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EVOLVING STROKES USING AESTHETIC MEASURES

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Abstract. *Computer-based evolutionary art is in the ascendant and widely applied in media contexts such as web design, games and video animation. The process of creating interesting images can be enjoyable if a useful method is involved. In this paper the effects of introducing novelty representation and evaluation in evolutionary art are explored. The technical aspects of using strokes to represent gene in evolutionary art are described, five types of strokes are defined mathematically, and genetic operators and evolutionary parameters are explained. Also, a novel aesthetic measure is provided based on data field, and used to evaluate fitness of individuals, as well as four existing aesthetic measures. A number of experiments using an unsupervised evolutionary art algorithm are performed. The results suggest that the proposed method can generate appealing images with different styles by choosing different fitness functions, and it would inspire graphic designers who may be interested in subtle aesthetic patterns created automatically.*
Keywords: Evolutionary art, Computational aesthetics, Genetic algorithm, Evolutionary computation

1. **Introduction.** Computers are changing our understanding of creativity in humans and machines, and presenting a radical new potential for extending our own creativity. Computer-based evolutionary art is an emerging field that investigates the application of evolutionary computation in the creation of aesthetically pleasing images [1]. The algorithms can be classified into two broad categories: interactive evolution and automatic evaluation-based approaches. For the latter, genetic programming (GP for short) has been previously used to create such images autonomously, and several aesthetic measures are used to calculate fitness values [2]. Generally, a lot of approaches have been proposed with relative success [3, 4, 5, 6], and deep learning is even introduced into evolutionary art [7]. In the majority of the works that have dealt with GP-based evolutionary art, there is one thing in common, using expression and tree-based genetic representation. In spite of two decades of investigation, the problem of evolving images without human-in-the-loop is still an open issue in evolutionary art. GP-based evolving images also have a number of drawbacks, and the most important one is abstract texture, which is one of the traces of computer. In fact, artists over centuries have experimented with art materials, layouts, subjects, techniques. All these have resulted in a wide variety of visual output. Thus, sustained effort is required for autonomous evolutionary art. Recently, Heijer and Eiben introduced the use of scalable vector graphics as a genetic representation for evolutionary art [8, 9], but the used evolutionary algorithm is still a tree representation-based GP.

In this context, we proposed an automatic generation method of aesthetic patterns with evolving strokes, and our intentions or research questions are three-folds: (1) Is evolving stroke a suitable representation for evolutionary art? (2) How different types of strokes can affect the aesthetic qualities of the rendered images? (3) Is it possible to evolve interesting, complex and aesthetically pleasing images using a measure of data field complexity? Thus, the study innovation includes that our proposal uses strokes as a genetic representation, mathematically defines several strokes to investigate the visual effect of evolving results, and proposes a novel aesthetic measure based on image data field to quantitatively evaluate the aesthetic quality of individuals.

The remainder of this paper is organized as follows. We propose the algorithm for evolving images generation and describe the method in detail in Section 2, as well as strokes-based genetic representation and aesthetic measures-based fitness functions. Then Section 3 shows several examples of resulting images with a brief discussion. Finally, the conclusions are drawn in Section 4.

2. Strokes Evolution Using Aesthetic Measures.

2.1. Strokes and genetic representation.

We represent each individual using a certain number of strokes. For simplicity, we mathematically define various strokes using a universal expression. Each stroke includes nine components as $[X_c, Y_c, R_x, R_y, \theta, C_r, C_g, C_b, C_a]$, denoted by s. Specifically, X_c, Y_c locate the position of control point of stroke, R_x, R_y are related with the size of stroke, θ is the tilt angle of stroke, and C_r, C_g, C_b define the color of stroke, whose transparency is determined by C_a.

(1) **Line stroke.** We first use four parameters X_c, Y_c, R_x, θ related with the location of strokes. Another parameter R_y is the line width, and we confine its value in the interval $[2, 10]$ to differ from rectangle. The remaining parameters C_r, C_g, C_b, C_a use in the later stage of drawing or filling. The discrete point set of line stroke is generated by,

$$X = X_c + R_x \cos(\theta), \tag{1}$$

$$Y = Y_c + R_x \sin(\theta). \tag{2}$$

(2) **Circle and ellipse strokes.** An ellipse stroke is a generalization of a circle stroke with $R_x = R_y$. The discrete point set of ellipse stroke is generated by,

$$X = X_c + R_x \cos(\alpha)\cos(\theta) - R_y \sin(\alpha)\sin(\theta), \tag{3}$$

$$Y = Y_c + R_x \cos(\alpha)\sin(\theta) + R_y \sin(\alpha)\cos(\theta), \tag{4}$$

where $\alpha = 0 : 2\pi$ denotes the discretely sampled points from the given ellipse.

(3) **Square and rectangle strokes.** A rectangle stroke is a generalization of a square stroke with $R_x = R_y$. The discrete point set of rectangle stroke is generated by,

$$X = X_c + d_X \cos(\theta) - d_Y \sin(\theta), \tag{5}$$

$$Y = Y_c + d_X \sin(\theta) + d_Y \cos(\theta), \tag{6}$$

where $d_X = [0, R_x, R_x, 0, 0]$, $d_Y = [0, 0, R_y, R_y, 0]$ denote coordinate values of four vertexes.

(4) **Petal-type stroke.** It is like a flower with several petals, and the number of petals is controlled by a random integer $\delta \in [3, 9]$. The discrete point set is,

$$X = X_c + R_x \sin^2(\delta\theta)\cos(\theta), \tag{7}$$

$$Y = Y_c + R_y \sin^2(\delta\theta)\sin(\theta). \tag{8}$$

(5) **Sine stroke.** It is composed of a line and a sine curve, whose point set is,

$$X = X_c + R_x \alpha \cos(\theta) - R_y \sin(\alpha)\sin(\theta), \tag{9}$$

$$Y = Y_c + R_x \alpha \sin(\theta) + R_y \sin(\alpha)\cos(\theta), \tag{10}$$

where $\alpha = 0 : 2\pi$ denotes the discretely sampled points from the given sine curve.

Each stroke can be considered as one chromosome. For each individual, the number of strokes is denoted as N_s, and then we plot each stroke, and construct an image with various strokes. To confine the strokes in a certain range, we define the bounds of coordinate axis with the height h and the width w. For the purpose of visual aesthetics, the size of strokes is limited by a constant η. That is to say, $X_c \in (0, w)$, $Y_c \in (0, h)$ and $R_x \in (0, \eta w)$, $R_y \in (0, \eta h)$. From the point of view of mathematical formalization, each individual is formed as $I = [s_1; s_2; \ldots; s_{N_s}]$, where $s = [X_c, Y_c, R_x, R_y, \theta, C_r, C_g, C_b, C_a]$ is defined on

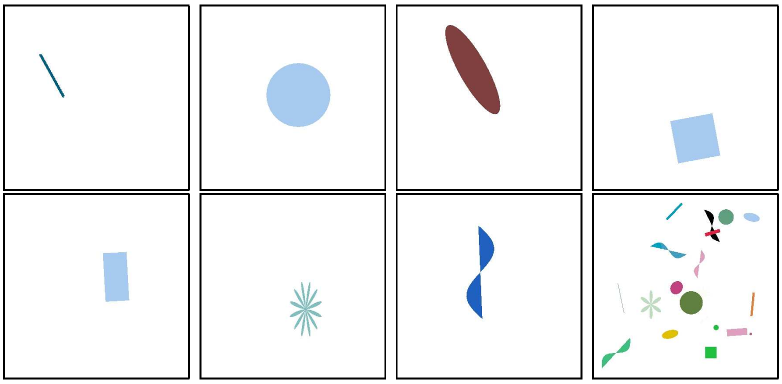


Figure 1. Examples of strokes and an individual

the above. The example strokes ($N_s = 1$) are shown in Figure 1, which in order are line, circle, ellipse, square, rectangle, petal-type and sine strokes, from left to right, from top to bottom. From the last one in Figure 1, there is an example image with $N_s = 20$ variable strokes, whose location and color are different from each other.

2.2. **Aesthetic measures and fitness functions.** In this subsection we describe the aesthetic measures used in our experiments, including Benford's law [10] (BL for short), fractal dimension [11] (FD for short), global contrast factor [12] (GCF for short) and Shannon's entropy [13] (SE for short). We provide a brief description of each measure, and full details refer to the original papers. In addition, we present a novel measure based on image data field [14, 15], named data field complexity (DFC for short).

(1) **Data field complexity.** Image data field is proposed by Wu and Gao [14] in recent years, and has been of particular interest to researchers. Its main idea is originated from physical field. Suppose $\Omega = \{p = (x_p, y_p)|x_p \in [1, w], y_p \in [1, h]\}$ is a finite space consisting of two-dimensional pixels, $f : \Omega \to [0, L-1]$ is a mapping, $f(p)$ denotes the intensity of the pixel p, and then an image is a pair $I = (\Omega, f)$, where h, w, and L are the height, width, and gray level of the image respectively.

Definition 2.1. *Each pixel $p \in \Omega$ is a particle with mass, and the intensity change interactions (attraction or repulsion) between each other form an image data field on Ω. Assuming two pixels $p, q \in \Omega$, let $\varphi(p, q)$ be the potential at any pixel p produced by q, and then it can be computed by,*

$$\varphi(p, q) = |f(p) - f(q)| \exp\left(-(\max(|x_p - x_q|, |y_p - y_q|)/\sigma)^2\right), \tag{11}$$

where $|f(p) - f(q)|$ is the strength of interaction, and can be the mass of data object, the latter is the distance of interaction, as well as the spatial weight, and σ denotes the influential factor related with interaction distance.

To obtain the precise potential value of any pixel under these circumstances, all interactions from pixels should be concerned. Thus, the potential of any pixel p in the data space is the sum of all data on radiation. Additionally, the distance of interaction is more like the Gaussian distribution, and then satisfies *three sigma rule*. The influential range of any pixel in image data field is rather finite, shorter than $3\sigma/\sqrt{2}$. Beyond this distance, pixels are almost not influenced by a specified pixel, and the potential values become zero. We fix the window size $k = 3$ in the following experiment, and $\sigma = \sqrt{2}k/3$ is calculated for Equation (11). Once $\varphi(p, q)$ is calculated according to Equation (11), the DFC measure of an image I can be determined by the average potential values of pixels, calculated as,

$$DFC(I) = \sum_{\substack{x_p=1:w \\ y_p=1:h}} \sum_{\substack{x_q=x_p-k:x_p+k \\ y_q=y_p-k:y_p+k}} \varphi(p, q)/(hw). \tag{12}$$

(2) **Benford's law.** It is a measure on the distribution of intensity of pixels. For an image, the intensity histogram is calculated using 9 bins, and the difference diff_i ($i = 1, 2, \ldots, 9$) between actual histogram and Benford histogram is calculated by,

$$\mathit{diff}_i = \mathit{Histogram}_i - \mathit{Benford}_i, \tag{13}$$

where $\mathit{Histogram}_i$ is the number of entries in the intensity histogram bin number i, and $\mathit{Benford}_i$ denotes the value from the Benford distribution.

Then the BL measure is determined by,

$$BL(I) = \left(\mathit{diff}^2_{\max} - \sum_{i=1}^{9} \mathit{diff}^2_i\right) \Big/ \mathit{diff}^2_{\max}, \tag{14}$$

where $\mathit{diff}^2_{\max} = 0.563$ is the maximal difference according to the original paper [10].

(3) **Fractal dimension.** It is characterized as a measure of the space-filling capacity of a pattern that tells how a fractal scales differently from the space it is embedded in. Images with a higher fractal dimension were considered complex, and those with a lower dimension were considered uninteresting. Considering dim as fractal dimension for a given image, calculated using box counting, the FD measure is defined by,

$$FD(I) = \max\{0, 1 - |1.35 - dim|\}. \tag{15}$$

(4) **Global contrast factor.** It computes the contrast of image at various resolutions. Images with low contrast are considered boring, that is a low aesthetic value. Contrast values at various resolutions $\mathit{Contrast}_i$ ($i = 1, 2, \ldots, 9$) can be calculated, and the GCF measure is defined by,

$$GCF(I) = \sum_{i=1}^{9} w_i \mathit{Contrast}_i, \tag{16}$$

where w_i ($i = 1, 2, \ldots, 9$) are the weight values of multiple resolutions.

(5) **Shannon's entropy.** It provides a probabilistic method for comparing pixels in an image. Using a histogram of 256 intensity values, the SE measure is defined as,

$$SE(I) = -\sum_{i=0}^{255} \mathit{Hist}_i \log_2(\mathit{Hist}_i), \tag{17}$$

where Hist_i refers to the probability of the ith bin.

For evolutionary art, we define each one of the above aesthetic measures as the fitness function. For each individual, we plot the figure according to the strokes, and then save as a bitmap. In other words, considering each individual as an image I, the fitness value of each individual can be easily calculated by Equations (12), (14)-(17).

2.3. Genetic operators.

(1) **Initialization and selection.** Initialization uses a number of parameters to create new individuals. In simple terms, the procedure for creating an initial population can be described as follows. For a given number N_p, that is, the number of the population individuals, also known as population size, we randomly generate a matrix with size of $N_p \times N_s$ for each parameter of stroke.

For selection operator, we use the well-known roulette wheel selection method, which selects potentially useful individuals according to fitness proportion, while for survivor selection we use elitist selection, that is, copying the best one into next generation.

(2) **Crossover operator.** Crossover is a genetic operator used to vary a chromosome or chromosomes from one generation to the next, and we use one-point crossover in the experiments. The crossover of the genetic code of two selected individuals I_a and I_b implies: (a) selecting one subsequence from each parent; (b) swapping the subsequence

to generate two new individuals. Supposing a crossover point $c \in [1, N_s]$, the new individuals are $I'_a = [s_{1a}; s_{2a}; \ldots; s_{ca}; s_{c+1b}; \ldots; s_{N_sb}]$ and $I'_b = [s_{1b}; s_{2b}; \ldots; s_{cb}; s_{c+1a}; \ldots; s_{N_sa}]$ respectively.

(3) **Mutation operator.** Mutation is a genetic operator used to maintain genetic diversity from one generation of a population of genetic algorithm chromosomes to the next, and we also use one-point operator. The mutation of the genetic code of one selected individual I_a implies: (a) selecting one subsequence from the parent; (b) randomly generating one subsequence with the equal length; (c) replacing the value of the chosen gene to generate the new individual. Supposing a mutation point $m \in [1, N_s]$ and the random subsequence $[sr_1; sr_2; \ldots; sr_{N_s-m}]$, the new individual is determined by $I'_a = [s_{1a}; s_{2a}; \ldots; s_{ma}; sr_1; sr_2; \ldots; sr_{N_s-m}]$.

3. Experimental Results and Discussion.

3.1. **Configuring evolutionary engine.** Table 1 specifies the parameters used to conduct the experiments for evolving art images. Certainly, it is still an open question of how to choose the evolutionary parameters. We perform 100 runs for each problem of evolving images, five aesthetic measures are used as fitness functions in the unsupervised evolutionary art, and no human evaluation or interactive evolution is involved.

TABLE 1. Evolutionary parameters of evolutionary art

No.	Name	Parameter	Value
1	Bounds of the location of strokes	h, w	256
2	Ratio of the size of strokes	η	0.2
3	Population size	N_p	50
4	The number of strokes	N_s	50
5	Generations	G	60
6	Crossover rate	P_c	0.8
7	Mutation rate	P_m	0.2

3.2. **Results and analyses.** In this subsection we describe our experiments in evolving art using the five aesthetic measures described in Section 2.2, and will answer our research questions of this paper by reporting various experimental results with a brief discuss.

(1) **Experiment 1: DFC.** First we fix different strokes to generate evolving images using the DFC measure. For each stroke, we perform 100 runs and collect the images of the 2 fittest individuals of each run. From these images, we handpick 10 images (two for each stroke) as shown in Figure 2, and almost all images have rich and variable colouring. Compared with previous works [1, 4, 6, 9], the result images are still abstract, but clearly with the texture of strokes, which is more like artworks by an artist or a painter.

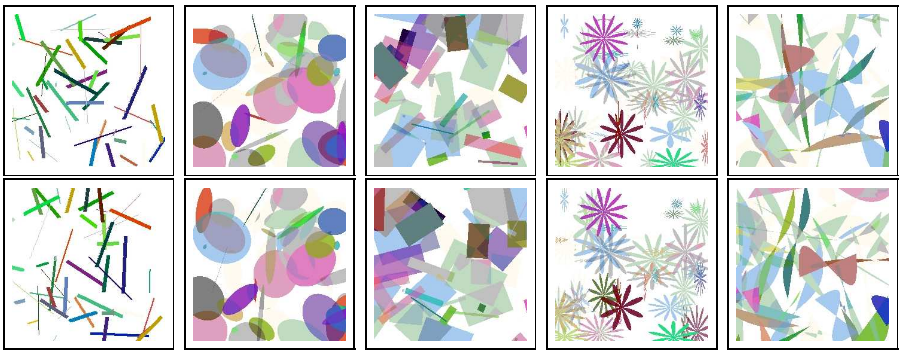
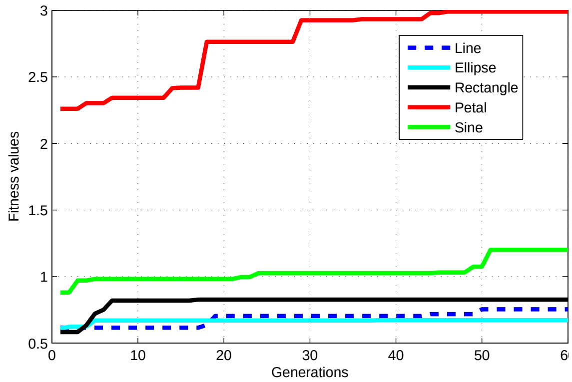
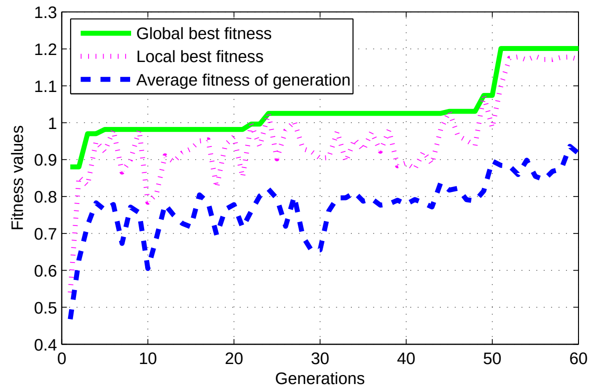


FIGURE 2. Visual results using the DFC measure



(a) Best fitness values



(b) Sine strokes

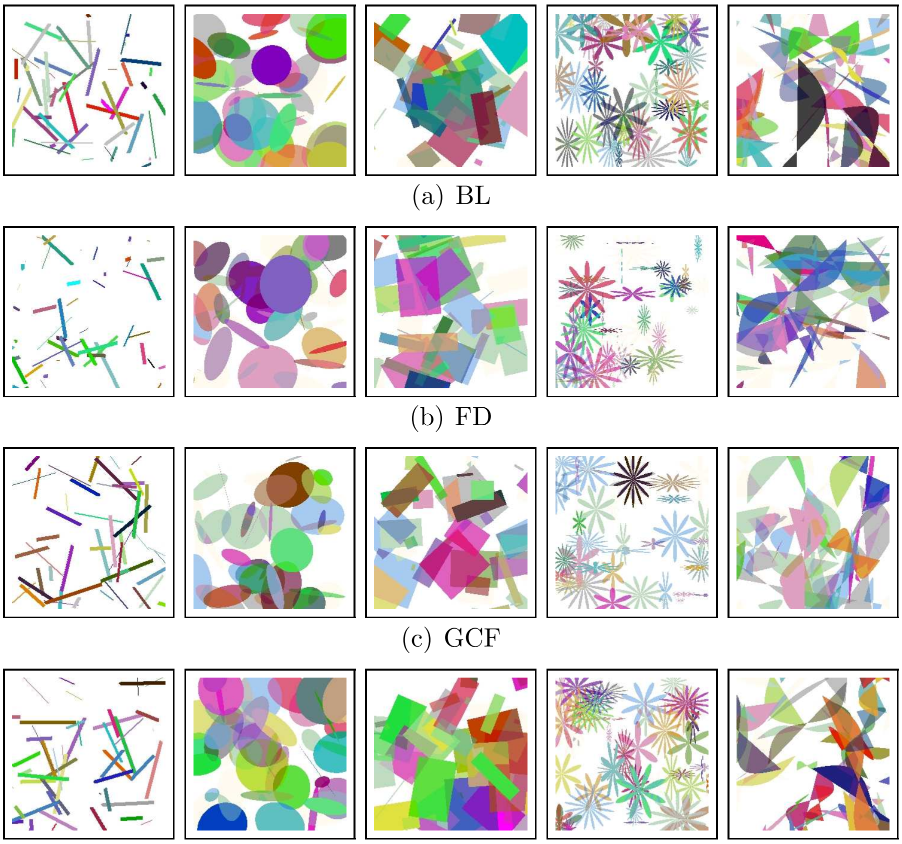
FIGURE 3. Statistics gathered over 100 runs

For the reference, we gather data to measure the statistics of our evolutionary art algorithm, that is, the global best, the local best and the average fitness, for each individual, for each generation and for all runs. Then we calculate the averages over 100 runs, and present the findings in Figure 3(a). The petal-type strokes obtain higher DFC values, which seem to dominate the look and feel of most space, and make images more interesting. The evolution processes become stable within 30 generations expecting sine stroke. Statistics using sine stroke gathered over 100 runs are listed in Figure 3(b). The evolving curves of the global best, the local best and the average fitness appear generally upward, although with a slightly fluctuation in an acceptable scope. Even so, the proposed method can quickly accomplish the iteration process, and the number of iterations is only near 50. In addition, it should be noted that the experiments only use the simple genetic algorithm, and further improvements can be implemented.

(2) **Experiment 2: BL, FD, GCF and SE.** We fix the different strokes to generate evolving images using the measures of BL, FD, GCF and SE. For each stroke and each measure, we perform 100 runs and collect the images of the fittest individual of each run, from which we handpick 20 images (one for each stroke and each measure) as shown in Figure 4. The images by the BL measure are more varied, and many images clearly occupy all of the space when compared to images evolved with the other aesthetic measures. What is apparent from images by the FD measure is that the style is different from other images since the results by FD are very simple, and with the least colourful. The images evolved using the GCF measure show a lot of contrast. Images using the SE measure are in general very colourful and seem to satisfy a uniform distribution of brightness values.

In order to know whether DFC has a similar preference with the others, we gather all the images that were produced in single aesthetic measure experiments. Then we calculate the aesthetic value of these images using all aesthetic measures, and normalize each aesthetic score between 0 and 1. With these data, we obtain the correlation in evaluation scores for all aesthetic measures. The correlations are presented in Table 2. The results from Table 2 suggest that DFC and GCF have a similar aesthetic preference since the two aesthetic measures show a high correlation in their aesthetic evaluation of the images (0.802), and there is the lowest correlation between DFC and FD (-0.842). Obviously, DFC is different from the existing aesthetic measures, including BL, FD, GCF and SE. Thus, DFC is an alternative to these aesthetic measures in evolutionary art.

(3) **Experiment 3: Various strokes and measures.** In the genetic representation, we add a parameter to s as the style of strokes, then perform 100 runs for each aesthetic measure and collect images of the fittest individual of each run. Five of them (one for each measure) are shown in Figure 5. All images show an abstract texture and are more



(a) BL

(b) FD

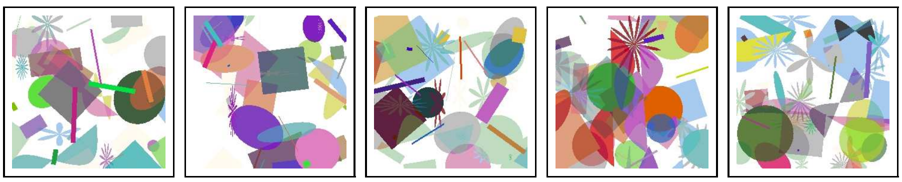
(c) GCF

(d) SE

FIGURE 4. Visual results using the BL, FD, GCF and SE measures

TABLE 2. Correlation of aesthetic evaluation between the aesthetic measures

	BL	FD	GCF	SE	DFC
BL	/	−0.592	0.567	0.643	0.338
FD	−0.592	/	−0.911	−0.057	−0.842
GCF	0.567	−0.911	/	0.005	0.802
SE	0.643	−0.057	0.005	/	−0.213
DFC	0.338	−0.842	0.802	−0.213	/



(a) BL (b) FD (c) GCF (d) SE (e) DFC

FIGURE 5. Visual results using various strokes

complex than those using single type of strokes. With the increase of N_s, results would be more like the style of computer art as shown in previous works [1, 4, 6, 9]. Thus, in some ways, our algorithm can be as an alternative to these existing methods.

3.3. Discussion. In this subsection, we provide a brief discuss on the proposal and three research questions in Section 1. Related to research question (1), we define five strokes as genetic representation and introduce them into evolutionary art. Evolving images can be generated reasonably, as shown in Figures 4 and 5. Related to research question (2), we conduct a series of experiments with various strokes. Acceptable images and statistics are shown in Figures 3 and 5. With different types of strokes, different styles of evolving images can be produced. Related to research question (3), we perform various experiments by choosing different fitness functions using aesthetic measures, and desired result images are shown in Figures 2 and 4. Effective correlations between DFC and other aesthetic measures are presented in Table 2.

4. **Conclusions.** In the paper, we provide the genetic representation using strokes with five types, and then propose an unsupervised algorithm of evolving art using aesthetic measures. Furthermore, we introduce image data field as a novel aesthetic measure in evolutionary art. The experimental results verify the efficiency and feasibility of the proposal, which can be an alternative to the existing methods.

There are a couple of issues that will be considered in the future research: (1) Introducing other aesthetic measures or evolutionary algorithms to improve the interestingness of the evolved images is currently under investigation, and will be reported later; (2) The journey of the pattern generation may be just as or more interesting than the result image; thus, the extension of the proposed method to produce an animated sequence of each selected stroke over the entire process is well worth further studying.

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