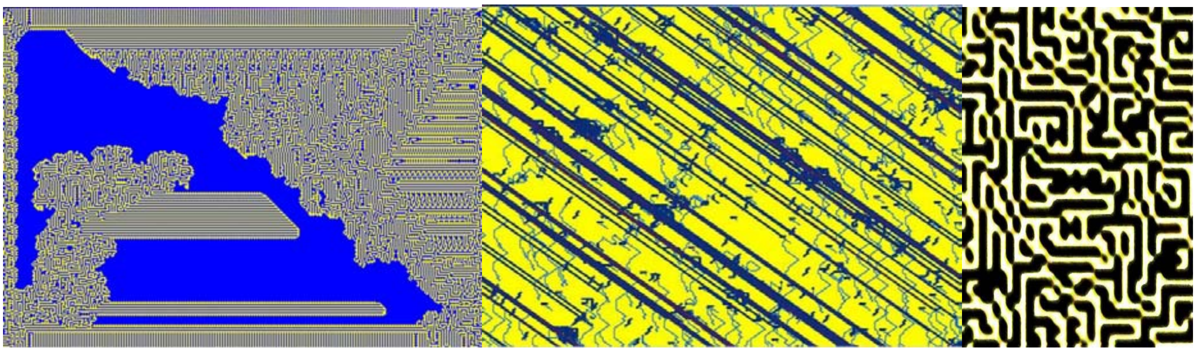

Figure 2: From left to right: Asynch Set CA *Game of Life* [25], PAS *Smudged Ink,* Aysnch Rand CA *Reticulation.*

Adaptation to Perturbations:

Fig 5 show that *Red Tiles* was able to adapt to perturbations in the states of a randomly chosen, random amount, of its cells, although the original high fitness was never fully recovered. The oscillatory nature of the steady periods reflects the presence of cyclic attractors in the developed pattern. Fig 5 also shows the effect of using one of the other updating environments on the fitness of this pattern. With Asynch Rand updating it climbed slowly to reach a similarly high fitness but with synch updating it was unable to reach even half the desired fitness. This highlights the importance of ascertaining the correct updating environment to evolve within and the huge difference that updating schemes can make to the formation of a pattern.

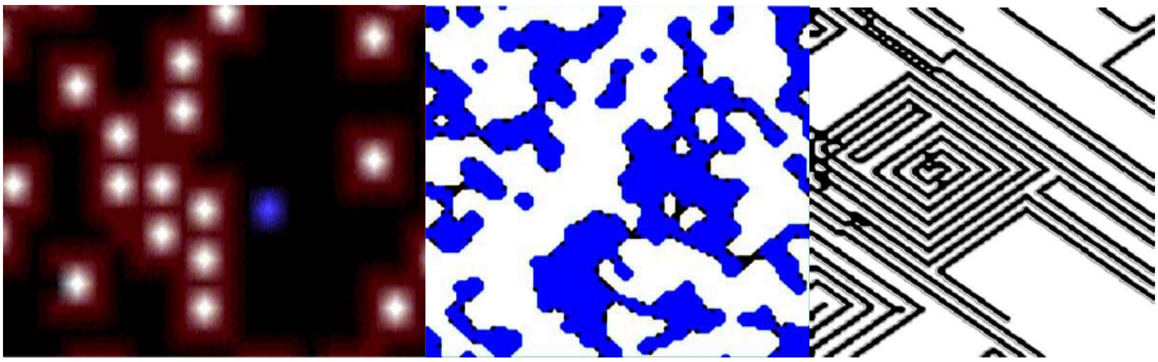

Figure 3: From left to right: Sections from evolved Asynch Set CA *Red Tiles,* Asynch Rand CA *Camouflage,* PAS pattern *Spirals.*

Fitness Function:
RC1: if $C0 = 8$ & $p = 2 \Rightarrow f(p) = 1 + \text{R2C1}$
RC2: if $\text{C1} = 8$ & $p = 3 \Rightarrow f(p) = 1 + \text{R2C2}$
RC3: if $\text{C}2 = 8$ & $p = 0 \Rightarrow f(p) = 1 + \text{R2C3}$
RC4: if $\text{C3} = 8$ & $p = 1 \Rightarrow f(p) = 1 + \text{R2C0}$
PC1: if zero or one or two or three $\geq (\text{N} \times \text{M}) - 30$

Rules Evolved:
if $p = 0$ & $C0 \geq 1 \Rightarrow p = 2$
if $p = 0$ & $C3 > 2 \Rightarrow p = 1$
if $p = 1$ & $C3 < 7 \Rightarrow p = 2$
if $p = 1$ & $C2 < 4 \Rightarrow p = 1$
if $p = 2$ & $C0 < 1 \Rightarrow p = 3$
if $p = 2$ & $C3 \leq 5 \Rightarrow p = p$
if $p = 3$ & $C3 < 3 \Rightarrow p = 2$
if $p = 3$ & $C0 = 2 \Rightarrow p = 0$

Figure 4: Fitness function and Rules for evolved Asynch Set CA *Red Tiles*

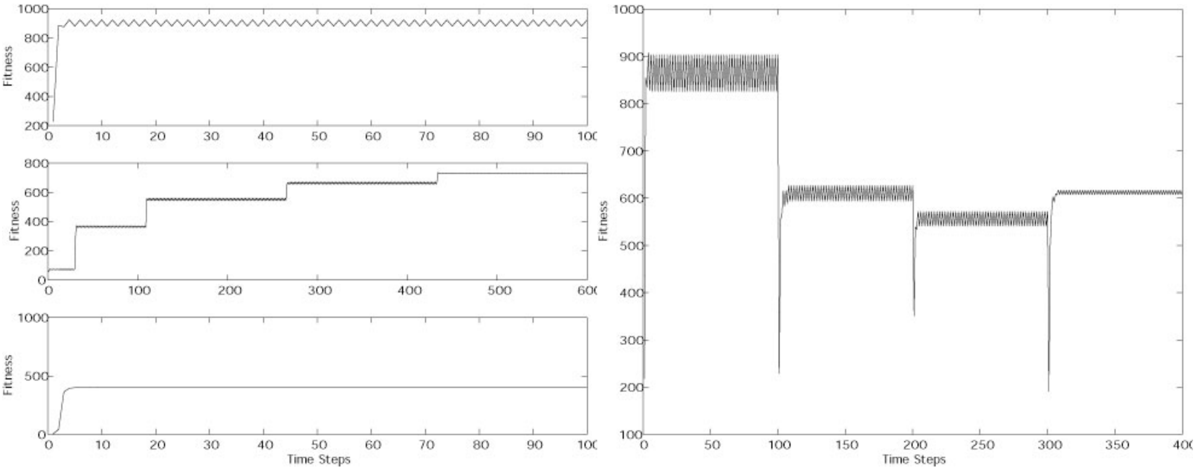

Figure 5: Left: graph showing the evolved Asynch Set CA *Red Tiles* when updated with (top to bottom) Asynch Set, Asynch Rand and Synch. Right: graph showing *Red Tiles'* ability to adapt to perturbations occurring at time steps 100, 200 and 300.

5.3 Evolved Asynch Rand CA Pattern: *Camouflage*

In order to evolve a pattern that didn't cheat the restrictions on blanket formation, by only developing into a blanket once the time step where fitness was judged, a tougher penalty was enforced. This did not completely rule out blanket formation, but it did mean it was considerably less likely. The desired outcome was clustering, that pixels of the same colour would cluster and be surrounded by a different colour. The resulting pattern, shown in fig 3, from the fitness function in fig 6 exhibited pseudo periodic behaviour such as that described in [2]. Shapes resembling army camouflage patterns formed with flickering boundary cells.

Fitness Function:

RC1: if $C0 = 8$ & $p = 0 \Rightarrow f(p) = 1 + \text{R2C1}$
RC2: if $C1 = 8$ & $p = 1 \Rightarrow f(p) = 1 + \text{R2C2}$
RC3: if $C2 = 8$ & $p = 2 \Rightarrow f(p) = 1 + \text{R2C3}$
RC4: if $C3 = 8$ & $p = 3 \Rightarrow f(p) = 1 + \text{R2C0}$
PC1: if zero or one or two or three $\geq (\text{N} \times \text{M}) \times 0.5$

Rules Evolved:

$p = 0$ & $C1 > 3 \Rightarrow p = 3$
$p = 0$ & $C0 = 3 \Rightarrow p = p$
$p = 1$ & $C2 < 0 \Rightarrow p = 0$
$p = 1$ & $C1 < 4 \Rightarrow p = 3$
$p = 2$ & $C0 \leq 2 \Rightarrow p = 1$
$p = 2$ & $C0 > 3 \Rightarrow p = 0$
$p = 3$ & $C2 < 6 \Rightarrow p = 2$
$p = 3$ & $C2 \geq 1 \Rightarrow p = 3$

Figure 6: Fitness function and rules for evolved Asynch Rand CA pattern *Camouflage*

Adaptation to Perturbations:

The graphs in fig 7 show that this pattern was highly successful at retaining its fitness in the face of perturbations in cell state and in updating scheme.

5.4 Evolved PAS Design: *Spirals*

Using a fitness function, shown in fig 8, that rewarded for a pixel to be partially surrounded by a specific colour other than that of the pixels, led to an interesting spiral pattern. The surrounding was partial because the agent system couldn't cope with the stricter full surrounding version. No RC was set for the surrounding to be partially *C0* as the agents CA began with a blanket 0 setting. The second PC was introduced in this case so that pheromone

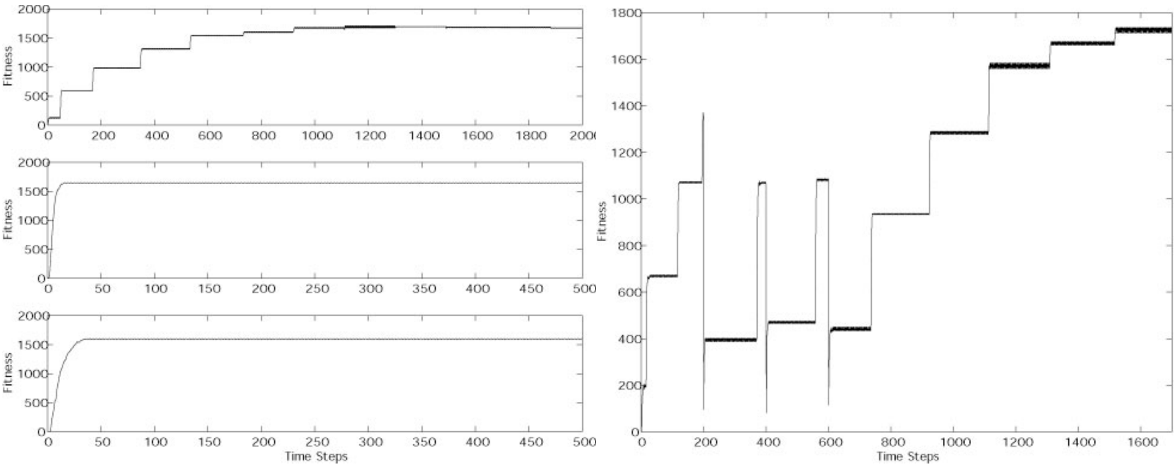

Figure 7: Left: graph showing the evolved Asynch Rand CA *Camouflage* when updated with (top to bottom) Asynch Rand, Asynch Set and Synch. Right: graph showing *Camouflages'* ability to adapt to perturbations, occurring at time steps 200, 400 and 600.

was definitely going to be used by the agents. When analysed the rules were particularly curious in their simplicity. The agents were only ever implementing one rule. The second rule, 'if C0 was less than or equal to eight', which of course it always was, occurred above any other rules meaning that, through the hierarchy system, the others were made obsolete. Essentially the agents were always leaving pheromone and always moving away from it. What emerged from this very simple set up was a spiraling pattern, interestingly similar to the aggregate spirals of social amoebae especially as it seems to be the opposite signaling system to that currently proposed [18]. Fig 9 shows the development of the pattern and an enhanced section of this image is shown in fig 3.

Fitness Function:
RC1: if $C1 \geq 5$ & $p \neq 1 \Rightarrow f(p) = 1$
RC2: if $C2 \geq 5$ & $p \neq 2 \Rightarrow f(p) = 1$
RC3: if $C3 \geq 5$ & $p \neq 3 \Rightarrow f(p) = 1$
PC1: if zero or one or two or three $\geq (N \times M) - 30$
PC2: if TIME = 0

Rules Evolved:
$C1 \geq 2 \Rightarrow p = p$, move away from pheromone, leave plume
$C0 \leq 8 \Rightarrow p = 3$, move away from pheromone, leave plume
$C3 = 0 \Rightarrow p = 2$, move away from pheromone
$C0 > 7 \Rightarrow p = p$, move towards pheromone, leave plume
$C2 = 2 \Rightarrow p = 1$, move away from pheromone, leave plume
$C2 > 0 \Rightarrow p = p$, move away from pheromone
$C3 \leq 4 \Rightarrow p = p$, move towards pheromone
$C0 > 4 \Rightarrow p = p$, move away from pheromone, leave plume
AGENTS = 18
t = 11
Q = 7.408590
D = 3.661763

Figure 8: Fitness function and rules for evolved PAS pattern *Spirals*

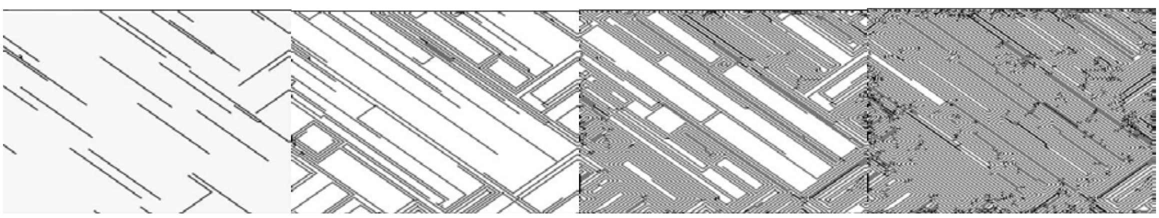

Fig 9: Development of Pheromonal Agent Design *Spirals*

Adaptation to Perturbations:

As the PAS was evolved with the initial CA as a 0 blanket, perturbing the state of cells within the range of *all* possible colours meant that the spiral design was irredeemable, see fig10. However changing a random amount of cells back to 0, i.e. ‘rubbing out’ some of the design didn’t stop the rules recovering to a high fitness, although the characteristic spiral pattern reverted to a reticulation design.

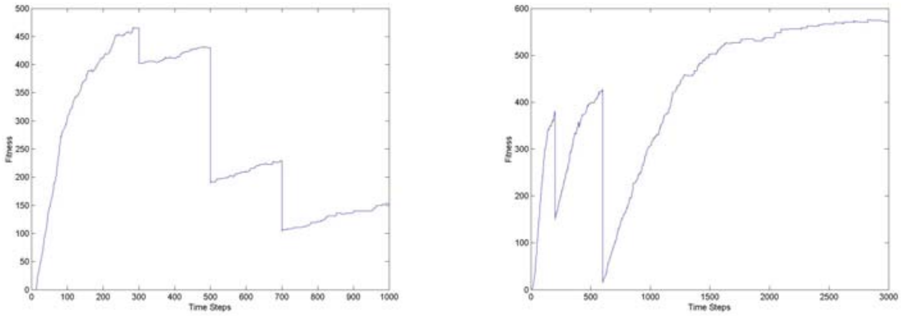

Figure 10: From left to right: Graph showing the evolved PAS *Spirals* lack of adaptation to perturbations at time steps 300, 500, 700. Graph showing the evolved PAS *Spirals* adaptation to ‘rubbing out’.

6 Conclusions

Inspiring insights can come from interdisciplinary research. This project has confirmed the hypothesis that the evolution of asynchronously updated systems (CA or PAS), in particular Asynch Rand updating, is a good generic method for the production of adaptive aesthetic patterns and images, in agreement with observations made of the artistic process and observations in nature.

Through this project it is clear that evolution *can* find robust solutions to form patterns in the face of random initial conditions, a random updating scheme and random perturbations as long as the population are exposed to this throughout the evolution.

The choice of time step for testing the fitness of the patterns played a crucial role in the type of pattern that formed. If the fitness was judged too early then the pattern could still dissolve away into a blanket state, and if it was too late then it rewarded for patterns with very long developmental periods.

``Maybe this is how science progresses: an initial mystery based on ignorance, then a discovery and a learning stage, and a final mystery based on knowledge. Sounds a bit like art." [14] Pp 25.

8. Acknowledgements

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