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 branch of generative art (Fernandes et al., 2012) created using 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.

There exist several metrics to score the generated images, such as opinion from humans, or image characteristics (for example, specific combination of colours). 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. Although the two histograms represent the same information, using HSV (instead as RGB) as a color model increases the accuracy in image retrieval and indexing, as explained in (Sebe and Lew, 2000). The results of this investigation can help in future evolutionary art algorithms, adding the most appropiate color model feature with other features available in the literature. For example, to be used as one of the features of any kind of classifier. 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 aesthet-

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ics 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 an EA to create complex images (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) and (Sims, 1991). It also can be achieved by using an automatic evaluation of fitness, as presented in (Aguilar and Lipson, 2008; Den Heijer and Eiben, 2010; DiPaola and Gabora, 2009; Li et al., 2012), 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 lies in the inherent complexity, subjectivity and dynamism of aesthetics. Nevertheless, a wide number of metrics has been presented. According to (Galanter, 2012), these measures can be classified into several categories in several pieces of research. The first category involves the evaluation of the aesthetics of a piece of art by a formula or 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 subclassification 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 on 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 in (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 in evolutionary art systems.

A brief classification of the aesthetic measures found in 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 describe Processing [1] and the histograms used. Processing (Reas and Fry, 2007) is a framework formed by a simple programming language and an integrated development environment (IDE) primarily created for 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.
- It is an Open Source software (licensed under the GNU Lesser General Public License), and counts with a large development community.
- It is based on 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.

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

[1] `http://www.processing.org/`

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 (Del Acebo and Sbert, 2005)
Based on Design Principles	Color contrast (hue) (den Heijer and Eiben, 2012), Color ingredient (Li et al., 2012), Composition, tonality and color (DiPaola and Gabora, 2009).
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, 2008)
Performance based goals	Evolving virtual creatures (Sims, 1994)
Complexity measures	Image complexity (Li et al., 2012), Machado and Cardoso aesthetic measure (Machado and Cardoso, 1998)

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. 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 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 Figure 2 (photo taken by the first author).

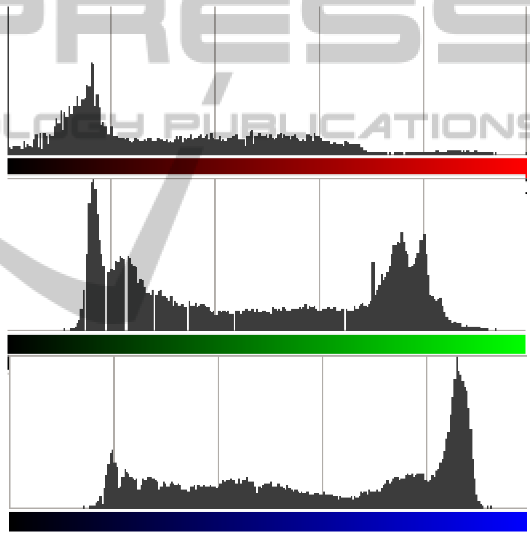

Figure 1: RGB histogram of Figure 2.

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

4 EXPERIMENTAL SETUP

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

4.1 Integrating Processing in Java

Processing can be integrated with Java just by adding a *jar* (a Java library) to existing software. In this work, Processing has been integrated to an existent EA framework, OSGiLiath (García-Sánchez et al., 2013), a service-oriented framework based on Java that includes a lot of primitives and services for Evolutionary Computation. A new module called OS-

GiLiART has been added to the publicly-available source code of OSGiLiath (available in `http://www.osgiliath.org`) under a LGPL 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 perform the experiments, the genome of the individual is a list of 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 these fitness function has 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

Because of the stochastic nature of the EAs, each algorithm has been executed 30 times for each different fitness. Table 2 shows the average 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

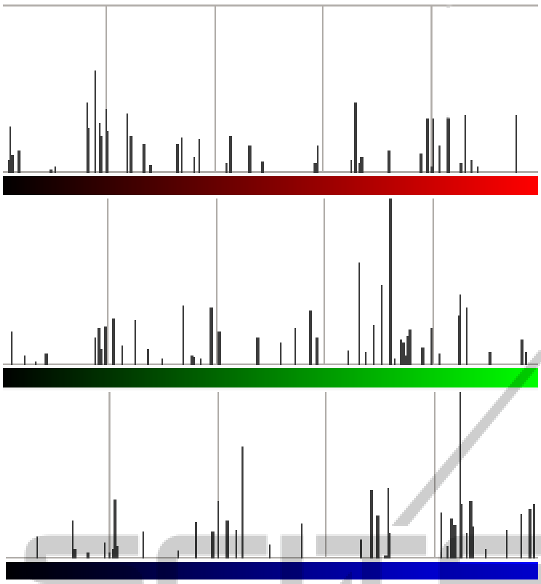

Figure 3: RGB histogram of a solution generated by the algorithm.

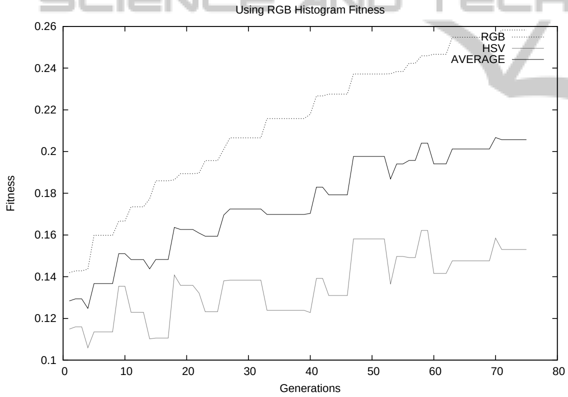

Figure 4: Evolution of the difference in RGB histogram of the best individual compared with the test image.

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

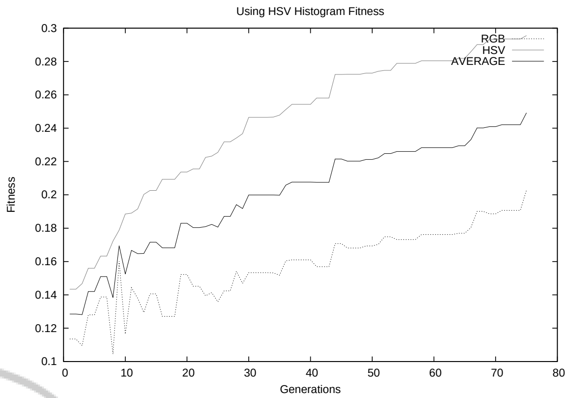

Figure 5: Evolution of the difference in HSV histogram of the best individual compared with the test image.

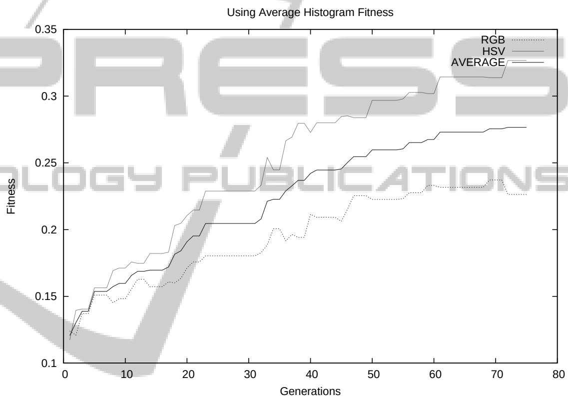

Figure 6: Evolution of the difference of average of RGB and HSV histogram of the best individual compared with the test image.

one evolution of the best individual using the HSV fitness in the first 64 generations.

6 CONCLUSIONS AND FUTURE WORK

This paper introduces an Evolutionary Algorithm that uses the Processing framework to generate images and to extract image information using HSV and RGB histograms. In this work individuals are represented as a list of Processing primitives (circles) and the fitness functions used are based on 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).

Table 2: Results for the different fitness (average of the 30 executions and standard deviation). Only one histogram type is used for fitness calculation, but the other values obtained are also added.

Differences used in Fitness	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).

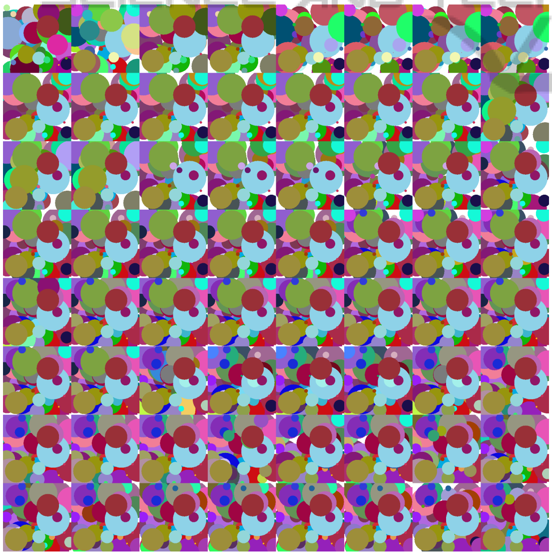

Figure 8: Evolution of the best individual using the HSV histogram difference.

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 the test image. Other metrics explained in previous sections will be also implemented. Finally, our intention is not only to 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 results will be gathered to create a database of different features to guide the evolution. More complex measurements will be studied in next works, taking into account that the HSV is the color mode that provides more information during the evolution, having less noisy behaviour.

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

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