Computational Music Aesthetics: a survey and some thoughts

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Abstract. While computational aesthetic evaluation has been applied to images and visual output, it is not as widely employed for generative music systems. Computational aesthetic evaluation is not to be confounded with numerical evaluation of the system's output; such a notion is in danger of offering a reduced and impoverished interpretation of the aesthetic experience, which is innately dialogical, between the creator or the user, the sociological context, and the creative process or product. This paper reviews common computational aesthetic measures that have been used for musical applications, whilst arguing for a pragmatist perspective and a framework foregrounding the primacy of intentionality and agency in inducing aesthetic responses.

Keywords: Computational Aesthetics, Computational Creativity, Music Aesthetics

1 Introduction

Computational aesthetics is an area of study relevant to the broader context of computational creativity. In its effortsf to overcome its ontological contradiction (representing experiences in an abstracted model), to endow systems with the ability to judge the aesthetic value of a digital process or artefact, or to provide humans with opportunities to re-assess their own aesthetic judgment and experience, computational aesthetics has had little application outside the domain of visual art, graphics and design. In particular, computational aesthetics is scarcely employed in systems able to autonomously generate music.

This paper reviews the developments in this area, arguing that more needs to be done to distinguish the notion of aesthetics in computing from that of evaluation and/or optimisation. Via employing cases of peculiar but highly aesthetically valuable musical works and genres, this paper highlights the contradictions of a challenging field, proposing that the aesthetic stance (of the human designer or of the machine) should be regarded as the core impetus of the generative, creative or artistic process, deeply rooted in the idiosyncrasies of the creator's aspirations, instead of emerging as a by-product of the system's design.

2 Computational Aesthetics

Computational aesthetics is thought of as the theory, practice and applications of aesthetics in computing. There can be two ways to approach this notion. One examines the aesthetic value that a computational process (e.g., an algorithm) or computational product (e.g., an algorithmically generated artwork) holds for a human. In other words, this approach sees computational aesthetics as a notion more closely related to an aesthetic of digital arts [1]. The other is instead concerned with endowing computational systems with the ability to evaluate the aesthetic value of their own process and/or product. Galanter [2] similarly proposes two types of computational aesthetics, one catering for human notions of beauty, the other catering for an emerging machine meta-aesthetics.

It has been noted [3] that perhaps the term *artistic* would be a more appropriate choice in place of *aesthetic*, since the latter has deep philosophical and cognitive implications that currently transcend the narrower domain of computational aesthetics. For example, Tischler [4] claims that relations linked to aesthetic value can be divided into internal and external relations. Internal relations entail syntactical, case specific, unique features to the medium. External relations are so broad as to encompass ethics, culture, morals, emotions, and so forth. It is perhaps premature to project such ambitions onto computational systems lacking a complexity and cognitive functionality of this magnitude.

The term computational aesthetics presents a peculiar paradox, suggesting that a relation between a method of abstraction (computing) and a theory of experience (aesthetics) is even attainable [5]. Through simulation of processes contributing to the appreciation of an artistic product, however, lessons can be learned which might provide insights and opportunities for philosophical and artistic investigation. Therefore, while “the assumed roles of aesthetics as applied to computing are too limiting” [6, p. 12], it is crucial to interrogate this notion.

Aesthetics in the broader context of creativity. Distinctions have been made between *personal* creativity (creative activity that is novel to the individual, but not necessarily novel to society) and *historical* creativity (creative activity that is novel at a societal level) [7]. Similarly, it is paramount to define whether the aesthetic evaluation carried out is personal (relevant to the aesthetic preferences of a human or a computational individual), context-specific (relevant to the aesthetic preferences of a given sample of humans or computational individuals) or context-agnostic (universally relevant). Therefore, the issue is about what specific aesthetic problems or goals one chooses to consider or pursue.

Computational aesthetics as a field has different connotations for different people. In fact, often it “has been appropriated by engineers to mean the automated evaluation of image quality, by critics to mean the distinctive material genres of computer arts, and by technologists to mean specific programming technologies” [3, p.88]. Thus, computational aesthetics might be confounded with numerical optimisation of the designers’ injected measures, such as complexity, information rate, and so forth, some of which will be reviewed in due course (see Section 4). Other times, computational aesthetics might be taken to mean a set of principles able to procedurally define and characterise the works of a specific art movement, artwork or theory. These reduced scopes, while congenial to automatised procedures and programmatic enquiry, might offer an impoverished version of the aesthetic experience or process.

Nevertheless, researchers in this area do not shy away from declaring the independence of computational aesthetics from broader critical considerations about art and nature, or "higher order semantic and meaning in the arts" [2], a strategy which might well be the Achilles' heel of computational aesthetics (see Section 3). It has also been posited that one needs not aim at grand results in the area of computational creativity, or "considering what it would mean to be radically original" [p. 78][8] but rather that one can proceed by scaffolding incremental advances and attainable results, thus building a solid body of knowledge from the ground up. According to this strategy, goal-oriented methods are valid options and, in constraining the scope of the application, they can provide useful insights. This strategy does however run the risk of falling foul of the same criticism as this critique of Artificial Intelligence researchers in 1974: "What they are doing is like trying to make a flying machine by sticking feathers into a potato. It looks like a bird, and they have discovered that if it is shot up into the air by a stronger catapult it will 'fly' better, in that it takes longer to reach the ground again. This is their measure of progress." [9]

Therefore, a few broader considerations are due on aesthetics in general and in music, before we are ready to review what has been done specifically in the domain of computational music aesthetics.

3 (Music) Aesthetics

In its historical trajectory starting from music as mathematics (going back to Pythagoras) up to music as emotional expression [10, 11] via music as language [12, 13], music aesthetics often inherits implications based on the vernacular meaning ascribed to aesthetics, one which identifies the objective of this field as the study of what is beautiful. However, aesthetics span a broader spectrum, one which considers "all the configurations of art" [14, p.50], to include the not-so-beautiful, the ugly and the unpleasant. Epperson, for example, poses that musical aesthetics is a comprehensive theory which aims at integration and synthesis. The trajectory of aesthetics has moved beyond the theory of taste and beauty expressed by Hume [15] and Kant [16], or of Hegel's philosophy of fine art [17], towards philosophy of criticism [18], art as experience [19] and pragmatist aesthetics [20]; unfortunately it has been argued that "aesthetic interpretation in computer science is developing in isolation from the aesthetic discourse in philosophy and art history" [21, p.16]. According to Dewey [19], an artwork does not have an innate, universal and abstract aesthetic dimension/value; instead this is defined in relation to the socio-economic and political context the artwork is embedded in. "Aesthetic is not something a priori in the world, but a potential that is released in dialogue" [22, p.3], thus an emergent phenomenon.

At current stages of development, a computational system aimed at generating music or art is usually a closed system, generally lacking on a dialogical and relational coupling with the external world, possibly with the exception of co-creative systems [23, 24]. Even with the two-way relationship of influence afforded by co-creative systems: although it is clear how the computational agent(s) might influence the human ones in their creative process and outlook, the reverse is not always certain and is less well understood. As for systems that include crowd-sourced injections to engage with the external world (e.g., mining Twitter[3] or crawling Wikipedia's[4] corpus), the *opinion* such systems end up with might not be sufficiently *individual* in terms of aesthetic preference and judgment. For example, in the case of a system employing aggregation or statistical procedures over the users' personal preferences, this would produce the dominant (majority or average) aesthetic sensibility over the sample population. This, in an artistic scenario, could be an undesirable notion of aesthetics. Forming an aesthetic preference through a dialogical relationship with the socio-cultural environment does not equate averaging everyone else's opinion, or deciding for the most trending choice, but rather negotiating personal goals and aspirations with the broader context. This might be a fuzzy process, originating a wide range of results, from contradictory and shifting to coherent and consistent.

In music (and in other domains, such as the visual arts), the notion of aesthetics foregrounds the intention to induce phenomenal experiences, thus aesthetics is linked to direct control, a conscious goal-oriented activity, or autonomous agency. This, when applied to a machine, begs many questions: an effective springboard for re-evaluating one's own process of aesthetic judgment. Aesthetics relates to our affective response to a (creative) process/object or phenomenon, thus links to perception. However, aesthetic judgment goes beyond sensory discrimination, involving some measure of pleasure derived from our experience, as well as considerations of, for example, moral, ethical or political nature.

While attempts to define aesthetics universals have been made [25], many works of art defy these axioms altogether. One example is conceptual art, where "the object only has value as a materialisation of the idea, not in and of itself" [26, p.137]. As a musical example of conceptual art, John Cage's *4'33"* [27] can be employed. What sort of discriminatory process would a designer have to embed into a generative system so to produce an instance of John Cage's work? What aesthetic measure could be used by a computational system to evaluate its output as valid, if this corresponded to a few minutes of silence? According to [28], creativity is a synthesis of four necessary strands, of which the creative product is but one isolated aspect of the whole phenomenon (the others being: person, process and press/environment). Therefore, in the case of *4'33"*, what would be more likely to be evaluated is the intention to output silence, the process and the motivations behind it, situated in a performance environment, rather than the end product. Since the use of this example might raise a few eyebrows, because it can be seen as a gratuitous, nihilist attempt to

[3] https://twitter.com/

[4] https://www.wikipedia.org/

pack the discourse before it can start, it is worth considering further examples that might confute universal aesthetic measures, in favour of strong, intentional aesthetic stances. One is the case of Japanoise [29–32], a combination of harsh noise, ear-shattering sound, feedback and distortion; another is the movement of Microsound [33–35] or Onkyokei artists [36, 37], who employ transient audio phenomena at the edges of the range of human hearing; yet another is Free Improvisation [38, 39], a musical expression that claims to have no idiomatic musical referent.

These examples can be considered rather atypical, in that they break sufficiently many conventions as to warrant them a tag that Boden terms *transformational* creativity [7]. One can think of transformational creativity as the qualitative difference that is applied to a conceptual space [40] such that the boundaries of the conceptual space are transformed to encompass new possibilities. In contrast, *exploratory* creativity is a milder degree of change, whereby possibilities only within the boundaries of the conceptual space are investigated and enquired. Of course, it is unreasonable to pose that all music works or processes should be cases of transformational creativity, as argued in [41], and it is often the case that artists and users prefer producing or listening to examples of exploratory (musical) creativity. Nevertheless, accounting for the possibility of an instance of transformational creativity autonomously emerging/arising in the context of a computational system seems a desirable option to keep for consideration. To appreciate why, it is helpful to remind ourselves that before anything was a *genre* or a *style* itself, it probably constituted either a case of transformational creativity or of successive, layered explorative acts (until a consensual threshold was met). Therefore, to concentrate exclusively on exploratory systems can only offer a partial account of both creativity and of aesthetics.

The next section reviews examples of computational aesthetic measures found in the music literature, examining how these account (or fail to) for the unpleasant, the peculiar, the un-normalised and the outlier. This will sometimes be complemented using instances of musical works that fail to meet such aesthetic measures, but which are nevertheless considered seminal musical exemplars with a high aesthetic value, such as the cases aforementioned (Japanoise, etc.).

4 Computational Music Aesthetics

While clear-cut distinctions are unreasonable to make, it is useful to distinguish some general categories of aesthetic measures. The examples presented in this section do not aim to be exhaustive, but rather representative of different viewpoints. In particular, a general knowledge of computational aesthetic evaluation is assumed, for the sake of space and to allow this article's scope to retain more focus on computational music aesthetics.[5]

[5] The reader is encouraged to consult [42, 2] for an overview of the general field of computational aesthetics

Information/complexity-based aesthetic measures. Several have been proposed, including measures by Birkhoff [43], Machado and Cardoso [44], Bense [45], Moles [46], Schmidhuber [47], and Gell-Mann and Lloyd [48]. A musical example is the *Audio Oracle* (AO) [49–51] algorithm. AO uses Information Rate (IR) as an aesthetic measure, combining Meyer's [11] insights on musical expectation and Shannon's information theory [52]. For a given signal x, IR is defined as

$$IR(x_{past}, x_n) = H(x_n) - H(x_n|x_{past}) \tag{1}$$

with $H(x_n)$ and $H(x_n|x_{past})$ being Shannon's entropy and conditional entropy, respectively. In other words: this aesthetic measure, the information rate, is calculated as the difference between the degree of uncertainty of the current musical information, compared to that which was expected, given the past observations.

The AO, a graph structure on indexed segments of a recording's audio features, inherits its aesthetic stance from the audio material it analysed offline or that is analysing in real-time. While yielding impressive results in the context of human-machine musical improvisation, AO depends on the musical aesthetic intrinsic in the audio it analyses. That is, the AO does not have an aesthetic opinion *per se*, nor does a system employing AO have an aesthetic opinion just by virtue of using it. One could bestow aesthetic responsibilities to the algorithm itself and its optimisation, perhaps not making justice to the complexity of the aesthetic discourse as outlined in Section 3.

Similarly to Birkhoffs's aesthetic measure, which is more of an indicator of orderliness than beauty (and ignores the problematic beauty-aesthetics association), AO is a measure of information that fails to shed light on what specific aesthetic intention the system has. Repetition or redundancy have qualitatively different meanings, interpretations and value in the arts, compared to information theory [53]. "[T]his is why the tempting prospect of applying information theory to the arts and thereby reducing aesthetic form to quantitative measurement has remained largely unrewarding" [54, p.16]. It is important to keep this in mind when engaging in cross-space mappings between domains. Using IR for *4'33"*, for example, would yield disappointing results, since the piece is completely redundant in terms of information, yet could be considered a masterpiece in terms of aesthetic stance. Using the term "computational aesthetics" to describe automatic evaluation methods of the system over a set of parameters or audio features makes for a difficult reconciliation of this notion of aesthetics with one that foregrounds the autonomous agency of the creator (human or machine).

Geometric measures of aesthetic value These include the application of sequences, such as the harmonic or the Fibonacci series, ratios such as Golden Ratio or Zipf's Law, and fractal dimension. In the broader context, the latter was investigated by Spehar et al. [55] and, based on their findings, by Heijer and Eiben [56]. In the musical domain, fractal dimension was studied by Voss and Clarke [57], who claimed that the $\frac{1}{f}$ distribution is a good model for pitch and loudness fluctuations in music.

Manaris, on the other hand, used Zipf's Law extensively in his work. Linked to the power law distribution, it expresses the occurence frequency of an n^{th}

ranked event e, using the ratio $\frac{1}{n^a}$, with a being close to 1. Essentially, this law states that the probability of an event occurring is inversely proportional to its frequency of occurrence. Manaris and his collaborators [58] examine, based on their bespoke metrics (11 in total), a corpus of 220 songs, in different genres. The statistical analysis of the combined metrics is presented as evidence that music abides by Zipf's and Mandelbrot law, with only the pieces following a white noise distribution (random) failing to meet the authors' R^2 threshold (0.7).

There are a couple of troublesome details in Manaris et al.'s study: firstly, the intrinsic assumption that there is, or there can be, a universal concept of "beautiful music". As stated in Section 3, the focus of aesthetics has moved beyond the definitions of what is beautiful or trying to define a generalisable sense of like/dislike. Just as "music theory has gotten stuck by trying too long to find universals" [59, p.328], so too have computational accounts of musical creativity often followed this quest for general notions of beauty and aesthetic value - to the detriment of a conceptual strength and individuality that are the landmarks of seminal musical works. Secondly, if one was to use Zipf's Law as a measure to evaluate, for example, Merzbow's *Woodpecker No.1*, from the album Pulse Demon [60], the herald of Japanoise would fail the aesthetic test. Countless more examples in this genre would contradict not just the power law distribution but also a consensual notion of what is beautiful or pleasant.

In another study [61], Manaris et al. present a three-stage process whereby they first train a neural network to predict song popularity, then use a genetic system to produce instances of 'popular' music based on the preceding stage, and finally compare results from evaluation of both artificial and human critics with respect to a selection of pieces taken from stage one and stage two. Despite the positive results, the paper and the experiments rest on an arguable foundation, that which foregrounds the correlation between popularity (measured by number of downloads) and aesthetics (beautiful or, at least, successful music) as well as a nebulous notion of *pleasantness*, or lack thereof. The latter was used to discriminate between 16 pleasant pieces (one original Bach's and 15 pleasant variations generated by the genetic system) and 2 unpleasant ones (also generated by the genetic system). The reader is never told what an actual unpleasant piece sounds like, being left to satisfy their curiosity with a quote from Barret and Russell which describes pleasantness as a "basic and universal dimension of affect" [62, p.13]. Furthermore, the authors used the MIDI [6] format, which can be problematic for conveying musical expression and emotional content. Such a symbolic notation can offer rather dry renditions of a musical work, and is perhaps more appropriate for tests on musical surface, structure, form or theory, rather than aesthetics.[7] Moreover, it is important to recall what was discussed in Section 2 regarding personal and historical creativity, and how these two different processes reflect on the aesthetic value of the products they generate. In other words, many artworks (or artists) that left a mark were not popular at

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6 https://www.midi.org/

7 We do not mean to imply here that surface, structure, form or theory are *independent* of aesthetics, and acknowledge that these can be contributory to aesthetics.

their time of production (or life). Therefore, popularity by number of downloads might not be the most useful strategy.

Psychological measures These are also commonly used in computational aesthetics. *Gestalt* principles of grouping (e.g., similarity, proximity, continuity, closure) have been applied to image analysis and visual art [63] but they have also been central in the music domain, with regards to meaning, expectation and grammar [11, 64, 12]. Theses ideas and their applications have deep ramifications in the aesthetic judgment of music.

Einsenberg and Thompson [65] tested Berlyne's Arousal Potential theory [66, 67] with respect to the evaluation and aesthetic appeal of improvised music. Berlyne discovered that factors such as novelty, uncertainty, complexity and conflict are important for aesthetic preference. In their study, Eisenberg and Thompson found no support for a non-linear relationship between complexity and liking. Strong correlations between complexity, creativity and technical goodness, and the overall liking of the improvised pieces were reported, however, the relationship complexity-liking was found to be linear. Their study provides yet one more example of a musical aesthetic (freely improvised music) that might defy universals and claim a bespoke approach to its appreciation.

Regarding Gestalt principles and their application to music aesthetics, one could not omit the contributions of Narmour's *Implication-Realization* model [64] and Lerdhal's and Jackendoff's *Generative Theory of Tonal Music* [12]. While the authors of the latter claim that such theory does not possess aesthetic attributes [68, p.307], in contrast to Schenker's *Ursatz* [69], these formal approaches describe the cognitive process of perceiving and understanding (some) music and, therefore, can be considered as frameworks which come with a strong, coherent aesthetic as an added bonus. These theories have had computational implementations [70–75] which, although used mostly for musical grammar parsing and structural segmentation (e.g., computational musicology), are useful tools in the context of music aesthetics. In [76], for example, the authors start from known notions of music theory or music cognition (preference rules such as proximity, range constraint, good continuation, closure, as well as Berlyne's arousal theory [66]) to decide which measures to choose for testing the aesthetic value of an artwork or art process.

Similarly to what was encountered in the Zipf's Law musical examples, the issue with Gestalt-based aesthetic measures for computational systems aimed at generating music is that they assume that the system should cater for a human-like sensibility, whereas, in fact, there are no cognitive processes at work insofar as the system is concerned, only operational rules. Gestalt-based measures might work well for a human notion of aesthetics but they need not be applied to what could be an emergent machine meta-aesthetic. As for grammar-based approaches (and despite the many similarities between language and music [77, 13]): these assume an innate, language-specific, universal grammar. Hierarchical approaches to structure in music ultimately hope to unveil "cognitive principals, or 'universals', that underlie all musical listening, regardless of musical style or acculturation" [68, p.289]. This is a problematic proposition since, not only local grammars are perfectly valid in music, but, even if it was the case that a universal grammar existed, it would probably be desirable to subvert it for artistic or aesthetic reasons. Meehan goes as far as to say: "from the fact that people often make perfect sense of sentences that are ungrammatical, we can conclude that grammar isn't very important." [78, p.61]

Biologically-inspired measures of aesthetics are strongly linked to genetic algorithms and frameworks including multi-agent systems. These add a social dimension to aesthetics, in that it becomes a negotiated and emergent notion. Groups of collaborating agents might outperform single agents, in accordance to the notion that "the definition of a creative artwork is thus a social construct of more than one agent" [79, p.20]. Evolutionary algorithms have been used for generative visual art and music systems [80] but are also widely employed in music [81–85]. Multi-agent [86] and swarm agent systems [87] are good examples of population-based music systems, while connectionist approaches such as artificial neural networks are now ubiquitous in the field of generative art, from image style transfer [88] to hallucinatory visual artefacts [89] and aesthetic selection [90], as well as in computational musical creativity [91–94].

There are limitations to the conceptual aesthetic contribution of automated fitness functions or evaluation metrics based on loss functions. That is to say, evolutionary or deep learning algorithms are used primarily as generative methods with an associated emergent aesthetic as a default by-product. Similarly, for multi-agent or swarm-based systems, the idea of social interaction is bounded by behaviours which are hard-coded and decided a priori by the designer of the system. This can misrepresent the idea of negotiation because it does not offer the opportunity, for any given agent, to exhibit totally radical behaviours. In terms of the dialogical nature of aesthetics, the dialogue between the sociocultural environment and the individual is greatly reduced due to a population of task-oriented monads who have no awareness of the system as a whole.

The examples examined so far not only reveal that the injected measures of beauty are subjective, but also that many experiments and theories on musical beauty, pleasantness, well-formedness and so forth, are strongly dependent on arbitrary assumptions about the very nature of what music is. Being so context-specific, these measures are unlikely to prove universal or even generalisable notions of aesthetic value and judgment (should such notions even be a reasonable target; see Section 2). Sometimes, aesthetic measures are chosen without interrogating too deeply on a conceptual or philosophical level, and often goal-oriented tasks such as generating music in a particular idiom or style are considered sufficient aesthetic motivations. This survey has highlighted some conceptual hurdles which need to be considered carefully in the discourse on computational music aesthetics as a field of inquiry.

5 Discussion

The examples above have particularly shown that aesthetic measures are often confounded with a numerical/consensual evaluation of the system's output. In fact, these measures coincide with, or are an intrinsic part of, the algorithms used to generate the musical output. Therefore, it can be useful to consider lessons learned in the evaluation of computational creativity and to analyse how these can help the discourse on computational music aesthetics.

Evaluation of computational creativity has proven an equally difficult topic, and different approaches have been proposed, from qualitative and user-centered [95–97], to mixed methods [98], via Turing-Test approaches [99][8] and bespoke formal methods [101–103]. Of particular interest to this paper is the method proposed by Jordanous [104], the Standardised Procedure for Evaluating Creative Systems (SPECS). Jordanous poses that, rather than seek generalised consensus on what is creative, the designer of a system should state clearly the specific notion of creativity that the system is supposed to exhibit. This construct would then be used to derive appropriate metrics and test the system based on these.

Similarly, rather than abdicating aesthetic responsibility in favour of an unattainable idea of generalisable and consensual beauty, an idea that has been long surpassed in the aesthetics historic discourse, one should aim at case-specific and personal aesthetic statements. These would be the core motivations for implementing a generative music computational system, conferring conceptual stature to the system and, consequently, to its product. In other words, the aesthetic stance would come first, informing subsequent choices on how to best let it come through, for example, which generative methods would be most appropriate or efficient, which internal acts of self-evaluation (of the system) with respect to the chosen aesthetics, and so forth.

Perhaps closer to how creative (human) practitioners operate, it is worth examining a perspective where the computational aesthetics of an artwork or product precede the methods, techniques and measures used to evaluate the artefact. Since the aesthetic stance is augmented and extended beyond unprecedented limits, through what has been referred to as the *algorithmic stance* [105], one no longer has to focus on metrics fit for humans to evaluate the product or process of computational systems, but can embrace the emerging machine meta-aesthetics. However, this does not mean relying entirely on it, or expecting that this emergence, akin to a by-product induced from the generative part of the system, will suffice to the aesthetic needs of an artwork. While this might be true in some cases, this approach could prevent the rise of radical aesthetic instances. Since "why we like or dislike something will often have a lot to do with motivational and emotional factors-considerations about which current Al has almost nothing to say" [106, p.354], it is unreasonable to expect, in a com-

[8] It should be noted that Turing-Test approaches to creativity evaluation have been roundly criticised by [100] for encouraging test-passing behaviour and 'pastiche' (uninformed replication of human creative activity) rather than genuine creativity.

putational system, human-like levels of autonomous agency, intentionality and motivation in the aesthetic judgment and aspiration level. Perhaps, until:

– an autonomous computer system that generates music is able to exhibit some degree of motivational and conceptual grounding for the aesthetic decisions that it makes
– this aesthetic motivation and intentionality is the source of the system's generative impetus rather that an a-posteriori tag or a by-product of its architecture or design
– the aesthetic measures used are sufficiently distinguished from the evaluation of the system's output or the optimisation of its algorithms and methods
– art historians are engaged in the field as much as computer scientists (who have so far been trusted with the responsibility of artistic interpretation)

one should be cautious in using the term computational aesthetics lightly. Lacking an agreed-upon general notion in this respect, it would be safer to "cede decisions to those others more concerned with what, for better or for worse, we call aesthetic form and fitness." [59, p.353]

A useful approach could be derived from the models of co-creativity, whereby one could treat the combination of the system and its designer as a co-aesthetics unit. One could begin with a partnership model with artist control [107], where the control is exercised at the conceptual stage, until the computational part of the combo is able to exhibit a sufficiently strong autonomous intentionality with respect to aesthetic motivations.

6 Conclusion

This paper reviewed some of the aesthetics measures used in computing for evaluating the musical product of a system. In doing so, several conceptual issues emerged, prompting discussion of an unresolved topic in this discipline: the relation (or lack) of computational aesthetics to the broader context of aesthetics.

While recognising that, to progress in this field, small attainments probably need to be sought, it is unreasonable and undesirable that computational aesthetics continues to develop disregarding the historical and philosophical discourse around the arts. In particular, boilerplate notions of musical beauty need to be reconsidered if one is to wish for truly creative computational systems. After all, if "machines do not allow their creativity to be frustrated by conventions" [108, p.156], why inhibit them with our own? At the same time, should we be content with the machine meta-aesthetic dimension offered by a system which might still lack intentionality in this regard?

With the augmented scope for aesthetic enquiry presented by the introduction of a new actor (the machine), new opportunities arise to question our cherished notions of beauty, pleasantness, order and purpose. In the field of computational music creativity, maintaining a dialogical approach and an open mind are key, as well as fostering and exploring notions of co-aesthetics and co-creativity, and the necessity for communication, attentive listening and a shared language across the many disciplines and sub-domains entailed in such endeavour.

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