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Evolving Art Using Multiple Aesthetic Measures

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Abstract. In this paper we investigate the applicability of Multi-Objective Optimization (MOO) in Evolutionary Art. We evolve images using an unsupervised evolutionary algorithm and we use two aesthetic measures as fitness functions concurrently. We use three different pairs from a set of three aesthetic measures and we compare the output of each pair to the output of other pairs, and to the output of experiments with a single aesthetic measure (non-MOO). We investigate 1) whether properties of aesthetic measures can be combined using MOO and 2) whether the use of MOO in evolutionary art results in different images, or perhaps “better” images. All images in this paper can be viewed in colour at <http://www.few.vu.nl/~eelco/>

1 Introduction

One of the fundamental problems in the field of evolutionary art is the issue of fitness assignment. Within evolutionary art there are two possible ways to assign fitness to an artefact; the first option is to delegate fitness assignment to a human being in an interactive evolutionary setup (Interactive Evolutionary Computation or IEC). Setting up an IEC environment to evaluate art, music or other artefacts is relatively simple, and IEC has been applied successfully in a wide variety of application domains (especially in domains where computational fitness functions are hard to come by) such as art, graphic design, music and many others [16]. IEC also has a number of drawbacks; the most important one is user fatigue, whereby the user that steers the evolution process (by evaluating artefacts) becomes tired and/ or loses interest (“fatigued”). This implies that typical IEC experiments have relatively small populations and relatively few iterations and this severely limits the potential output of any IEC setup. The other way of fitness assignment within evolutionary art is unsupervised evolutionary art, whereby a computational fitness function assigns a score to an artefact without human intervention. The creation of fitness functions for the evaluation of art is regarded as one of the open problems in evolutionary art [9]. In previous work we investigated the use of six aesthetic measures as fitness functions [6] [7]. We showed that the choice of the aesthetic measure has a significant impact on the style of the evolved images.

1.1 Research Questions

In this paper we investigate whether it is possible to combine the effect of multiple aesthetic measures concurrently using a Multi-Optimization Evolutionary Algorithm (MOEA). In previous work we have shown that the choice of the aesthetic measure significantly determines the “style” of the generated art [6] [7]. With MOEA, we want to investigate whether the influence of different aesthetic measures can be combined into the same image. For example, if we use one aesthetic measure that focuses on the use of contrast in an image, and one aesthetic measure that focuses on certain color transitions within an image, then we would like to evolve images that have both properties. So our first research question is; can we combine the effects from multiple aesthetic measures into the same image using a MOEA? Second, we want to know whether the use of a MOEA results in “better” images in evolutionary art. Beautiful images often have multiple “good” properties; good use of contrast, interesting color transitions, good level of interestingness (not too simple, not too complex/ chaotic) etc. If we evolve images by optimizing multiple objectives simultaneously, it should – in theory – lead to “better” images.

The rest of the paper is structured as follows. First we discuss evolutionary art and the use of MOEA in evolutionary art (section 2). Section 3 briefly discusses our software environment Arabitat. Next, we describe the experiments and their results in section 4. Section 5 contains conclusions and directions for future work.

2 Evolutionary Art

Evolutionary art is a research field where methods from Evolutionary Computation are used to create works of art (good overviews of the field are [11] and [2]). Some evolutionary art systems use IEC or supervised fitness assignment (e.g. [15], [12]), and in recent years there has been increased activity in investigating unsupervised fitness assignment (e.g. [5], [13]).

2.1 The Use of MOEA in Evolutionary Art

MOEA’s have not been used frequently in the field of evolutionary art; in [14] Ross & Zhu describe research into evolving procedural art by comparing evolved images with a target image. The fitness functions in their MOEA setup are distance metrics that calculate the difference between an individual and the target image. Our approach is different since we do not evolve images with a target image in mind. Our approach is more similar to [5] in which Greenfield evolves images and fitness components concurrently in a co-evolution setup. Our approach is different in two ways; first, we do not use co-evolution in our experiments, and second, we have a number of “fixed” aesthetic measures that we use as the fitness functions.

Table 1. Evolutionary parameters of our evolutionary art system used in our experiments

Symbolic parameters	
Representation	Expression trees, see table 2
Initialization	Ramped half-and-half (depth between 2 and 5)
Survivor selection	Tournament, Elitist (best 3)
Parent Selection	Tournament
Mutation	Point mutation
Recombination	Subtree crossover
Fitness function	Multiple aesthetic measures (see 2.2)
Numeric parameters	
Population size	200
Generations	20
Tournament size	3
Crossover rate	0.9
Mutation rate	0.1
Maximum tree depth	8

2.2 Aesthetic Measures

The aesthetic measures that we use in this paper have different mechanisms and backgrounds, and we will describe them briefly. For a more detailed description we refer to the original papers. We will briefly describe the aesthetic measures Benford Law, Global Contrast Factor, and Ross & Ralph Bell Curve.

Benford Law. We use an aesthetic measure based on Benford Law [1]; Benford Law (or first-digit law) states that list of numbers obtained from real life (i.e. not created by man) are distributed in a specific, non-uniform way. The leading digit occurs one third of the time, the second digit occurs 17.6%, etc. We use the Benford Law over the distribution of brightness of the pixels of an image. We used the same implementation and settings as in previous experiments so we refer to [7] for details.

Global Contrast Factor. The Global Contrast Factor is an aesthetic measure described in [8]. Basically, the global contrast factor computes contrast (difference in luminance or brightness) at various resolutions. Images that have little or few differences in luminance have low contrast and are considered ‘boring’, and thus have a low aesthetic value. We used the same implementation and settings as in previous experiments so we refer to [7] for details.

Ross and Ralph (bell curve). A second aesthetic measure that we implemented is Ross & Ralph [13]. This measure is based on the observation that many fine art painting exhibit functions over colour gradients that conform to a normal or bell curve distribution. The authors suggest that works of art should

have a reasonable amount of changes in colour, but that the changes in colour should reflect a normal distribution (hence the name ‘Bell Curve’). The computation takes several steps and we refer to [13] for details.

3 Arabitat: The Art Habitat

Arabitat (Art Habitat) is our software environment in which we investigate evolutionary art. It uses genetic programming with Lisp expressions and supports both supervised and unsupervised evaluation. The details of Arabitat have been described in detail in [7] so we will not repeat it here. In addition to our system described in [7] we have implemented the Multi-Objective Optimization algorithms NSGA-II [3] and SPEA2. In this paper we will only discuss the experiments we did with NSGA-II. NSGA-II finds an optimal Pareto front by using the concept of non-domination; a solution A is non-dominated when there is no other solution that scores higher on all of the objective functions. Furthermore, NSGA-II uses elitism and a mechanism to preserve diverse solution by using a crowding distance operator. For more details, we refer to [3].

Function set. Many functions used are similar to the ones used in [15], [12] and [13]. Table 2 summarizes the used functions (including their required number of arguments);

Table 2. Function and terminal set of our evolutionary art system

Terminals	x,y, ephem_double, golden_ratio, pi
Basic Math	plus/2, minus/2, multiply/2, div/2, mod/2
Other Math	log/1, sinh/1, cosh/1, tanh/1, atan2/2, hypot/2, log10/1, squareroot/1, cone2/2, cone3/2, cone4/2
Relational	minimum/2, maximum/2, ifthenelse/3
Bitwise	and/2, or/2, xor/2
Noise	perlinnoise/2, fbm/2, snoise/2, vlnoise/2, marble/2, turbulence/2
Boolean	lessthan/4, greaterthan/4
Other	parabol/2

The function set has already been described in detail in [7] so we will not repeat it here. There are a few new functions since [7] which we will describe briefly; *cone2*, *cone3* and *cone4* all draw circle-like patterns with the center in the middle (so the image looks like a cone from the top) and are variations on the *cone* function from [4].

4 Experiments

We did a number of experiments to evaluate the use of a MOEA in evolutionary art. First, we performed 10 runs with a single aesthetic measure (non-MOEA).

Fig. 1. Portfolio of images gathered from ten runs with Benford Law (left) and Global Contrast Factor (middle) and Ross & Ralph (right)

This resulted in 3 experiments (one for each aesthetic measure described in 2.2 consisting of 10 runs each. We hand-picked a number of images from these runs and created portfolios for each aesthetic measure. Basically, this is the same setup as the research we did described in [6] and [7], but we repeated these experiments since we altered the function set. Figure 1 shows three portfolios of the three experiments with a single aesthetic measure. As in [6] and [7] we see a clear difference in “style” between the three aesthetic measures. We will use Figure 1 (as a kind of benchmark) to evaluate the output of the experiments with the MOEA. Next, we performed three experiments with the NSGA-II algorithm [3] using 1) Benford Law and Ross & Ralph, 2) Global Contrast Factor and Ross & Ralph and 3) Benford Law and Global Contrast Factor. We did 10 runs with each setup, using the exact same experimental setup (evolutionary parameters from Table 1 and the function set from Table 2) except for the combination of aesthetic measures. From each run, we saved the Pareto front (the first front, with rank 0) and calculated the normalized fitness for image I for each objective f using $f_{normalized}(I) = f(I)/f_{average}$. This way, we normalized all scores between 0 and 1. Next, we ordered each individual on the sum of the normalized scores of the two objectives, and we stored the top 3 individuals from each run. With 10 runs per experiments, we have 30 individuals per experiment that can be considered the “top 30”. Using this approach, we have a fair and unbiased selection procedure (since we did not handpick images for these selections). In the top 30 portfolio of the experiment with Benford Law and Ross & Ralph (Figure 2) we can clearly see the influence of both aesthetic measures in the images. The Benford Law aesthetic measures produces images with an organic, natural feel and the Ross & Ralph measure tends to produce image with a “painterly” feel (since it focuses on smooth transitions in colours). We can see these properties in most images and in some images they are combined (i.e. in the first three images in Figure 2). The last two images of the second row and the first image of the third row also appear in the close-up of the Pareto front in Figure 5. In the top 30 portfolio of the experiment with Global Contrast Factor and Ross & Ralph (Figure 3) we see again that the properties of both aesthetic measures appear in the images. GCF tends to produce images with stark contrast at various

Fig. 2. Portfolio of images gathered from ten runs with NSGA-II with Benford Law and Ross & Ralph

Fig. 3. Portfolio of images gathered from ten runs with NSGA-II with Global Contrast Factor and Ross & Ralph

Fig. 4. Portfolio of images gathered from ten runs with NSGA-II with Benford Law and Global Contrast Factor

resolutions and Ross & Ralph tends to produce “painterly” images. If we compare this portfolio with the previous portfolio, we can clearly see more dark colours (especially black) in the images. This can be attributed to the influence of the GCF measure. There seems to be less “synergy” between the two measures; images either have a strong GCF signature or a strong Ross & Ralph signature, but few images have both. Apparently, it is difficult to mix the “styles” of these two aesthetic measures into one image. The 5th, 6th and 7th image of the second row appear in the close-up of the Pareto front in Figure 6. In the top 30 portfolio of the experiment with Benford Law with GCF (Figure 4) we clearly see the influence of the Global Contrast Factor; many images have a stark contrast and have dark areas. Nevertheless, if we compare these images with the portfolio of the Global Contrast Factor (Figure 1) then we can also detect the influence of the Benford Law aesthetic measure (although clearly not in all images). The Benford Law aesthetic measure produces images with a grainy, natural feel (see more images in [7]) and in a way these two properties seem to blend in a number

of images (although not in all). It appears that these two aesthetic measures do not combine very well. The 2nd, 3rd and 4th image of the third row also appear in the close-up of the Pareto front in Figure 7.

4.1 Close-Ups of Pareto Fronts

We wanted to know in detail how a single Pareto front was organized, and whether we could see a gradual transition of the influence of measure A to measure B while moving over the Pareto front. We zoomed in on a single Pareto front and reconstructed the images that belong with each individual in that front. In the following figure we show the Pareto front for each pair of aesthetic measure (note that we did 10 runs per experiments, but we only show the Pareto front of one run). In Figure 5 we see the 15 individuals plotted based on their scores on the Ross & Ralph measures and the Benford Law measure. We normalized the scores between 0 and 1.

Fig. 5. Details of the Pareto front of Benford Law and Ross & Ralph with the corresponding images per element of the front

If we look at the individuals of the Pareto front in Figure 5, we can see a transition of the influence from aesthetic measure to the other. At the top we see “typical” Ross & Ralph images (we saw this type of images in Figure 1, right picture, and in [6]), and at the bottom/ right we see more typical Benford Law images. In between, at the right/ top we see the images where the influences blend most. Not that the images of the individuals in the upper right of the front (where the combined score is highest) are gathered in the Top 30 selection of Figure 2 (fourth row, first three images).

In Figure 6 we see the 12 individuals of a run of Ralph & Ross and the Global Contrast Factor. On the far left we see one individual that scores low on GCF and high on the Ralph & Ross measure. This image is a ‘typical’ Ralph & Ross

Fig. 6. Details of the Pareto front of Ralph & Ross and Global Contrast Factor with the corresponding images per element of the front

Fig. 7. Details of the Pareto front of Benford Law and Global Contrast Factor with the corresponding images per element of the front

image (we see similar images in Figure 1, right), and it is quite different from the cluster of images on the lower right; in this cluster we can clearly see the influence of the GCF measure, with heavy contrast and a lot of black.

In Figure 7 we see the 12 individuals of a run of Benford Law and GCF. In the Pareto front we see three clusters and one outlier on the lower right. Again we see a nice transition from one style to another; on the left we see two images in Benford Law style (we also see this type of images in Figure 1, left). Again we

see images with high contrast and lot of black in the lower right of the Pareto front. Remarkable is the recurring ‘zebra’/ ‘tiger’ print motif that recurs in a number of images.

5 Conclusions and Future Work

Our first research question was “can we combine the effects from multiple aesthetic measures into the same image using a MOEA?”. The answer to this question is ‘Yes, but not necessarily with success’. We have seen that some combinations of aesthetic measure work better than others; some combinations of aesthetic measures result in images where the aesthetic properties do not blend very well. It suggests that it is very important to carefully select the aesthetic measures in a MOEA setup. Combinations of aesthetic measures with opposing goals (e.g. stark contrast vs. little contrast) will most likely not result in images with new or surprising results. Most likely, they will result in images where one property is dominant. However, it will not always be clear whether two aesthetic measures have opposing goals. Furthermore, in order to improve the artistic range of an evolutionary art system, it can be wise to use aesthetic measures that have “somewhat” different goals. So it seems that the most interesting combinations are of aesthetic measures that are different from each other but not too different.

Another strategy could be to use aesthetic measures that act on different dimensions of an image. For example, if one aesthetic measures focuses on texture, one focuses on a certain aspect of contrast and one focuses on composition aspects of the images, then the outcome of the different measures can be merged more efficiently. This strategy looks like an interesting direction to explore in future work.

The second research question was whether the use of MOEA would result in “better” images; we think that some combinations of aesthetic measures certainly result in more interesting images, whereby properties of both aesthetic measures are merged nicely. We also think that some combinations of aesthetic measures work counter-productive, and do not result in “better” images. Nevertheless, we think it can be a powerful tool for evolutionary art systems.

References

1. del Acebo, E., Sbert, M.: Benford’s law for natural and synthetic images. In: Neumann, L., et al. (eds.) [10], pp. 169–176
2. Bentley, P.J., Corne, D.W. (eds.): *Creative Evolutionary Systems*. Morgan Kaufmann, San Mateo (2001)
3. Deb, K., Pratap, A., Agarwal, S., Meyarivan, T.: A fast elitist multi-objective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation* 6, 182–197 (2002)
4. Greenfield, G.R.: Mathematical building blocks for evolving expressions. In: Sarhangi, R. (ed.) *2000 Bridges Conference Proceedings*, pp. 61–70. Central Plain Book Manufacturing, Winfield (2000)

5. Greenfield, G.R.: Evolving aesthetic images using multiobjective optimization. In: Sarker, R., Reynolds, R., Abbass, H., Tan, K.C., McKay, B., Essam, D., Gedeon, T. (eds.) *Proceedings of the 2003 Congress on Evolutionary Computation CEC 2003*, pp. 1903–1909. IEEE Press, Canberra (2003)
6. den Heijer, E., Eiben, A.: Comparing aesthetic measures for evolutionary art. In: Di Chio, C., Brabazon, A., Di Caro, G.A., Ebner, M., Farooq, M., Fink, A., Grahl, J., Greenfield, G., Machado, P., O'Neill, M., Tarantino, E., Urquhart, N. (eds.) *EvoApplications 2010. LNCS*, vol. 6025, pp. 311–320. Springer, Heidelberg (2010)
7. den Heijer, E., Eiben, A.: Using aesthetic measures to evolve art. In: *IEEE Congress on Evolutionary Computation (CEC 2010)*, Barcelona (2010)
8. Matkovic, K., Neumann, L., Neumann, A., Psik, T., Purgathofer, W.: Global contrast factor—a new approach to image contrast. In: Neumann, L., et al. (eds.) [10], pp. 159–168
9. McCormack, J.: Open problems in evolutionary music and art. In: Rothlauf, F., Branke, J., Cagnoni, S., Corne, D.W., Drechsler, R., Jin, Y., Machado, P., Marchiori, E., Romero, J., Smith, G.D., Squillero, G. (eds.) *EvoWorkshops 2005. LNCS*, vol. 3449, pp. 428–436. Springer, Heidelberg (2005)
10. Neumann, L., Sbert, M., Gooch, B., Purgathofer, W. (eds.): *Computational Aesthetics 2005: Eurographics Workshop on Computational Aesthetics in Graphics, Visualization and Imaging 2005*, Girona, Spain, May 18–20. Eurographics Association (2005)
11. Romero, J., Machado, P. (eds.): *The Art of Artificial Evolution: A Handbook on Evolutionary Art and Music. Natural Computing Series*. Springer, Heidelberg (2007)
12. Rooke, S.: Eons of genetically evolved algorithmic images. In: Bentley, P.J., Corne, D.W. (eds.) [2], pp. 339–365
13. Ross, B., Ralph, W., Zong, H.: Evolutionary image synthesis using a model of aesthetics. In: *IEEE Congress on Evolutionary Computation (CEC 2006)*, pp. 1087–1094 (2006)
14. Ross, B.J., Zhu, H.: Procedural texture evolution using multi-objective optimization. *New Gen. Comput.* 22(3), 271–293 (2004)
15. Sims, K.: Artificial evolution for computer graphics. In: *SIGGRAPH 1991: Proceedings of the 18th Annual Conference on Computer Graphics and Interactive Techniques*, vol. 25, pp. 319–328. ACM Press, New York (1991)
16. Takagi, H.: Interactive evolutionary computation: Fusion of the capacities of ec optimization and human evaluation. *Proceedings of the IEEE* 89(9), 1275–1296 (2001)