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***Abstract*—¡Text of the summary of your article¿**

I. Introduction

Evolutionary art blah, blah, blah, ...

The main goal of this paper is ... We show ...

This paper is organized as follows: in Section **??**, a brief review on Evolutionary Art is presented. The methodology and experiments are presented in Sections **??** and **??**, respectively. Finally, the conclusions and future work can be found in Section **??**.

II. Evolutionary Art

Computational Aesthetics "is the research of computational methods that can make applicable aesthetics decisions in a similar fashion as humans can" [**?**]. In the field of computational aesthetics, evolutionary systems can play an important role, enabling the evolution of aesthetically pleasing or innovative structures [**?**].

A. Art Representation for Evolutive Art

- Symbolic expression. The genotype is a tree of expressions and the phenotype consists in the image produced by the evaluation of the tree.
- Grammars. A shape grammar is used as a formal description of the image.
- Using existing images as a source.
- Others, such as fractals or cellular automata.

B. Aesthetic measures for evolutive art

One of the main challenges in Evolutionary Art is how to measure aesthetic value of an piece of evolutive art.

Definition Two modes of aesthetics measures can be defined [**?**]:

1) "*Aesthetics evaluations are expected to simulate, predict or cater to humans notions of beauty and taste.*" This will be the definition used in this paper.
2) "*Is an aspect of meta-aesthetic exploration and usually involves aesthetic standards created by software agents in artificial worlds.*"

According to Galanter [**?**], computational aesthetics measures can be classified in the following categories:

- Based on Formulaic and Geometric Theories. The aesthetics of a piece of art are evaluated using a formula o principle (e.g., pythagorean proportions).
- Based in Design Principles. Like the rule of thirds or theory of color (e.g., using opposite colors).
- Based in Neural Networks and Connective Models.
- Complexity Based Models.
- Based in Evolutionary Systems:
  - Interactive Evolutionary Computation. The fitness of the individuals is determined by human agents.
  - 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).
  - Error relative to Exemplars. The individual fitness is measured using a real-world example (e.g., a photography).
  - Complexity measures. This type of measures is based in the idea the complexity is directly related to aesthetics and follows the path firstly stablished by Birkhoff [**?**].
  - Multi-objective. Given the multidimensional nature of aesthetics judgement, multi-objective EAs are a clear option in order to deal with this multidimensionality.
  - Extensions to EA (such as, coevolution, agent swarm behavior, etc.).

A brief classification of the aesthetic measures found in a short review can be fount in Table **??**.

III. Genetic Operators

In this section we will describe the genetic operators ...

A. Representation

Genotype -¿ list of shapes

B. Initialization

??

C. Mutation

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TABLE I. 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 [?], Image order [?], Benford Law [?]
Based in Design Principles	Color contrast (hue) [?], Color ingredient [?], Composition, tonality and color [?].
Interactive Evolutionary Computation	The electric sheep project [?]
Error relative to Exemplars	Resemblance score [?], pixel comparation [?]
Performance based goals	Evolving virtual creatures [?]
Complexity measures	Image complexity [?], Machado and Cardoso aesthetic measure [?]

D. Crossover

??

E. Fitness Functions

For this piece of research, we focused on two measures of aesthetics: basic histogram comparison and image matching. The fitness functions are included in the "Error relative to Exemplars" category, using Galanter [?] classification.

1) Histogram comparision: An histogram is a graphical representation of the tonal distribution in an image. The histogram for the property i is computed following (**??**).

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

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

$$d_R(i) = diff(H(i, RED), H(target, RED)) \tag{3}$$

$$d_G(i) = diff(H(i, GREEN), H(target, GREEN)) \tag{4}$$

$$d_B(i) = diff(H(i, BLUE), H(target, BLUE)) \tag{5}$$

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

$$d_H(i) = diff(H(i, HUE), H(target, HUE)) \tag{7}$$

$$d_S(i) = diff(H(i, SAT), H(target, SAT)) \tag{8}$$

$$d_V(i) = diff(H(i, VAL), H(target, VAL)) \tag{9}$$

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

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

2) Image Matching:

IV. EXPERIMENTAL RESULTS

V. CONCLUSIONS AND FUTURE WORK

This paper introduces a ...

The future work for this research work includes ...

Aknowledments.:

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