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Published in:
17th International Conference on Manufacturing Research 10/09/2019 → 12/09/2019 Belfast, United Kingdom

Document Version:
Peer reviewed version

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Bio-Inspired Growth: Introducing Emergence into Computational Design

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Abstract In today’s age of neural networks and brain study, creativity is being introduced into lifeless systems by modelling the concept of learning. Many believe the artificial intelligence that is leading technology will eventually do most of a designer’s work. However, this artificial intelligence only results after long hours of training and is limited to the area within which it is trained. In nature, many systems can produce unpredictable solutions without the retention of information - such as trees. Although computers cannot accurately model nature’s growth mechanisms, it can be approximated with the concept of predictive non-determinism – where what is not understood is treated as random - and the rest of the system built around this. This paper lays out a four-tiered structure, inspired by growth principles seen in nature, for introducing emergence into the design system. The models presented are grown by random functions, controlled by a restriction of misfit and guided by the concept of fitness. It gives a bottom up approach to the design, with the user providing the desired functionality and asking what the possible designs are. The resulting models grown by these stochastic rules are emergent, providing the computer with the chance of creating unexpected and innovative solutions.

Keywords. Bio-inspired design system, growth rules, computer aided design, emergence, innovation, predictive non-determinism

1. Introduction

Artificial Intelligence (AI), the simulation of human intelligence processes by machines, is consistently improving. The desire is to create automatic systems which have the ability to make decisions without human supervision. AI experts seek to model the functionality of a human brain by utilizing complex learning systems, known as neural networks. In 2017, AI overtook human performance for object detection [1]. Google DeepMind’s acclaimed project AlphaGo, was able to compete and defeat a human expert at Go, a game with more possible combinations than atoms in universe. To develop such a system it was fed thirty million human moves and then left to play against older versions of itself thousands of times, each time learning more [2]. With this new intelligence comes the need for learning, as with humans.

What separates man and machine is the human ability to ‘think outside the box’. Creativity can be defined as having two primary components, originality and functionality. The mathematical potential of any computer is awe-inspiring and their

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functionality cannot be refuted. AI has also shown signs of originality, coming up with ideas that humans weren’t previously aware of [3]. However, large-scale neural networks that produce such results are limited to the areas within which they are trained.

Decision-making can also occur within non-neuronal organisms, systems which lack any semblance of a neural network, and therefore the ability to learn [4]. One well-studied example is Physarum Polycephulum, which is seen as a simple system, incapable of learning, yet capable of creating a complex system. This ‘slime mold’ can be modelled simply [5] yet was used to accurately model the Tokyo Rail Network [6].

Trees are also able to grow without the need for previous learning. However, modelling a dynamic growth system becomes complex quickly. The cause and effect of each motion cannot be fully understood and so, many unique traits are missed. Computer models created to mimic such growth behave logically, and the emergent and diverse shapes seen in nature are not forthcoming. Originality cannot be found in such logical and unlearned systems as any input will produce the same results every time.

Genetic algorithms designed to model dynamic growth systems, rely on a fitness function. Here the analysis is monitored by giving each iteration, or simulation, a score (fitness) and choosing the best value depending on the analysis [7]. Most research focuses on optimising the solution, creating a top-down system that will find what it deems the ‘best’ solution, bringing with it some limitations. The final solution is constrained by the designer’s initial inputs and so influenced by human presupposition and, if the simulation is carried out again, an identical solution is produced, as there is only one supposed ‘best’ solution for a given set of inputs.

The principle of predictive non-determinism is a solution for when a cause within a system cannot be understood or modelled, and an answer for introducing unpredictability and multiple solutions within the design process. It states that all effects must have a cause, but what cannot be understood, may be treated as random [8]. The flipping of a coin is treated as a random occurrence and yet in reality its result is caused by many attributes such as force, time, etc. This principle is used widely within computing, as a stochastic process, where an ongoing process depends upon the previous event plus some random element.

This work is part of a wider project investigating approaches to growing designs in a manner analogous to biological development. These approaches, inspired by natural growth systems such as observed in trees, require a range of growth strategies and systems to generate designs. This paper proposes to set out a guided growth system which uses the principle of predictive non-determinism to introduce emergence into design process. Section 2 will outline the four tiers of the growth system and how they will instigate and influence growth. Section 3 will showcase a sample setup of this system with four example cases simulated, and the results presented. The final sections will then discuss and conclude on the findings of this work, and lay out any future work.

2. Four-tiered Growth System

The proposed growth system operates within a four tier structure, separating each level.
Each stage of the growth being distinct from the others, they can be controlled independently allowing the introduction of unpredictability into the system while still producing useful results. The tiers are labelled as; geneset, restriction, growth and guidance [Figure 1]. Figure 2 shows the proposed system’s flow.

2.1. Geneset

The geneset is a definition of the individual components of growth. Like every organism has its own unique DNA, every system will have its individual characteristics. What is included within the geneset is a description of the entities that can be grown. Entities are the building blocks of the model and are defined by shape, material properties and relevant characteristics. This geneset will then be placed within the system at a starting position, called the seed point, and growth will commence from there. Starting from nothing and growing to a final model allows the computer complete control of the design without human interference, an example of bottom-up design. The detailed description of an example geneset can be found in an accompanying paper [9].

2.2. Restriction

Instead of a positive process for achieving best fit, i.e. iterating until a single best solution is found, the process of achieving fitness could instead be thought of as the negative process of neutralising any misfits within a system [10]. A similar solution can be found in nature’s division of cells, mitosis. Before a new cell is created, the original cell undergoes a ‘restriction’, where it checks to see if growth is needed [11]. This ensures that unnecessary growth doesn’t occur, and the model simply meets all the requirements rather than exceeding them to a ‘best’ solution.

This restriction, or neutralising of misfits, can be implemented by creating a binary list, where misfit is represented as a ‘1’ and fit as a ‘0’. Within the system, growth only occurs if there is misfit (‘1’) and a model is deemed fit, or suitable for its required purpose, when all misfits are neutralized (‘0’). This system offers the option of a range of possible solutions rather than aiming for a single ‘best’ solution. The condition for fit or misfit is based upon the required constraints and goals of the designer.

2.3. Growth

Growth is a definition of the directions that the geneset will grow in. Internal rules will give the basis of direction and movement within the growth. This is where randomness may be incorporated into the system at a base level. Complex natural systems make small, and sometimes unnoticeable, movements with which it is hard to model a cause for. This system will therefore base any low level movements on random choices.
In order to guide the system and give it a choice of options, multiple growths will occur from the same current growth position. The amount and length of growths will dictate how random the solution may be, offering some control over the output.

2.4. Guidance

D’Arcy Thompson points out that all structures have to grow, or be built, however the living thing can be seen as “complete during every phase of its existence” [12]. This leads to a reactive system, which chooses the best option at the current step, without any thought of the end goal – much like a greedy algorithm [13].

This greediness will be directed using external influences. Stimuli will be introduced to the design environment which will interact with the system’s growth. These will be a reflection of the goals of the system. If the system must meet a certain target location then the closest point will be chosen or if a load must be supported then the growth which supports the greatest load will be chosen.

The fitness will make a choice from multiple growths, and it becomes the new growth position. This varies from regular optimisation systems as choices are made locally, without knowing the end goal, and so produces a reactive system that only cares for it’s current phase of existence.

3. Example Cases

In order to showcase the emergent nature of this growth system, four test scenarios were chosen. They each involved bridging a gap between specified target points. For each of these, the seed was placed at (0, 0) in 2D space.

Only one discipline, geometry, was considered. This meant the results were easier visualized and monitored by the human user, making post-analysis more beneficial. For this particular growth the geneset was a single line in any direction with a unit length. Growth was chosen to be ten steps long with a random direction for each step. Fifty growths were evaluated at each phase. The goal set for restriction was to reach the target points, and guidance was based upon a proximetric fitness function [Equation 1].

\[
F = (T_x - G_x)^2 + (T_y - G_y)^2
\]  

where \(F\) is fitness, \(T\) is target point, \(G\) is growth position and \(x\) and \(y\) are the point’s respective \(x\) and \(y\) co-ordinates.

Table 1 shows the chosen targets for each test. Target points are represented as Cartesian coordinates – (wall co-ordinate, target co-ordinate), i.e. case A, left wall target would be (-100, 0). For each target within a case, a new growth was added to grow towards each target, i.e. Case D had 3 targets and so had 3 growths.

**Table 1.** Target points for each case simulated

<table>
<thead>
<tr>
<th>Case</th>
<th>Left Wall (-100)</th>
<th>Right Wall (100)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Target Points</td>
<td>Target Points</td>
</tr>
<tr>
<td>A</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>B</td>
<td>0</td>
<td>66, -66</td>
</tr>
<tr>
<td>C</td>
<td>40, -90</td>
<td>30</td>
</tr>
<tr>
<td>D</td>
<td>90, 30, -50, -70</td>
<td>40, -60</td>
</tr>
</tbody>
</table>

Figure 3 shows an example set-up.
Figure 4 shows the 2D models from the example cases. Each case was seen to meet its objectives, i.e. reach the target points. The results show that the best, straight-line shape for each problem was approximated, yet the exact final solution is unpredictable. When the simulation is run for a second time, with identical inputs, the resulting model differs when compared to the initial, showing multiple solutions for the same inputs.

Figure 4 – Final models produced by growth system. The red point represents the seed position, purple growths the first simulation run and green growths the second simulation run.

4. Discussion

The ability to grow a model stochastically will allow for unpredictable shapes to emerge from a system. Current methods of engineering design rely mainly on human knowledge and/or presupposition, and without iteration or learning within a system, the results are logically and predictably arrived at. Random growth, with the correct guidance, allows multiple creative (original and functional) solutions to the same problem, without the time needed for that system to learn or iterate over the solution.

What has been proposed here is a system with a reactive growth mechanism, a greedy growth algorithm making decisions based upon its current shape or form, without influence from end goals. The system is effectively blind to the overall objective, meaning it does not optimize towards a single point of ‘best fit’ but rather has room to choose from a range of solutions. The element of randomness included gives the system an air of unpredictability, leaving room for emergent behavior.
This work has focused on constructing geometric shapes for simplicity, but further work will include the introduction of more than one discipline, i.e. structural, thermal, manufacturing constraints. These may be reflected in the external influences or internal rules which guide the growth. Growth rules need to be explored to better influence how the model grows. Currently the model grows randomly and this may remain the same at a base level to ensure emergence. Yet internal rules could include extra logic such as growing perpendicular to a force or parallel to a temperature gradient. With the introduction of greater complexity to the growth process, more complex, and unpredictable, models will emerge.

Future work will be done in conjunction with accompanying papers, using a complex version of a geneset [9] and streamlining the entire process through a smart cloud manufacturing service [14]. This new geneset will allow the system to introduce more complex entities and the cloud framework will add the functionality of keeping the entire growth process alive until completion.

5. Conclusion

This is a bottom-up design system which starts from nothing and allows internal rules and external stimuli to influence the growth. The four-tier structure allows random functions within a single component of the system, introducing unpredictability while still guiding the growth towards an output model which meets the design requirements. This means we can successfully introduce emergence into computational design.

Acknowledgements

This work is funded by the Engineering and Physical Sciences Research Council (EPSRC) in association with the QUB Biohaviour Programme also funded by EPSRC, grant No. EP/R003564/1 through the Design the Future 2 Programme. We would like to thank EPSRC and our sponsoring companies, Glen Dimplex, ITI, Deloitte and Airbus, for their support and advice in progressing this work.

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