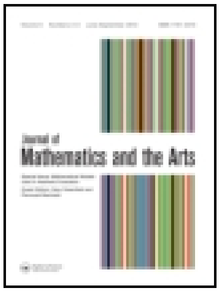

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Guest editors' introduction

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Guest editors' introduction

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> I often say when you can measure what you are speaking about, and express it in numbers, you know something about it; but when you cannot measure it, when you cannot express it in numbers, your knowledge is of a meager and unsatisfactory kind. — Lord Kelvin

> Let proportion be found not only in numbers and measures, but also in sounds, weights, times, and positions, and whatever force there is. — Leonardo da Vinci

1. Motivation

To oversimplify, interest in mathematical models for aesthetics began in the 1930s with Birkoff's formulation of his famous $M = O/C$ equation, measuring the aesthetic value M of an art object based on its order O, and complexity C [6]. It flourished, after a fashion, with the advent of Shannon information theory thanks to Bense, Moles, Berlyne and others until the early 1970s. It flared again briefly in the late 1970s following the appearance of the Stiny and Gips book *Algorithmic Aesthetics* [40]. And then it seemingly went dormant. What events led to a renewed interest in the subject, and in turn inspired us to organize and guest edit this special issue?

Regardless of the label one chooses — algorithmic art, generative art, swarm art, evolutionary art, etc. — and in spite of the fact that one can identify historical antecedents tracing back to the 1960s, or possibly even earlier, it seems safe to say that the spark that ignited the eventual resurgence in mathematical models for aesthetic evaluation occurred in the early 1990s with the publication of Karl Sims's [35] seminal paper *Artificial evolution for computer graphics* and Todd and Latham's [41] book *Evolutionary Art and Computers*. Granted, it took a while for this renewed interest to firmly take hold; but for us, for several contributors to this special issue, and for legions of others, these two publications, coupled with the publicity and popularity of artworks exhibited by Sims and Latham at the time, provided the impetus for a cadre of researchers to embark upon their own explorations of generative art schemes, which in turn *irresistably* and *unavoidably* led to the consideration of mathematical models for evaluating aesthetics. Irresistably? Unavoidably?

For those of us whose interests lie at the intersection of art and computing, the seductive power underlying generative art rests in designing and developing 'engines' for computationally generating *potential* works of art. For Sims and Latham, the paradigm for selecting, or identifying, works of art produced by such an engine relied on using the technique known as user-guided aesthetics or interactive evolution, which required a human to sit for hours at a terminal sifting through hundreds, if not thousands, of images assisted only by simple interface tools to accomplish this task. The challenge of taking the next step and automating this evaluation process by using a mathematical model to evaluate the aesthetic content of an art object, whether image, poem, or music fragment, was therefore irresistable and unavoidable.

2. Does it make sense?

It is fascinating to note that back in 1975, at the dawn of computer generated art, in discussing the nature of computer art, Kawano [22] observed:

> . . . a computer artist should be a programmer who can teach his computer to produce works of art *by itself*. [emphasis added]

and that by 1980, in response to the growing realization that computer artists could 'cover the earth' in art works, Coleman [8], one of the harshest of critics, begged:

> Therefore let me take this occasion to make a formal request to the image makers working in this form — a request not for more images but for more writing. *You must provide a set of clear ground rules if you want an attentive and responsive audience*. [emphasis added]

From personal experience, we can attest to the aversion some feel at the mere thought that one might wish to consider a mathematical model for aesthetic evaluation. This sentiment is expressed bluntly in

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Bentley and Corne's [4, p. 377] highly regarded 2002 book:

> ...the aesthetic value of an art piece cannot be described as a mathematical fitness function and further might depend on individual taste.

Fortunately, this sentiment is not universal, and it is heartening that by 2005, regarding evolutionary art where the art works, or phenotypes, are generated from abstract representations, or genotypes, Jon McCormack [28] included among his five open problems in evolutionary art and music:

> To devise formalized fitness functions that are capable of measuring human aesthetic properties of phenotypes. These functions must be machine representable and practically computable.

Recalling that as late as 1988, we find no less a figure than Herbert Franke [11] still staunchly defending the use of *mathematics* in computer generated art, perhaps it seems wisest to understand that there will always be disagreement about our irresistable and unavoidable pursuit, and to leave it to philosophers to debate the question of whether or not it makes sense to use mathematical models for aesthetic evaluation.

3. Early efforts

The papers appearing in this special issue cover much of the literature regarding the use of mathematical models for aesthetic evaluation in the post Sims and Latham era, but we would like to take this opportunity to acknowledge some early efforts that may not be as well known, often due to limited publication opportunities.

Fractal art offers a convenient and popular platform for experimentation. From 1993 to 1995, Sprott [34–36] published three papers in the journal *Computers & Graphics* on the 'automatic generation' of fractals. In 1996, Sprott reached out to a wider audience with his chapter provocatively titled *The Computer Artist and Art Critic* in a book edited by Pickover [37]. In a subsequent 1998 book, Pickover republished Sprott's original three articles [31]. Even though, in our opnion, the study of automatic generation of fractals got sidetracked by a broader discussion of whether fractal art should qualify as Art with a capital 'A' (a topic beyond our scope), it also seems appropriate to mention further related work in this area in 2004 by Linkov and Staudek [24].

It seems quite natural that early on a literature developed for automating the identification of aesthetic *patterns*. As an experimental platform, small arrays of black and white cells are computationally tractable, plus they offer a concomitant tie-in with the ever popular subject of cellular automata. Thus, we note relevant contributions by K. Bentley [3] in the 2002 Generative Arts Conference Proceedings, Jones and Agah [21] in a 2002 IEEE Transactions journal, and Staudek in both the 2002 SIGGRAPH Conference Applications [39] and 2003 ISAMA/Bridges Conference Proceedings [38].

We would be remiss if we did not also mention the 2001 agent-based approach to design by Saunders and Gero [32] at the Key Centre and, following a trail first blazed by Noll [30], the 2004 paper in the journal *LEONARDO* by Feijs [10] on nonfigurative works in the style of Mondrian, which stands apart as one of the rare, early rule-based models for aesthetic evaluation.

4. Building a community

Putting aside the thorny question of how the older discipline of generative music has interacted with the newer disicpline of generative art, as stated earlier, it is our premise that following Sims and Latham, beginning in 1991 a significant number of researchers were attracted to establishing themselves as programmer-artists by exploring generative art schemes. As a result, by the late 1990s, a steady stream of research papers on generative art began to appear. Subsequently, as the thrill, exuberance, and novelty of being able to generate thousands of 'artistic images' began to loosen its grip, irresisitably and unavoidably the focus turned to automated aesthetic evaluation of generative artworks. With the exception of a singularity that occurrred in 1994 with the publication by Baluja, Pomerleau and Jochem [2] of a lengthy paper in the journal *Connection Science* on the use of nerual nets to automate aesthetic evaluation of images generated using a simplified version of Sims's generative art system, for the most part such research did not begin to appear until the turn of the century. In 2000, one of us (Greenfield) published on the use of co-evolutionary methods to achieve a similar goal to that of Baluja et al. in the Alife VII Proceedings [13]. In this predator-prey approach, the aesthetically weakest images in a population were preyed upon by digital image filters. In 2002 Machado and Cardoso — whose abstract appropriately includes 'The automation of fitness assignment is one of our present research interests'. — used compression complexity to achieve the same goal as Baluja et al. in their paper published in the journal *Artifical Intelligence* [25]. In 2005, one of us used indirect behavioral measures in an agent-based simulation to evolve ant paintings [16].

As more and more conferences receptive to such efforts have come into existence (e.g. Bridges, EvoMUSART, CAe, GA, ISAMA, M&D), it has become easier to identify interested participants, share results, and to self-organize. Over the past decade, the number of researchers who have become involved coupled with the influx of papers that has appeared make an exhaustive survey prohibitive. To return to the question of why we have chosen this moment to seek further exposure through a special issue devoted wholly to mathematical models for aesthetic evaluation, we must turn to the contributions in this issue. But before before doing so, a digression is necessary.

5. The terminology quagmire

The announcement of the first ever workshop on 'computational aesthetics' in 2005 might seem to have heralded a summit for mathematical models for aesthetic evaluation. This turned out not to be the case for two reasons. First, besides the notion of computational aesthetics as it traces back to Birkhoff, the term was interpreted differently by psychologists vis-à-vis Leyton's International Society for Mathematical and Computational Aesthetics; computer scientists vis-à-vis Fishwick's Aesthetic Computing Manifesto; and computer graphics researchers vis-à-vis Sbert's initiative for automating tools that involve aesthetic choices (but see Blackwell and Dodgson [7] conference). Second, even in the sense of Birkhoff, 'computational aesthetics' can at best be seen as an umbrella term encompassing: information aesthetics, generative aesthetics, abstract aesthetics, experimental aesthetics, algorithmic aesthetics, emergent aesthetics, exact aesthetics, simulated aesthetics and so on [17]. For this special issue, we have chosen to embrace the term generative art in its broadest sense and to focus on mathematical models for aesthetics relevant to analysis and generation of art objects within this embracing framework.

6. Our contributors

In a 1998 *LEONARDO* editorial, Frieder Nake [29] wrote:

> Information aesthetics was the heroic attempt by Bense and Abraham A. Moles to use Shannon's and Weaver's concept of information as the guiding principle for an analysis of aesthetic processes, both analytic and generative. Although some exciting insight into the nature of aesthetic processes was gained in this way, *the attempt failed miserably*. Nothing remains today of their theory that would arouse any interest for other than historical reasons. [emphasis added]

We were aware of Nake's feelings, and heard him reiterate these sentiments during his lecture at the Creativity and Cognition Conference in London in 2005. We are delighted that Nake has (1) taken this opportunity to provide us with a long-awaited expanded treatment of the history of the information aesthetics movement by someone who 'was there' and (2) chosen to somewhat ameliorate his strident tone (partly, we would like to think, due to the encouraging and supportive comments of our reviewers). The result is a timely reminder about a lesson that many of us have taken over a decade to re-discover, but that Nake realized almost half a century ago, and now elegantly puts into words — any model that assigns a purely *objective* numerical value purporting to measure the aesthetics of an art object must yield a value that is constant across a broad [equivalence] class of such objects.

To phrase this a different way: for every high-valued aesthetic image/music fragment/poem identified by the analysis module of your generative art system, almost surely there are dozens more with that *same* exact value. Therefore, if you are unsatistified with a system that — succumbing to a little hyperbole — you expect can identify and procure scores of potential Mona Lisas, how should you proceed? Multi-objective optimization is one possiblility [9,14], but that brings you back to square one, since now you are tasked with post processing scores of generated objects that are not just constant for one aesthetic numeric value, but vary across two or more such values. Multi-objective optimization may have its place in practice, but it is not a theoretical advance.

This is not to say that the techniques from information theory should be summarily dismissed. In this special issue, Kevin Burns explains how he uses information theory to analyze and explain humorous haiku poems and, in turn, suggests a procedure for generating haiku that, unfortunately, cannot quite yet be realized in a computational setting. (However, in the visual arts and music, generative results based on his methods have already appeared.)

Continuing this journal's admirable tradition of featuring mathematical models that serve to help analyze and understand the art work of famous *painters* (see Lee et al. [23] for Jackson Pollock and Aboufadel et al. [1] for Chuck Close), in this issue Neil Dodgson invokes higher order entropy measures and local entropy measures to help analyze the stripe paintings of Bridget Riley.

It is becoming more and more apparent that external factors must be brought to bear in our computational models in order to overcome the limitations of purely objective measures. Recent research based on that observation offers intriguing initial results. In an attempt to construct 'artificial art critic' modules for generative art systems, Machado et al. investigated the use of neural nets that were first trained on a corpus of 800 artworks ranging from Goya to Picasso [27]. By 2008, they had developed this approach into a bootstrapping method that allowed automated evolution to progress through a succession of 'styles' [26]. In 2008, following a three-month collaboration, Greenfield and Machado implemented a full simulation of artificial artists interacting with artificial critics. Artworks were produced by the artists according to their preferences in response to feedback from the critics; in turn, their artworks were evaluated by the critics based on previous such works *and* critic preferences for external artworks [20]. However, both of these efforts were simulations that did not directly involve any human participants.

In this issue, two tantalizing and promising contributions addressing this oversight are included. First, Ekárt et al. resolve the impasse over using objective measures absent external factors by tuning automated evolution to individual users. They record and analyse four aesthetic measures obtained from each user during a short interactive phase, and then select two of those measures for use in a subsequent automated phase. Readers should take note of their technical skill and ingenious experimental design. The analysis of their results, and their conclusions, raise several interesting questions that will entice both experts and novices alike. Second, by making use of a database of *photographs* that were previously evaluated on the basis of aesthetics by humans, Romero et al. use machine learning techniques to discriminate between 'favourable' and 'unfavourable' images at success rates that are human competitive. Their work is particularly significant because it helps establish benchmarks and targets for future such efforts.

7. What lies ahead?

As co-editors, we hope this introduction, together with the contributions appearing in this special issue, will help provide a representative snapshot of the state of the art in mathematical models for aesthetic evaluation. Of course, due to space limitations and deadlines, it was not possible to comprehensively survey all the current work that is being done in this area. For example, the use of 'crowd sourcing' as an external factor to help evaluate the results of automated evolution will no doubt occur to many readers. While the idea has been flirted with from time to time, only recently, thanks to careful experimental design and subsequent anlaysis by Bergen and Ross [5], have meaningful results emerged. Their work is especially interesting because the evolutionary framework they implemented invokes L-systems to generate 3D virtual sculptures as opposed to genetic programming to generate abstract 2D images. We were also unable to include any of the recent work on automated evaluation involving swarm art simulations where external factors are 'borrowed' from well-established principles in the biological world (see, e.g., Greenfield [18]).

One of the challenges that lies ahead is integrating colour theory into mathematical models for evaluating aesthetics. In this special issue, Ekárt et al. view colour as an attribute orthogonal to composition, and choose to focus on composition alone by restricting their attention to grayscale images. Romero et al., on the other hand, convert colour photographs to grayscale digital images, and based on the results of their image classification task suggest that at least under some circumstances, colour may not play as important or critical role as is commonly believed. However, there can be no argument that in most cases recolouring an image can drastically affect its aesthetic evaluation. It is ironic that in this issue Dodgson uses the opponent-based Lab digital colour scheme whose origins lie in photography to analyse paintings, while Romero et al. use the HSV digital colour scheme whose origins derive from the iconic *plein air* painter's palette to analyse photographs. Clearly, the question of how best to treat colour cannot be easily sidestepped or finessed.

A grayscale image defined using a single 8-bit channel can be pseudocoloured by interpreting the channel values as indices into a colour look-up table. This observation has been used to evolve palettes for recolouring images by one of us (Greenfield) using both interactive evolution [12] and automated evolution [15]. There also exist colour images of a special nature that can be recoloured on a pixel by pixel basis given a small, fixed set of colours (see Dodgson in this issue, or Greenfield and Field [19]). Perhaps examples such as these can serve as future testbeds and controls for integrating colour theory into our mathematical models in a more natural way.

In conclusion, we will be pleased if readers come away from this issue with added interest and insight concerning not only the many facets involved in designing, implementing, and using mathematical models for aesthetic evaluation, but also the philosophical issues regarding the nature of aesthetics, art and authorship that this line of work raises.

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