Multi-Objective Evolutionary Art

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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 use two aesthetic measures as fitness functions concurrently. We use three different pairs from a set of three aesthetic measures and 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 or merged using MOO and 2) whether the use of MOO in evolutionary art results in different, or perhaps even "better" images.

1. Introduction

This paper is an abstract of recent work (den Heijer & Eiben, 2011) in which we investigate whether it is possible to evolve aesthetic images by combining the effects of multiple aesthetic measures concurrently using a Multi-Objective Evolutionary Algorithm (MOEA). In previous work we have shown that the choice of the aesthetic measure significantly determines the "style" of the generated art (den Heijer & Eiben, 2010). With MOEA, we want to investigate whether the influence of different aesthetic measures can be combined or merged into the same image. 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.

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2. MOEA and Evolutionary Art

Multi-Objective Evolutionary Algorithms (MOEA) are evolutionary algorithms that use multiple fitness functions (or objectives) to evolve solutions to certain problems. In our research we approach the evolution of art as an optimization problem, and use multiple aesthetic measures in order to combine different aspects of aesthetic evaluation concurrently. MOEA's have not been used frequently in the field of evolutionary art (den Heijer & Eiben, 2011). In our experiments we used three aesthetic measures as fitness functions. Aesthetic measures are functions that assign an aesthetic score to an image. The aesthetic measures that we use in our experiments are Benford Law, Global Contrast Factor and Ross & Ralph (den Heijer & Eiben, 2011).

3. Experiments and Results

We did a number of experiments to evaluate the use of a MOEA in evolutionary art. Our evolutionary art system uses genetic programming (den Heijer & Eiben, 2011). In all our experiments we used a population size of 200, 20 generations, a tournament size of 3, a crossover rate of 0.9 and a mutation rate of 0.1.
We performed three experiments with the well-known NSGA-II algorithm using two aesthetic measures of the following three: 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 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 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

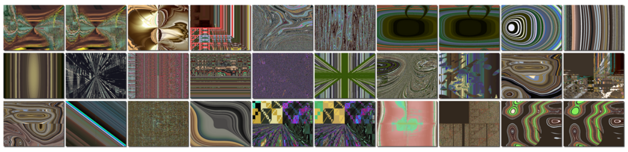

Figure 1. Portfolio of images gathered from ten runs with NSGA-II with Benford Law and Ross & Ralph

with Benford Law and Ross & Ralph (Figure 1) 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 1). 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 2. For more details and images of the experiments with the other combinations of aesthetic measures we refer to (den Heijer & Eiben, 2011).

3.1. 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 2 we see the 15 individuals plotted based on their scores on the Ross & Ralph measure and the Benford Law measure. We normalized the scores between 0 and 1.

If we look at the individuals of the Pareto front in Figure 2, we can see a transition of the influence from aesthetic measure to the other. At the top we see "typical" Ross & Ralph images (den Heijer & Eiben, 2010; den Heijer & Eiben, 2011), and at the bottom/ right we see more typical Benford Law images. In

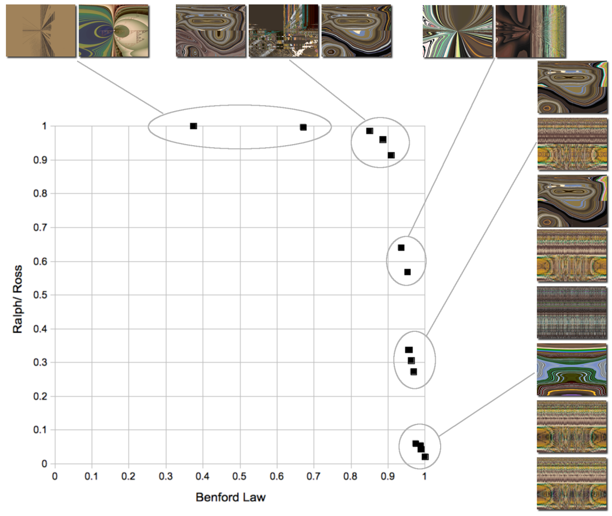

Figure 2. Details of the Pareto front of Benford Law and Ross & Ralph with the corresponding images per element of the front.

between, at the right/ top we see the images where the influences blend most.

4. Conclusions and Future Work

Our first research question was whether the influence of different aesthetic measures could be combined into the evolved images. From our experiments we can conclude that we actually can, but that the combination of aesthetic measures should be chosen with care. Combinations of aesthetic measures that have opposing goals will result in inefficient search behaviour, and will not result in images with "synergy" of the aesthetic measures. Our experience shows that combinations of aesthetic measures that have "somewhat" different goals result in the most interesting images. Our second research question was whether the resulting evolved images are more interesting when using multiple aesthetic measures. If we compare the images of our MOEA experiments with images of previous work with a single aesthetic measures, we can conclude that the MOEA images are (on average) more interesting.

References

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