

# On Symmetry, Aesthetics and Quantifying Symmetrical Complexity

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**Abstract.** The concepts of order and complexity and their quantitative evaluation have been at the core of computational notion of aesthetics. One of the major challenges is conforming human intuitive perception and what we perceive as aesthetically pleasing with the output of a computational model. Informational theories of aesthetics have taken advantage of entropy in measuring order and complexity of stimuli in relation to their aesthetic value. However entropy fails to discriminate structurally different patterns in a 2D plane. In this work, following an overview on symmetry and its significance in the domain of aesthetics, a nature-inspired, swarm intelligence technique (Dispersive Flies Optimisation or DFO) is introduced and then adapted to detect symmetries and quantify symmetrical complexities in images. The 252 Jacobsen & Höfel's images used in this paper are created by researchers in the psychology and visual domain as part of an experimental study on human aesthetic perception. Some of the images are symmetrical and some are asymmetrical, all varying in terms of their aesthetics, which are ranked by humans. The results of the presented nature-inspired algorithm is then compared to what humans in the study aesthetically appreciated and ranked. Whilst the authors believe there is still a long way to have a strong correlation between a computational model of complexity and human appreciation, the results of the comparison are promising.

**Keywords:** Human aesthetic perception · Symmetry and complexity · Aesthetics · Swarm intelligence · Dispersive flies optimisation

## 1 Introduction

For decades, evolutionary computation enthusiasts and researches have been working on generating aesthetically pleasing images, which include Bimorphs of Dawkins [10], Mutator of Latham [39], and Virtual Creatures of Sims [37] and many more. Acknowledging the presence of some impressive outcome by researchers and digital artists, one of the remaining key questions is how to conduct the aesthetic selection. According to McCormack [25], the subjective

comparison process in the evolutionary process is slow and forms a bottleneck, even for a small number of phenotypes. Human users would take hours to evaluate many successive generations that in an automated system could be performed in a matter of seconds. Secondly, genotype-phenotype mappings are often not linear or uniform. That is, a minor change in genotype may produce a radical change in phenotype. Such non-uniformities are particularly common in tree or graph based genotype representations such as in Genetic Programming, where changes to nodes can have a radical effect on the resultant phenotype. In this study we approach the problem in the framework of dynamical systems and define a criterion for aesthetic selection in terms of its association with symmetry. The association of aesthetics and symmetry has been investigated from different points of view. This work is an extension of an earlier work [17], where the correlation between human aesthetic judgement and spatial complexity measure has been explored using information gain model.

In this paper, the authors present an overview of symmetry and its significance on aesthetics, giving examples of types of symmetries as well as providing an account on symmetric vs asymmetric analysis and their links to aesthetics and beauty. Then Dispersive Flies Optimisation<sup>1</sup> (DFO) [1], a swarm intelligence algorithm, is presented, followed by explanation on how the algorithm could be adapted to detect symmetries in images. This process is then further expanded to generate a quantitative figure representing the symmetrical complexity of an input image. The results of the swarm intelligence algorithm are then compared against a collection of images, which are ranked by humans for their aesthetics (the images are created by Jacobsen and Höfel, who have designed the dataset to study the human perception of aesthetics).

## 2 Symmetry and Aesthetics

The association of aesthetics and symmetry has been extensively investigated in the literature. A study to investigate the effect of symmetry on interface judgements, and the relationship between a higher symmetry value and aesthetic appeal for the basic imagery, showed that subjects preferred symmetric over non-symmetric images [4]. Further studies found that if symmetry is present in human face or body, the individual is judged as being relatively more attractive [14, 33].

Symmetry plays a crucial role in theories of perception and is considered a fundamental structuring principle of cognition [23]. In the Gestalt school of psychology, things or objects are affected by where they are and by what surrounds them, with the aim of understanding the things or objects as more than the

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<sup>1</sup> Despite the algorithm's simplicity, it is shown that DFO outperforms the standard versions of the well-known Particle Swarm Optimisation, Genetic Algorithm (GA) as well as Differential Evolution (DE) algorithms on an extended set of benchmarks over three performance measures of error, efficiency and reliability [1]. It is shown that DFO is more efficient in 84.62% and more reliable in 90% of the 28 standard optimisation benchmarks used; furthermore, when there exists a statistically significant difference, DFO converges to better solutions in 71.05% of problem set.

sum of their parts [5]. The Gestalt principles emphasise the holistic nature of perception where recognition is inferred (during visual perception) more by the properties of an image as a whole rather than its individual parts [18]. Thus, during the recognition process, elements in an image are grouped from parts to whole based on Gestalt principles of perception such as proximity, parallelism, closure, symmetry, and continuation [29]. In particular, symmetric objects are more readily perceived [8]. It is not surprising that humans find sensory delight in symmetry, given the world in which we evolved. In our world the animals that have interested us and our ancestors (as prey, menace, or mate) are overwhelmingly symmetric along at least one axis [32]. Evolutionary psychologists examine physical appearances such as symmetry as an indirect measure in mate selection [26, 27]. Additionally, symmetry is positively linked with both psychological and physiological health indicators [36]. In geometry, symmetrical shapes are produced by applying four operations of translations, rotations, reflections, and glide reflections.

Despite the above developing computational methods that generate symmetrical patterns is still a challenge; this is partially due to the difficulty of associating mathematics with the noisy, imperfect, real world, resulting in a small number of computational tools dealing with real-world symmetries [24].

Applying evolutionary algorithms to produce symmetrical forms leaves the formulation of fitness functions, which generate and select symmetrical phenotypes to be addressed. Lewis describes two strategies in evolutionary algorithms approach for generating and selecting symmetrical forms: “A common approach is to hope for properties like symmetry to gradually emerge by selecting for them. Another strategy is to build in symmetry functions which sometimes activate, appearing suddenly. However this leads to a lack of control, as offspring resulting from slight mutations (i.e. small steps in the solution space) bear little resemblance to their ancestors [22]”.

## 2.1 Symmetry Examples

Symmetry exists not only in geometry but also in natural world and human works. For example, water, when in liquid state, has bilateral symmetry, with the symmetric stretch of the two O-H bonds and some molecular vibrations [19, 34]. When frozen, water becomes symmetrical in various ways (however, not always), usually developing the hexagonal crystals. Many molecules such as carbon dioxide, benzene, or carbontetrachloride are perfectly symmetrical. Ice, snowflakes, feather ice on the twigs, hail, sleet, icicles, glaciers, and polar caps, all develop their own order of symmetry and various arrangements of symmetry axes. Crystals such as table salt or copper contain not many kinds of atoms and have a simple structure. Proteins, for example those building teeth, usually have complex crystalline structure and many kinds of molecules. Average local molecular orientations in liquid crystals (fluids made of spontaneously aligning rod-like molecules) are described with a head-tail symmetry [35]. We cannot ascribe the crystalline structure to inanimate forms only. Crystalline material has been separated from the tobacco-mosaic virus protein in 1933 [38].

Some viruses can organize themselves into liquid crystals. Thus, for several reasons, “current knowledge about nanostructures makes difficult defining the distinction between organic and inorganic, living and inanimate, natural and artificial, or human and machine” [9].

## 2.2 Types of Symmetry

There are several types of symmetry, for example, the line or mirror symmetry, the radial, cylindrical, or spherical symmetry. Mirror symmetry of a symmetrical object is often defined as the correspondence in size, form, and arrangement of similar parts on the opposite sides of a point, line (axis), or plane.

Radial symmetry in an object occurs when it can be rotated around an imaginary line called the rotation axis and retain the same appearance as before rotating, repeating itself several times during a complete rotation. A centre of symmetry is equally distant from any point on the surface of a symmetrical object. For example, if a crystal has a centre of symmetry, then, when laid down on its face on a tabletop, it has at the top an inverted horizontal face of equal size and shape.

Several types of geometrical symmetry include bilateral (reflection or mirror), rotational (when an object looks the same after rotation), cylindrical, spherical, and helical symmetry (like in a drill bit), and also translational (where a particular translation - moving in a specified direction does not change the object), glide reflection (in a line or plane combined with a translation), or rotoreflection symmetry (which presents rotation about an axis, combined with reflection in a plane perpendicular to that axis).

Fractals, patterns, and symmetry exist in nature and in art projects. Fractals represent form of scale symmetry that appears when the objects magnified or reduced in size have the same properties. Fractal related concepts and processes are examined in selected fields of physics, biology, or computing, and to studies on astronomy. At the same time they pertain to our Planet’s life and our own everyday experience. Mathematicians name some objects symmetrical with respect to a given mathematical operation applied to this object, when this operation preserves some property of the object. Such operations form a symmetry group of the object.

Claude Lévi-Strauss [21] recalled the opinion of a German philosopher Immanuel Kant (1724–1804) about an aesthetic judgement. Kant wrote about judgement of knowledge (conceptual judgement) and aesthetic judgement (non-conceptual judgement). In an aesthetic theory developed by Kant, judgements about beauty rest on feeling but they should be validated in harmony with mental structure, so they are not merely statements of taste or opinion. According to Kant, there are judgements of taste that are subjective and judgements of reason that are universally valid. Aesthetic judgement falls somewhere between these two kinds. Lévi-Strauss stated that, in this intermediary space, fractals are given the status of a work of art, because they are appealing and at the same time, objectively governed by reason.

### 2.3 Symmetry and Asymmetry Analysis

Scientists and artists see a purpose in symmetry investigations, for example, mathematicians, anthropologists, artists, designers, architects who conduct computer analysis of the facades, friezes, and some architectural details, as well as researchers in many fields of natural sciences, medicine, pharmacology, biology, geology, or chemistry. Many artists have created masterpieces this way. Artists used to transform patterns and repetitions to apply the unity or symmetry in their compositions (for example, by examining a Fibonacci sequence, prime numbers and magic squares, a golden section, or tessellation techniques).

Genetic algorithms and other evolutionary computing techniques are applied not only to the artistic areas but also many industries, including aeronautic and automotive design, electronic circuit design, routing optimization, modelling markets for investment, among other domains. Analysis of generative art systems may reveal an analogy with the natural systems; both systems maintain balance between order and disorder. While biological life takes on most of its forms in a spectrum between unstructured atmospheric gases and ordered crystals and minerals, generative art systems and artificial life (A-life) are placed somewhere in the middle of a continuum between disordered randomization, chaotic systems, and fractals or L-systems, and highly ordered forms such as symmetry and tiling [12, 13]. With generative approach, artists draw from natural phenomena observed in biology and physics, and their creative process may evolve into a sequence of iterative solutions and modifications transforming the artwork.

### 2.4 Aesthetics and Beauty

Natural objects displaying symmetry evoke wonder and surprise because their intricacy. For example, architecture and architectural details, such as stain windows, mosaics, and friezes, visual arts, pottery and ceramics, quilts, textiles, and carpets make a varied use of symmetry as an important principle in their design. Ferreira [11] examined architecture and cell biology in terms of biosemiotics, with architectural structures discussed as context-dependent semiotic objects with functional and/or aesthetic values. Both the natural and man-made environment can be perceived as locus, place, site, or a part of a mental map of a cultural framework. Maybe for that reason symmetry is so often seen not only beautiful but also conducive to visual communication. Possibly, artwork resulting from coding is able to convey the correctness of natural lines, symmetries, patterns, textures, light, and color, thus being something more than identification of natural objects.

In words of Andres Gaviria [15] (p.481), “aesthetics is concerned with the theory of sensual perception, while art is a social practice involved in certain forms of research and investigation processes and in the construction of particular types of artefacts.” The field of aesthetics involves studies in the arts, philosophy of art, and our judgements about art works’ qualities. Beautiful, harmonious, or emotionally pleasing objects have been traditionally considered aesthetic and thus valuable. The postmodern philosopher Jean-Francois Lyotard (1924–1998)

posed they would be sublime (Lyotard, *Lessons on the Analytic of the Sublime*, 1994). Then the criteria of beauty broadened, and judgements of aesthetic values examined also social, political, moral, and many other aspects of the art objects. Modern analytic approach in aesthetics is no longer restricted to an analysis of natural beauty because, in opinion of cubists, dadaists, constructivists, conceptual artists, generative artists, and many others, beauty ceased to be central to the definition of art. Computing science specialists examine aesthetics of electronic projects' usability, efficiency, and discuss aesthetics in terms of possible applications to controlling computer products. Evaluation of tag clouds in terms of the aesthetic quality obtained from an extensive user study confirms that aesthetic values correlate with product usability.

The foundation for the digital exploitation would include the mathematical measure of aesthetics proposed by a mathematician George David Birkhoff (2003/1933); the golden ratio (where the ratio of the smaller to the larger sub-segment is the same as the ratio of the larger sub-segment to the whole segment); the Zipf's law (studying the relation between the rank and frequency of natural language utterances); fractal dimension (providing a ratio of the change in detail to the change in the scale); basic gestalt design principles (telling about the principles of figure-ground articulation, proximity, similarity, closure, symmetry, continuity, past experience, common fate, and the good gestalt of perceptual scenes), and the rule of thirds (advising that an image should be imaginary divided into nine equal parts by two horizontal and two vertical lines, and that important compositional elements should be placed along these lines or their intersections). Computational aesthetic evaluation of evolutionary art systems may refer to the empirical studies and psychological modelling of aesthetics and neuroaesthetics.

Semir Zeki explored the domain of neuroaesthetics, a cross-disciplinary research field related to the neural basis of artistic creativity and achievement. Zeki examined brain activity associated with the perception of images. He arrived at conclusion, the visual brain functions in search for dependable qualities to obtain knowledge about the external world. Our survival in the world may thus strongly depend on the accuracy and completeness of mental models used by our mind to represent real life [28,41].

Birkhoff (1884–1944) proposed in his book entitled “Aesthetic Measure” a mathematical theory of aesthetics intended for artistic purpose: in the equation  $M=O/C$ , Aesthetic Measure (M) is a function of Order (O) divided by Complexity (C.) (see [7] and Mathematical poetry, 2015<sup>2</sup>). The Gestalt psychology theory of mind postulated that brain has self-organizing tendencies and recognizes the whole of a figure rather than its individual parts [7].

Some scientists use intuition as a guide in developing hypotheses, since laws are reflection of symmetries, and there is a connection between beauty and symmetry.

The theme of symmetry can certainly be considered inspirational to create biologically inspired art, because symmetrical forms and shapes possess an

<sup>2</sup> <http://mathematicalpoetry.blogspot.com/2006/09/equation-for-aesthetic-measure-by.html>.

aesthetic beauty and an order reflected by their geometry. We can appreciate these forms finding the importance of adaptations that animals develop as an answer to the conditions of life, examining mathematical order in natural forms, and re-creating it in our own artwork.

## 2.5 Graph and Visualisation Aesthetics

The optimal layout aesthetics has been investigated in the field of graph drawing and the aesthetics of graph drawing algorithms, to understand the effect of minimizing edge bends, minimising edge crossings, and improving symmetry. Node and edge shape, size, texture, and color are variables that could play a significant role in improving graph aesthetics [40]. Purchase [30] argued that Gestalt principles and neurophysiology can help explain which aesthetics might be important and why. The results obtained suggested that reducing the number of edge crossings, aligning nodes and edges to an underlying grid, and making the best use of symmetry, e.g. by maximizing symmetry of subgraphs were significant for graph aesthetics [20, 31]. The overall layout and the spatial relationship between nodes and edges, including graph's symmetry, area, flow, and aspect ratio, determine the aesthetics of a graph [6].

The next section explains the swarm intelligence algorithm which will be used in detecting symmetries.

## 3 Dispersive Flies Optimisation

Dispersive Flies Optimisation (DFO) is an algorithm inspired by the swarming behaviour of flies hovering over food sources. DFO, which is a recently proposed algorithm, is one of the simplest yet robust continuous optimisation techniques with only two tunable parameters which makes it an easy-to-implement yet strong optimiser. This algorithm has been applied to various fields including optimisation, medical imaging and digital art [2, 3].

To describe this algorithm, as detailed in [1], the swarming behaviour of flies in DFO is determined by several factors and that the presence of threat could disturb their convergence on the marker (or the optimum value). Therefore, having considered the formation of the swarms over the marker, the breaking or weakening of the swarms is also noted in the proposed algorithm.

In other words, the swarming behaviour of the flies, in Dispersive Flies Optimisation, consist of two tightly connected mechanisms, one is the formation of the swarms and the other is its breaking or weakening. The algorithm and the mathematical formulation of the update equations are introduced below.

The position vectors of the population are defined as:

$$\mathbf{x}_i^t = [x_{i1}^t, x_{i2}^t, \dots, x_{iD}^t], \quad i = 1, 2, \dots, NP \quad (1)$$

where  $t$  is the current time step,  $D$  is the dimension of the problem space and  $NP$  is the number of flies (population size).

In the first generation, when  $t = 0$ , the  $i^{th}$  vector's  $j^{th}$  component is initialised as:

$$x_{id}^0 = x_{min,d} + r(x_{max,d} - x_{min,d}) \quad (2)$$

where  $r$  is a random number drawn from a uniform distribution on the unit interval  $U(0, 1)$ ;  $x_{min}$  and  $x_{max}$  are the lower and upper initialisation bounds of the  $d^{th}$  dimension, respectively. Therefore, a population of flies are randomly initialised with a position for each flies in the search space.

On each iteration, the components of the position vectors are independently updated, taking into account the component's value, the corresponding value of the best neighbouring fly (consider ring topology) with the best fitness, and the value of the best fly in the whole swarm:

$$x_{id}^t = x_{nb,d}^{t-1} + U(0, 1) \times (x_{sb,d}^{t-1} - x_{id}^{t-1}) \quad (3)$$

where  $x_{nb,d}^{t-1}$  is the value of the neighbour's best fly in the  $d^{th}$  dimension at time step  $t - 1$ ;  $x_{sb,d}^{t-1}$  is the value of the swarm's best fly in the  $d^{th}$  dimension at time step  $t - 1$ ; and  $U(0, 1)$  is the uniform distribution between 0 and 1.

The algorithm is characterised by two principle components: a dynamic rule for updating the flies positions (assisted by a social neighbouring network that informs this update), and communication of the results of the best found fly to other flies.

As stated earlier, the swarm is disturbed for various reasons; one of the positive impacts of such disturbances is the displacement of the disturbed flies which may lead to discovering a better position. To consider this eventuality, an element of stochasticity is introduced to the update process. Based on this, individual components of flies' position vectors are reset if the random number,  $r$ , generated from a uniform distribution on the unit interval  $U(0, 1)$  is less than the *disturbance threshold* or  $dt$ . This guarantees a proportionate disturbance to the otherwise permanent stagnation over a likely local minima. Algorithm 1 summarises the DFO algorithm<sup>3</sup>. This algorithm has been applied to several others domains including medical imaging [2].

The next section details how DFO is instructed to detect symmetries in Jacobsen and Höfel [16] stimuli.

## 4 Symmetry Detection and Quantifying Symmetrical Complexity with DFO

This section details the process through which DFO is adapted for the purpose of symmetry detection. The algorithm is designed to detect symmetries around any focal points, these symmetries could be full or partially existing in part of the input image. The search space of the algorithm is 2D and consisting of

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<sup>3</sup> The source code of DFO algorithm can be downloaded from the following web page: <http://doc.gold.ac.uk/mohammad/DFO/>.



**Algorithm 1.** Dispersive Flies Optimisation

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1: while FE < function evaluations (FEs) allowed do
2:   for  $i = 1 \rightarrow NP$  do
3:      $\mathbf{x}_i.\text{fitness} \leftarrow f(\mathbf{x}_i)$ 
4:   end for
5:    $sb \leftarrow \{sb, \forall f(\mathbf{x}_{sb}) = \min(f(\mathbf{x}_1), f(\mathbf{x}_2), \dots, f(\mathbf{x}_{NP}))\}$ 
6:    $nb \leftarrow \{nb, \forall f(\mathbf{x}_{nb}) = \min(f(\mathbf{x}_{\text{left}}), f(\mathbf{x}_{\text{right}}))\}$ 
7:   for  $i = 1 \rightarrow NP$  do
8:     for  $d = 1 \rightarrow D$  do
9:        $\tau_d \leftarrow x_{nb,d}^{t-1} + U(0, 1) \times (x_{sb,d}^{t-1} - x_{id}^{t-1})$ 
10:      if  $(r < dt)$  then
11:         $\tau_d \leftarrow x_{min,d} + r(x_{max,d} - x_{min,d})$ 
12:      end if
13:    end for
14:     $\mathbf{x}_i \leftarrow \tau$ 
15:  end for
16: end while

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all the  $(x, y)$  coordinates of the pixels in the input image; as such the vector representing each fly is set to be its  $(x, y)$  coordinate.

The fitness of the each fly is determined by a random  $d_x$  and  $d_y$ , pointing to two equally distanced *areas* in the search space (see Fig. 1). In other words, the fly position is tested against being the point of symmetry in the image without having to evaluate all the possibilities. The rationale behind using a certain area (vs the whole image) lies in reducing the computational expense of running the algorithm; therefore, instead of comparing each pixel against its corresponding pixel, the symmetry of the point is only partially evaluated (by comparing to areas equally spaced from the position of the fly and calculating the difference between the two areas<sup>4</sup>).

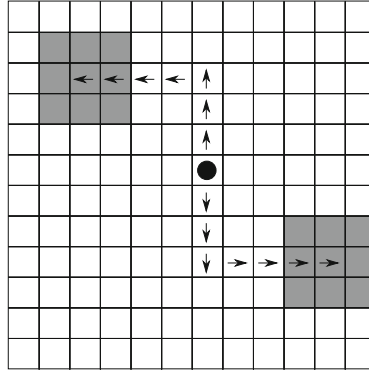
In this work, the population size of the flies is empirically set to 100 (approximately quarter of the image side), the disturbance threshold is set to 0.01, the area of comparison is set to 10px (approximately checking  $\frac{1}{500}$  of the search space in each evaluation) and 300 iterations are allowed. The size of original images are  $453 \times 453$ .

#### 4.1 Experiments and Results

All the 252 experimental stimuli were adapted from an empirical study of human aesthetic judgement [16]. Jacobsen and Höfel [16] report on an empirical trial of human aesthetic judgement. Fifty-five young adults (15 males) participated in the experiment for course credit or partial fulfilment of course requirements. All were first or second year psychology students at the University of Leipzig.

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<sup>4</sup> In this research, for simplicity, the difference of the sums of the two areas are considered. Other more sensitive or computationally expensive measures, such as the histogram of oriented gradients (HOG), could alternatively be used.



The fly's position is shown as a circle, with  $d_x = 4$  and  $d_y = 3$ ; radius is set to 1.

**Fig. 1.** Partial symmetry evaluation

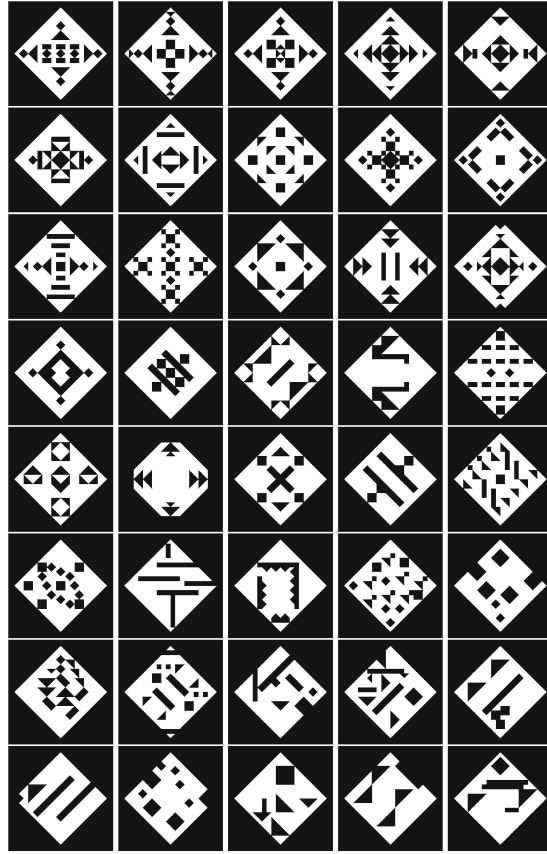
None of them had received professional training in the fine arts or participated in a similar experiment before. Participants reported normal or corrected-to-normal visual acuity. Subjects were asked to evaluate images from two groups; a group of asymmetrical images and a group of symmetrical images with at least one axis of reflection symmetry. The images consisted of a solid black circle showing a centred, quadratic, rhombic cut-out.

The black circular background was replaced by a square in order to reduce aliasing errors. The images in Fig. 2 show some of the images from Jacobsen and Höfel's research. The images are ordered by their mean aesthetic ratings (from the most aesthetically pleasing to the least).

Each image is fed into the DFO symmetry detection algorithm and the  $x, y$  coordinates of the best fly is logged, therefore each image will result in 300 coordinates showing where the the best fly in each iteration has mostly been located. This will clearly highlight the strongest point of symmetry in the image. In order to visualise the process, a few of the processed images are shown in Fig. 3. The best fly in each iteration leaves a mark in red (with transparency), therefore the areas will the strongest presence of red circle indicates the presence of symmetry.

In order to quantitatively calculate the performance of DFO over the input images, the collection of all best fly's positions are taken into account<sup>5</sup> and the *interquartile range* is calculated, highlighting the sparsity of the swarm concentration over the image well-depending on the nature of the patterns. In other words, the communications between the members of the swarm, result in identifying the best member. The communications between the members of the swarm are repeated in every iterations, and the best member of each iteration is identified and stored. It is the aggregation of the entire best members (throughout

<sup>5</sup> In other words, the  $(x, y)$  coordinate of the best fly in each iteration is logged, giving rise to 300 coordinates (the number of iterations allowed) for evaluating each image.

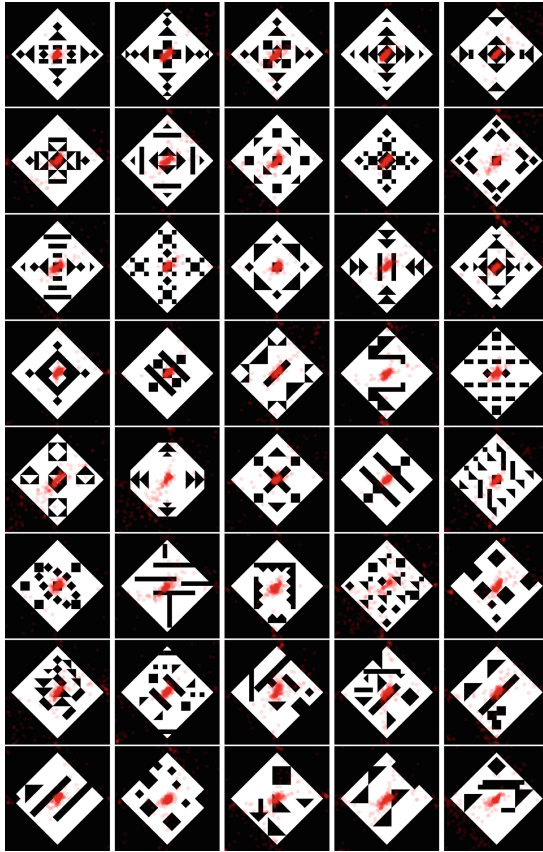


**Fig. 2.** Some randomly picked stimuli from Jacobsen and Höfel’s dataset ordered in rows from the most beautiful pattern to the least beautiful one, starting in the upper left corner

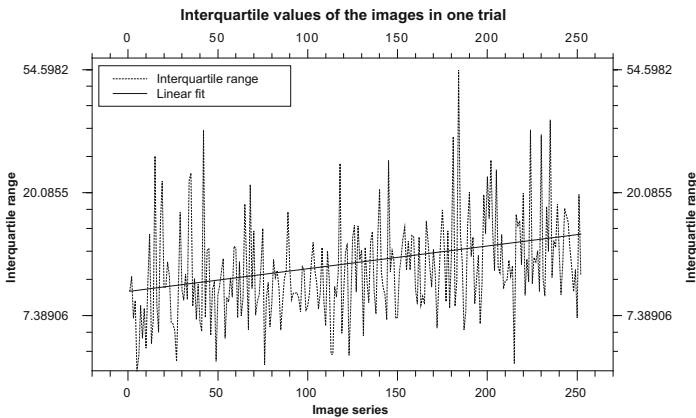
the entire iterations) that forms the results. This gives every individual iteration a stronger say in dictating the overall outcome, representing every image in the dataset. Figure 4 shows the performance of the algorithm in one trial over all the images.

In order to verify the consistency of the results, the experiment is run 10 times for each of the 252 images and the results are shown in Fig. 5. In Jacobsen and Höfel’s image dataset, the first image has the highest rank by the human observes, with the mean rating of 74.73 and the last has the lowest ranking with the mean rating of 28.58. The fitted line in the rating of these images are shown in Fig. 6.

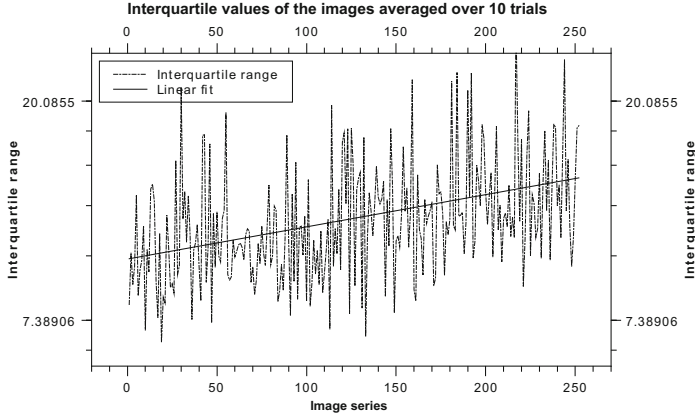
As the results and the graphs illustrate, although there might be a long distance in having a close correlation between the output of a computational model and the human judgement of aesthetics, this paper aims to highlight the



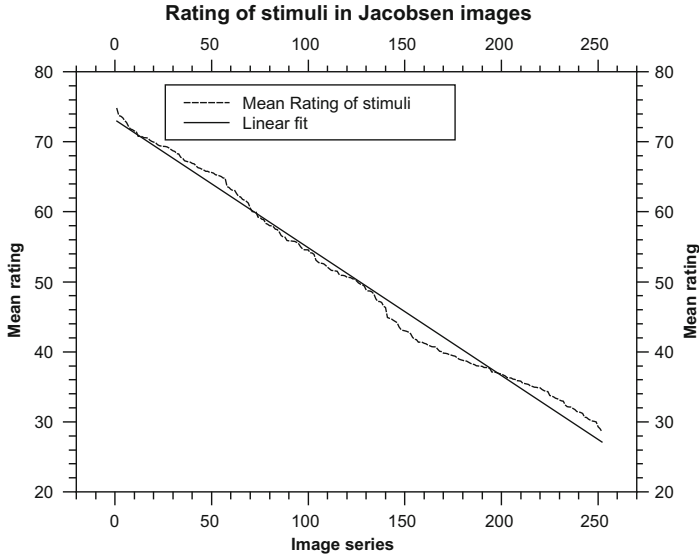
**Fig. 3.** Images processed by DFO algorithm in one trial



**Fig. 4.** Measuring symmetrical complexities in stimuli using interquartile range in one trial, running DFO over all the input images



**Fig. 5.** Measuring symmetrical complexities in images using interquartile range in 10 trials with slope = 0.021, intercept = 8.99,  $\chi = 8,032.65$ ,  $R^2 = 0.069$



**Fig. 6.** Jacobsen and Höfel's image ratings: from the most beautiful (image #1) to the least beautiful (image #252)

result of using a simple swarm intelligence technique, which is sensitive to both global symmetry as well as the localise ones in the patterns.

## 5 Conclusion

Quantitative evaluation of order and complexity has always been the heart of computational aesthetics. In this work, in addition to presenting an overview on

symmetry and its role in measuring aesthetics, a simple swarm intelligence technique is deployed to offer a method for measuring local and global symmetries. This technique focuses on utilising the essence of the collective (vs individual) intelligence in the population; this is facilitated by aggregating the “core” of each iteration (i.e. each iteration’s best member), which is then used in determining the outcome of the process for each input image. This outcome is then contrasted against the Jacobsen and Höfel image dataset which itself is ranked by humans based on their aesthetic judgements. It is demonstrated that whilst there is a long way from having a close correlation between human and machine aesthetics, there is a present, albeit not very strong, correlation between the human rankings and the ones proposed by the presented computational model.

Further research is ongoing to utilise more complex measurements for the fitness function of the swarm intelligence technique (e.g. histogram of oriented gradients or HOG), as more complex measurements could provide a more robust comparison between the areas. In addition to applying the proposed technique to the computational models of aesthetic evaluation, the result of this study could be applied to evaluate dynamically changing patterns of cellular automata and as such be able to amend the rules if the aesthetic (symmetrical complexity) of the generated patterns move away from a predefined threshold. The performance of the proposed techniques on other synthetic and ‘natural’ image datasets is currently being investigated.

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