# ARTIFICIAL EMBRYOLOGY AND CELLULAR DIFFERENTIATION

**Hugo de GARIS**

Head, Brain Builder Group,
Evolutionary Systems Department,
ATR Human Information Processing Research Labs,
2-2 Hikaridai, Seika-cho, Soraku-gun,
Kyoto-fu, 619-02, Japan.
tel. + 81 774 95 1079, fax. + 81 774 95 1008,
degaris@hip.atr.co.jp
http://www.hip.atr.co.jp/~degaris

## 1. Introduction

The broad aim of this chapter is to create an awareness that self assembling, "artificial embryological" type systems need to be studied, so that future molecular scale technologies (Drexler, 1992) will be able to build machines which have too many components for sequential mechanical assembly. With this broader aim in mind, a more concrete aim is to introduce the concept of embryological differentiation into Genetic Algorithms. Traditionally, GAs have contained such ideas as reproductive fitness, crossover, mutation, etc, but nothing equivalent to the way genes switch on and off in natural embryogenesis. The ideas of differentiation are used in this chapter to pursue a third aim, namely to try to grow nonconvex artificial shapes of colonies of cells in reproductive cellular automata. Earlier publications aimed at creating an "Artificial Embryology" resulted in the growth of successful convex shapes but nonconvex shapes failed to evolve (e.g. de Garis, 1992b).

The new field of Artificial Embryology (or at least the self assembly of complex systems) is felt to be important for the future development of complex system design. New technologies, such as WSI (Wafer Scale Integration), Molecular Electronics (Carter et al, 1988), and Nanotechnology (Schneiker, 1989), promise to allow the construction of devices with a huge number of components (e.g. billions, trillions, and up to Avogadro's number). This in turn will create problems for the design and construction of these devices. If a device contains literally trillions of components, it cannot be built by a machine which positions one component at a time, because such a machine would be too slow. The device will either have to be built by positioning many components simultaneously, (which will become increasingly difficult as the number of components to be simultaneously placed increases), or, the device will have to build itself in a form of embryological self assembly.

It is this second option which is of interest to the author. It is also the solution employed by nature to build its (hyper) complex systems, such as embryos and brains. However, if one is to employ self assembly techniques to build complex systems, how can one be sure that the self assembled product is useful to human beings? The self assembly will need to be tested for its quality of performance. Those self assemblies which do poorly can be abandoned. Those that do well, may be used. But what if all the initial attempts at self assembly do poorly? How is progress in the design to be made when the self assembled device is massively complex?

The answer to this question may be to mimic nature by using a form of "applied evolution" called Evolutionary Engineering (EE), i.e. using GAs to build/evolve complex systems (de Garis, 1990, 1991, 1992). Improvement in a hypercomplex system may be achieved blindly by randomly mutating linearly coded instructions for self assembling devices. Those mutations which are "positive", will produce devices with superior performance values. The linear codes which contain these positive mutations can be allowed to produce more offspring in the next generation of a population of such codes.

The author feels that it is important to begin investigating how to build and evolve (EE style) self assembling devices. This chapter is an attempt in this direction. It is part of a general "vision" that future devices may be used to "grow" complex systems, such as electronic circuits at various levels of granularity. At a very basic level, simple RLC circuits could be coded and grown on an electronic substrate in a special hardware device called a "Darwin Machine". At a higher level of granularity, circuits of component parts such as flips-flops and amplifiers could be grown. At a still higher level of granularity, circuits of artificial neurons and synapses could be grown etc. Thus self assembling (and self testing) artificial nervous systems might be grown in these Darwin Machines. This is the vision and the longer term direction in which the work of this chapter is aimed.

With this vision in mind, present day computer technology should begin raising its sights beyond the usual style of "homogeneous" architectures. A homogeneous architecture is defined to be one which contains a large number of copies of a small number of relatively simple (i.e. humanly understandable) components or modular designs, which are then connected using simple rules to make the whole. The net result is a machine whose functioning is humanly understandable, because it is built according to a plan, a blueprint. Obvious examples are mass computer memories, von Neumann computers, the Connection Machine (Hillis, 1985), etc. A "heterogeneous" computer architecture is "non homogeneous", e.g. it may contain complex modules which differ greatly one from another, and be connected in very complex ways. The paradigm example of such an architecture is the human brain.

If, for example, one is attempting to build a million or a billion processor machine, (assuming that the underlying technologies allow such a thing), then why restrict oneself to a homogeneous architecture, when one could "almost" as easily (in purely technological implementation terms) build a heterogeneous machine, with all its greater sophistication and subtlety of behavior. Of course, the obvious answer to this question is that a million (billion) processor heterogeneous machine would be hyper-complex and would compare to the complexity level of simple biological nervous systems, in terms of dynamics, structure and most importantly, "un-understandability".

Traditionally, engineers and scientists have shied away from building hypercomplex machines, because of this "un-understandability", i.e. a lack of theoretical principles to explain their structures or functions. However, recently, a new approach to building (hyper) complex systems has been demonstrated. It is called "Evolutionary Engineering" (EE) (de Garis, 1990, 1991, 1992), which uses Genetic Algorithms (GAs) as a tool to build things, where the internal complexity of the system being built/evolved is (within certain limits) irrelevant to its successful construction. So long as the GA being used gets a fitness value which continues to increase over the generations, (i.e. the system has a non zero "evolvability") then a steady improvement in the system being evolved will result. One does not care about the internal complexity. The system is in effect, a "black box". It is possible that this EE approach to building (hyper) complex systems may have a strong future, and play a vital role in 21st century technology and engineering. It is essentially the approach taken by nature to build/evolve such hypercomplex systems as ourselves.

If the prospect of a one million (billion) processor computer raises the issue of homogeneous vs. heterogeneous architectures and the problem of complexity of heterogeneous machines, then this level of complexity pales into insignificance when one considers the molecular scale technologies now exploding in research labs around the world. The author's lab (ETL) has whole sections of people devoted to building and testing devices which can pick up atoms at one point and place them at some other point to build desired molecular scale structures or tools. Molecular scale technologies ("nanotech" (Drexler, 1992)) offer the long term prospect of building Avogadro Machines, i.e. machines containing an Avogadro number (i.e. of the order of a trillion trillion) components. With such a huge number, it will obviously be impossible to assemble them one by one. Somehow they will have to self-assemble, in an embryological like way, as mentioned earlier. Thus the reasoning behind the need for self-assembling, self-testing, EE-style design and construction techniques, will be all the more compelling when it comes to 21st century nanotechnology.

This chapter attempts to take some initial steps at using EE techniques to build/grow structures in an embryological like manner, and in particular to use ideas analogous to the phenomenon of "differentiation" in the biological world. It is hoped that the initial ideas presented in this chapter, will inspire other researchers to work on the embryological "growth" of (neuro) electronic circuits, thus creating a new speciality called "Embryonics" (Embryological Electronics). A device which "EEs" (i.e. evolves) a complex (neuro) electronic circuit has been called a Darwin Machine (de Garis, 1991a) by the author. It is envisioned that such machines may play a role in building artificial nervous systems for future artificial creatures (or biots, i.e. biological robots).

The artificial "embryos" presented in this chapter are two dimensional "shapes" formed by a colony of "cells" in reproductive cellular automata. The basic idea is that a GA is used to evolve sets of reproduction rules of these cells. These rule sets are spread out (one set per "operon") along a bit string GA chromosome, and are switched on and off according to whether the state of a cell matches the "condition" field of the operon, and if so, the corresponding "action" field controls the reproduction (or not) of the cell. One has in effect a type of "production system" on a chromosome, which is similar is some ways to Holland's "Classifier System" ideas (Holland, 1986).

The remainder of this chapter is structured as follows. Section 2 provides a more general introduction to differentiable chromosomes and shape genes. Section 3 contains a more detailed description of the algorithms used in this chapter to grow nonconvex shapes. Section 4 presents some results of experiments using the ideas of the previous section.

## 2. Differentiable Chromosomes and Shape Genes

FIG. 1 shows what the author means by a "differentiable" chromosome, which in this particular example, consists of four genes (or "operons", a term taken from molecular biology), where each operon (separated by double vertical lines) contains a condition field C and an action field A. These operons switch on and off over time, as in nature. The actions of earlier operons cause other operons to switch on and off. The desired net result of this sequential operon switching is the controlled growth of an (artificial) embryo.

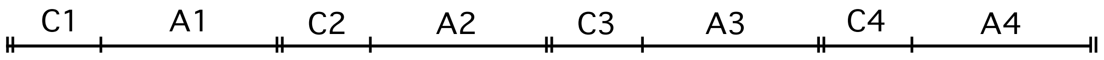


FIG. 1 A DIFFERENTIABLE CHROMOSOME

Each cell of a particular cellular automaton described in this chapter contains the same chromosome. At each stroke of a clock (where the cellular automata are assumed to be synchronous or clocked), each cell calculates its present "state" by observing the states of its neighboring cells at the end of the previous cycle (where a cycle is the time between two clock strokes). Each cell then compares its present state with all the coded condition fields $C_i$ of its genes (or operons). If one of the conditions (e.g. $C_m$) "matches", then the corresponding action field $A_m$ is "activated" or "expressed", and the instructions coded in that action field are executed. The activation of these instructions may change the state of some of the cells, and thus activate new instructions, which in turn may change further states etc. Thus it is possible to generate a time sequence of state changes and execution of instructions, which result in some final desired product, e.g. an embryo or colony of cells having a desired shape.

The ideas contained in the previous paragraph are very general, and may be applicable to many kinds of concrete situations. The above ideas have similarities with traditional "production systems" of Artificial Intelligence and Holland's Classifier Systems (Holland, 1986). Perhaps future research might be able to incorporate ideas from the extensive work already done on Production and Classifier Systems into differentiable chromosomes.

In order to give a more concrete example of what coded instructions might be like, a brief introduction to some earlier work of the author on Artificial Embryology will now be given (de Garis, 1991a, 1992b). Basically, the main idea of this earlier work was to evolve reproduction rules for cellular automata (CA), such that the final shape of a colony of cells attained, as closely as possible, some desired shape, such as a square, triangle, ellipsoid, tadpole, etc. The state of a cell in one of these experiments was defined in terms of the configuration of its neighborless sides. Assuming only edge cells can reproduce, (where reproduction is defined as putting a daughter cell in a vacant square contiguous with the parent cell), there are 14 possible states, as shown in FIG. 2.

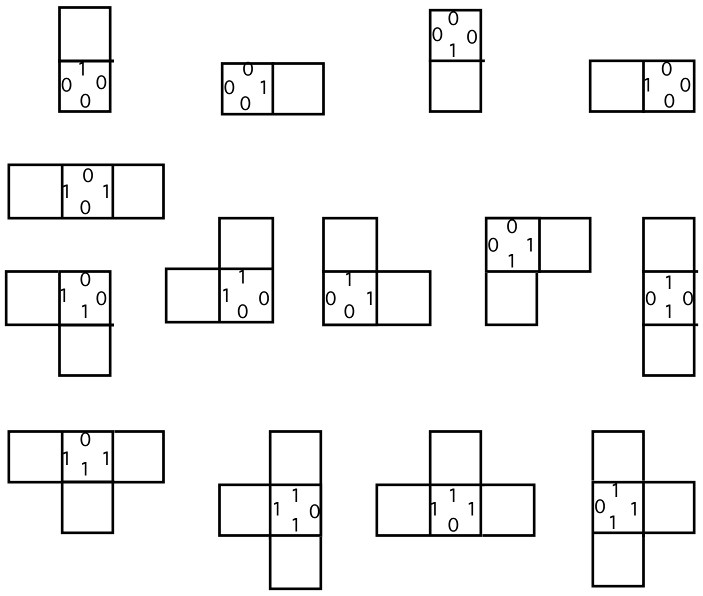
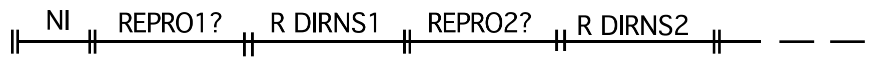


FIG. 2 The 14 Neighborless STATES for 2D Cells

For a 2D cellular automaton, each cell has one of the above 14 states (assuming only edge cells can reproduce, and that no isolated cells are generated). For each cell, for each cycle, a cell can reproduce or not, hence 14 bits (one per state) are needed to specify which cells in a given cycle will reproduce, as shown in FIG. 3 with the REPRO? fields (one per cycle). If a cell is to reproduce, it needs to know in which direction (E, N, W, or S). If there is only one neighborless side, then no R DIRNS (reproduction directions) field bits are needed to specify the side for the daughter cell, because there can only be one choice.

For two neighborless sides, 1 bit is needed (for 6 such states). For 3 neighborless sides, 2 bits are needed (for 4 such states). If an occupied side is specified with these 2 bits, it is ignored. Hence to specify the reproduction directions, ${}^4C_2*1 + {}^4C_3*2 = 14$ bits are needed, as shown in FIG. 3 by the R DIRNSi fields. Thus, 14 + 14 = 28 bits per cycle are used, with separate REPRO? and R DIRNS fields for each cycle. The number of cycles (or iterations) NI is also coded onto the bitstring chromosome and evolves along with the other fields.



NI = NUMBER OF ITERATIONS
REPRO1? = WHICH STATES CAN REPRODUCE IN ITERATION 1
R DIRNS1 = REPRODUCTION DIRECTIONS IN ITERATION 1
REPRO2? = WHICH STATES CAN REPRODUCE IN ITERATION 2
R DIRNS2 = REPRODUCTION DIRECTIONS IN ITERATION 2

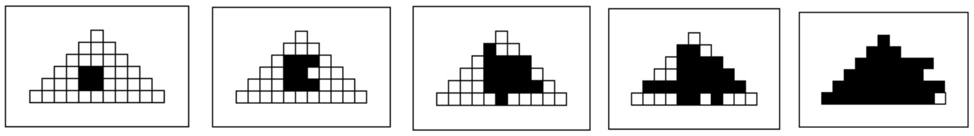
FIG.3 FORMAT OF A SIMPLIFIED "EMBRYO" CHROMOSOME

These chromosomes are then evolved using a Genetic Algorithm (Goldberg, 1989), such that the resulting colony of cells attains as closely as possible some desired or target shape. The fitness of the chromosome (i.e. the measure of closeness of the final and the target shapes) was defined as follows :-

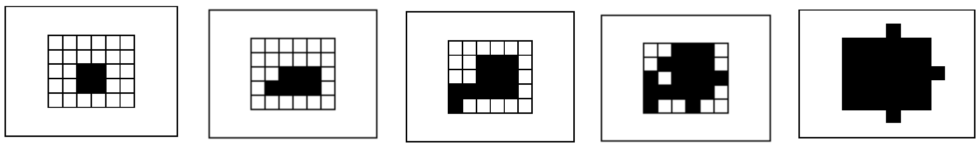
Fitness = (#ins - 0.5*#outs)/(#des) where :

| | | |
|---|---|---|
| #ins | = | the number of **filled** cells inside the desired shape |
| #outs | = | the number of **filled** cells outside the desired shape |
| #des | = | the number of cells inside the desired shape |

Some examples of this type of evolution (for triangular and rectangular target shapes), are shown in FIG. 4, with one frame per cycle or iteration. Note that NI evolved to be 4, for both shapes.



(Fitness = 93%)



(Fitness  = 95%)

FIG. 4   TRIANGULAR & RECTANGULAR TARGET SHAPES

The above ideas were tested on various shapes (de Garis 1992b), both convex and non-convex. The convex shapes worked well (with fitness values around 95%, e.g. FIG. 4), but non-convex shapes evolved poorly, with low fitness values (e.g. as low as 20% for an arch shape). The challenge then was to evolve arbitrary non-convex shapes, e.g. 3D embryo shapes with a head, body, limbs, fingers and toes etc. Evolving such an "artificial embryo" implies a type of sequential, time dependent "unfolding" of shapes, e.g. first the body is grown, then the limbs and head emerge from the body, then the fingers and toes emerge from the limbs etc. It appears that one needs some means of switching on and off shape forming instructions for the various components.

## 3.    Evolving a (Non-Convex) "L" Shape

To illustrate the ideas contained in the above section, a concrete example is now introduced, which is to "grow" a simple nonconvex target shape in the form of the letter "L". FIG. 5 shows the set up. To keep things simple, it is assumed that there are only 2 operons in the "L chromosome", and that the first operon is used to code for instructions to grow region A, and the second operon is used to code for region B. The trick then is to decide how to define the state of a cell, plus the nature of the condition fields, so that operon "A" switches off at the appropriate time and operon "B" switches on. What is required is that once the region A has been filled, all the edge cells (except those in region R) stop reproducing. The R cells then grow region B. Hence we need some means to distinguish the R region from the rest of the edge cells of region A (assuming only edge cells reproduce). The R region lies south-east of the A region, so one idea might be to let the A region grow for a given number of iterations (as in the above section) and then let only the south-east cells reproduce beyond that number. So, the condition for region A might be simply :-

[nbr of iterations < X]

where X needs to be evolved. The conditions(s) for region B might be :-

[nbr of iterations = X]&[cell region type = south-east]
OR
[X < nbr of iterations =< X+Y]

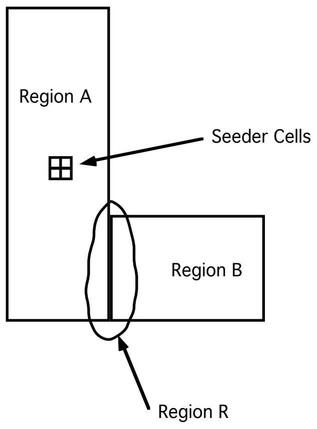


FIG. 5 TARGET SHAPE "L"

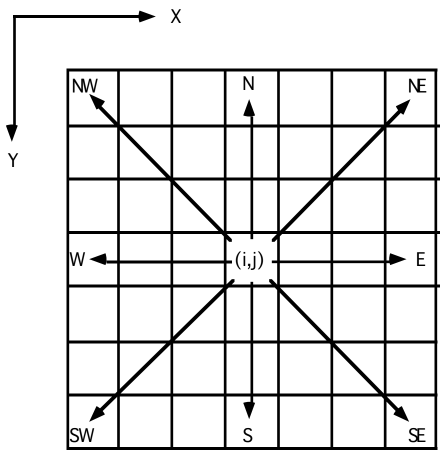


FIG. 6 CELL NEIGHBORHOOD

Alternatively, the region B operon could be split into 2 operons B1 and B2, where the condition for B1 would be the first disjunct, and the condition for B2 would be the second disjunct. What are needed now are means to specify the number of iterations, and "south-east-ness". (Note that in an iteration, all edge cells in a colony of cells which are allowed to reproduce, do so). One idea to specify something similar to the number of iterations (in cellular terms), might be to give each cell a "generation count" (GC), such that a parent cell with a GC of "g", would have a daughter cell with a GC of "g+1".

To specify "south-east-ness", one might use a concentration gradient of some "chemical", which is passed in (fractionally) decreasing quantities from parent to daughter cell, e.g. a parent cell may have a quantity "q" of this chemical, which is fractionally reproduced and transmitted to the daughter cell which receives (for example) a quantity "0.95q" of this chemical. Assume that each cell uses this chemical to create another chemical which is diffused into the intercellular environment. By measuring the "q value" of neighboring cells, each cell can determine the "q gradient", and hence determine its "position".

To calculate the "q gradient" at each cell, the following approach is suggested, as shown in FIG. 6. A square block of 49 cells, i.e. the 7 by 7 "neighborhood" of a cell is used. The average "q value" over 4 cells is calculated (i.e. over the "middle" cell, and the other 3 cells in the same direction). For example, if the middle cell is given coordinates (i,j) then the average "q value" in the north-west direction ($Q_{nw}$) would be :-

$$Q_{nw} = 0.25*[q(i, j) + q(i-1, j-1) + q(i-2, j-2) + q(i-3, j-3)]$$

Similar q values are calculated for all 8 directions (i.e. E(ast), NE, N, NW, W, SW, S, SE). Since these calculations are only performed at the edge cells, about half of these 8 directions will involve empty cell positions. Hence the average "q value" in such directions will be low. The high "q value" directions are likely to be towards the "center" of a colony of cells, i.e. perpendicular to the edge of the colony at the point (i,j). The "q gradient" (QG) at a cell, is defined to be the direction (one of the 8 possible) which has the largest q value. For example, those cells lying at the south-east edge of a colony of cells, will have their "q gradients" pointing north-west.

The notions of "generation count" and "q gradient" can be used to decide when cells should switch from their first operon to their second. What now needs to be discussed is how these notions can be coded on the operon, (i.e. how to express the condition part of the operon) and how the cells are to reproduce, (i.e. how to express the action part of the operon).

The following chromosome format is suggested, as shown in FIG. 7.

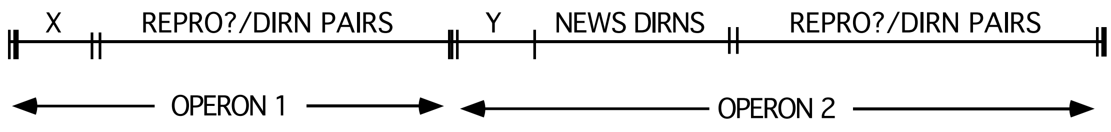


FIG. 7  TWO-OPERON CHROMOSOME FORMAT

This format requires some explanation. X is the iteration count (IC) when Operon 1 switches off and Operon 2 switches on. When the iteration count is X+Y, Operon 2 switches off. Note, in one iteration, all edge cells which can reproduce, do so synchronously.

The NEWS DIRNS field is 8 bits long, and is used to specify which cells can reproduce beyond X iterations. Only those cells whose "q gradients" have their corresponding bits set in this field can reproduce further. For example, if a cell's "q gradient" is NE, and the bit corresponding to NE is set (i.e. the second bit), and the iteration count is X, then that cell can use Operon 2 when the iteration count IC obeys $X =< IC =< X+Y$.

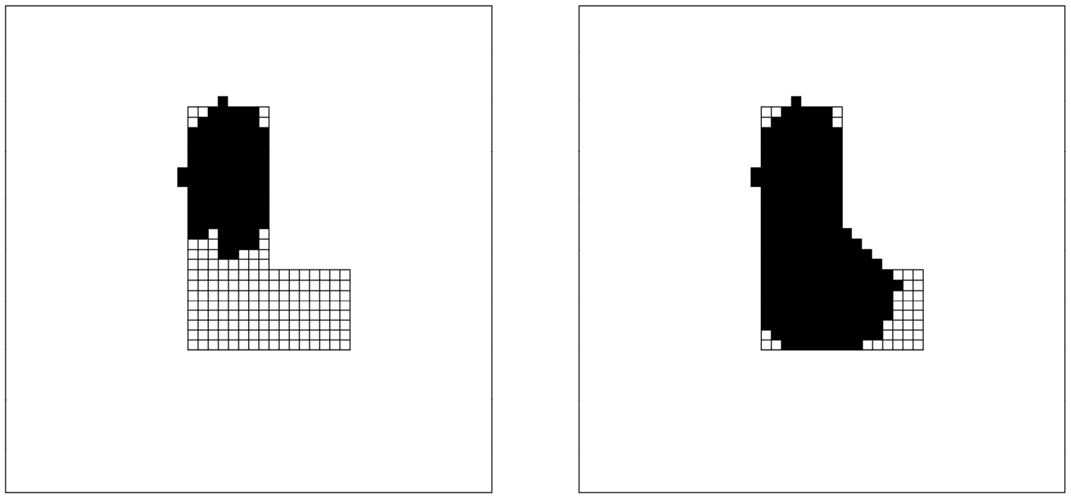
REPRO?/DIRN PAIRS (or RD Pairs) are the pairs of fields shown in FIG. 3. The "i"th pair of fields in Operon 1 applies to cells when the IC is "i". The "j"th pair in Operon 2 applies to cells when the IC is "X+j".

If "m" bits are reserved for the X field, then $2^m$ RD pairs are needed in Operon 1. Similarly, if "n" bits are reserved for the Y field, $2^n$ RD pairs are needed in Operon 2. Hence the length of the chromosome can be calculated as $(m + 28*2^m + n + 8 + 28*2^n)$ bits. The fitness definition is the same as defined earlier, i.e. Fitness = (#ins - 0.5*#outs)/(#des), where the target shape is the "L" (double rectangle) of FIG. 5.

## 4. Experimental Results

This section presents some experimental results of the ideas introduced in earlier sections. These results were obtained from programs run on a MAC IIci computer, in "C" language. Two general approaches to the evolution were usually taken. In the first approach, both operons were switchable during a "run" (i.e. the second operon was able to switch on later in the run). In the second approach, so called "shaping" techniques were used. The concept of "shaping" has been defined in earlier publications (de Garis, 1991a,b, 1992a). "Shaping" is simply splitting up an evolutionary process into intermediate phases, with intermediate targets. The results of a previous phase (i.e. the population of evolved chromosomes), are fed as the starting conditions (i.e. initial chromosomes) for the next phase. This is done to "push" the evolution in a desired direction by suitable choices of intermediate targets. When shaping is used, the behavior or structure evolved in phase A, carries over into phase B. By suitable choice of A, a desired B (or C etc.) can often be attained. Shaping can increase the odds of obtaining a desired result, by reducing the size of the search space, thus accelerating the evolution. In some cases, shaping is needed just to get a required evolution.

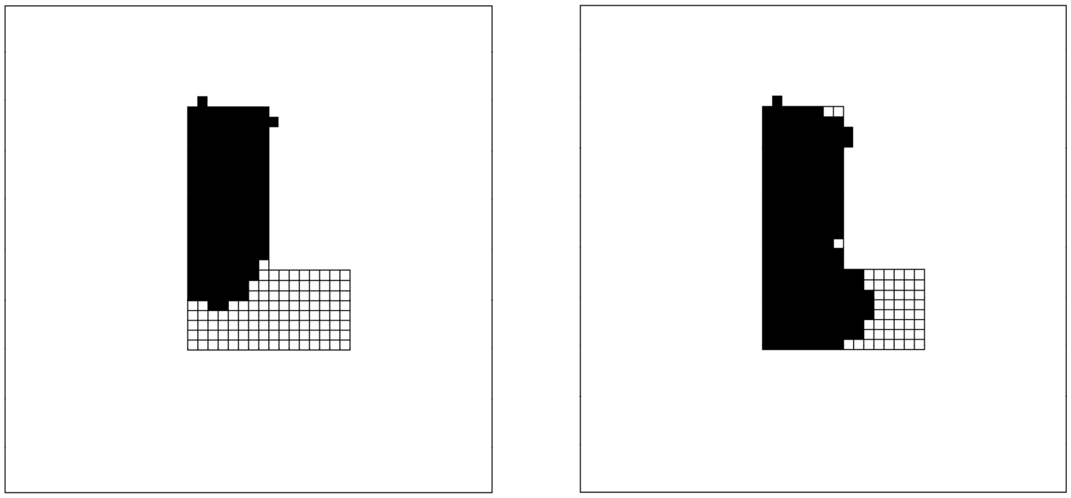
In a first experiment, no shaping was used, i.e. both operons were allowed to be active, starting with random chromosomes. FIG. 8 shows the results after 600 generations, and little further fitness growth. The X and Y values evolved to be 13 and 15 respectively, the NEWS DIRNS were [00100010]. The fitness was about 80%. FIG. 8a shows the colony of cells grown using the instructions of the first operon (i.e. before the switching to the second operon). FIG. 8b shows the final result after both operons have finished, i.e. after X+Y iterations. An 80% result was not thought to be particularly impressive, although at least a definite "L" shape began to emerge. A second experiment was undertaken using shaping techniques to see if a better result could be obtained. In this second experiment, initially only operon 1 was allowed to evolve (using the L target shape). Operon 2 was switched permanently off. In a second phase of evolution, the resulting chromosome population from the evolution of operon 1 was used as a starting set of chromosomes, in an evolutionary phase in which operon 2 was able to switch on.



(a) AFTER OPERON 1 (b) AFTER OPERONS 1 & 2

FIG. 8 "L" SHAPE RESULTS USING BOTH OPERONS

FIG. 9 shows the results using shaping techniques. FIG 9a resulted from 1200 generations of evolution of Operon 1 alone. FIG 9b resulted from taking operon 1 from FIG. 9a and allowing it to evolve a further 1500 generations with both operons. FIG. 9b shows that a definite turning occured before fitness values stagnated, and that a nonconvex shape was being formed. For FIG. 9a, the X value evolved to be 15, and in FIG. 9b, both the X and Y values evolved to be 15. For FIG. 9a, the NEWS DIRNS were [11000110], which evolved to [01000100] for FIG. 9B.



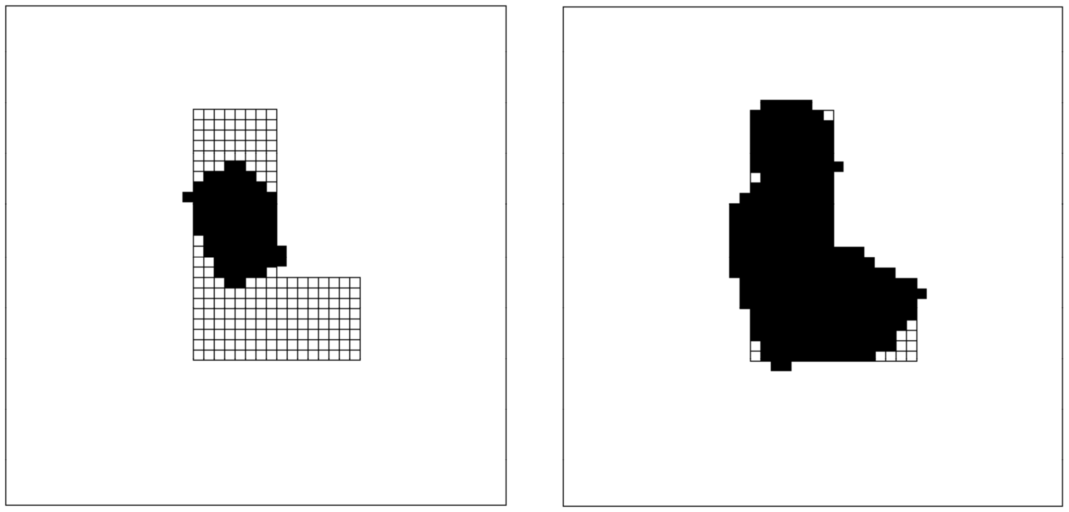
(a) OPERON 1 ONLY (b) AFTER OPERONS 1 & 2

FIG. 9 "L" SHAPE RESULTS USING SHAPING TECHNIQUES

The final fitness value of FIG. 9b was also about 80%, so shaping did not seem to have much of an effect. The vertical part of FIG. 9a is deeper and "cleaner" than in FIG. 8a, as one would expect, but the net result in FIG. 9b is not particularly praiseworthy.

These 80% results were rather disappointing, and showed the difficulty of the task. With convex shapes (circles, squares, rectangles, ellipses) in earlier experiments (de Garis, 1992b) fitness values around 95% (using the same fitness definition as in this chapter) were typically obtained, but nonconvex shapes failed badly. The results of FIGs 8 and 9 show that at least nonconvex shapes can been obtained, but not yet to high quality. This relative failure is probably not surprizing with hindsight. The algorithm as presented in this chapter, effectively causes one convex shape to grow out of a subset of edge cells of a previous convex shape. By having a series of switch-ons and offs, one could probably generate some interesting shapes, but fully random shapes will probably require new kinds of algorithms.

A third experiment using the "L" target shape was undertaken, which gave better results. The four seeder cells were moved down 6 squares, so that they were positioned more centrally relative to the vertical part of the L. This seemed to constrain the evolutionary path less. The X and Y values which evolved in FIG. 10 were 10 and 15 respectively, and the NEWS DIRNS were [01100011]. Note that FIGs 10a and 10b are from the same run, with no shaping. The resulting fitness value was 87%.



(a) AFTER OPERON 1 (b) AFTER OPERONS 1 & 2

FIG. 10 "L" SHAPE RESULTS WITH MORE CENTRAL SEEDER CELLS

The parameter values used for the above experiments were as follows :-

| | |
|---|---|
| Population Size | 20 chromosomes |
| Chromosome Length | 1810 bits |
| MaxX | 32 |
| MaxY | 32 |
| Max Number of Bits for X Field | 5 |
| Max Number of Bits for Y Field | 5 |
| Seeder Cells Chemical Q Value | 1.0 |
| Chemical Transmission Coefficient | 0.95 |
| Cell Grid Size | 48*48 cells |
| Seeder Cell Coords (FIGs 8, 9) | (20,14), (21,14), (20,15), (21,15) |
| Seeder Cell Coords (FIG 10) | (20,20), (21,20), (20,21), (21,21) |
| (Uniform) Crossover Probability | 0.6 |
| Mutation Probability | 0.005/bit |
| Linear Scaling Constant | 2.0 |

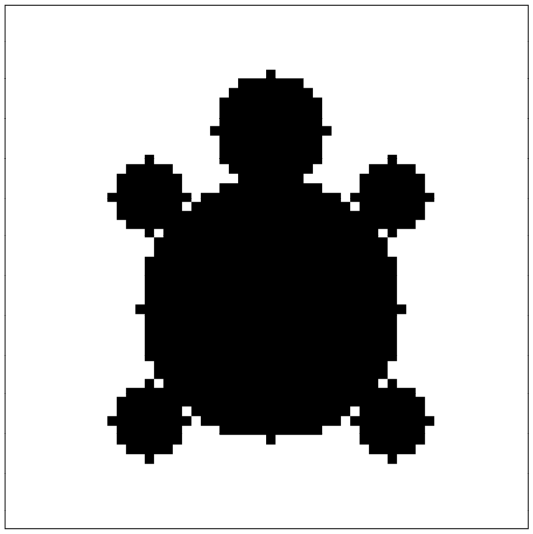
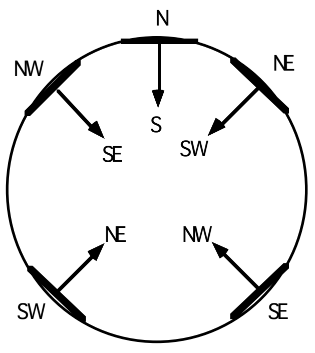
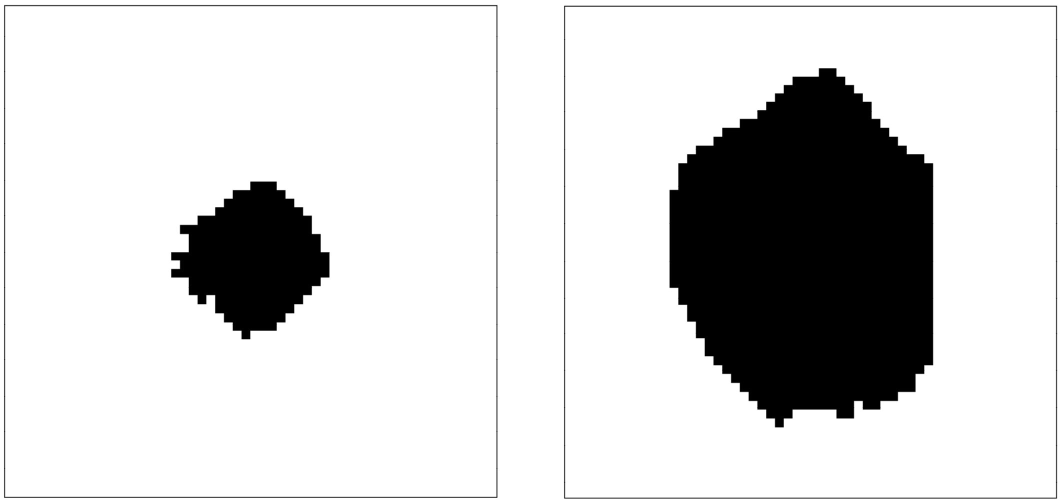


FIG. 11 TURTLE TARGET SHAPE



| E | NE | N | NW | W | SW | S | SE |
|---|---|---|---|---|---|---|---|
| 0 | 1 | 0 | 1 | 0 | 1 | 1 | 1 |

FIG. 12 DESIRED NEWS DIRNS

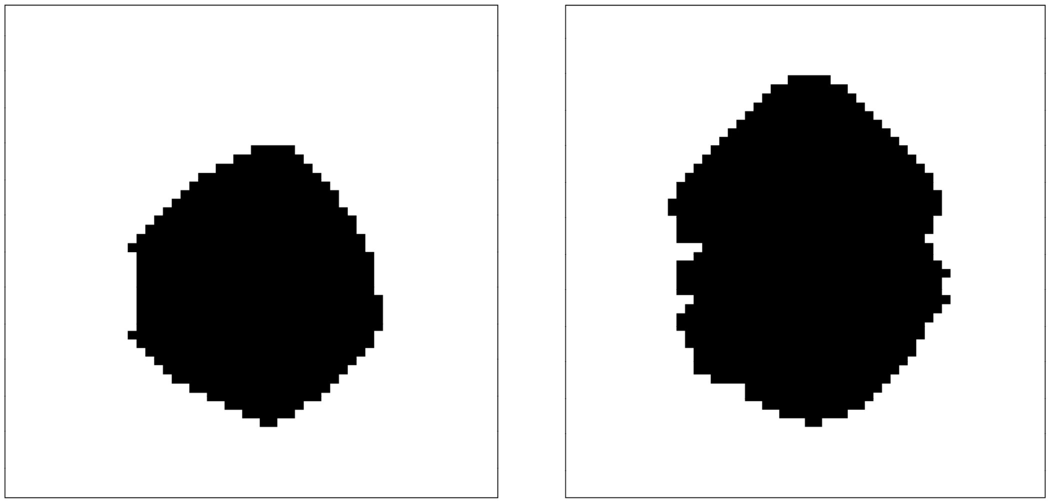


(a) AFTER OPERON 1

(b) AFTER OPERONS 1 & 2

FIG. 13 TURTLE SHAPE WITHOUT SHAPING

The relative success of FIG. 10 suggested trying a more complex nonconvex shape. FIG. 11 shows a target shape in the form of a turtle. It was thought that the first operon might grow the circular body, and that the N, NW, NE, SW and S edges of the body (corresponding to NEWS DIRNS of [01010111] (see FIG. 12)) would switch on, and grow the head and 4 limbs with the second operon. The best actual result obtained after 200 generations and little further fitness improvement is shown in FIG. 13 (where X and Y evolved to be 17 and 27 respectively, and the NEWS DIRNS was [11001101]. The fitness was only 80% and does not look anything like a turtle. It looks more like a blob. This is probably because the X value is too small and the Y value too large. If the switching had occurred later, the "Y shapes" might have been more limb like.



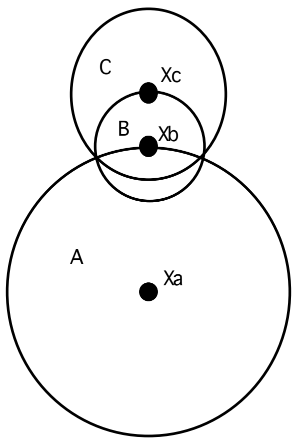
(a) OPERON 1 ONLY (b) AFTER OPERONS 1 & 2

FIG. 14 TURTLE SHAPE USING SHAPING

Perhaps a better result could be obtained by using shaping techniques. For example, a circular target shape could be used with only operon 1 allowed to be active. Previous experience shows that generating good circular shapes is not difficult. In a second phase of evolution (with the full turtle target shape), and using the chromosome population evolved from the first phase, hopefully a rather small Y value and the desired NEWS DIRNS [01010111] would be evolved to generate the turtle.

The results of using this approach are shown in FIG. 14. FIG. 14a shows the circular shape evolved for the body of the turtle. X was 31 (a lot larger than the 17 of FIG. 13a). These chromosomes were then fed as the initial chromosomes in a further stage of evolution in which both operons were allowed to operate. The net result is shown in FIG. 14b. The X and Y values were 31 and 6, and the NEWS DIRNS were [11001011]. This is a better result than FIG. 13b. At least one is beginning to see four (five?) limb buds on the sides of the figure. The space between the upper limbs and the head however has been filled with undesired cells. It appears that the target shape of a turtle is too ambitious for the two operon algorithm.

In all of these experiments, there was only one switching, and many iterations. Perhaps one could increase the number of switchings and thus obtain better shapes (i.e. shapes with higher fitness values). It seems that once a cell becomes reproductive, it and its descendents, will form a circular colony of cells (in 2D), with the original cell roughly at its center. If a cell (which lies along a long straight edge of cells) becomes reproductive, its descendents will form a colony which will be roughly semicircular and lie against the original edge of cells. Perhaps the art of growing arbitrary shapes is to use multiple switchings, and to select a subset of edge cells recursively, to be the reproductive cells in the next iteration of switching.



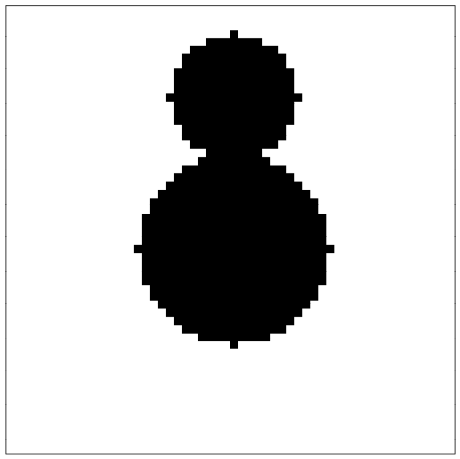


FIG. 15 SNOWMAN SHAPE FIG. 16 SNOWMAN TARGET SHAPE

With this idea in mind, an experiment with two switchings was undertaken, using a target shape that was thought to be more "realistic", i.e. it consisted of agglomerations of crescent shaped regions. FIG. 15 shows an example of such a shape. It looks like a "snowman", where the first operon is supposed to grow the "body" A (where Xa is the position of the original seeder cells). The second operon is supposed to grow the "neck" B (where Xb is the position of the edge cells of body A, which switch on), and the third operon is supposed to grow the "head" C (where Xc is the position of the edge cells of the neck B, which switch on). This shape is less ambitious in some ways than the turtle. If a body, neck and head can be grown, then at a later stage, perhaps four limbs can be grown as well. The actual target shape based on FIG. 15 is shown in FIG. 16.

We assume that cells which are switched on for the third operon, can only be descendents of those cells which were switched on for the second operon. This type of "embryological chaining" allows a certain degree of morphogenetic control. One can add layers of cells progressively to form desired shapes. The chromosome format for these double-switching (triple operon) experiments is shown in FIG. 17. This format is a simple extension of FIG. 7. The results of the three-operon "snowman" shape, where all three operons were switchable (i.e. there was no shaping) are shown in FIG. 18. To highlight which operons generated which cells, a grey coding is used. The four seeder cells are shown in light grey. Cells generated under control of operon 1 are shown in black. Cells generated under control of operon 2 are shown in light grey. Cells generated under control of operon 3 are shown in dark grey. The X, Y and Z values for FIG. 18 were 30, 3 and 15 respectively. The NEWS DIRNS Y and NEWS DIRNS Z were [00100010] and [01000111]. The number of generations used for the evolution of FIG. 18 was 100. The other parameter values were as in the above experiments.

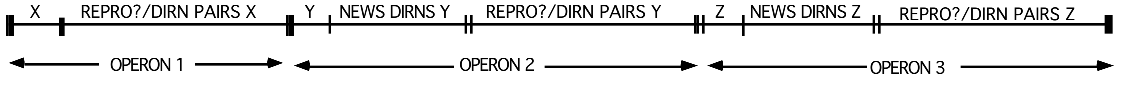


FIG. 17 THREE-OPERON CHROMOSOME FORMAT

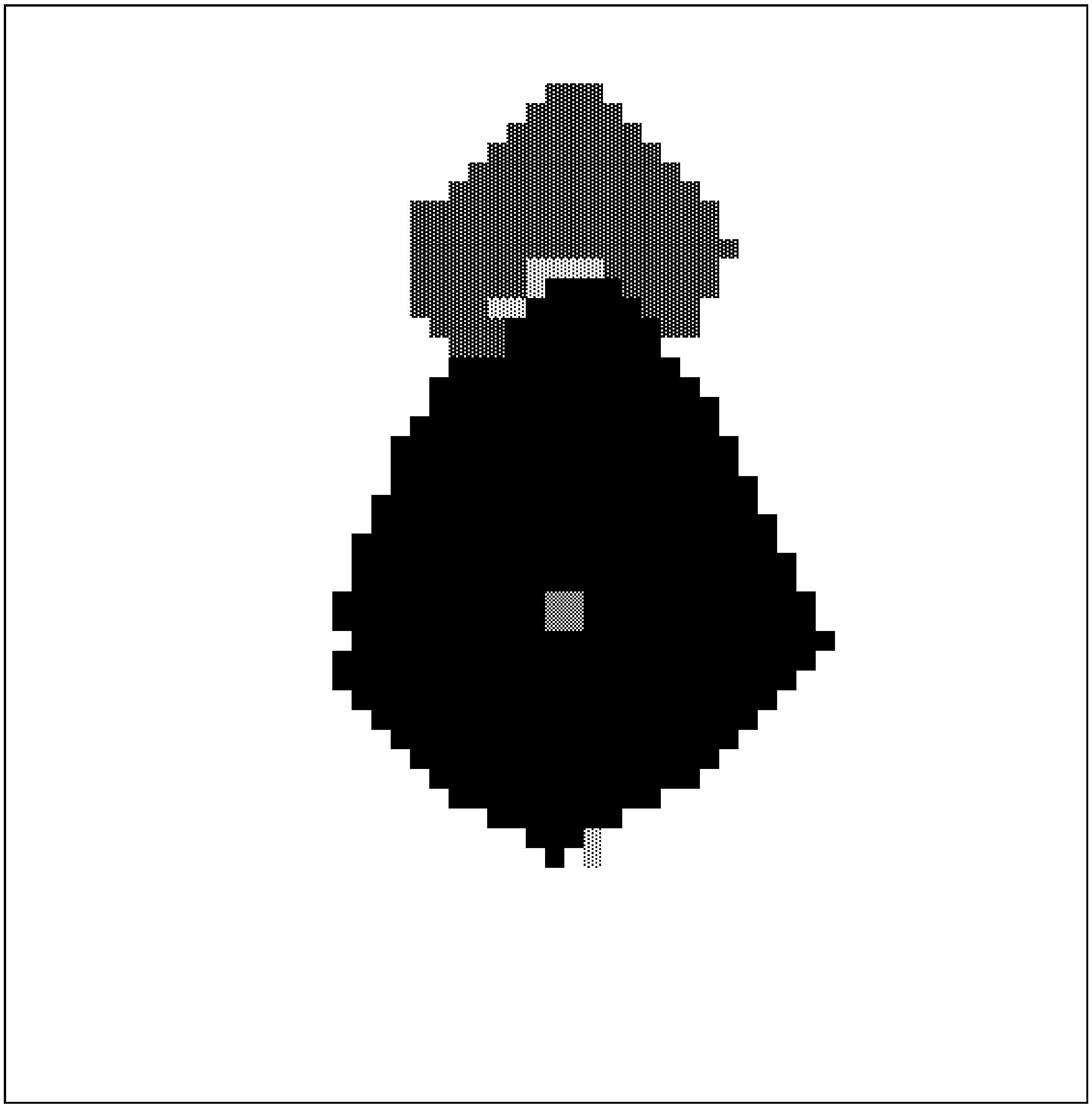


FIG. 18 THREE-OPERON SNOWMAN RESULTS

FIG. 18 was thought to be reasonably successful. The resulting figure does look a bit like a snowman, with a body and a head. The overall shape is also nonconvex. Encouraged by this result, an attempt was made to see whether a three-operon chromosome could generate a better turtle shape, using the same turtle target shape as in FIG. 11. The results are shown in FIG. 19. This time, results were a lot better than in FIGs. 13 and 14, but still not recognizably turtle-like. Admittedly, a head formed and so too, an upper left foot. Two feet on the right side also formed, but were too low. The bottom left foot seems more like a tail. Ironically, if one looks at the shape from the south east, it does look rather like a turtle. The X, Y and Z values for FIG. 19 were 27, 11 and 13 respectively. The NEWS DIRNS Y and NEWS DIRNS Z were [11010100] and [00101010]. The number of generations used for the evolution of FIG. 19 was 180.

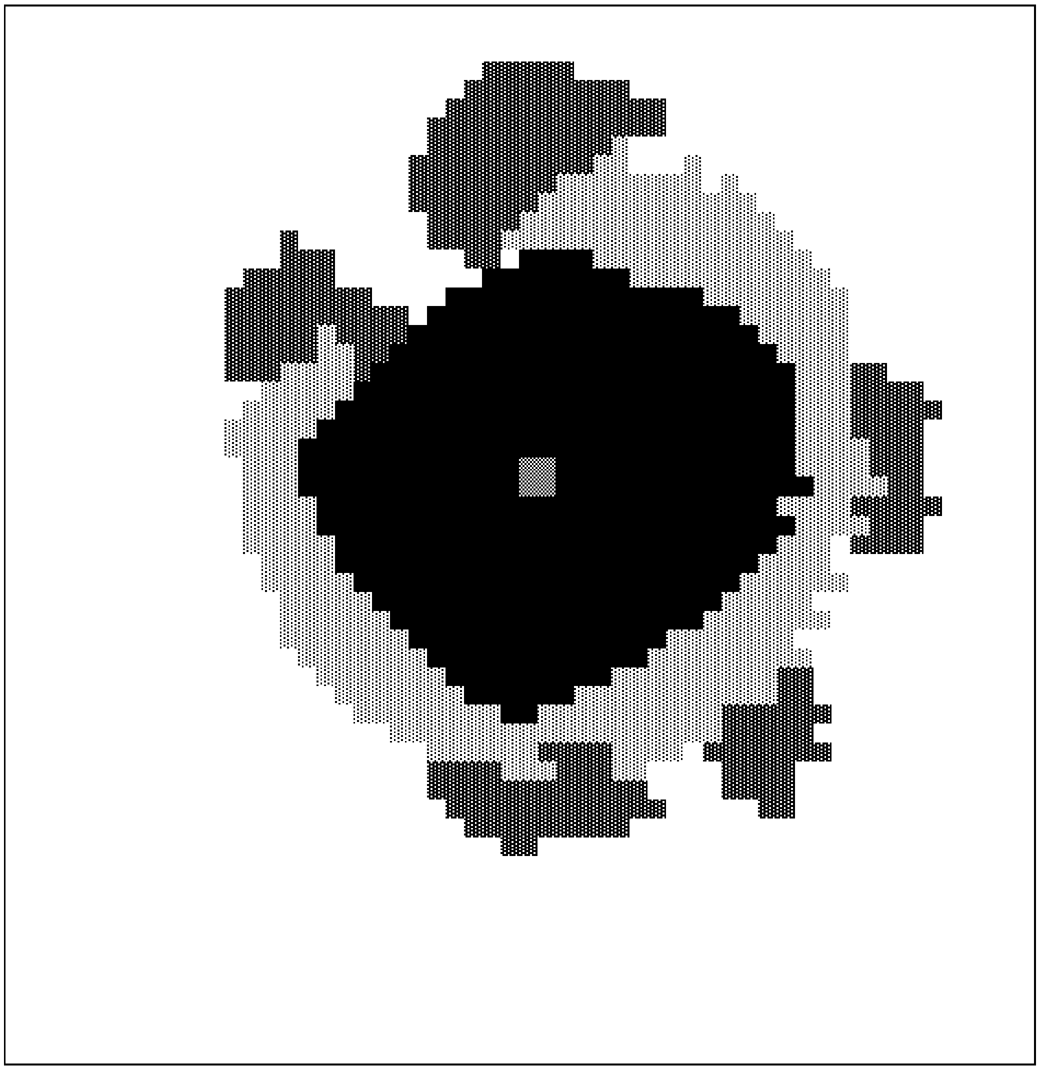


FIG. 19 THREE-OPERON TURTLE RESULTS

The more complex shape obtained in FIG. 19 with a third operon, motivated an experiment with a greater number of operons. FIG. 20 shows the results obtained with a 5 operon chromosome using the same turtle target shape. The 5 operon system is a simple extension of the 3 operon system explained above. The The X, Y and Z (and S, and T) values for FIG. 20 were 13, 15, 10, 6 and 12 respectively. The NEWS DIRNS Y (NEWS DIRNS 1), NEWS DIRNS Z (NEWS DIRNS 2), NEWS DIRNS 3, and NEWS DIRNS 4 were [01011110], [10000001], [10101110] and [01100011]. The number of generations used for the evolution of FIG. 20 was 60. Operon 1 cells are shown in black; operon 2 cells in light grey; operon 3 cells in dark grey; operon 4 cells in black; operon 5 cells in light grey. Unfortunately, the light grey cells of operons 2 and 5 have merged, so are difficult to distinguish. The light grey cells forming a C shape around the inner black cells are the operon 2 cells. FIG. 20 shows that the head and left limbs evolved moderately well. They are at least recognizable as a head and limbs. The right hand side however did not evolve limbs. With longer evolution times on a more powerful computer, better results would probably be obtainable.

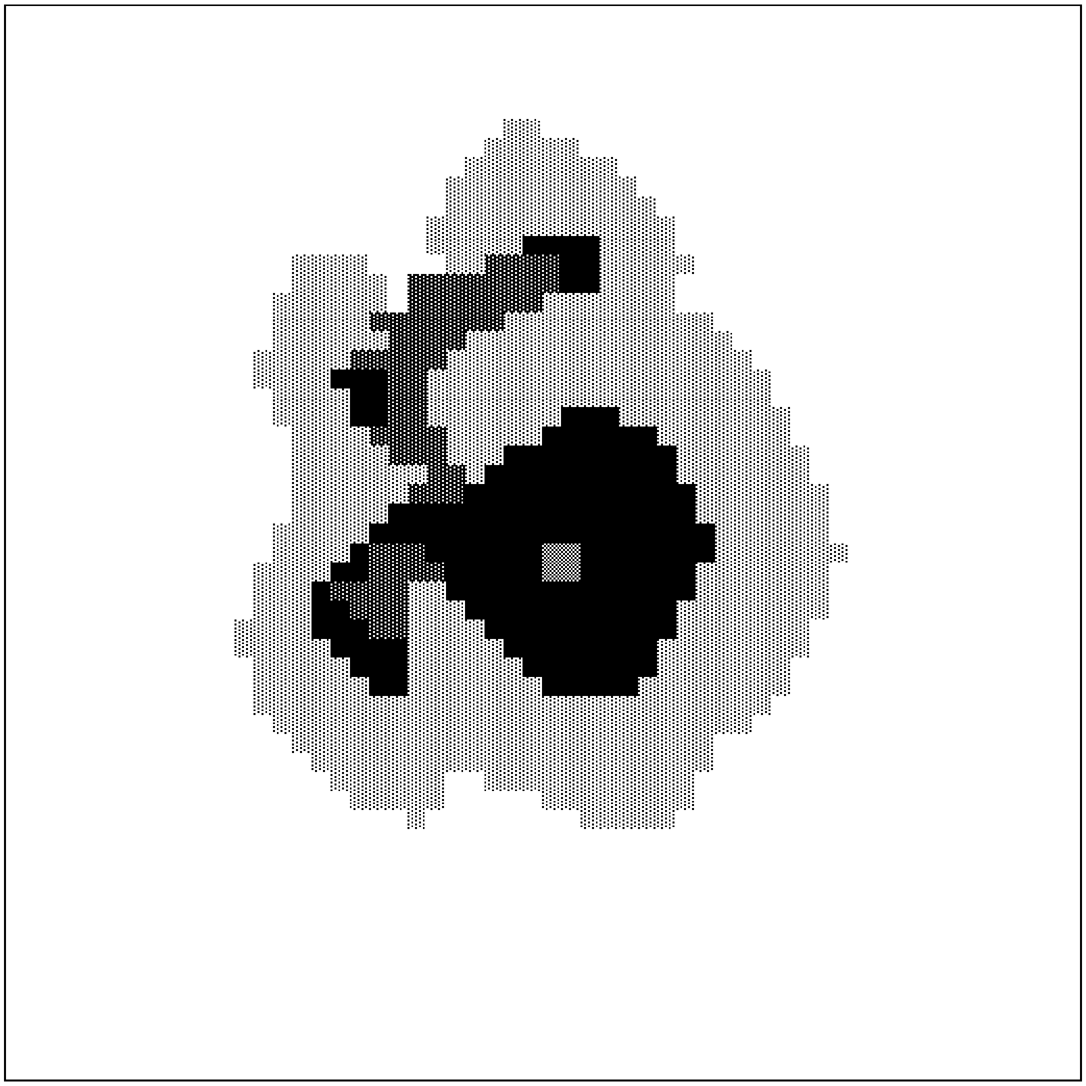


FIG. 20  FIVE-OPERON TURTLE RESULTS

## Conclusions :

The above results show that it is possible to apply genetic algorithms to the growth of reproducible cellular automata to produce desired final shapes, although admittedly, the turtle results could do with a lot more work to "get them into shape" (pun intended). The above work also shows that time sequential, switch able "genes" or instruction subsets can be used in an "embryological" way. The author would love to pursue these studies further but unfortunately for the past 5 years, he has been totally preoccupied in trying to build artificial brains using evolvable electronic neural network modules, rather than evolvable shapes (de Garis, 1998). Perhaps one day it might be possible to combine both interests in creating directly in electronics at electronic speeds, a form of neuro-embryology, with cellular automata equivalents of time switchable and multivaried NGFs (neural growth factors) concentration gradients that neurites (baby neurons) follow in their wiring up phase. I believe that for the moment, such dreams are beyond state-of-the-art electronics. But it would be nice. Perhaps in a future life. At he time of writing (March 1998), the author knows of no real applications of the above techniques, but still dreams that someone will use similar ideas to grow artificial brains in "embryo-electronics".

Further down the road, molecular scale technologies will be capable of building devices with a huge number of components (Drexler, 1992). It will be totally impractical to build these devices one component at a time. They will probably have to self-assemble in an embryological like way. However, due to the large number of components and the complexity of their connections, the global behavior of the device will be too complex to be predictable, i.e. one will not be able to map its structure to its performance. Under such circumstances, the only way to proceed, may be to use a EE approach, i.e. to imitate nature's method of building complex devices (creatures). However, very little is known about how to self-assemble devices artificially in an embryological-like manner. This chapter has made some initial attempts at providing some solutions to this problem, and has contributed towards the creation of an "artificial embryology".

It is hoped that the challenge to "grow" artificial embryos will appeal to other ALife researchers, so that some real progress can be made in this field in the next few years. If so, it is possible that ALife's "algorithmic, engineering" approach to embryology may even generate clues as to how nature performs its morphogenesis, and hence be of interest to the biologists. However, such interest need not be confined to the biologists. Electronic and molecular engineers may also be interested. The author intends getting into a field he calls "Embryonics", i.e. "Embryological Electronics", which will attempt to "grow" electronic circuits, using EE techniques. Hopefully this approach will allow extremely complex yet functional electronic (neural) circuits to be built/evolved, using special hardware devices called "Darwin Machines". Darwin Machines may accelerate the evolution of artificial nervous systems for artificial creatures or biots (biological robots).

Once it is possible to evolve arbitrary shapes successfully, the next step might be to add extra operons which switch internal cells to give them the ability to move, or act as muscles etc, so that the colony of cells can perform some useful function. Later, it might be possible to evolve systems which act as tools to help build other systems. It might even be possible to evolve systems which build copies of themselves, which later work together to build some larger system. These ideas might be implemented on "Cellular Automata Darwin Machines" (CADMs). At a later date, when nanoscale technologies come on line, it might be possible to carry over these ideas to molecular scale devices.

## A Note on the Term "Evolutionary Engineering"

Until a few years ago, I used to use the term "Genetic Programming", instead of my current term of "Evolutionary Engineering", to describe what I do. This created so much confusion with John Koza's use of the term with a different definition, that I abandoned my use of it. Hence do not be confused to find the term Genetic mming in many of my papers in the references. Simply substitute the term Evolutionary Engineering in your mind and dont be confused with Koza's definition (i.e. evolving tree structured software programs to solve problems).

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