

The Problem with Evolutionary Art Is ...

Philip Galanter

Department of Visualization, Texas A&M University, College Station, Texas, USA
galanter@viz.tamu.edu

Abstract. Computational evolutionary art has been an active practice for at least 20 years. Given the remarkable advances in that time in other realms of computing, including other forms of evolutionary computing, for many a vague feeling of disappointment surrounds evolutionary art. Aesthetic improvement in evolutionary art has been slow, and typically achieved in ways that are not widely generalizable or extensible. So what is the problem with evolutionary art? And, frankly, why isn't it better? In this paper I respond to these questions from my point of view as a practicing artist applying both a technical and art theoretical understanding of evolutionary art. First the lack of robust fitness functions is considered with particular attention to the problem of computational aesthetic evaluation. Next the issue of genetic representation is discussed in the context of complexity and emergence. And finally, and perhaps most importantly, the need for art theory around evolutionary and generative art is discussed, and a theory that stands typical evolutionary art on its head is proposed.

1 Introduction

In this paper I will discuss several problems around evolutionary art (EA). Since EA has been an active practice for at least 20 years [1], some of this will be review. It is my hope that I can offer some new light on these matters as a practicing artist developing an art-theoretical understanding of evolutionary art.

First the lack of robust automatic aesthetic fitness functions for EA is reviewed, and possible new venues for research are presented. Next genetic representation in EA systems is reviewed. The focus is not so much how genes are used as a medium for evolution, but instead how current gene representation and expression limits emergence and innovation. And finally art theory for EA is considered, and a specific theory rooted in what I've called "truth to process" is offered.

2 The Problem of Fitness Functions for Evolutionary Art

Genetic algorithms and other evolutionary computing techniques are methods to search large multidimensional solution spaces for optimal results. Applications include automotive and aeronautic design, electronic circuit design, routing optimization, modeling markets for investment, and more.

What each of these applications has in common is that an a priori fitness function can be defined, and individuals can be automatically scored as to fitness. [2] In the case of an investment model the score might simply be an amount representing

estimated profit. For circuit design a weighted formula might be used to combine scores for functionality, cost and number of components, power efficiency, and so on. Fully automated evolutionary systems can run with very large populations for hundreds or thousands of generations. Evolutionary art systems are at a significant disadvantage because it is not at all clear how aesthetic judgment can be automated for use as a fitness function. The alternatives for dealing with this problem follow.

2.1 Interactive Evolutionary Computing

One alternative to an automated fitness function for EA is to use aesthetic judgments made by people. From the first historical examples [1] to present interactive evolutionary computing (IEC) dominates the evolutionary art field. In a recent wide-ranging overview of evolutionary visual art Lewis has cataloged a large number of projects with nearly 200 citations. [3] The vast majority of the systems noted are interactive using some form of case-by-case human judgment.

The most obvious problem with having an artist or other judge “in the loop” is that it becomes the rate-limiting step of the iterative process. This is sometimes called “the fitness bottleneck.” [4] EA systems can produce new populations orders of magnitude faster than a human can score them. The practical result is that IEC systems typically suffer from relatively small populations and few generations.

Human judgment is also limited by fatigue. Over time user choices will become less consistent, and skew towards novelty for its own sake rather than quality. [5, 6]

One strategy to finesse the fitness bottleneck and fatigue problems is to “crowd-source” the evaluation task. In Sims’s Galapagos piece the length of time a visitor spends looking at a particular display is used as a fitness function. In Drave’s Electric Sheep system the generated art is displayed on thousands of personal computers as a screen saver and the users of those systems can provide feedback as to their preferences. [7] But as satirically demonstrated by artists Komar and Melamid, making aesthetic choices by polling the public does not produce the unique kind of vision expected from artists. The resulting art trends towards a mediocre mean. [8]

2.2 Computational Aesthetic Evaluation

The Mechanical Turk was a device created in the 18th century that appeared to be a machine that could play chess. [9] The Mechanical Turk was, of course, more a feat of stage magic than computation. Despite the fact that it appeared otherwise, a human operator was hidden inside the cabinet. And it was this operator who made all the playing decisions and won or lost the game.

From a certain point of view using IEC to create art is a similar trick. Perhaps the most important and difficult component in traditional art creation is the exercise of aesthetic judgment while the artifact is being made.¹ And hidden in the IEC system is a human operator playing the game and making those critical decisions.

Autonomous EC systems capable of producing art would be much more satisfying. And using computational aesthetic evaluation (CAE) to provide automated fitness

¹ Art in the 20th century took a decidedly conceptual turn. Since then aesthetics as the pursuit of physical beauty is often not the first priority in art making.

scores would allow populations and generations akin to other applications, presumably resulting in better evolutionary art.

However, CAE is a distinctly non-trivial unsolved problem. Not that there haven't been partial attempts. For example, Sanders and Gero [10] and Greenfield [11] have researched agent-based evaluation systems. Jaskowski et al [12], Fornari et al [13], and Ciesielski et al [14] have reported on systems with automated scoring based on some form of error measurement with reference to an exemplar.

McDermott et al [15] used a combination of perceptual measures, spectral analysis, and low-level sample-by-sample comparison to develop synthesizer voices relative to exemplar sound targets. Khalifa and Foster [16] devised a two stage music composition system that analyzes note intervals and ratios for use in a fitness function.

Various numeric measures as aesthetic indicators have been explored such as Zipf's law (Manaris et al [17]), fractal dimension (Mori et al [18] and Taylor [19]), and various complexity measures (Birkhoff [20], Machado and Cardoso [21]).

Attempts to use connectionist models such as neural networks in computational aesthetic evaluation include Machado et al [22], Phon-Amnuaisuk et al [23], and Gedeon [24].

2.3 Hybrid Aesthetic Evaluation

Some researchers trying to deal with the fatigue problems associated with IEC have attempted to create hybrid aesthetic evaluation methods. In such systems a subset of the population is scored by human evaluation, and then those scores are somehow leveraged across the entire population. Takagi offers a broad overview of over 250 cited attempts to fuse EC and IEC systems in creating art systems as well as other application areas. [5] More recent reports on hybrid aesthetic evaluation include Yuan and Gong [6], Machado et al [25], and Machwe and Parmee [26].

2.4 The Future of Aesthetic Evaluation for Evolutionary Art

The bad news is that one needn't get very far into the above literature to see that the fitness bottleneck restricting evolutionary art has not yet been conquered. IEC still well outperforms EC in terms of artistic results. And those EC and hybrid systems that have had limited success use methods that are generally idiosyncratic and quite specific to a given medium, style, and artistic goal.

This shouldn't be terribly surprising because we don't know much about how human aesthetic evaluation works either. And worse, CAE tends to ignore the culturally determined aspects that fluctuate in time both over the short and long term.

But there is some hope on the horizon. Journals such as *Psychology of Aesthetics, Creativity, and the Arts*, *Empirical Studies of the Arts*, and the *Journal of Consciousness Studies* should be of interest to those researching computational aesthetic evaluation. Experimental psychology is assembling, one detailed study at a time, a scientific picture of how human aesthetics works.

Joining these recent but more traditional efforts is the nascent field of neuroaesthetics. Neuroaesthetics involves the scientific study of the neurological bases for the creation, experience, and contemplation of works of art. A good place to start might be the chapter by Martindale where he has outlined a basic neural network model, and

then cites 25 empirical studies of specific and varied types of aesthetic experience compatible with, and suggestive of, this model. [27] It's important to note that Martindale has not implemented a computational neural network to exploit his model, but this kind of research may well give others an incentive for doing so.

And indeed this new science, and especially analysis at the level of neurology, is beginning to impact the way those in computer science think about connectionist computing. For example Hawkins has introduced a new design he calls "hierarchical temporal memory" (HTM) which is based on a theory of the neocortex. [28]

Finally, some in evolutionary psychology have speculated that our general aesthetic capabilities have been mostly driven by adaptations for mate selection. And animals with far simpler neurological systems than ours also seem to select mates based on a form of aesthetics. In some animals this capability is generalized. [29] With further advances in psychology, neuroaesthetics, and connectionist computing, CAE may not be as far away as it sometimes seems.

3 The Problem of Genetic Representation and Innovation

Many observers have noted that EA systems tend to produce works that have a certain cast or sameness about them. Some pieces will be better than others, and of course the evolutionary process can capture and reapply incremental improvements. But there seems to be an inevitable plateau beyond which the work does not improve, and most importantly, does not exhibit innovation.

In modern western culture the most highly valued artists are those who exhibit innovation. This rarely happens in a single giant leap of course. For example, if you study the paintings of Jackson Pollock in historical sequence you will first note mid-dling cubist-inspired figurative work. Over time the figuration becomes more and more abstract. And finally the figures disappear entirely in the explosion of lines, drips, and splashes Pollock is so well known for. [30]

While one can somewhat imagine an EA system designed for figurative work "loosened up" to create abstract work, consider the counter example of Philip Guston. He famously, and very quickly, went from well-known abstract expressionist work to (deceptively) simple cartoon-like figurative work. [31] It's hard to imagine a current evolutionary system designed for abstraction suddenly producing the human form. The problems of sameness and lack of innovation are real and worth close study.

3.1 Complexification in Nature and Genetic Representation

Evolutionary computation may be inspired by natural evolution, but it is far less complex than the real thing. Perhaps artificial evolutionary systems lack the kind of innovation found in natural evolution due to this lack of complexity. The notion of complexity here is different than both complexity in information theory [32] and the notion of algorithmic complexity. [33-35] Those in complexity science tend to embrace notions similar to what Murray Gell-Mann has called "effective complexity." [37] In this view simple systems are either highly ordered or highly disordered, and complex systems exhibit a dynamic tension between order and disorder. This tension allows complex systems to exhibit emergence across multiple scales. (See figure 1).

To measure effective complexity, at least in principle, Gell-Mann proposes to split a given system into two algorithmic terms. The first algorithm captures structure and the second algorithm captures random deviation or noise. Effective complexity is proportional to the size of the optimally compressed program for the first algorithm that captures structure. Gell-Mann points out that this process is exactly what a complex adaptive system, such as an animal, does as it learns (models) its environment. Aspects that are random, or noise, are forgotten and aspects that exhibit structure are compressed (abstracted and generalized). Structural aspects that resist compression are experienced as being complex.

When a system moves from simplicity to complexity this is sometimes called complexification. [36] In nature gene related complexification happens in at least two ways. Complexification over a long time scale begins with simple single celled organisms, and evolves complex creatures such as humans. But complexification can also refer to developmental biology; the cascade of construction as DNA assembles proteins, proteins form organelles and then cells, cells organize into tissues and organs, and so on. Genes thus have two roles, both as machines that allow long-term evolution and as machines that initiate short-term construction exhibiting multiple levels of emergence and increasing scale.

The suggestion offered here is that EC with a single level of emergence from genotype to phenotype is not capable of the complexification that art requires.² Most evolutionary artists concentrate on the first function of genes (evolution) and do very little with the second (construction through multiple levels of emergence). Without sufficient complexification capacity EA systems cannot exhibit innovation in the sense seen in Pollock and Guston. They remain trapped in a phase space of overly similar aesthetics.

In the design of any evolutionary system the genetic representation has meta-significance in that it may constrain the space of not only all possible evolutionary paths, but also all possible developmental paths. Four types of genetic representation follow in complexification capacity order.

The simplest genetic representation is *fixed parametric* representation. Imagine a system for creating drawings of insects. There might be a gene for head size, another for body color, another for leg length, and so on. While such a system may draw a wide variety of insects it will never draw a spider because unless there is a “number of legs” gene all results will have six legs. The complexification capacity of this system is highly constrained.

Slightly more complicated is an *extensible parametric* representation. Such a system might have one gene per leg, and thus the ability to draw insects, spiders, and even centipedes and millipedes. But it will not be capable of drawing fish or birds because it lacks fin and wing genes. The complexification capacity of this system is still fairly constrained.

More complicated yet is a *direct mechanical* representation. In our example this genetic system doesn’t describe the end result, but rather describes machines that can draw. Such a representation will, in theory, allow most anything to be drawn. In addition, during reproduction the genes themselves may mutate making the child different

² The developmental aspect of gene expression has been an object of previous discussion. See for example Bentley and Corne’s discussion of embryogeny [37].

than the parent. For example, a machine that creates thin pencil lines may mutate into a machine that makes brushed ink marks. Such a system may seem to be of unlimited potential, i.e. unlimited complexification capacity. But such a system is only capable of a single layer of emergence. The machines immediately and directly draw the picture, and that is that.

The final genetic representation is a *reproductive mechanical* representation. Such a system is similar to the previous one, with the addition that within a single individual a machine may also create another machine, reproduce itself, or contribute to an emergent machine at a higher level of complexity and scale. This is, in fact, the kind of genetic representation found in nature. There is an upwardly layered increase of complexity as DNA creates proteins, proteins organize to create organelles, organelles organize to create cells, cells organize to create organs, and so on.

Reproductive mechanical genetic representation maximizes complexification capacity because it can initiate multiple layers of emergence across multiple scales. EA has focused on evolution while mostly ignoring this second aspect of genes. Reproductive mechanical genes may help solve the sameness and innovation problem.

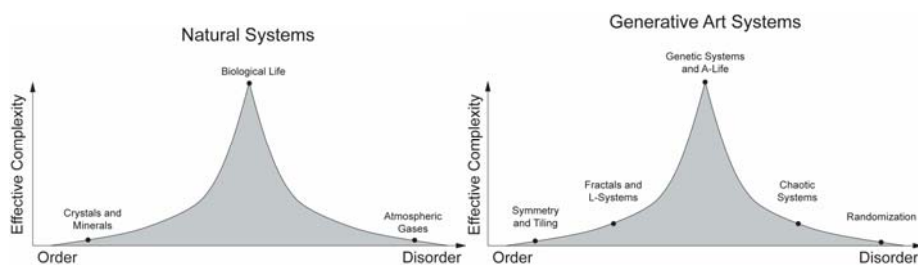


Fig. 1. On the left, effective Complexity in Natural Systems. On the right, effective Complexity in Generative Art Systems.

4 The Problem of Art Theory for Evolutionary Art

Art is more than a series of sensory experiences³. It is also a stream of ideas that bind art production, art criticism, and art meaning to the larger culture. A natural place to start is with the question “what is art?” Most agree that to define art is to propose a theory of art. [38] And as a corollary, art without theory loses its definition, its identity, and its meaning. As a practical matter evolutionary art theory will be required before EA will be able to gain entry to the wider art world and inclusion in the general cannon of art.

As part of a broad future-oriented overview McCormack recently offered a number of grand challenges with regard to evolutionary art. [39] The last and least discussed of his grand challenges is the development of art theory for evolutionary and generative art. McCormack *does* refer to a new sense of aesthetics related to artificial life and evolutionary art as reflected in theorist Mitchell Whitelaw’s notion of

³ Please note that at this point that we are shifting gears from primarily scientific or technical considerations to a discussion of art theory. And art theory has its own traditions, rules of evidence, and notions of acceptable rhetoric.

metacreation. [40] Metacreation refers to the role of the artist shifting from the creation of artifacts to the creation of processes that in turn create artifacts. But, in fact, what Whitelaw has called metacreation is not new, nor is it intrinsically digital.

In previous writings I've noted that the common element of all generative art is the ceding of control by the artist to an autonomous system. [41] With the inclusion of systems such as symmetry, pattern, and tiling one can view generative art (or Whitelaw's metacreation) as being as old as art itself. This view of generative art also includes 20th century chance procedures as used by Cage, Burroughs, Ellsworth, Duchamp, and others. What is new today isn't generative art per se, but rather the use of complex systems such as artificial life or evolution rather than the previously used simple systems.

Given that this generative art theory turns on the use of systems by the artist it should not be surprising that Gell-Mann's notion of effective complexity in systems can be used to classify various kinds of generative art. When generative art systems are viewed in this way it suggests a robust theory of generative art. (See figure 1).

This view of generative art casts a very wide net that is independent of any particular past or future technology. It correctly identifies the use of systems, rather than computers, as being the defining aspect of generative art. And by including artists and generative work already well accepted in the art world other forms of generative art are pulled into to the standard art canon. Generative subgenres such as evolutionary art should no longer be left isolated as awkward art world orphans.

While further discussion is beyond the scope of this paper, it's worth noting that in other writing I've used this framework to provide a bridge to a more general critique of the modern/postmodern dialectic I've called "complexism." [42, 43] From that view evolutionary art not only rehabilitates formalism as being significant and meaningful, it also reintroduces dynamism and the aesthetics of process and motion.

4.1 Evolutionary Art Theory and Truth to Process

At various points in art history the notion of "truth to materials" has ascended. In modern architecture this meant that concrete was presented as concrete, and steel beams were presented as steel beams. Clement Greenberg took a similar tack in his critique of abstract expressionism. [44] This involved the rejection of illusory space and representation where the canvas acts as a simulated window. Instead the canvas was simply considered as a flat surface supporting non-representational paint. The underlying idea is that aesthetic power comes from the honest presentation of the essential nature of the medium being used in its purest form.

Given the relative lack of art theory for evolutionary art this essentialist approach may be a good first approximation. So what is the one thing that all evolutionary art shares, and without which it would cease to be evolutionary art? In this case what is essential is not a material property at all, but rather the evolutionary process itself. And so by extension evolutionary art aesthetics should focus on the process rather than the material results. And so what can be said about this process?

It's already been noted that evolution in nature depends on multiple layers of emergence at ever increasing scales. *Evolution is by nature a bottom up process.*

And although the factual details are sketchy, the levels of emergence that created DNA, then proteins, then organelles and cells, happened long before a trace of more

complex multicellular organisms appeared. DNA did not form so that someday man could appear. Rather DNA likely emerged from existing autocatalytic complexes and then sustained itself through reproduction. *Evolution is not teleological.* [45]

In addition evolution does not produce complex creatures by a direct mapping of genotype to phenotype. *Evolution depends on multiple levels of complex emergence.*

Compare this to how most evolutionary art is created. Most EA systems can't innovate via multiple levels of emergence. They generate results with a troubling sameness. To compensate EA systems end up being designed from the top down. The gene pool may start in a random state, but the dice are already loaded because the genetic representation has been designed to lead to the general kind of result desired.

In typical evolutionary art a single level of emergence limits complexity. The bottom up nature of evolution is turned top down. And the teleology that doesn't exist in natural evolution is introduced in the art that it supposedly inspired.

From an essentialist art theory point of view typical fitness function driven evolutionary art is incoherent due to self-contradiction.

Evolutionary art in the context of fine art and rigorous art theory cannot assert itself while it contradicts itself. The process is what makes evolutionary art unique, powerful, and meaningful. And truth to process in evolutionary art is what will turn the field away from self-contradiction and incoherence⁴.

Truth to process in evolutionary art demands a bottom up approach. Gene expression should not directly produce a final work but merely trigger the first of many levels of emergence. The artist's primary aesthetic concern should be about putting on display the process, not the product, of complexification.

Generative art theory in general, including that of evolutionary art in particular, moves from noun-dominated art to new practices where verbs become the content. The artifact may be less important than the process. The artifact may even be entirely irrelevant. Truth to process is where the beauty will be found.

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⁴ Systems that eschew a priori fitness function objective optimization, and instead rely on co-evolutionary and artificial life-based methods, point towards a truer process-oriented form of evolutionary art. But these systems still typically lack the gene-initiated mechanics for creating multiple levels of emergence and complexification.

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