Testing the Differences of Using RGB and HSV Histograms During Evolution in Evolutionary Art

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Abstract: This paper compares the use of RGB and HSV histograms during the execution of an Evolutionary Algorithm. This algorithm generates abstract images that try to match the histograms of a target image. Three different fitness functions have been used to compare: the differences between the individual with the RGB histogram of the test image, the HSV histogram, and an average of the two histograms at the same time. Results show that the HSV fitness also increases the similarities of the RGB (and therefore, the average) more than the other two measures.

1 INTRODUCTION

Evolutionary Art (Corne and Bentley, 2001) is a type of generative art (Fernandes et al., 2012) created by a computer, following the principle of the survival of the fittest, using Evolutionary Computation methods (Eiben and Smith, 2005). A population of artistic works (individuals) are evaluated with an aesthetic measure to yield a score (fitness). These individuals are combined and mutated to generate an offspring with inherited properties of the parents, during a certain number of times.

The main goal of this paper is to study the differences of using the information of the HSV (Hue, Saturation, Value) and RGB (Red, Green, Blue) histograms during the evolution. The secondary goals is to test the advantages of using In this work the Processing (Reas and Fry, 2007) framework is used inside an Evolutionary Algorithm (EA) to model the individuals, generate their associate images and extract information of them (HSV, RGB and Average histograms) to fit with the histograms of a test image. Processing has been integrated in the OSGiLiath (García-Sánchez et al., 2013) evolutionary framework to take advantage of the capabilities offered in image manipulation and analysis.

The rest of the work is organized as follows: in Section 2, a brief review on Evolutionary Art is presented. Processing framework and image information are described next (Section 3). The experimental setup and results are presented in Sections 4 and 5, respectively. Finally, the conclusions and future work can be found in Section 6.

2 STATE OF THE ART

Computational Aesthetics "is the research of computational methods that can make applicable aesthetics decisions in a similar fashion as humans can" (Hoenig, 2005). In the field of computational aesthetics, evolutionary systems can play an important role, by enabling the evolution of aesthetically pleasing or innovative structures (DiPaola and Gabora, 2009). Evolutionary art is characterized by the use of evolutionary principles and natural selection as a generative process. One of the earliest applications of evolutionary systems to generate art is the proposal of Sims to use a Genetic Algorithm (GA) to create complex structures (Sims, 1991) or virtual creatures (Sims, 1994). In evolutionary art systems, the evaluation of the aesthetics can be done using human feedback, with some interactive evaluation of the population, such as, (Ashlock, 2006; Draves, 2006; Moroni et al., 2000; Sims, 1991) and (Takagi et al., 2001). It also can be achieved by using an automatic evaluation of fitness, as presented in (Aguilar and Lipson, 2008; Del Acebo and Sbert, 2005; Den Heijer and Eiben, 2010; DiPaola and Gabora, 2009; Li et al., 2012; Machado and Cardoso, 1998), and (Sims, 1994).

One of the main challenges in Evolutionary Art is how to measure aesthetic value of a piece of evolutive art. The source of this difficulty lays in the inherent complexity, subjectivity and dynamism of aesthetics. Nevertheless, a wide number of metrics has been presented. According to Galanter (Galanter, 2012), these measures can be classified in the several categories in several pieces of research. The first category involves the evaluation of the aesthetics of a piece of art by a formula o principle (e.g., pythagorean proportions). Other measures apply certain principles of design, such as the rule of thirds or color theory (e.g., using complimentary colors in Pop Art (den Heijer and Eiben, 2012)), neural networks or complexity measures.

This classification also provides a sub-classification for evolutionary systems. First, it identifies interactive evolutionary systems, where the fitness of the individuals is determined by human agents. Another category is performance based goals: certain properties of the art piece are evaluated and optimized based in performance measures (e.g., usable surface in a furniture design generator). Other systems use an exemplar (i.e., real world example) as a way to measure the fitness of the individuals. Finally, some models use the idea that the complexity is directly related to aesthetics and follow the path firstly stablished by Birkhoff (Birkhoff, 2003). Given the multidimensional nature of aesthetics judgement, multi-objective EAs are a straightforward option to deal with this multidimensionality. Other extensions to EA, like coevolution or agent swarm behavior, can be used to in evolutionary art systems.

A brief classification of the aesthetic measures found in a the evolutionary art systems mentioned in the previous paragraph is shown in Table 1.

Several methods for the representation of the art in evolutionary art have been proposed. In symbolic expression the genotype is a tree of expressions and the phenotype consists in the image produced by the evaluation of the tree. Shape grammars can also be used as a formal description of the image. Previously existing images can be used as a basis for the evolution process. Finally, other representations can be based on mathematical models, like fractals or cellular automata.

3 PROCESSING AND HISTOGRAMS

In this section we will describe Processing (`http://www.processing.org/`). Processing (Reas and Fry, 2007) is a framework formed by a simple programming language and an integrated development environment (IDE) mainly focused on electronic and visual artists, designers, musicians, etc. Processing offers the following advantages:

- Processing was created for artists, rather than programmers. So, it allows very complex drawings and interactive applications with few lines of code. For example, Figure **??** shows the sketch (in the IDE) necessary to create the Figure **??**.
- It is an Open Source software (licensed under the GNU Lesser General Public License), and counts with a large development community.
- It is based in OpenGL, thus providing 3D acceleration.
- It also includes more than 100 libraries for video, sound, physics, computer vision, networking, etc.
- Easy integration with Java, HTML5 and Android.
- Finally, it is fairly light when installed.

However, being a light framework, there exist some disadvantages:

- More complex applications require more programming skills.
- The calculations of large computer images are a bit inefficient (although expert programmers can manage OpenGL at low level to fix this).

There exist a lot of interactive artistic projects made with Processing; examples include art generation, artificial life, interactive music and other. A good selection can be seen in `http://processing.org/exhibition/`.

The Color module can be used to analyze images taking into account their histogram. The color histogram represents the frequency of occurrence of each color intensities present in the image, by accounting for such sharing pixels color intensity values.

The histogram is composed of different ranges or bins that represent a value or set of values of color intensity. The color space is defined as a model representation with respect to color intensity values.

Table 1: Classification of the aesthetic measures used in a brief review of the literature on evolutive art.

Type	Aesthetic Measure
Formulaic and Geometric Theories	Fractal dimension (Den Heijer and Eiben, 2010), Image order (Li et al., 2012), Benford Law
Based in Design Principles	Color contrast (hue) (den Heijer and Eiben, 2012), Color ingredient (Li et al., 2012), Compo
Interactive Evolutionary Computation	The electric sheep project (Draves, 2006) (Ashlock, 2006; Moroni et al., 2000)
Error relative to Exemplars	Resemblance score (DiPaola and Gabora, 2009), pixel comparation (Aguilar and Lipson, 20
Performance based goals	Evolving virtual creatures (Sims, 1994)
Complexity measures	Image complexity (Li et al., 2012), Machado and Cardoso aesthetic measure (Machado and C

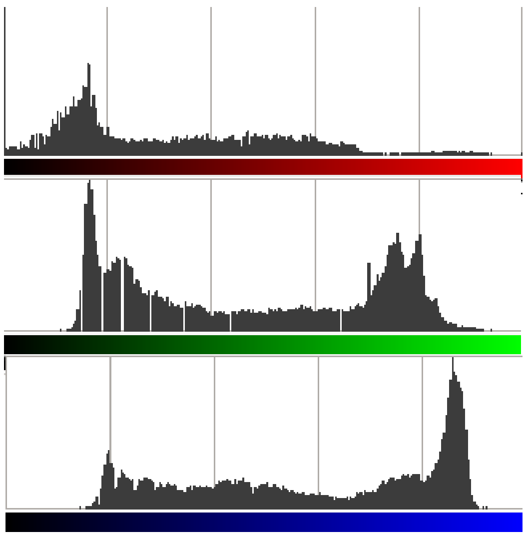

Figure 1: RGB histogram of the Figure 2.

Two color models are used in this paper: RGB (Red, Green, Blue) and HSV (Hue, Saturation and Value). The RGB model is an additive color model in which red, green and blue are added together in different proportions to reproduce a wide range of colors, while the HSV is based on hue or tone, saturation and brightness. While the RGB model is the most closest to the way color is processed in some machines, the HSV representation provides a more accurate way to model how humans perceive colors, and also provides more information in image retrieval (Sebe and Lew, 2000). Figure 1 shows the RGB histogram of the image in the Figure 2 (photo taken by the first author).

4 EXPERIMENTAL SETUP

This section shows how Processing have been used in the EA, the individual representation, the fitness functions, and the parameters of the experiments.

Figure 2: Test image to compare with the Fitness functions of our algorithm.

4.1 Integrating Processing in Java

Processing can be integrated with Java just by adding a *jar* (a Java library) to existing software. The simplified code of the sketch (for example, the one shown in Figure **??**) is accessed by extending the *PApplet* class. In this work, Processing has been integrated to an existent EA framework, OSGiLiath (García-Sánchez et al., 2013), a service-oriented framework based in Java that includes a lot of primitives and services for Evolutionary Computation. A new module called OSGiLiART has been added to the publicly-available source code of OSGiLiath (available in `http://www.osgiliath.org`) under a GPL License. Then, using the packages available in the Processing library the EA can generate individuals, manipulate images or extract information.

4.2 Individual Representation

To test the Processing advantages and perform the experiments, the genome of the individual is a list of Processing Circles. Each circle has a position, radium and color. This list can be recombined or mutated (changing the color, position or radium of a circle of the list).

4.3 Fitness Used

For this piece of research, we focused on the aesthetics measure of histogram comparison. The fitness functions are included in the "Error relative to Exemplars" category, using Galanter (Galanter, 2012) classification. The idea is to obtain an image with the same proportion of tones and colors of a aesthetical existent image.

Three different fitness functions have been tested:

- *RGB difference*: The difference of the RGB histogram of the individual with the RGB histogram of the test image.
- *HSV difference*: The difference of the HSV histogram of the individual with the HSV histogram of the test image.
- *Average difference*: An average of the two previous differences.

The range of the previous fitness have been normalized to vary from 0 (totally different histograms) to 1 (the same histogram).

For every color property (i.e., RED, GREEN, BLUE, HUE, SATURATION and VALUE), the histogram is computed using the expression (1) for each possible value (0-255). Then, again for every property, the difference between the target image and the individual histograms is obtained using (2). Finally, the three fitness are calculated: RGB fitness (6), HSV fitness (10) and AVERAGE fitness (11).

$$H(c, prop) = \frac{1}{N}\sum_{j=0}^{N}\begin{cases}1 & prop(j) = c\\ 0 & otherwise\end{cases} \quad (1)$$

$$diff(h_1, h_2) = \sum_{j=0}^{255} |h_1(j) - h_2(j)| \quad (2)$$

$$d_R(i) = diff(H(i, RED), H(target, RED)) \quad (3)$$

$$d_G(i) = diff(H(i, GREEN), H(target, GREEN)) \quad (4)$$

$$d_B(i) = diff(H(i, BLUE), H(target, BLUE)) \quad (5)$$

$$fitness_{RGB}(i) = 1 - 128\frac{d_R(i) + d_G(i) + d_B(i)}{3} \quad (6)$$

$$d_H(i) = diff(H(i, HUE), H(target, HUE)) \quad (7)$$

$$d_S(i) = diff(H(i, SAT), H(target, SAT)) \quad (8)$$

$$d_V(i) = diff(H(i, VAL), H(target, VAL)) \quad (9)$$

$$fitness_{HSV}(i) = 1 - 128\frac{d_H(i) + d_S(i) + d_V(i)}{3} \quad (10)$$

$$fitness_{AVERAGE}(i) = \frac{fitness_{RGB} + fitness_{HSV}}{2} \quad (11)$$

4.4 Parameters Used

A steady-state evolutionary algorithm has been used. Each individual is randomly generated at the initialization of the EA. The genome size is 50 elements (circles of maximum radium of 128 pixels). Population size has been set to 32 individuals. Uniform crossover rate is 0.5, and a binary tournament has been chosen for selection (that is, a pool of 16 parents is selected and crossed). Mutation probability is 0.04 (the usual value of *1/genomesize*). Finally, the image size for each individual is 256x256 pixels. The individuals have been compared with the histograms obtained from the image of Figure 2 to guide the evolution.

5 RESULTS

Each algorithm has been executed 30 times for each different fitness. Table 2 shows the differences (and standard deviation) attained with each fitness used. As can be seen, using the HSV histogram differences as fitness produces a higher RGB similarity (and therefore, average) than using the RGB or Average fitness. However, using the average between the two histogram differences produces higher similarity in HSV (0.294) than only taking into account the HSV. The maximum fitness is around 25% of similarity with the original image since the individual is a list of 50 circles, and therefore, only a maximum of 50 different colors are used (while in the original jpg image can be more than millions). See the histogram of a generated best individual by the algorithm in Figure 3. An example of evolution for each fitness can be seen in Figure 4, 5 and 6. Comparing with the RGB histogram as fitness, a bigger fluctuation in the HSV is produced (Figure 4). This can be explained because the RGB information tends to be more noisy than HSV information: in fact, in (Sebe and Lew, 2000) authors explain the problems this histogram offers with respect to HSV in image retrieval. Although there is the same information modeled in both histograms, the transformation from one to another is not linear, so there is no relation with the histograms of individuals generated during the evolution.

The best individuals attained are shown in Figure 7. Note that, although the numeric fitness is similar, they produce different color tones. This can be explained for the limitation of colors used in the individual representation, as previously said, or the noisy characteristic of the RGB histogram. Figure 8 shows one evolution of the best individual using the HSV fitness in the first 64 generations.

Table 2: Results for the different fitness. Only one histogram type is used, but the other values obtained are also added.

Differences used	Obtained RGB	Obtained HSV	Obtained Average
RGB Histogram	*0.267 ± 0.012*	0.170 ± 0.010	0.218 ± 0.009
HSV Histogram	0.227 ± 0.017	*0.265 ± 0.021*	0.246 ± 0.010
Average Histogram	0.173 ± 0.012	0.294 ± 0.013	*0.234 ± 0.010*

(a) Best individual using RGB (b) Best individual using HSV (c) Best individual using AVERAGE

Figure 7: Best individuals obtained with the three fitness used (HSV, RGB and AVERAGE).

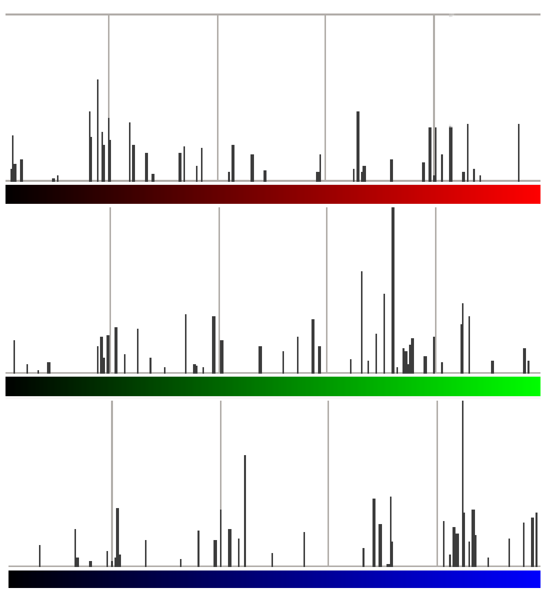

Figure 3: RGB histogram of a solution generated by the algorithm.

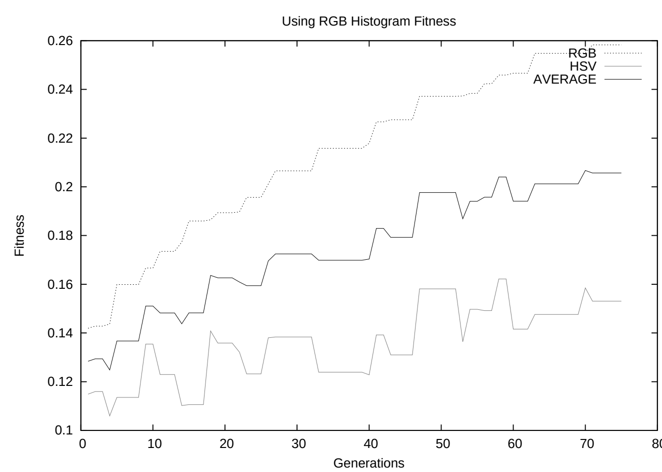

Figure 4: Evolution of the difference in RGB histogram of the best individual compared with the test image.

6 CONCLUSIONS AND FUTURE WORK

This paper introduces an Evolutionary Algorithm that uses the Processing framework to generate images and to extract image information. In this work individuals are represented as a list of Processing primitives (circles) and the fitness functions used are based in the similarity with an existent aesthetic image. Three different fitness functions using color histogram have been tested: difference between the HSV and RGB histograms, and an average difference of the two histograms at the same time. Experiments show that better results in terms of similarity are obtained using the HSV comparison (due to the noisy information provided by the RGB). This is a basic image metric, only used by purposes of proof-of-concept and more complex measurements will be studied in next works.

The future work for this research also includes more experiment with other kind of individuals, apart from circles: using other primitives, such as rectangles or triangles, for example. The use of textures and gradients will generate images with higher number of colors, obtaining more fidelity (more than 25%) with

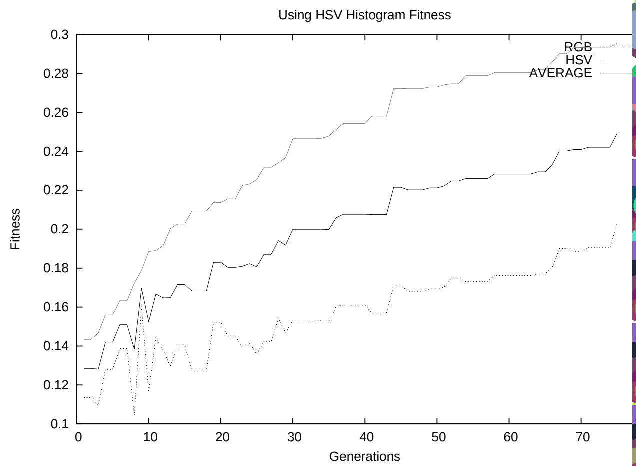

Figure 5: Evolution of the difference in HSV histogram of the best individual compared with the test image.

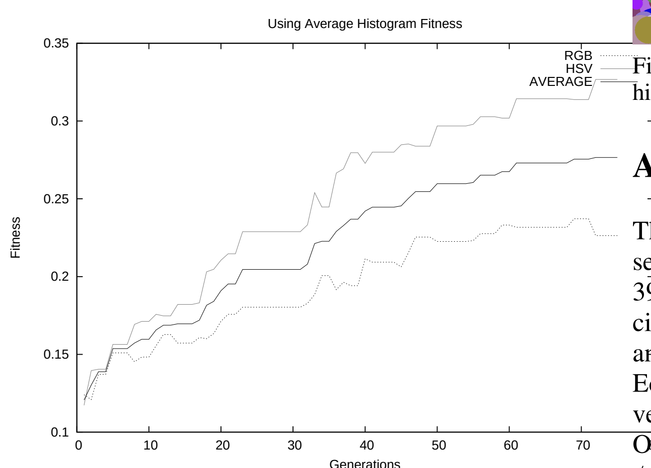

Figure 6: Evolution of the difference of average of RGB and HSV histogram of the best individual compared with the test image.

the test image. Other metrics explained in previous sections will be also implemented. Finally, our intention is not create only static images, but use the Processing libraries to create evolutionary interactive art combining sounds and motion. A human guidance tool is also being developed to obtain human feedback to create a knowledge base for future experimentation (available in `http://evorq.ugr.es:8080/HumanGuidance`).

The used software and algorithms presented are Open Source under a GPL license, and can be obtained from `http://www.osgiliath.org`.

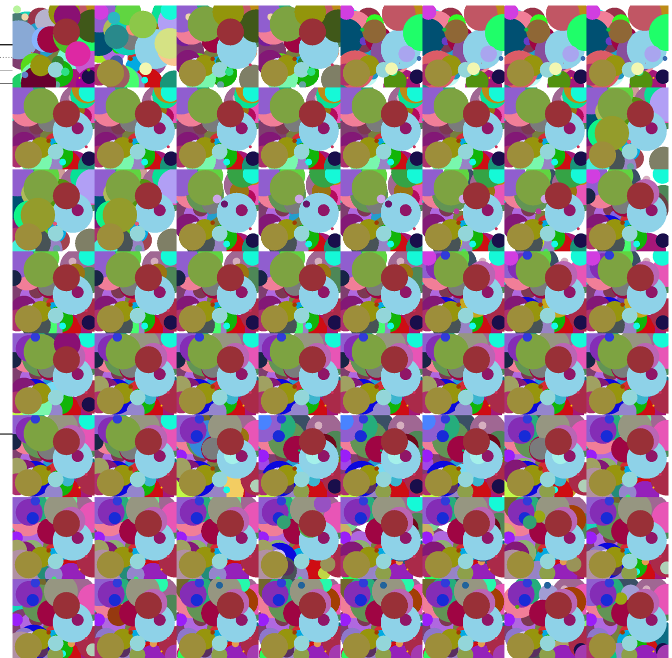

Figure 8: Evolution of the best individual using the HSV histogram difference.

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