Use of GCF Aesthetic Measure in the Evolution of Landscape Designs

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Abstract: This paper explores the use of a global contrast factor (GCF) as an aesthetic measure to aid the generation of fractal landscapes. In an attempt to auto generation virtual landscapes, we added a global contrast factor as an aesthetic measure based fitness function to the genetic algorithm (GA). This GA is used to explore a multi-dimensional parameter space that defines how 3D fractal landscapes are created. Two types of experiments were conducted using GCF that facilitated fluid evaluation of computationally intensive fitness evaluation, with preliminary results reported.

1 INTRODUCTION

Computer-generated digital artefacts are often considered to be genuine works of art. They are used across a variety of fields, for example in advertising, games development (Halo, 2001); (Assassin's Creed, 2007), as well as in the film industry (Rhythm and Hues Studio, 1987); (Lightwave, 1993). However, designing virtual artefacts is a time consuming process that requires highly artistic skills and knowledge of specialist techniques. Users generally create these using sophisticated drawing tools and graphic software (Photoshop, 1990) (Gimp, 1996). There are also semi-automatic software tools (Vue, 2012); (Bryce, 2010) available, which can help designers to create 3D artefacts more intuitively. However, these require a great deal of manual input, patience and time. Also, users of these tools often require extensive training and experience before they can actually deliver the desired product.

A new field of procedural techniques has emerged recently based on evolutionary algorithms, where a computer generates digital artefacts automatically by allowing users to direct an algorithm towards the desired output, without requiring any specialist expertise. Authors (Walsh and Gade, 2010) have implemented such a technique for generating landscape designs, primarily of terrains, using an interactive genetic algorithm (IGA). An IGA is an extended version of a genetic algorithm (GA) where the fitness evaluation is done according to the user's preferences. Figure 1 gives the result of our work where a user generated digital landscape designs using real-world scenery (Alpine, 2011); (Desert, 2011) as a target.

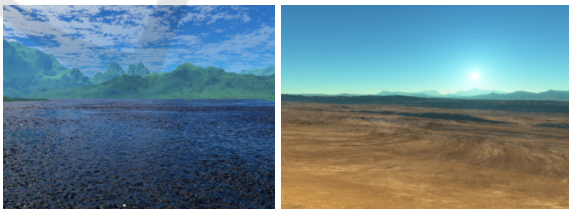

Figure 1: Evolution of a real world using IGA.

There are significant drawbacks to this process, i.e. user fatigue resulting in loss of interest; patience or miss-guidance of the system during the evaluation phase. However, we address this by the use of an aesthetic measure where the evolution of images is guided without the need for significant user involvement. In previous work, (Walsh and Gade, 2011) implemented a Kolmogorov complexity aesthetic measure (Li, 1997) to generate landscape designs automatically. The results were encouraging and have led us to integrate additional aesthetic measures into our library, hoping to improve the ability of our algorithms to generate more pleasing landscape designs for users. We investigate the utility of using computational aesthetic measures to design and compose artefacts by testing these concepts within a 3D virtual world.

In any image processing system, the contrast attribute can play an important role in defining the

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features of that image. So we implement a new approach to aesthetic measures in our system, based on a global contrast factor (GCF) that was introduced by (Matković et al., 2005) in order to evolve the best landscape designs with good contrast levels automatically.

We also attempted to increase the performance of the IGA system by helping users to identify the best landscapes in every generation by testing against the aesthetic fitness scores, GCF and Kolmogorov complexity. Users can select aesthetic measures individually, or in combination with each other, to guide the evolution. In addition, if a user is not satisfied with the results generated by particular aesthetic measures, they can choose their own preferred landscapes by ranking images manually.

Two types of test were conducted in section 6 to test the effectiveness of the aesthetic measures, GCF and IGA, in directing a search for evolving landscapes.

The remainder of the paper is organized as follows: Section 2 describes previous aesthetic measures used to evolve digital artefacts; Section 3 describes the GCF aesthetic measure fitness function; Section 4 describes the parameters involved in landscape designs; Section 5 explains the details of the experiment setup; Section 6 shows the results from the experiments and follows with conclusions, outlining findings, and future scope.

2 BACKGROUND

(Bentley, 1999) describes how evolutionary designs generated by computers are surprisingly better than those designed by humans. They allow the designer to explore numerous techniques for novel design concepts. However, as IGAs are not fully autonomous, researchers implement various aesthetic measures to help identify the best digital art that can satisfy human aesthetic tastes, to some extent.

In recent decades, research has been applied to the challenge of using evolutionary computation (EC) with aesthetic measures as fitness scores to evolve digital artefacts automatically, thus replacing user involvement. This allows a directed search on a population of randomly generated individuals over a number of generations, whereby successive generations are selected via a fitness function. The fitness function is a key aspect of this search heuristic and is commonly based on a computational measure within the domain of interest, which in this case is the quality and utility of the generated landscapes. There are some common aesthetic measures which are applied to the evaluation of digital artefacts.

Based on observation of visual preferences on images selected by humans, authors (Li and Hu, 2010) have selected a set of multiple aesthetic measures: Bell Curve, (Ross et al., 2006), Image Complexity Theory (Machado and Cardoso, 1998), Birkhoff (Birkhoff, 1933) & Shannon Entropy (Rigau et al., 2008), and combined them to use as a new aesthetic fitness score to evolve human preferred images.

Likewise, authors (den Heijer and Eiben, 2011) used two well-known aesthetic measures, Bell Curve and GCF, as their fitness function to generate digital art of vector graphics. In the same process, authors (Bergen and Ross, 2012) used source image as an aesthetic fitness measure by reading its colour pixels to evolve an automatic vectorisation of that image.

In the evolution of art authors (den Heijer and Eiben, 2010); (den Heijer and Eiben, 2011), used four main various aesthetic measures: Benford's Law (Jolion, 2001), GCF, Information Theory and Ross & Ralf's Bell curve, to generate digital images automatically. Many authors have applied aesthetic measures to evolve various digital artefacts, 3D structures (Bergen, 2011) (Bergen and Ross, 2012), virtual creatures (Hornby and Pollack, 2001), evolutionary art (Bergen and Ross, 2011), 3D art (Pang and Hui, 2010), images (Romero et al., 2012) etc. in recent decades.

Even though there is steady progress in applying various aesthetic measures to evolve digital artefacts, there is still much room for improvement when compared with human evaluation. For example, a survey was conducted by (Raffe et al., 2012) on existing approaches of using evolutionary algorithms for digital terrain generations that use various fitness evaluations. Results showed both the advantages and disadvantages of each approach. Authors suggest that there is still need for robust algorithms to evaluate aesthetics; in this case, procedural terrain generation techniques, as none of the existing tools can, at present, be practically used for game development.

3 GCF AESTHETIC MEASURE

The main aesthetic measure used in this paper is GCF, which we use to find the best computer generated digital landscape designs by balancing the contrast levels.

2.1 Global Contrast Factor

The main idea behind GCF (Matkovic et al., 2005) is to take the average of various local contrast factors and then compute a result with a weighting factor. It starts by creating perceptual luminance L as shown in Equation 1.

$$L = 100 * \sqrt{l} \tag{1}$$

Where l is the linear luminance of each pixel with applied gamma correction, γ = 2.2, as shown in Equation 2.

$$l = \left(\frac{k}{255}\right)^{\gamma} \tag{2}$$

Taking all 4 surrounding perceptual luminances, $lc_{i,}$, a local contrast factor C_i is created using Equation 3.

$$lc\_i = (|L\_i - L\_(i-1)| + |L\_i - L\_(i+1)| + |L\_i - L\_(i-w)| + |L\_i - L\_(i+w)|)/4 \tag{3}$$

$C_{i,}$ average local contrast factor is used to compute the average of all the local contrast factors, $lc_{i,}$, that are produced at various resolutions. In our case, six local contrast factors are performed.

$$C_i = \frac{1}{w * h}\sum_{i=0}^{N} lc_i \tag{4}$$

At this stage the original image has been reduced to half of its size in height and width by transforming pixels to new 'super pixels'. A super pixel is an average of its surrounding pixel values. Figure 2 shows the size of the original image resolution divided into 4 different resolutions when the averaging of local contrast factors is performed.

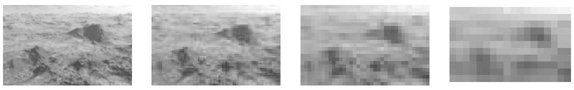

Figure 2: Super Pixels stage at various resolutions.

In the final step, the GCF value is evaluated using the summation of the entire average local contrast factor, generated with weighting factors as shown in Equation 5.

$$GCF = \sum_{i=1}^{N} w_i * C_i \tag{5}$$

Where,

$$w_i = \left(-0.406385 * \frac{i}{9} + 0.334573\right) * \frac{i}{9} + 0.0877526 \tag{6}$$

The two images in Figure 3 show the GCF value after performing the GCF aesthetic test.

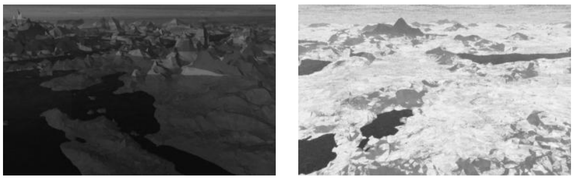

Figure 3: GCF value of the left side image is 2.2695393 and right side image is 11.2654189.

4 PARAMETERS

The landscape designs used in our paper are generated by use of a third party software component called Terragen (Terragen, 2005). It reads more than 800 parameter values in an xml format called TGD and generates their graphical representation as an image. We created a plugin which generates an XML file with default and altered parameter values which Terragen can read, and thus generate landscapes accordingly. For testing the evolution of landscape features, we explore only 14 parameters in the evolutionary process, based on the fitness evaluation.

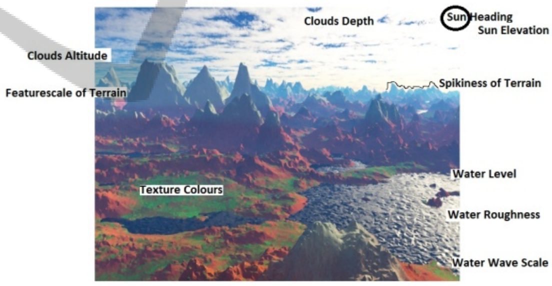

Figure 4: Digitally generated scenery showing all the parameters in details.

Table 1: Evolutionary parameter values range.

Parameter	Min	Max
Sun Elevation	0	90
Sun Heading	0	360
Terrain Height	2000	20000
Terrain Spikes	0	1
Cloud Altitude	5000	20000
Cloud Propagation Mix	0	1
Cloud Density	0	0.05
Cloud Depth	0	100
Water Waves	0	100
Water Roughness	0	0.3
Water Level	-800	500
Sand Texture (RGB)	0	255
Rock Texture (RGB)	0	255
Grass Texture (RGB)	0	255

Parameters used in this paper include terrain (height and spikiness), cloud (density, circulation, depth and altitude), sun (elevation and heading), water (roughness, wave height and level) and textures (grass, sand and rock colours).

All parameter values are encoded using an 8-bit binary representation for genetic operations and then they are reverted back to their original values before they are graphically represented. Floating point values are converted to an 8-bit binary, index range [0, 255] using Equation 7 and reverted to original values using Equation 8.

$$\mathrm{Conv\_To\_Bin_v} = \frac{\mathrm{Input_v} - \mathrm{Para_{min}}}{\mathrm{Ratio}} \tag{7}$$

$$Con\_To\_Para_v = Para_{min} + (Input_v * Ratio) \tag{8}$$

Where,

$$Ratio = \frac{Para_{max} - Para_{min}}{Binary\_bit_{max} - Binary\_bit_{min}} \tag{9}$$

5 PROCESS

We implement an interactive tool that will evolve landscape designs automatically based on an aesthetic fitness score, GCF. An enhanced IGA is also implemented to give the user direct access the fitness measure used to evaluate landscape designs. Users can overwrite the aesthetic measures with their own ranking during the process.

Evolution of landscape design process is divided into 5 core phases: Initial Population, Fitness Evaluation, Selection, Genetic Operation and New Population.

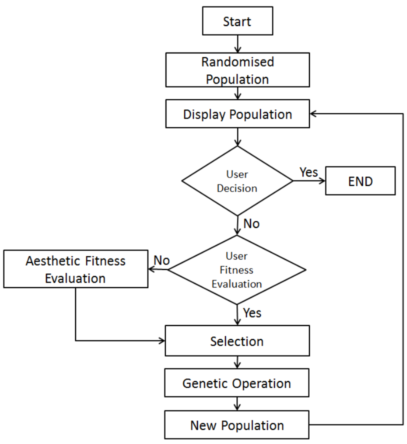

Figure 5: Evolutionary system – Flow chart.

5.1 Phase 1: Initialization

Our program generates a set of sixteen XML files containing the randomised design parameters of digital landscapes before they are rendered by the scenery generator, Terragen. After rendering, sixteen landscapes are presented by our GUI, as shown in Figure 7.

5.2 Phase 2: Fitness Evaluation

The user is optionally allowed to rank their preferred landscape designs to guide the evolution towards their desired landscape. At this phase, the user selects the best three parent templates from the GUI. In an attempt to decrease user fatigue, we have given the following options to help users evaluate the landscapes:

5.2.1 Guidance during Evaluation

During user evaluation, each landscape is scored using GCF, Kolmogorov aesthetic measure, or both together, giving the top three ranked landscapes. Users can follow these hints when in a dilemma over which landscape to choose.

Note: When users select both the GCF and Kolmogorov complexity aesthetic measures, the mean value of both fitness scores is taken as the final score and ranked accordingly using *TotalScore* as shown in Equation 12.

$$GCF\_Score = \frac{(GCF_V - S_{min}) * (S_{Max} - S_{min})}{(GCF_{Max} - GCF_{min})} \tag{10}$$

$$K\_Score = \frac{(K_V - S_{min}) * (S_{Max} - S_{min})}{(K_{Max} - K_{min})} \tag{11}$$

$$\Rightarrow \boldsymbol{TotalScore} = \frac{GCF_{Score} + K\_Score}{2 * (S_{Max})} \tag{12}$$

5.2.1 Search via Computational Aesthetic Measure

Users can pass control to the computational aesthetic measures during the evolutionary process. At any point in the process, users can set the number of generations and allow the automated process of computational aesthetic fitness measures to direct the exploration of the fitness landscape. After those set generations are evolved, the computational aesthetic measure fitness evaluations are disengaged and the control is handed back to the user for further human evaluation.

5.3 Phase 3: Selection

The selection of parents is done using a ranking based roulette wheel selection where the first selected landscape, Rank 1, will have more probability of being selected than the second, Rank 2, and more again than the third one, Rank 3. The least probable selections are done on the remaining landscape designs that have the least fitness values, as shown in Figure 6.

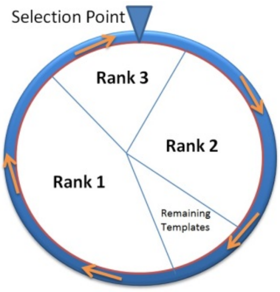

Figure 6: Roulette wheel selection.

5.4 Phase 4: Genetic Operations

In this phase, a pair of selected parents produces two new offspring with their own characteristics using crossover and mutation operators.

5.4.1 Crossover

Each parameter value is converted to 8-bit binary format before genetic operations take place. At a random crossover point, random numbers of bits are exchanged between each other to give two new binary numbers offspring.

5.4.2 Mutation

In the mutation process, after the original value is converted to binary format, at a random selection point a binary bit is flipped over to its opposite value, 1 to 0 or 0 to 1, giving random features.

5.5 Phase 5: New Population

A set of sixteen new XML files are generated, defining the graphical properties of the new offspring population. They are rendered by the Terragen software component to produce novel landscape designs and are then displayed in the GUI for further evaluation. The whole process is repeated until termination: when a user is satisfied or a set number of generations are produced.

6 EXPERIMENTS AND RESUTLS

Two sets of experiments were performed.

- The first experiment was conducted to test the evolutionary search for digital landscapes using a GCF aesthetic fitness function with default parameter settings.
- The second experiment was conducted to check the efficiency of contrast levels over terrains only. This was necessary to reduce the effect of cloud reflection over water levels as seen in Figure 8.

6.1 Experiment 1: GCF Aesthetic Test

In the first experiment, the effectiveness of the GCF fitness measure is tested. With a random distribution of parameter values, within the range as shown in Table 1, a set of 16 digital landscape designs are generated with random colours in the initial phase as shown in Figure 7. Then the GA is applied to identify the top 3 digital images in each population; to generate a new population automatically until the required number of generations is met.

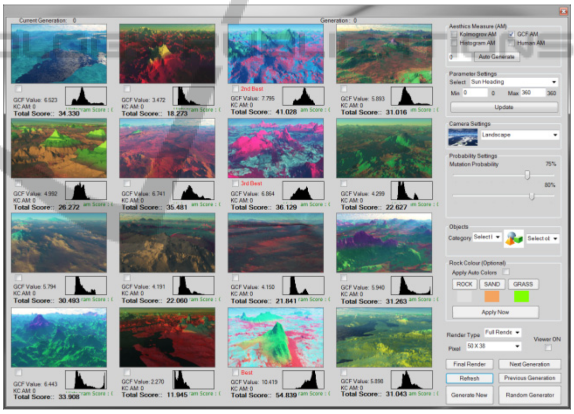

Figure 7: Initial set of randomly generated population of Digital landscapes in search of GCF.

During the process of evolution, the GA selects the parameters that maximizes the fitness factor and adjusts them via crossover and mutation. In this case the parameters such as cloud, water, terrain texture and sun are adjusted to optimize the global contrast factor in the generated digital images.

Even though the GCF fitness function reads and adjusts the luminance of the pixels from a *grey scale* image, the colour textures of the terrain are evolved automatically by finding the right combination of RGB values to match the contrast levels produced by the GCF fitness function. The final generation of this experiment is shown in Figure 8. Note that these images contain high water levels as this tends to give a high GCF score. The chart in Figure 9 shows that there is an emerging trend of higher average fitness scores over successive generations, which shows that the evolutionary search mechanism is operating as expected on the fitness function. Mutation occasionally disrupts this upward trend to ensure an element of diversity remains in the population.

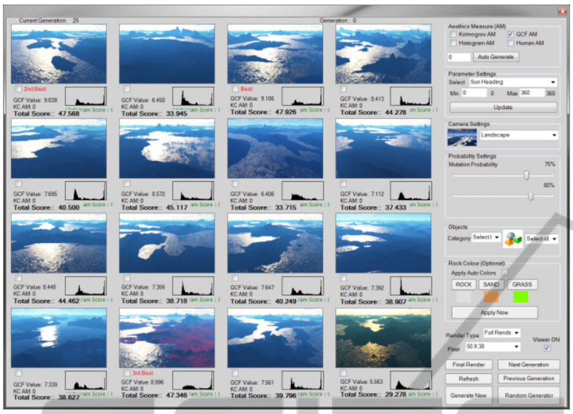

Figure 8: Final generation of Digital landscapes in search of GCF.

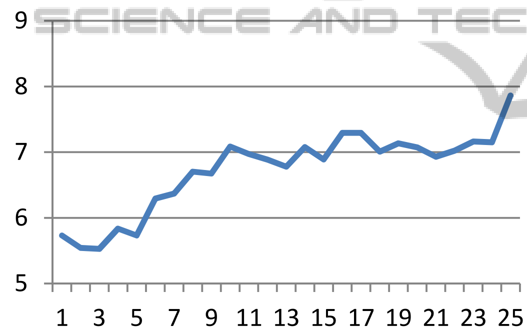

Figure 9: Experiment 1 – Fitness graph.

6.2 Experiment 2: GCF Aesthetic Test with reduced Water and Clouds

Experiment 2 has the same goal as Experiment 1, except in this case the effect of clouds and water are reduced. This was done after feedback from experts suggested that the reflective properties of water can bias the contrast factor to high values.

Both the initial and final generation are shown in Figure 10 and Figure 11 respectively. Again it can be seen that the algorithm automatically directs the evolution of landscapes towards a set of parameters that represent balanced compositions. Interestingly, the best-ranked generated landscapes tend to have fairly naturalistic compositions compared to the original generation, without any input from the user.

Table 2: Adjusted parameter values range

Parameter	Min	Max
Sun Elevation	0	90
Sun Heading	0	360
Terrain Height	2000	20000
Terrain Spikes	0	1
Cloud Altitude	5000	20000
Cloud Propagation Mix	0	1
Cloud Density	0	0.01
Cloud Depth	0	10
Water Waves	0	100
Water Roughness	0	0.3
Water Level	-1200	-500
Sand Texture (RGB)	Static	Static
Rock Texture (RGB)	Static	Static
Grass Texture (RGB)	Static	Static

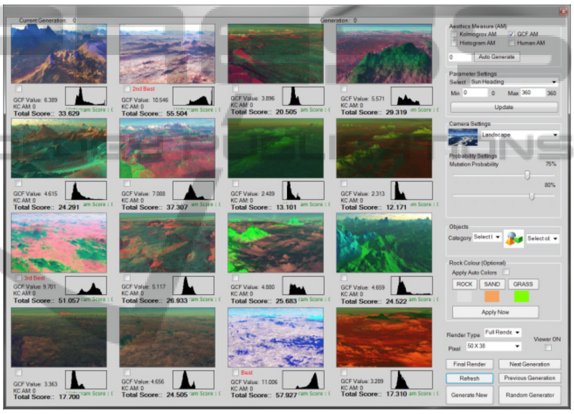

Figure 10: Initial generation of IGA test.

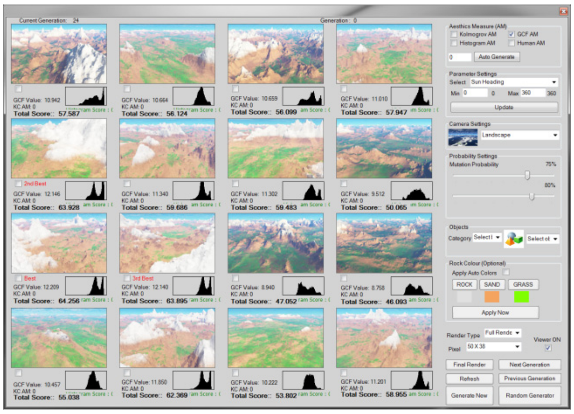

Figure 11: Final generation of IGA test.

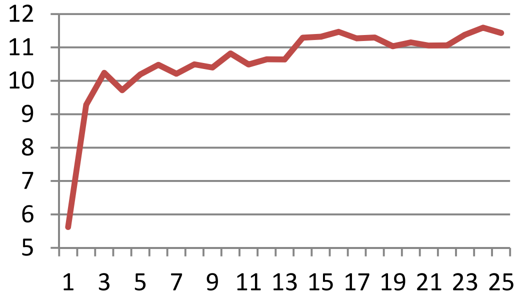

Figure 12: Experiment 2 – Fitness graph.

7 CONCLUSIONS AND FUTURE WORK

Our objective in this study was to investigate GCF aesthetic measures; to test GCF with our existing tools, and verify the results as to whether or not they can evolve towards balanced contrast levels. Both aesthetic measures direct the evolutionary process towards images that have balanced and naturalistic characteristics. This would validate findings of other researchers who employ similar aesthetic measures for the auto-generation of art works and suggest that there is some utility in computational fitness evaluations. It is note-worthy that the images were completely generated automatically and did not require user input. This suggests that computational aesthetic measures could be employed to reduce user fatigue in interactive genetic algorithms, and perhaps replace the user altogether. Further studies with cohorts of real users will be planned to evaluate the utility of this approach in future studies.

There is also an opportunity to add more fractal terrain parameters into the GA process for achieving more realistic digital artefacts. Moreover, adding objects like plants, flowers, rocks and trees will give a richer look to our output. We would also like to implement more of our aesthetic measures and investigate them with our existing ones in the creation of evolutionary art.

REFERENCES

Alpine. (2011). *Landscape Design using Interactive Genetic Algorithm - target Alpine scenery* . Available: http://www.youtube.com/watch?v=OISauX-XAVY. Last accessed 21st June 2013.

Assassin's Creed. (2007). *Assassin's Creed IV Black Flag*. Available: http://assassinscreed.ubi.com/. Last accessed 21st June 2013.

Bentley, P. (Ed.). (1999). *Evolutionary design by computers*. Morgan Kaufmann. Bergen, S., & Ross, B. J. (2012). Automatic and interactive evolution of vector graphics images with genetic algorithms. *The Visual Computer*, *28*(1), 35-45.

Bergen, S. (2011). Automatic structure Generation using genetic programming and fractal geometry. *Brock University, Ontario*.

Bergen, S., & Ross, B. J. (2012). Aesthetic 3d model evolution. In *Evolutionary and Biologically Inspired Music, Sound, Art and Design* (pp. 11-22). Springer Berlin Heidelberg.

Bergen, S., & Ross, B. J. (2011). Evolutionary art using summed multi-objective ranks. In *Genetic Programming Theory and Practice VIII* (pp. 227-244). Springer New York.

Birkhoff, G. D. (1933). *Aesthetic measure*. Cambridge, Mass.

Bryce. (2010). *What is Bryce*. Available: http://www.daz3d.com/products/bryce/bryce-what-is-bryce. Last accessed 21st June 2013.

Desert. (2011). *Landscape Design using Interactive Genetic Algorithm - target Desert scenery* . Available: http://www.youtube.com/watch?v=qDey8uyzvqg. Last accessed 21st June 2013.

den Heijer, E., & Eiben, Á. E. (2011, July). Evolving art with scalable vector graphics. In *GECCO* (pp. 427-434).

den Heijer, E., & Eiben, A. E. (2010, July). Using aesthetic measures to evolve art. In *Evolutionary Computation (CEC), 2010 IEEE Congress on* (pp. 1-8). IEEE.

den Heijer, E., & Eiben, A. E. (2011). Evolving art using multiple aesthetic measures. In *Applications of Evolutionary Computation* (pp. 234-243). Springer Berlin Heidelberg.

Gimp. (1996). *The GNU Image Manipulation Program*. Available: http://www.gimp.org/. Last accessed 21st June 2013.

Halo Bungie. (2001). *Halo Official Site*. Available: http://www.halowaypoint.com/en-us/. Last accessed 21st June 2013.

Hornby, G. S., & Pollack, J. B. (2001). Evolving L-systems to generate virtual creatures. *Computers & Graphics*, *25*(6), 1041-1048.

Jolion, J. M. (2001). Images and Benford's law. *Journal of Mathematical Imaging and Vision*, *14*(1), 73-81.

Li, M. (1997). *An introduction to Kolmogorov complexity and its applications*. Springer.

Li, Y., & Hu, C. J. (2010). Aesthetic learning in an interactive evolutionary art system. In *Applications of Evolutionary Computation* (pp. 301-310). Springer Berlin Heidelberg.

Lightwave. (1993). *Lightwave*. Available: https://www.lightwave3d.com/community/gallery/category/film/. Last accessed 21st June 2013.

Machado, P., & Cardoso, A. (1998). Computing aesthetics. In *Advances in Artificial Intelligence* (pp. 219-228). Springer Berlin Heidelberg.

Matković, K., Neumann, L., Neumann, A., Psik, T., &

Purgathofer, W. (2005, May). Global contrast factor-a new approach to image contrast. In *Proceedings of the First Eurographics conference on Computational Aesthetics in Graphics, Visualization and Imaging* (pp. 159-167). Eurographics Association.
Pang, W., & Hui, K. C. (2010). Interactive evolutionary 3D fractal modeling. *The Visual Computer*, *26*(12), 1467-1483.
Photoshop. (1990). *Photo editor software.* Available: http://www.adobe.com/ie/products/photoshop.html. Last accessed 21st June 2013.
Raffe, W. L., Zambetta, F., & Li, X. (2012, June). A survey of procedural terrain generation techniques using evolutionary algorithms. In *Evolutionary Computation (CEC), 2012 IEEE Congress on* (pp. 1-8). IEEE.
Rhythm and Hues Studio. (1987). *Rhythm and Hues Studio.* Available: http://www.rhythm.com/home/. Last accessed 21st June 2013.
Rigau, J., Feixas, M., & Sbert, M. (2008). Informational aesthetics measures.*Computer Graphics and Applications, IEEE*, *28*(2), 24-34.
Romero, J., Machado, P., Carballal, A., & Correia, J. (2012). Computing aesthetics with image judgement systems. In *Computers and Creativity* (pp. 295-322). Springer Berlin Heidelberg.
Ross, B. J., Ralph, W., & Zong, H. (2006). Evolutionary image synthesis using a model of aesthetics. In *Evolutionary Computation, 2006. CEC 2006. IEEE Congress on* (pp. 1087-1094). IEEE.
Terragen. (2005). *Terragen.* Available: http://planetside.co.uk/. Last accessed 21st June 2013.
Vue. (2012). *e-on softwares.* Available: http://www.e-onsoftware.com/products/?page=%20artist. Last accessed 21st June 2013.
Walsh, P., & Gade, P. (2010, July). Terrain generation using an interactive genetic algorithm. In *Evolutionary Computation (CEC), 2010 IEEE Congress on*(pp. 1-7). IEEE.
Walsh, P., & Gade, P. (2011, June). The use of an aesthetic measure for the evolution of fractal landscapes. In *Evolutionary Computation (CEC), 2011 IEEE Congress on* (pp. 1613-1619). IEEE.