**Philip Galanter**

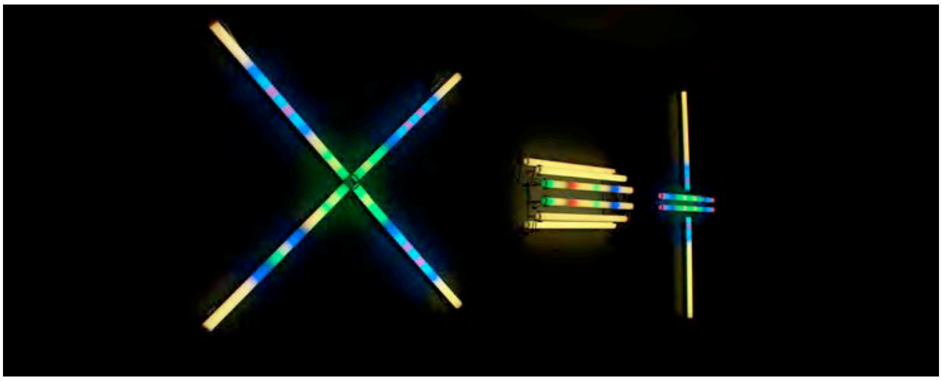
*Paper:* **XEPA: color and pattern algorithms for intelligent light sculptures**

*Topic: Fine Art*

***Authors:***
***Philip Galanter***
Texas A&M University
Department of Visualization
USA
http://www.viz.tamu.edu/

***References:***
[1] Galanter, P., Computational aesthetic evaluation: past and future, in Computers and creativity, J. McCormack and M. d'Inverno, Editors. 2012, Springer: Berlin.
[2] http://philipgalanter.com

***Abstract:***
Over the years generative artists have created art using systems such as genetic algorithms, reaction diffusion systems, cellular automata, artificial life, deterministic chaos, fractals, and Lindenmayer systems. While these systems can offer a seemingly unending stream of visuals and sound, they typically do so without discrimination, and they lack any self-critical functionality. This is most apparent in genetic or evolutionary systems where the fitness function is frequently not automated, and is simply the artist making manual interactive choices.
Computational aesthetic evaluation remains an unsolved problem. 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 behaviour 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.
After a system overview, some of the algorithms used in XEPA for color scheme selection and pattern generation are presented. In particular attention is given to the creation of "painterly" color palettes, complex patterns, and emergent synchronization.



*Three XEPAs in alpha testing during software development*

***Contact: email***

***Keywords:***
Computational aesthetic evaluation, physical computing, sculpture, cellular automata, emergence, complexity

# XEPA: Color And Pattern Algorithms For Intelligent Light Sculptures

**Philip Galanter, MFA, BA**
*Department of Visualization, Texas A&M University, College Station Texas, USA*
*philipgalanter.com*
*e-mail: galanter@viz.tamu.edu*

## Premise

Over the years generative artists have created art using systems such as genetic algorithms, reaction diffusion systems, cellular automata, artificial life, deterministic chaos, fractals, and Lindenmayer systems. While these systems can offer a seemingly unending stream of visuals and sound, they typically do so without discrimination, and they lack any self-critical functionality. This is most apparent in genetic or evolutionary systems where the fitness function is frequently not automated, and is simply the artist making manual interactive choices.

Computational aesthetic evaluation remains an unsolved problem. 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 behaviour 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.

After a system overview, some of the algorithms used in XEPA for color scheme selection and pattern generation are presented. In particular attention is given to the creation of “painterly” color palettes, complex patterns, and emergent synchronization.

## 1. Generative Art as a Way of Making 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]

The key element in generative art is the use of an external system to which the artist cedes partial or total subsequent control. Under the general rubric of complexity science various systems, and various kinds of systems, have been studied, compared, contrasted, and mathematically and computationally modelled. 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.

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 1 Shannon's information complexity increases with disorder, but effective complexity peaks where there is a mix of order and disorder. [2, 3]

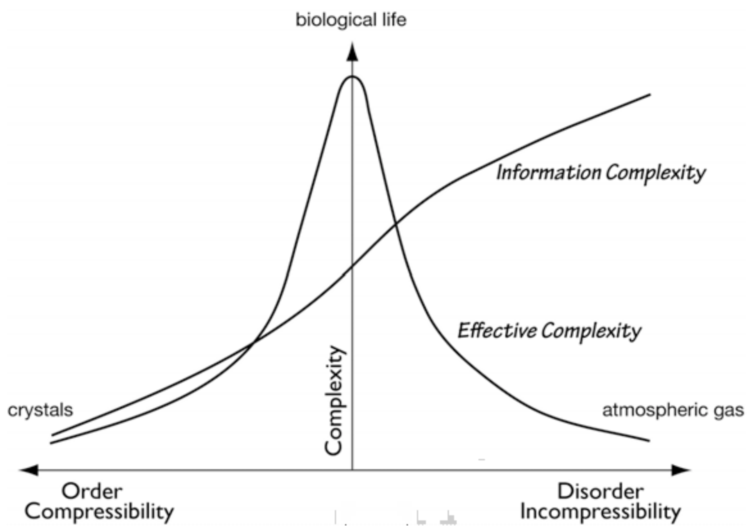



*Figure 1 – Effective complexity increases in systems that combine order and disorder*

This notion of effective complexity can be used to classify the various systems used in generative art. This is illustrated in figure 2.

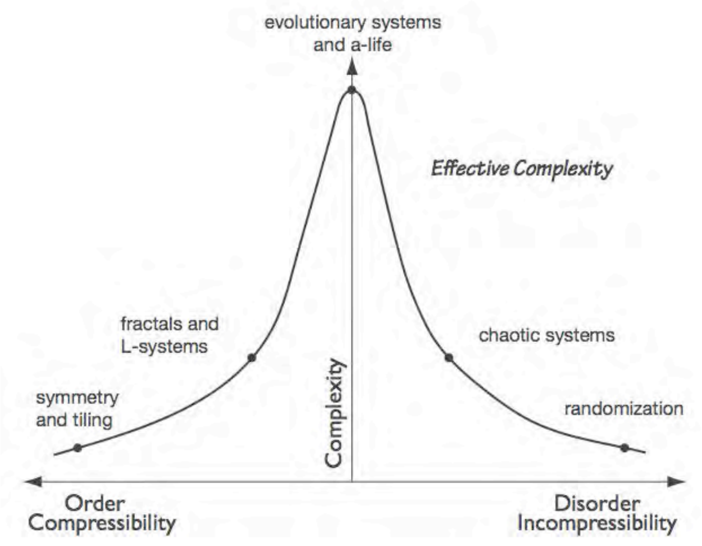



*Figure 2 - Generative systems organized by effective complexity*

## 1.1 Generative Art and Computational Aesthetic Evaluation

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. It also comes into play when trying to categorize art as to genre or movement.

Most generative art systems don't involve aesthetic evaluation. While the various systems noted above can provide an apparently endless stream of forms, images, sounds, and so on, selection of results and direction of the systems is left to the manual intervention of the human artist/operator. Where the generative system does have a form of normative aesthetics it is most typically in the form of purely forward generation, and are not applied retrospectively providing a kind of back propagation of error measures or other form of feedback.

Many writers such as Boden 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. [4]

This problem is perhaps most acutely felt in the realm 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, the genotype for an electronic circuit can be fed to circuit simulation software. The phenotype, i.e. the circuit, is then tested virtually with a span of inputs and the resulting outputs. These can then be scored with a fitness function that weights the parts count, ease of construction, price of components, conformity to input/output specifications, power consumption, and so on. 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 problem for generative artists using evolutionary systems is that we don't know how to create general robust aesthetic fitness functions. Outside of some narrow automated attempts, the typical solution involves putting the artist in the loop and manually scoring each new phenotype. 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." [5]

While it is true that computational aesthetic evaluation remains a fundamentally unsolved problem, it is not for lack of trying. [6] 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. The mathematician George David Birkhoff suggested 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 specifics of his proposal were almost immediately disproved in empirical studies, he was one of the first to identify complexity and order relationships as being key, and was also the first to claim a formula rooted in neurology. [7]

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. This has been contested and arguably debunked by writers such as Livio in reputed examples such as the Great Pyramids, the Parthenon, the Mona Lisa, compositions by Mozart, and Mondrian's late paintings. [8]

Somewhat more successful has been Machado and Cardoso's adaptation of Birkhoff's aesthetic measure in their NEvAr system. [9] NEvAr generates images using an approach first introduced by Sims called evolving expressions. [10] Three mathematical expressions are used 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. 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.

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 a complete robust model is probably many years away, some tantalizing research has been offered.

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.

Unfortunately Arnheim's theory of aesthetics is much more descriptive than normative. Direct application to computational aesthetic evaluation is not obvious and would likely require breakthroughs in computer vision well beyond the current horizon.

Daniel E. Berlyne has offered the concept of arousal potential and its relationship to hedonic response. Arousal potential is a quantitative property of stimulus patterns to arouse the nervous system. 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.

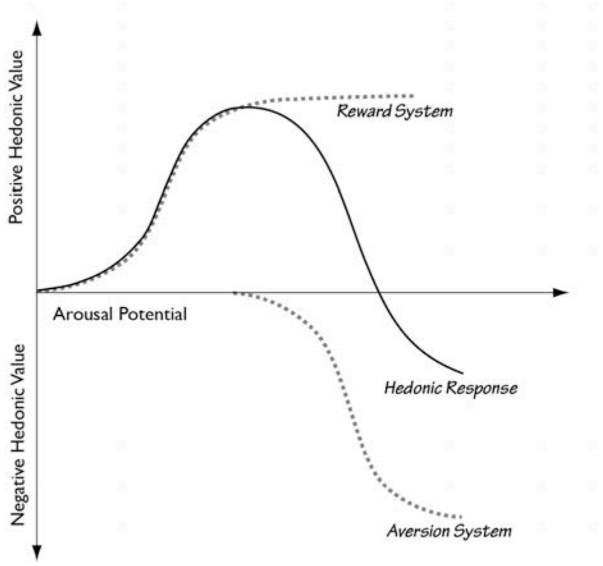



*Figure 3 - Arousal potential as the summation of two Gaussian cumulative distributions*

From this point of view art 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 the human nervous system is optimized for the processing of life forms in the natural living world.

Colin Martindale developed a (natural) neural network model of aesthetic perception dynamics he referred to as prototypicality. 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. [11, 12]

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.

## 2. XEPA and Experiments in Computational Aesthetic Evaluation

XEPA is an art project that, among other things, introduces a platform for experiments in computational aesthetic evaluation. The project is fundamentally artistic in motivation, however, 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.

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.

### 2.1 XEPA Hardware Design

As light sculptures each XEPA is constructed using four to eight one meter length tubes. XEPAs can be wall mounted, free standing, or suspended sculptures. Different installations may have differing numbers of XEPAs of different designs. 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.

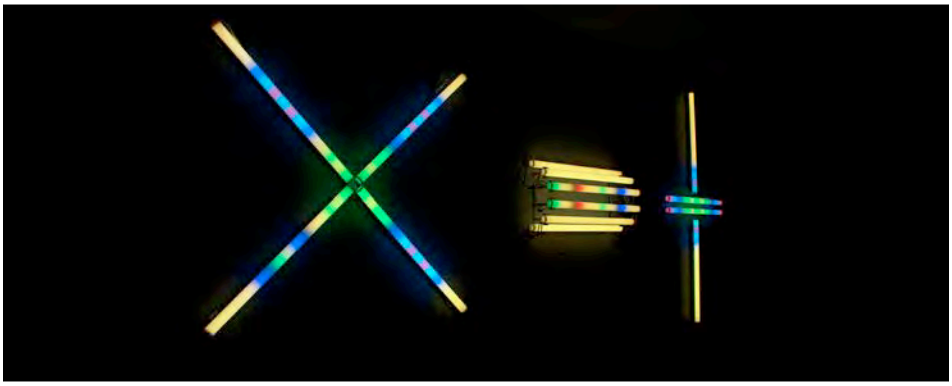


*Figure 4 – Three wall mounted XEPAs, each about 6 feet tall*

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, and 4 UARTS that assist with serial communications.

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, and 1 UART for serial communications.

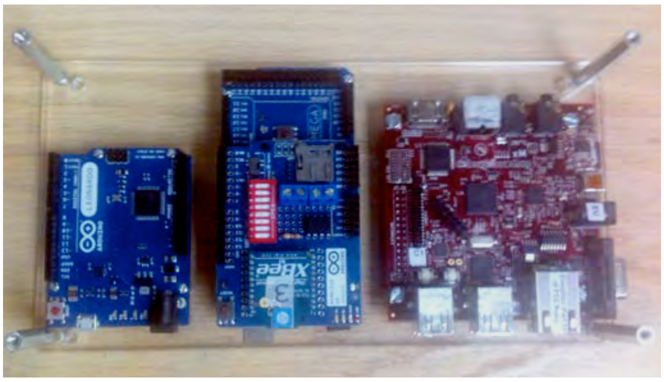


*Figure 5 – XEPA "Brain" without front acrylic cover and processor interconnects*

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.

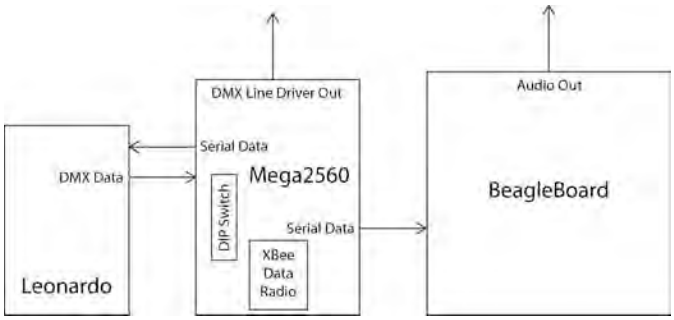



*Figure 6 – XEPA “Brain” interconnection design*

Figure 6 gives some details as to how the three processor boards work together. The Mega 2560 has an extra “shield” board for additional circuitry I designed. 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.

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.

## 2.2 XEPA Software Design

XEPAs create a performance by executing light animation and sound phrases. At the beginning of each phrase a given XEPA sends out a message that merely describes what that XEPA is doing. In principle it is as if each XEPA is watching all the others. There are no “commands” telling each XEPA what to do. Each XEPA decides for itself which of the other XEPAs it should adapt to based on their coarse behavior.

The XEPA algorithms have been heavily influenced by lessons learned from my personal experience as an improvisational musician and performance artist, as well as ideas noted in the previous section on computational 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. Each XEPA’s performance can only be evaluated in the context of the choices of all the other performers.

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 and the notion that our perceptual processing is tuned for high effective complexity.

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. 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.

XEPA is designed to execute effective improvisations that never repeat. 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 been force-fed. It’s entirely possible that future work can integrate machine learning.

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. In the current implementation most of the patterns are generated using cellular automata in a way that elaborates on my previous pieces RGBCA #1 (2010) and RGBCA #2 (2010). Where the earlier pieces strictly assigned an automaton to each of the 3 additive primary colors (red, green, blue), XEPA can use an arbitrary number of automata combined and mapped into arbitrary color schemes.

The sound component includes harmonies, scales, finite but large sets of melodies of fixed length, timbres, and so on also in all possible combinations. The cross product of the audible and visual possibilities further exponentiates the media space.

A hierarchical model inspired by Martindale is used to gain leverage over this combinatorial explosion. 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 every 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.

In performance each XEPA independently executes table-driven computational aesthetic evaluation of the other XEPAs, and then adapts its own performance. Each follows this general algorithm:

- Whenever a new packet is received from another XEPA
    - Time-stamp the packet for possible later synchronization
    - 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
    - If there are lower error scores use a Monte Carlo technique to select the genotype of another XEPA
    - Apply crossover to the current genotype using the selected genotype
    - 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.

## 3.0 How XEPA implements “painterly” color palettes

In previous light sculptures I’ve noted a dominance of cool colors and a lack of strong yellows and oranges. In LED pieces yellow is typically created by mixing a red LED and a green LED. The balance of these two light sources is delicate, and it can be difficult to get a yellow without a green or orange tint.

In fact my informal survey of generative works that create color palettes reveals a similar dominance of cool blues, greens, and violets, and fewer warm reds, oranges, and yellows, and especially a lack of subtle steps between. Light pieces in particular lack a painterly use of color and will over-emphasize the harsh additive secondary colors magenta and cyan.

This is all primarily due to the use of the additive RGB color system and the resultant spacing of colors around the color wheel. The typical RYB subtractive system used to describe color mixing in paints spreads the warm colors further around the color wheel.

It’s interesting to note that if one uses the HSV color mode in either Adobe Photoshop™ or the Processing programming language, or virtually any other digital color application, one will get the cool color dominant spacing seen in the RGB color wheel. The upshot of this is that if hues are selected “randomly” one gets more cool colors than warm colors. The difference between the two is clearly shown in figure 7 and figure 8.

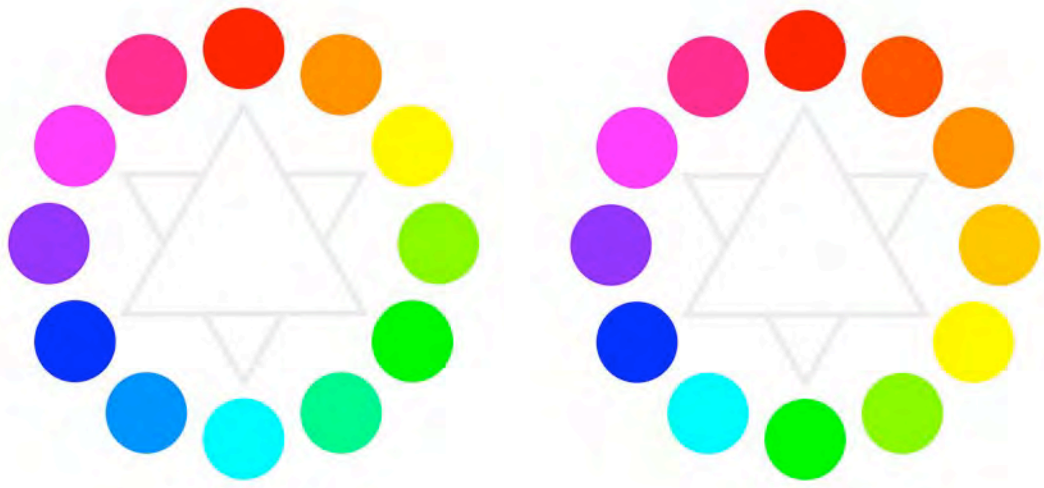


*Figure 7 – The additive RGB system (left) versus the subtractive RYB system (right)*

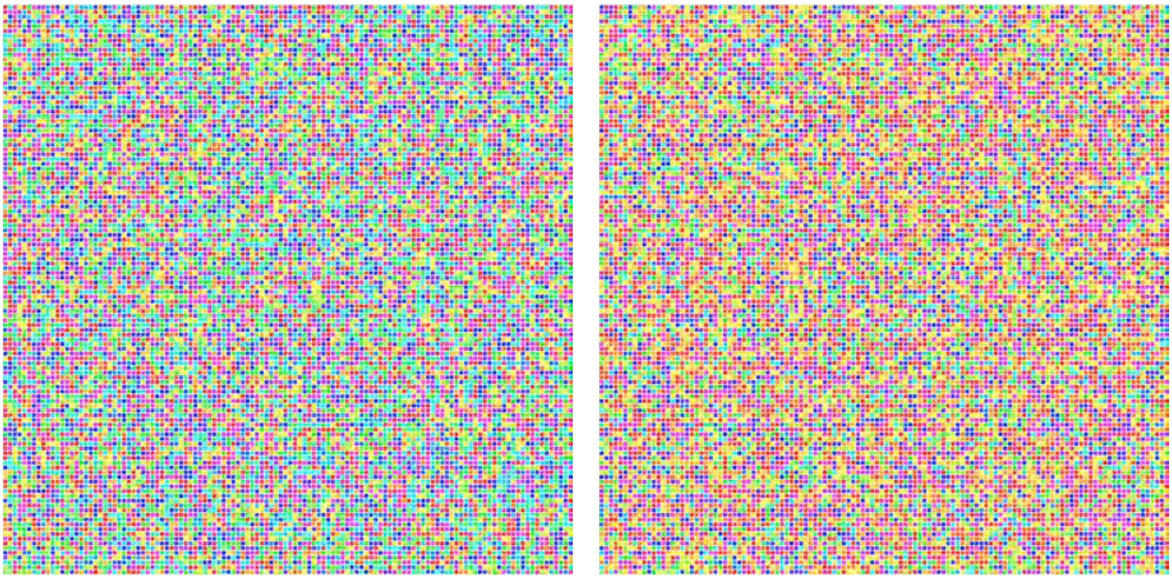


*Figure 8 – Random RGB colors (left) versus Random RYB colors (right)*

In order to achieve a more even handed balance of warm and cool colors, and to encourage painterly color palettes, XEPA does all of its color calculations and representations using a RYB color system. Those colors are converted into the device specific RGB values needed by the lighting fixtures late in the process at the device driver level. In other words XEPA uses a RYB system.

But in order to achieve a more painterly look the RYB system one would get simply by interpolating primary and secondary color values has been modified a bit by eye.

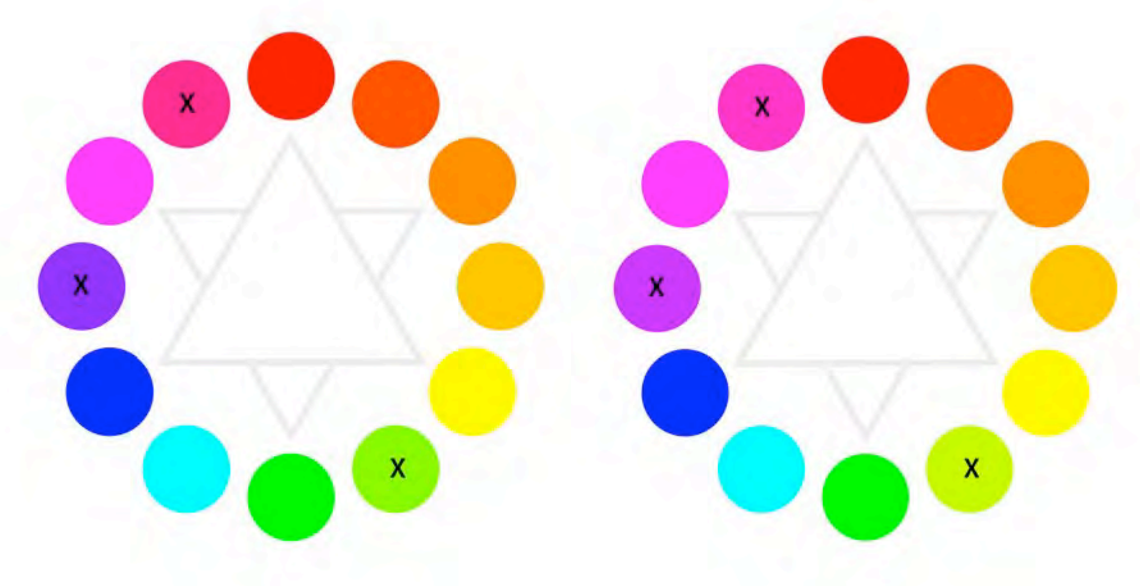



*Figure 9 – The RYB system (left) versus the RYB Plus system (right)*

In XEPA the color system is defined by the 12 primary, secondary, and tertiary colors. Hues in between those colors are calculated by linear interpolation. To my eye the color spacing of three of the tertiary colors are subjectively too biased to one side. These have been manually adjusted to move red-violet half again towards violet, green-yellow half again towards yellow, and blue-violet half again towards violet. I believe this helps all 12 colors to claim a distinct place in the color semantic space. I've named this color system RYB Plus.

It's important to note that the spacing around the color wheel does more than just balance cool and warm colors in the case of random selection. Perhaps more importantly it has a significant impact on the generation of color schemes using color harmony, i.e. relative spacing on the color wheel. This is where the aspect of creating a painterly palette comes to the fore.

The impact on color schemes is demonstrated in figure 10 (3 colors evenly spaced around the color wheel) and figure 11 (4 colors evenly spaced around the color wheel).

The details of the RGB, RYB, and RYB Plus systems are shown in the final figures.

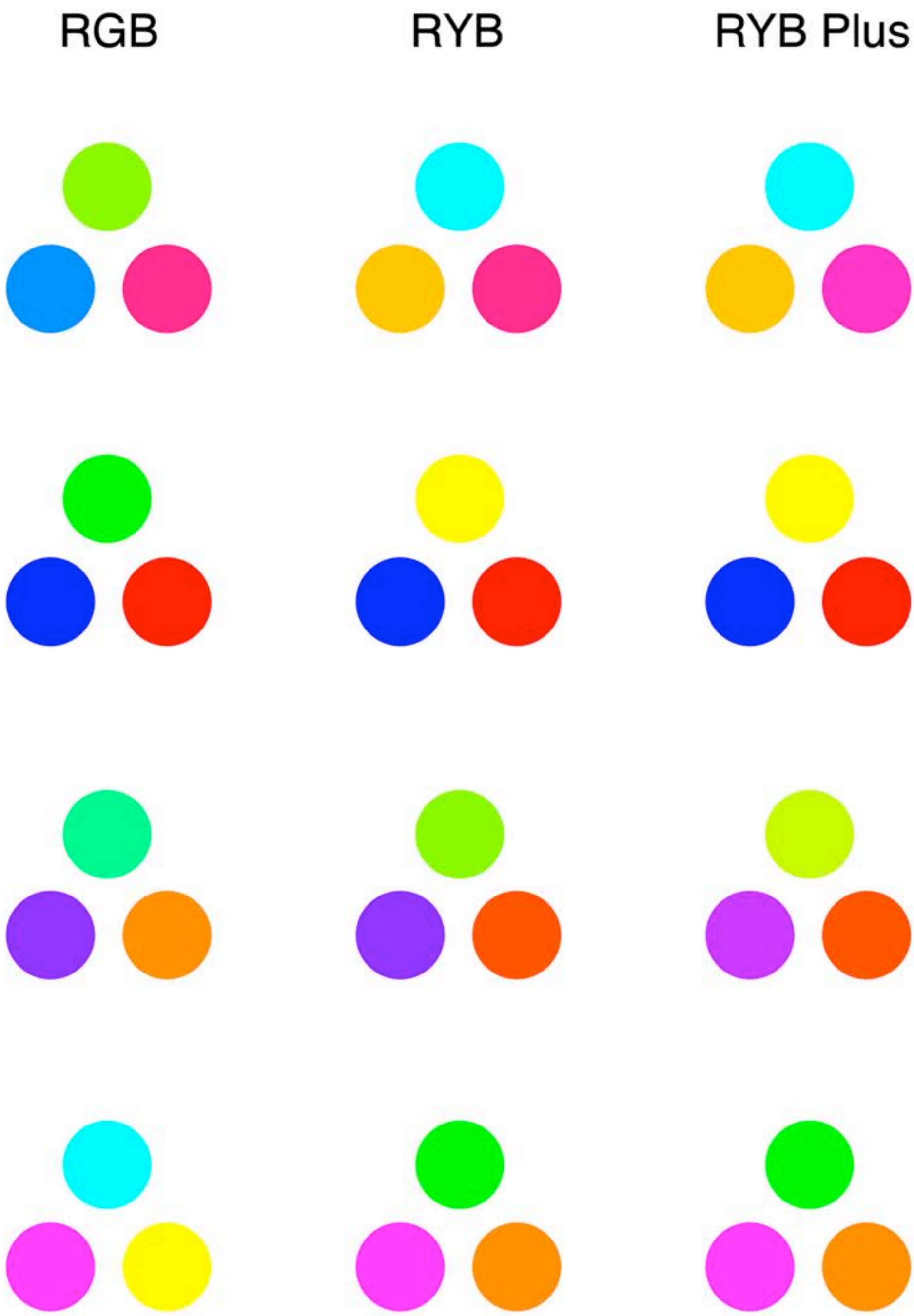



*Figure 10 – A comparison of triadic color schemes in the three color systems*

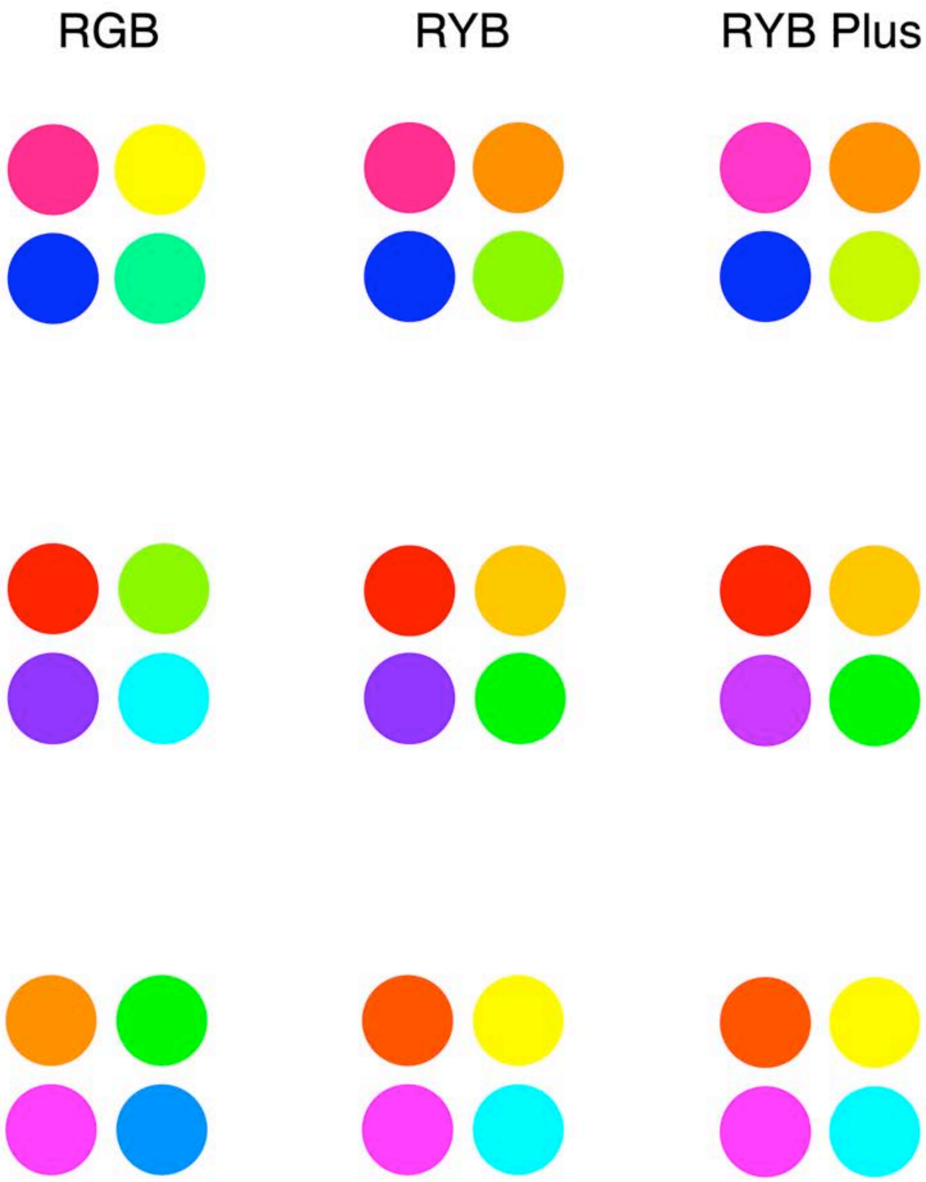



*Figure 11 – A comparison of tetradic color schemes in the three color systems*


*Figure 12 – How RYB and RYB Plus are mapped into RGB in the device driver*

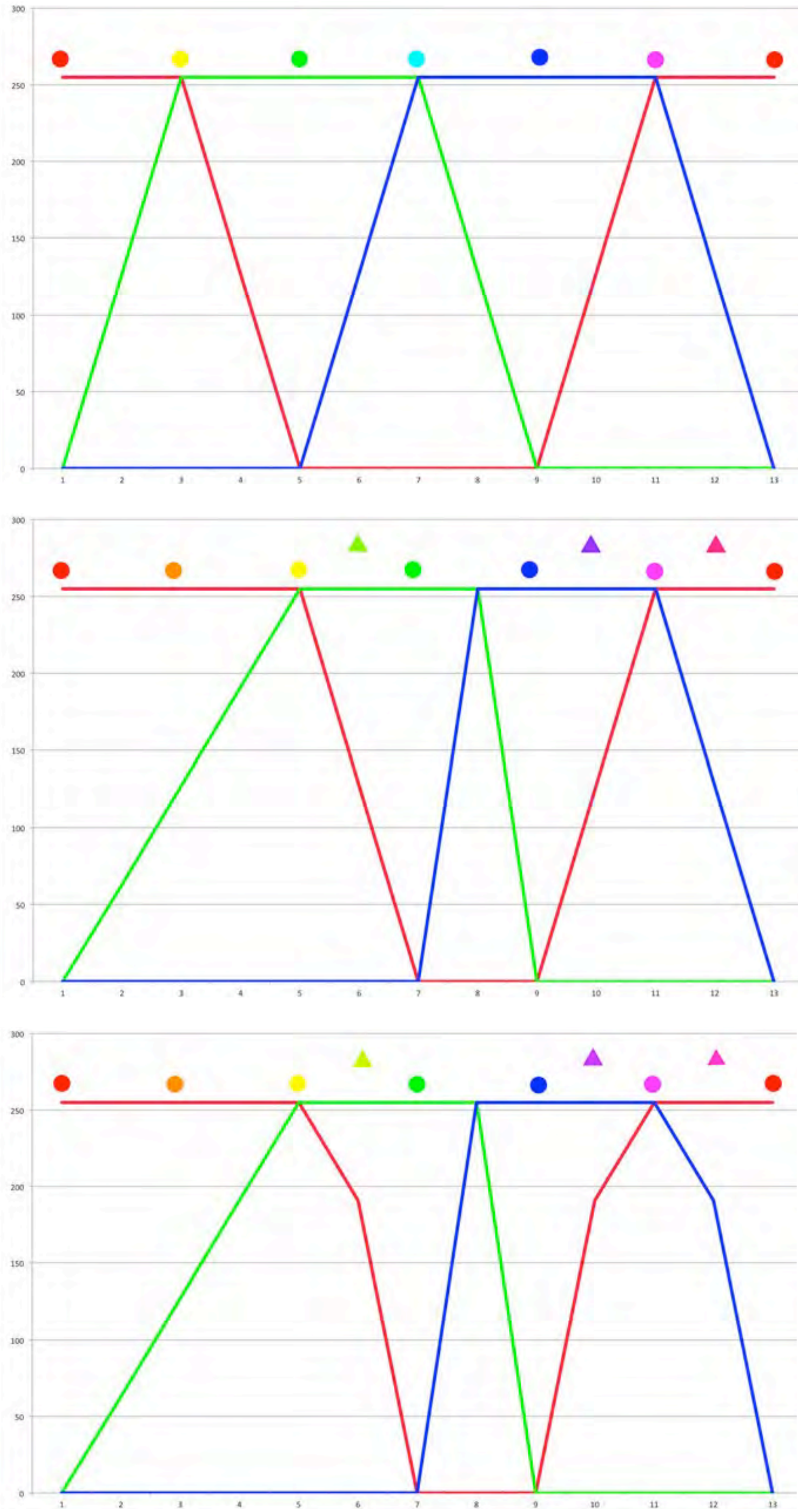


Figure 13 – Interpolation of RGB values for the RGB (top), RYB (middle), and RYB Plus (bottom) systems

## References


1. Galanter, P. *What is Generative Art? Complexity theory as a context for art theory*. in *International Conference on Generative Art*. 2003. Milan, Italy: Generative Design Lab, Milan Polytechnic.
2. Gell-Mann, M., *What is complexity?* Complexity – John Whiley and Sons, 1995. **1**(1): p. 16-19.
3. Shannon, C.E., *A mathematical theory of communication.* The Bell System Technical Journal, 1948. **27**(3): p. 379--423.
4. Boden, M.A., *The creative mind : myths and mechanisms*. 2nd ed. 2004, London ; New York: Routledge. xiii, 344 p.
5. Todd, P.M. and G.M. Werner, *Frankensteinian Methods for Evolutionary Music Composition*, in *Musical networks: Parallel distributed perception and performance*, N. Griffith and P.M. Todd, Editors. 1998, MIT Press/Bradford Books: Cambridge, MA.
6. Galanter, P., *Computational Aesthetic Evaluation: Past and Future*, in *Computers and Creativity*, J. McCormack and M. d'Inverno, Editors. 2012, Springer: Berlin.
7. Birkhoff, G.D., *Aesthetic measure*. 1933, Cambridge, Mass.,: Harvard University Press. xii, 1 p., 2 l., 3-225, 1 p.
8. Livio, M., *The golden ratio : the story of phi, the world's most astonishing number*. 1st trade pbk. ed. 2003, New York: Broadway Books. viii, 294 p.
9. Machado, P. and A. Cardoso, *All the Truth About NEvAr.* Applied Intelligence, 2002. **16**(2): p. 101-118.
10. Sims, K., *Artificial Evolution For Computer-Graphics.* Siggraph 91 Conference Proceedings, 1991. **25**: p. 319-328.
11. Martindale, C., *Relationship of preference judgements to typicality, novelty, and mere exposure.* Empirical Studies of the Arts, 1988. **6**(1): p. 79-96.
12. Martindale, C., *A Neural-Network Theory of Beauty*, in *Evolutionary and neurocognitive approaches to aesthetics, creativity, and the arts*, C. Martindale , P. Locher , and V.M. Petrov Editors. 2007, Baywood: Amityville, N.Y. p. 181-194.