XEPA: Intelligent Sculptures as Experimental Platforms for Computational Aesthetic Evaluation

Philip Galanter

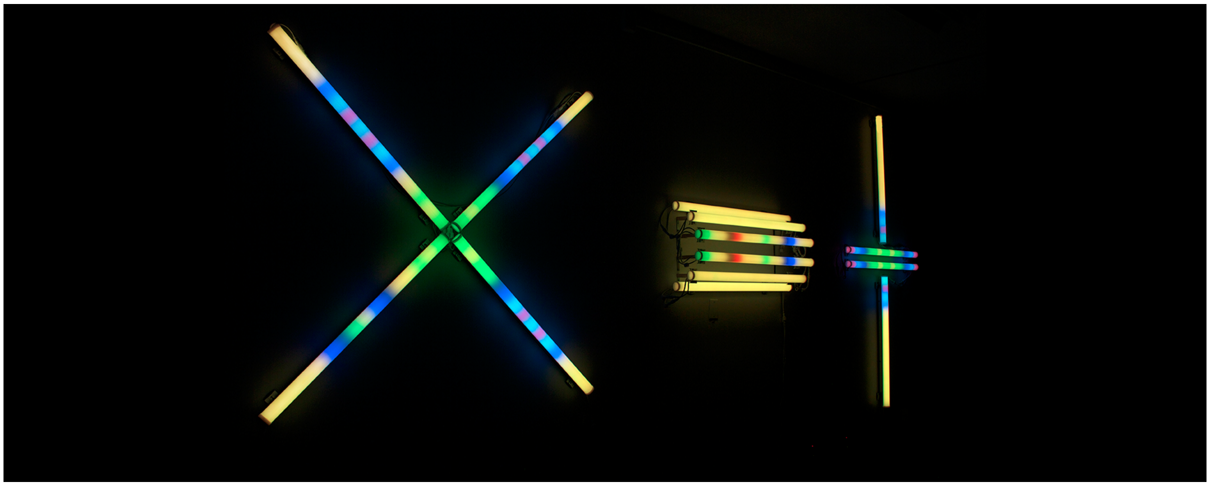

Fig. 1. Three XEPAs in alpha testing during software development

Abstract—In recent years artists have created an explosion of generative art and physical computing installations using the systems studied in complexity science, and leveraging open source technologies such as the Processing programming language and Arduino microcontroller hardware. By using genetic algorithms, reaction diffusion systems, cellular automita, artificial life, deterministic chaos, fractals, Lindenmayer systems, and more artists can generate a seemingly unending stream of visuals and sound. But while these systems offer incredible quantity and variation, they usually lack any self-critical function and simply stream forth without discrimination. This is most apparent in genetic or evolutionary systems where the fitness function is typically not automated and requires interactive selection by the human artist/operator.

The next phase of development seems likely to be the study and implementation of computational aesthetic evaluation. Only when computer-based systems are both generative and self-critical will they be worthy of consideration as being truly creative.

XEPA is the name of both the art project and individual intelligent sculptures that display animated colored light and produce music and sound. XEPA is an acronym for “XEPA Emerging Performance Artist.” Each XEPA “watches” the others (via data radio) and modifies its own aesthetic behavior to create a collaborative improvisational performance. In doing so each XEPA independently evaluates the aesthetics of the other sculptures, infers a theme or mood being attempted, and then modifies its own aesthetics to better reinforce that theme. Each performance is unique, and a wide variety of themes and moods can be explored.

Index Terms—Art, generative art, emergence, computational aesthetic evaluation, complexity, installation, multi-processor systems

1 Introduction

One important class of computer applications in the arts is the realm of digital hand-tools such as Adobe Photoshop™ or Corel Painter™. But as important as such software is, what many find more compelling are applications where the computer seems to directly create art in a hands-off manner. This kind of art is typically referred to as ***generative art.***

In this paper we will explore what generative art has offered to date, and how contemporary digital generative art falls short of instantiating truly creative computers. This provides the background for a discussion of the XEPA project currently in development and previewed at IEEE VIS 2013 in a pre-release form. Among other things XEPA provides a platform for experiments in computational aesthetic evaluation. Because of the highly interdisciplinary nature of this work we will have to freely shift between approaches and writing conventions used by scientists and engineers, and artists and humanists.

2 Generative Art

From the point of view of art theory generative art is not a subset of computer art. In a now decade old paper I offered what has come to be the most widely cited definition of generative art to date.

> Generative art refers to any art practice where the artist uses a system, such as a set of natural language rules, a computer program, a machine, or other procedural invention, which is set into motion with some degree of autonomy contributing to or resulting in a completed work of art. [1]

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It's worth noting that "procedural inventions" can include systems of chemistry, biology, smart materials, or other physical processes. The key element in generative art is the use of an external system to which the artist cedes partial or total subsequent control. In recent decades scientists from diverse fields have been working together to create a new multidisciplinary understanding of systems. Under the general rubric of ***complexity science*** various systems, and various kinds of systems, have been studied, compared, contrasted, and mathematically and computationally modeled. An abstract understanding of systems that spans the physical, biological, and social sciences is beginning to emerge. And it is these very systems that are being used as state-of-the-art generative systems by artists.

2.1 Generative Art and Complexity Science

Prior to the era of complexity science the most well known measure of complexity was found in information theory as defined by Claude Shannon in 1948. [2] In considering the complexity of an information channel Shannon equated complexity with a lack of redundancy. Therefore a maximally complex channel is one that transmits random data. Following this lead Max Bense applied the notion of information complexity to create a theory he called "generative aesthetics." [3]

With the advent of complexity science physicists Murray Gell-Mann and Seth Lloyd observed that equating randomness with complexity conflicted with our everyday notions of what constitutes a complex system. For example, a crystal can be considered a simple system in that there is a high degree of order created by its atoms being arranged in a lattice. This results in a system that is easy to describe, and any one crystal is quite similar to another. But a highly disordered system such as a cubic foot of atmospheric gas emerges as a simple system as well. Even though each molecule is moving about randomly, at human scale each cubic foot of atmospheric gas is easy to describe and similar to the others.

Things we think of as complex systems defy simple description and easy prediction. Many would agree that the most complex systems we encounter are other living things. And life requires a mix of order and disorder; order to maintain integrity and survival; and disorder to allow flexibility and adaptation.

It was this kind of intuition that lead physicists Murray Gell-Mann and Seth Lloyd to suggest the notion of effective complexity. As illustrated in figure 2 Shannon's information complexity increases with disorder, but effective complexity peaks where there is a mix of order and disorder.

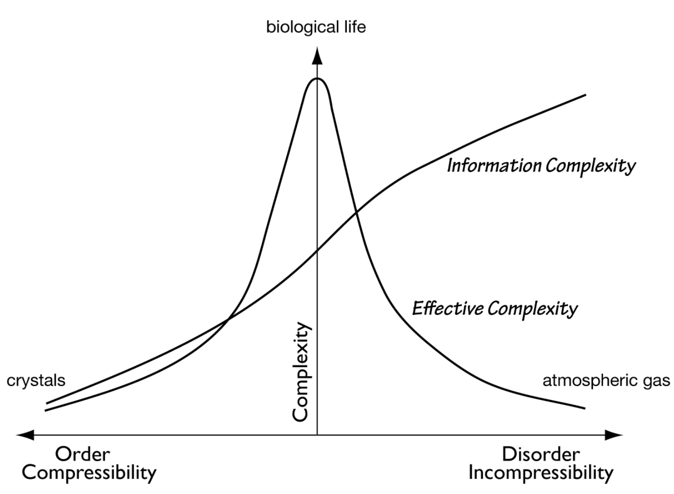

Fig. 2. A comparison of Information complexity and effective complexity.

Effective complexity introduces a paradigm where high degrees of order and disorder both create simple systems, and where complex systems exhibit a mixture of both. Given this we can classify various forms of generative art as simple-ordered, simple-disordered, and complex systems. Going beyond classification, however, is the discovery that the history of generative art roughly follows the history of our cultural embrace of these different system types.

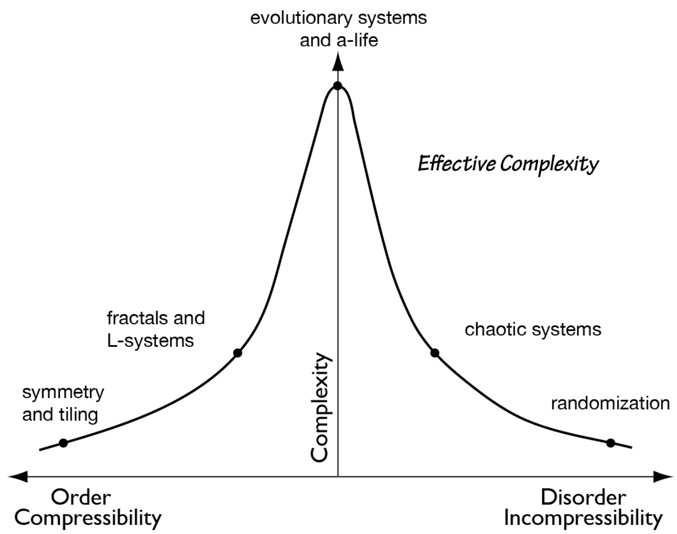

Fig. 3. Systems used in generative art organized by effective complexity

The earliest known use of generative art dates back some 75,000 years ago to some of the earliest design artifacts we have. [4] In every time and place for which we find artifacts there are examples of symmetry, tiling, and pattern in the creation of art. Note that just because an artifact is created manually that doesn't mean it isn't generative. With patterns and tiling the moment to moment intuitive choices of the artist are no longer in play, and the art is fully determined by an autonomous, albeit simple, system. It's probably no coincidence that simple highly ordered systems were generally the first systems integrated into early societies.

It wasn't until the 17th century with Fermat and Pascal that mathematical models for chance events were developed. Prior to that time randomness was associated with the irrational, and was even somewhat suspect as privation from the Logos and thus evil. The use of highly disordered systems, e.g. chance operations, typically yields artistic results little more complex than highly ordered art. One of the earliest documented uses of randomization in the arts is often attributed to Wolfgang Amadeus Mozart, but the actual inventor is probably lost to the ages. [5] Randomization in the arts came into its own primarily in the 20th century. Artists making use of chance methods included a young Ellsworth Kelly to create collages, William Burroughs to create shotgun paintings and cut-up novels, and perhaps most famously John Cage to enforce a Zen-like acceptance of all sounds.

In the last decade or so generative art has experienced a boom in part thanks to art, music, and design oriented open source programming environments such as Processing, Pure Data, and Supercollider, as well as open source microcontroller platforms such as the Arduino. Moving up the effective complexity curve, systems used to create contemporary generative art include fractals for recursive self-similar patterns [6]; L-systems for the creation of both organic and abstract branching systems [7]; physical chaotic systems such as video feedback or coupled pendulums such as in the case of my own piece "Chaotic Conductor"; simulated reaction diffusion systems for the kind of pattern formation found in animal fur and on seashells [8, 9]; and perhaps most of all systems based on artificial life and evolutionary computing [10, 11]

2.2 Evolutionary Art and the Fitness Bottleneck

Artists exercise critical aesthetic judgment in all phases of their work. Aesthetic evaluation comes into play when studying other artists, while applying micro-decisions while creating a piece, in learning from a newly created piece prior to beginning the next piece, and so on. Aesthetic evaluation includes more than making simple good/bad decisions as to the quality of work. It comes into play when trying to categorize art as to genre or movement, as well as when trying to understand the content of the work.

For the most part the generative art methods and examples noted above, and in fact throughout the practice, exercise no or very little aesthetic evaluation. While the ordered, disordered, and complex systems used in generative art can provide an apparently endless stream of forms, images, sounds, and so on, selection of results and direction of the systems are left to the human artist/operators.

Many writers on creativity emphasize that novelty is a necessary but insufficient criteria for creativity. Creativity also carries with it the implication that the results are useful or otherwise of value. To fully qualify as creative artists computers will have to at least combine generative systems with computational aesthetic evaluation. [12] This is perhaps best illustrated in the case of evolutionary art systems.

When genetic algorithms and other evolutionary approaches are applied to industrial applications a key element is the fitness function. For example, if designing electronic circuits a type of data structure serves as the ***genotype*** describing a set of components and connections. The genotype is then expressed as a ***phenotype***, i.e. a completed circuit. While this completed circuit could be physically constructed and evaluated, more typically the phenotype is an accurate model used with circuit simulation software. The phenotype, i.e. the circuit, is the tested with a span of inputs and the resulting outputs measured.

The way the genetic system makes progress is by making random changes to genotypes selected from the gene pool, discarding those new genotypes that do not constitute an improvement, and further breeding genotypes that do. Improvement here is relative to a ***fitness function*** that captures the aspects of the designed to be optimized. This is typically a weighted sum of scores. In this case the scores would represent properties such as parts count, ease of construction, price of components, conformity to input/output specifications, power consumption, and so on. By adjusting weights the designer can steer the evolution towards inexpensive circuits, or high precision circuits, or low power circuits, and so on as desired.

Because the evolutionary process is completely automated optimal solutions can be rapidly approximated by allowing gene pools with many dozens of competitors evolving for hundreds of generations.

The difficulty for generative artists using evolutionary systems is that we don't know how to create general robust aesthetic fitness functions. While there have been narrow automated attempts, the typical solution involves putting the artist in the loop and manually scoring each new phenotype. This means the system is no longer entirely automated. This places a severe upper limit on both the size of the gene pool and the number of generations that can be run. This has been referred to as the ***fitness bottleneck.*** [13]

Along with the fitness bottleneck evolutionary art faces a number of other technical and art theoretical problems. [14] More generally it is safe to say that most other examples of generative art entirely ignore the computational aesthetic evaluation problem. The XEPA project, in part, provides a platform for experiments in computational aesthetic evaluation and, perhaps, the eventual invention of truly artistically creative systems.

3 COMPUTATIONAL AESTHETIC EVALUATION

While it is true that computational aesthetic evaluation remains a fundamentally unsolved problem, it is not for lack of trying. Before describing the XEPA project what follows is a quick review of attempts to model aesthetics. A more detailed account is available in a chapter recently published as well as other sources. [15]

3.1 Simple Formulaic Approaches

There have been attempts to measure or define aesthetics in terms of relatively simple formulas, but all have been found to be inadequate and problematic. Perhaps most well known was the mathematician George David Birkhoff's ***aesthetic measure***. He proposed the formula $M=C/O$ where M is the measure of aesthetic effectiveness, O is the degree of order, and C is the degree of complexity. While the way he operationalized this formula was fraught with difficulties and almost immediately disproved in empirical studies, he was one of the first to identify complexity and order relationships as being key. He was also among the first to claim such a formula would have to be rooted in neurology. [16]

The Golden Ratio ϕ, an irrational constant approximately equal to 1.618, and the related Fibonacci series have been said to generate proportions of optimal aesthetic value. It has been claimed they are embedded in great works of art, architecture, and music. This has been contested and arguably debunked by writers such as Livio in examples such as the Great Pyramids, the Parthenon, the Mona Lisa, compositions by Mozart, and Mondrian's late paintings. [17]

On somewhat firmer ground is a principle commonly referred to as Zipf's law. Given a large body of text, when each word is tallied and then listed in frequency order, for a word of given rank i its frequency relative to the first word will approximately be the reciprocal $1/i$. This is related to $1/f$ power laws that can be observed in statistical distributions as varied as notes in melodies, colors in images, city sizes, incomes, earthquake magnitudes, and more. However, even though this kind of distribution is somewhat common, it's at most a suggestive partial test for use in aesthetic evaluation. [18, 19]

3.2 Complexity Measures

Noted earlier was Bense and his notion of information theory-based generative aesthetics. Despite being called "generative" his theory was more descriptive than normative. As applied by his colleague Moles information complexity provided a way of specifying a multi-dimensional media space, but offered little guidance as to how to discriminate between aesthetic objects of high and low quality. [20]

Somewhat more successful has been Machado and Cardoso's adaptation of Birkhoff's aesthetic measure in their NEvAr system. [21] That system generates images using an approach first introduced by Sims called evolving expressions. [22] It uses three mathematical expressions to calculate pixel values for the red, blue, and green image channels. The set of math expressions operates as a genotype that can reproduce with mutation and crossover operations.

Similar to Birkhoff, Machado and Cardoso evaluate the aesthetics of these images as a ratio of image complexity and perceptual complexity. To implement this as an automatic fitness function the degree to which an image resists jpeg compression is considered image complexity, and the degree to which it resists fractal compression is considered perceptual complexity. They reported surprisingly good imaging results but to date there is no particular evidence that this approach generalizes to other kinds of images.

3.3 Psychological and Neurological Models

A number of generative artists have observed that success in the realm of computational aesthetic evaluation is unlikely until psychological and neurological research suggests models of how aesthetics in humans works. While research in this area is increasing, most notably with the establishment of neuroaesthetics as a subfield and related brain imaging studies, there are as of yet no robust models let alone software implementations. Offered here is a brief look at three foundational researchers in the psychology of aesthetics.

Rudolf Arnheim applied the principles of gestalt psychology to aesthetic perception, and in doing so established the notion of aesthetic perception as cognition. Many see this as suggesting that aesthetic perception can be modelled computationally. The law of pragnanz in gestalt states that the process of perceptual cognition endeavours to order experience into wholes that maximise clarity of structure. From this law come the notions of closure, proximity, containment, grouping, and so on now taught as design principles. Unfortunately Arnheim's theory of aesthetics is much more descriptive than normative, and direct application to computational aesthetic evaluation is not obvious. [23]

Daniel E. Berlyne's most significant contribution to the psychology of aesthetics is the concept of ***arousal potential*** and its relationship to hedonic response. Arousal potential is a property of stimulus patterns and a measure of the capability of that stimulus to arouse the nervous system. Berlyne explicitly notes the correspondence between arousal potential effects and concepts from Shannon's information theory. He proposes that hedonic response is the result of separate and distinct reward and aversion systems. The reward and aversion systems activate in proportion to the number of neurons stimulated, and the number of neurons responding will increase as a Gaussian cumulative distribution. Berlyne further proposes that the reward system requires less arousal potential exposure to activate, but that when activated the aversion system will produce a larger response. This is illustrated in figure 4. [24].

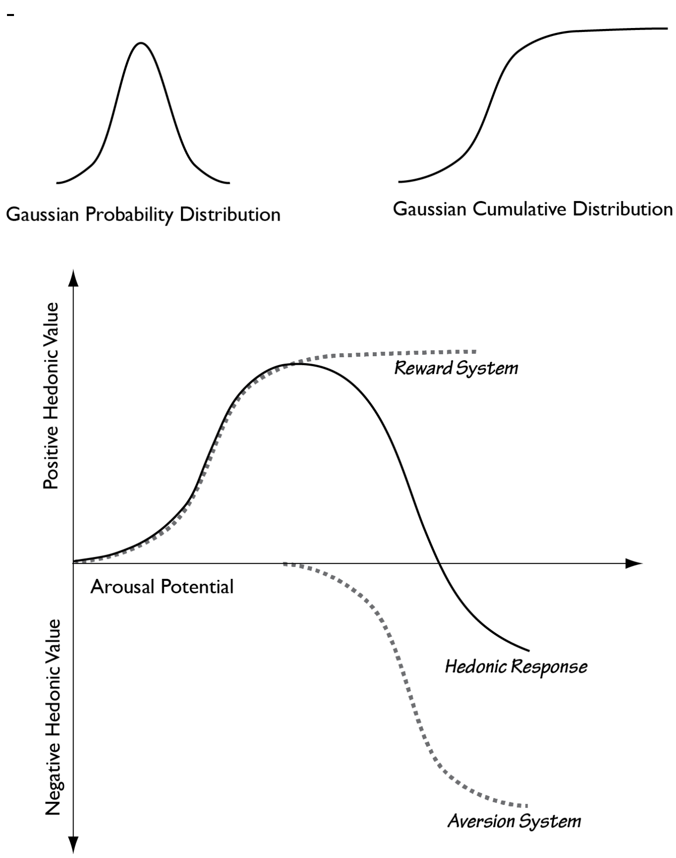

Fig. 4. Arousal potential as the summation of two Gaussian cumulative distributions

Berlyne notes that in the general neurological case this function is usually called the Wundt curve. In Wundt's model the x-axis represents low-level neural intensity. Berlyne's arousal potential on the x-axis includes psychophysical intensity, ecological stimuli, and most importantly collative effects. Increasing collative effects such as novelty and surprise represent increasing complexity in the information theory sense. From this point of view works of only moderate information complexity maximise the hedonic response. This is consistent with the artistic notion that audiences respond best to works that are not so ordered as to be boring, and not so disordered so as to be chaotic. An alternate interpretation would be that this response echoes effective complexity, and that high effective complexity in turn has, in a sense, the balance of order and disorder "built in." If our most important and challenging survival experiences have to do with other living things, perhaps that created evolutionary pressure leading to the optimisation of the human nervous system for effective complexity. And perhaps human aesthetics reflects that optimisation.

Colin Martindale developed a (natural) neural network model of aesthetic perception dynamics he referred to as ***prototypicality.*** He found that prototypicality did a better job of explaining a series of experimental observations than Berlyne's arousal potential. Martindale suggests that neurons form nodes that accept, process, and pass on stimulation from lower to higher levels of cognition. Low level processing tends to be ignored, and high level semantic nodes encoding for meaning have the greatest strength in determining preference. [25, 26]

Nodes are described as specialised recognition units connected in an excitatory manner to nodes corresponding to superordinate categories. Nodes at the same level, however, will have a lateral inhibitory effect. The result is that nodes encoding for similar stimuli will be physically closer together than unrelated nodes thus creating semantic fields. As a result the overall nervous system is optimally activated when presented an unambiguous stimulus that matches a prototypically specific and strong path up the neural hierarchy. Preference is then determined by the extent to which a particular stimulus is typical of its class. The obvious suggestion is that computational aesthetic evaluation is a strong candidate for an artificial neural networks approach. However, the fact that the human brain includes approximately 10^{15} neural connections should give us pause as to how daunting a project that might turn out to be.

4 XEPA

XEPA is an art project that, among other things, introduces a platform for experiments in computational aesthetic evaluation. It should be kept in mind, however, that the project is fundamentally artistic in motivation, and no pretense of controlled scientific research is implied. There is, however, an engineering aspect to the work.

At the time this paper was written XEPA had just reached an alpha-stage of development. The hardware design and software possibilities are versatile enough that a number of approaches will be possible in the future, and those described here are just a beginning.

XEPA as a project is intended to be reconfigurable and suitable for a number of different settings. XEPA is the name of the project, but an individual device is also referred to as a XEPA. XEPA is a recursive acronym with an intentional double meaning as "the XEPA Emerging Performance Artist."

Each XEPA is a light sculpture that can display animated colored light sequences as well as high fidelity sound/music. In addition each XEPA "watches" and "listens" to the other XEPAs, and then attempts to change its own performance so as to fit in better and improve the aesthetics of the group performance. Each performance lasts a minute or two, and each performance is a unique improvisation different than the rest.

4.1 XEPA hardware design

As light sculptures each XEPA is constructed with four to eight one meter tubes. XEPAs can be wall mounted, free standing, or suspended sculptures. Different installations may have differing numbers of XEPAs of different designs. For example, in one installation the XEPAs may all be the same and all mounted on a single wall. In another installation XEPAs of various design may hang from the ceiling.

Each light sculpture tube is a milky white diffuser with 16 RGB LED lighting units inside acting as 16 pixels. Each pixel is individually addressable as a 24-bit color using the lighting industry DMX control protocol.

Sound is produced using a single studio quality monitor with built-in amplification. A typical speaker of this kind is the Genelec 1029A. Because a given XEPA acts as a performer or instrumentalist rather than an ensemble, a single speaker rather than a stereo pair is appropriate. Various XEPAs will produce sound simultaneously and mix in the air not unlike a band using acoustic instruments.

Each XEPA uses three inexpensive processors. An Arduino Mega 2560 is used for high-level observation and decision making. The Mega 2560 is an open source hardware platform using an ATmega2560 microcontroller chip with 256 KB of flash memory for code, 8 KB of SRAM for variable memory, and 4 KB of EEPROM for non-volatile storage not requiring frequent updates. The Mega 2560 has 4 UARTS that assist with serial communications, and built-in hardware support for SPI. (The Mega 2560 has other features not used by XEPA and so not described here.)

An Arduino Leonardo is used for real-time DMX communications used to control the LED tube animation. Also an open source hardware platform, the Leonardo uses an ATmega32u4 microcontroller chip with 32 KB of flash memory for code, 2.5 KB of SRAM for variable memory, and 1 KB of EEPROM for non-volatile storage not requiring frequent updates. The Leonardo has 1 UART for serial communications, and unlike other low end Arduinos, separate support for USB communications used to upload code while programming. (Other Leonardo features not used by XEPA are not described here.)

The third processor is an open source hardware single-board computer produced by Texas Instruments called the BeagleBoard. The BeagleBoard-xM used by each XEPA uses a TI DM3730 Processor running at 1 GHz with an ARM Cortex-A8 core. The BeagleBoard has 512 MB of RAM for both code and data, and boots from a 4 GB microSD memory card. The BeagleBoard is designed to be a complete single board computer and includes DVI-D video output, USB interfaces, and so on. However, XEPA uses the BeagleBoard as a sound engine for real-time high fidelity music synthesis, and only requires the built-in audio output hardware, and a USB port for serial-over-USB data communications.

All three boards are mounted on laser-cut clear sheet acrylic enclosures that can either stand freely or be wall mounted. The enclosures are open and clear to present the "XEPA Brain" as a deconstructed demystified element. This is illustrated in figure 5.

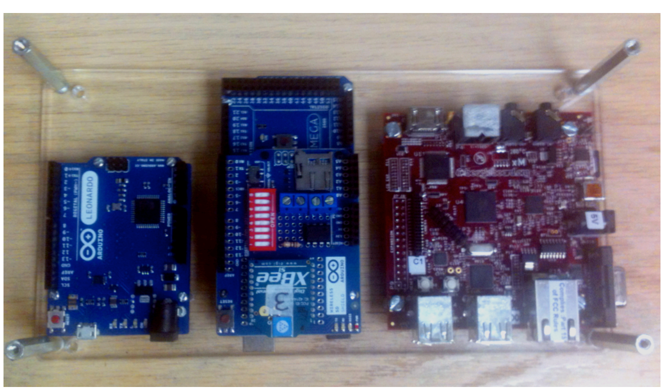

Fig. 5. XEPA "Brain" with front acrylic panel removed and without processor boards interconnected

Figure 6 gives some details as to how the three processor boards work together. The Mega 2560 has an extra "shield" board for artist-designed circuitry. It provides an XBee data radio to broadcast very short messages announcing what the XEPA is doing, and picks up broadcast messages from other XEPAs to "view" and "hear" what they are doing. The XBee data is transparently presented to the Arduino software as serial data. There is also an 8-bit DIP switch that can be used to assign the XEPA a unique ID number, or to set various debug modes. The shield also provides a small line driver circuit used to convert the +5 volt data from the Leonardo to the balanced signal required by DMX. Not shown is a microSD memory card reader that can be used in the future for additional storage of large look-up tables and such.

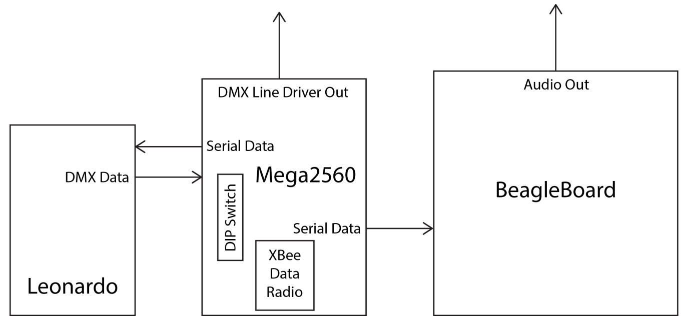

Fig. 6. XEPA "Brain" interconnection design.

As previously noted the Mega 2560 takes care of all higher level functionality including "watching" other XEPAs, executing aesthetic evaluation, and deciding what light animation and sound phrases will be performed. At regular intervals related to the rhythm and tempo of the performance the Mega 2560 sends short commands to the Leonardo and BeagleBoard. The Leonardo reacts to each message by executing an animation sequence, and the BeagleBoard reacts to each message by generating a sound phrase in real-time.

4.2 XEPA software infrastructure

XEPAs create a performance by executing animation and sound phrases. At the beginning of each phrase the given XEPA sends out a short data radio packet that merely describes what the XEPA will do in the phrase about to begin. In principle it is as if each XEPA is watching all the others. There are no data radio "commands" telling each XEPA what to do. Each XEPA decides for itself which of the other XEPAs to synchronize with, and which of the other XEPAs should influence its performance.

The two Arduino-based processor boards, the Leonardo and Mega 2560, use the standard open source Arduino IDE along with libraries for DMX and serial communications. The BeagleBoard uses the open source Supercollider music synthesis language for audio processing running on a Linux variant configured as part of the Satellite CCRMA project at Stanford University.

4.3 Lessons from improvisation

The XEPA algorithms used to date have been heavily influenced by lessons learned from my personal experience as an improvisational musician and performance artist, as well as additional lessons noted in part in the previous sections on generative art and aesthetic evaluation.

One lesson is that our perceptual cognition will meet an improvised performance more than half way. As Arnheim discovered our gestalt mechanisms will "fill in" and otherwise structure our perception to maximize clarity in experience. Improvised performance doesn't have to be perfect to be effective, and in fact there is never a single correct performance choice. Each individual's performance can only be judged in the context of the choices of all the other performers, and more often than not there will be several equally valid choices.

Another lesson is that the audience wants to be surprised, but the audience doesn't want to be left behind by a performance too unpredictable to follow. This is not unlike Berlyne's concept of arousal potential, or for that matter the notion of effective complexity, where beauty or aesthetically pleasing complexity will exhibit a mix of mild and strong stimulation, and a mix of order and disorder.

A third, and perhaps most important, lesson is that micro-aesthetic decisions by themselves don't matter nearly as much as the contribution they make to a clear high-level semantic impression. One of the wonderful mysteries of music is how purely abstract assemblages of sound can not only convey an emotion such as anger, they can communicate specific emotions such as the epic anger of war versus the comic anger of slapstick. This is similar to Martindale's notion of prototypicality where low-level sensations result in successful aesthetics when they resonate with a unified abstraction at a high level of cognition.

4.4 Initial implementation

XEPA is initially designed to execute effective improvisations that never repeat through the explicit programming of aesthetic possibilities. XEPA is not, at this time, intended to be a system that learns aesthetics other than being "taught" by tables of aesthetic correspondences provided by the artist. In other words the current project is to build a system that can gainfully use what it has learned. It's entirely possible that future work can integrate machine learning.

An information aesthetics analysis of a XEPA as per Moles would reveal a very large multi-dimensional media space. The visual component can include a large number of color palettes, animation sequences, tempos, rhythms, fades, flashes, pulses, and so on in all possible combinations. To this one would have to add the sound component including the harmonies, scales, finite but large melodies of fixed length, timbres, and so on also in all possible combinations. Finally the cross product of the audible and visual possibilities further exponentiates the media space. The notion of creating multi-dimensional tables and manually scoring each possible combination is not practical, and other methods of computational aesthetic evaluation remain to be invented.

To gain leverage over this combinatorial explosion a hierarchical model inspired by Martindale is used. First, a set of high level semantic fields are invented called ***themes***. Each theme is a suggestive phrase such as "artic zone" or "house on fire" or "spring life." For each of these each color palette, scale, animation sequence, and so on is given a weight based on artistic intuition. For example, a palette of blues and whites would be given a large weight for the theme "artic zone", while a palette of reds and yellows would be given a low weight for that particular theme. While this is a combinatorial burden, it's not at all impossible for twenty or so themes.

Because the XEPAs begin in random states and explore a complex media space, having only 20 themes does not at all mean that there will only be 20 kinds of performances. The current state of a XEPA acts as a genotype. The tables create the basis for a kind of fuzzy logic for theme membership given a genotype. And it is theme membership, i.e. conformance to Martindale's prototypicality, that acts as a fitness function.

In performance each XEPA independently executes table-driven computational aesthetic evaluation of the other XEPAs, and then adapts its own performance.

- Whenever a new packet is received from another XEPA
    a. Time-stamp the packet for possible later synchronization
    b. Compare the packet (genotype) to the weights for each theme generating an error score (fitness score) for each
- At the end of a phrase compare your error score to the error scores of the other XEPAs
    a. If there are lower error scores use a Monte Carlo technique to select the genotype of another XEPA
    b. Apply crossover to the current genotype using the selected genotype
    c. Synchronize with the selected XEPA

XEPAs initialized in random states will execute this quasi-evolutionary system in a loosely coupled manner. Over time the performing XEPAs will converge on a coherent theme. Heuristics are used to prevent duplications in the genotype exercised by each XEPA to guarantee variety among the players.

5 Conclusion

Generative art has been described as a systems-based art practice. It is notable that ideas from complexity science have impacted generative art providing a context for understanding simple ordered, simple disordered, and complex systems. In addition those systems have been exploited by generative artists in their relative historical order.

What generative art currently lacks, and what is required to create truly creative computers, is a mastery of computational aesthetic evaluation. In particular aesthetic models from perceptual psychology and neuroaesthetics are greatly needed.

XEPA has been created as both an artwork and a platform for experiments in computational aesthetic evaluation. The initial XEPA software creates a quasi-evolutionary system that seeks convergence on a theme in a way reminiscent of Martindale's prototypicality. Future development may replace manually developed intuitive weights with forms of machine learning or new computational aesthetic evaluation algorithms.

Acknowledgments

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