Visual Creativity

Ping Xiao
Topics in Visual Creativity

• Images & Paintings
• Design: Graphical, Industrial
• Evolutionary Architecture
• Choreography
• …
Major ‘Concerns’ of Computer Visual Artists

• Representation
• Generation
• Intention
• Evaluation
Images & Paintings: Representation

I. Descriptive:
   – Raster: a matrix of pixels, BMP, GIF, PNG, JPG, ...
   – Vector Graphics: Bézier curve, ...
   – Plan of composition

II. Procedural:
   – Mathematical function
   – Shape grammar
   – Commands for drawing robots
   … Any sequence of ‘operations’
Example Representation: Bézier Curve

**typEm**\(^1\) by Catarina Maçãs

- Generates fonts based on the emotion of a text
- Using Fontastic\(^2\), a Processing library

1. [https://vimeo.com/74389105](https://vimeo.com/74389105)
There were some interesting findings in these results. Firstly, we noted that anything but a 0.001 mutation rate resulted in premature convergence, which – as suggested by a reviewer – is probably due to the roughness of the fitness landscape. We found little discernable difference between 1 point and 2 point crossover, and as expected, with evolution only, the fitness achieved was largely proportional to the population size and number of generations. The quickest setup (labelled setup A in figure 1) achieved a fitness of 0.78 in only 9 seconds, using hill-climbing with repetition factor 1. We found that hill-climbing with a repetition rate of 100 achieved a fitness of 0.88, but took more than 10 minutes to achieve (setup C). In comparison, the best evolved (non-hill-climbing) scene had a fitness of 0.82 and took 670 seconds to produce (setup B). In contrast, an evolutionary approach with population size 100 for 100 generations followed by a hill-climbing session with repetition factor 10 achieved fitness 0.9 in only 98 seconds (setup D). It seems likely that we could achieve better results with different settings, and perhaps by using an iterative hill-climbing approach. However, as our main focus is on automatically generating fitness functions, and setup D performs adequately for that task, we have not experimented further yet.

In figure 2, we show the scene generated using search setup D, which achieved a fitness of 0.9. We see that, while there are a few outliers amongst the scene elements, the desired properties of the scene are there. That is, the buildings at the left and right of the scene are smaller in both width and height, less saturated and higher, which gives them the appearance of distance. Also, the buildings at the back of the scene are taller, less saturated and slightly brighter, again giving the impression of distance. In figure 2, we also present two rendered versions of the cityscape. The first is rendered using simulated coloured pencil outlining (with a reduced palette of urban colours) of the buildings over a simulated pastel base on art paper. The second is rendered using simulated acrylic paints over a pastel base, on primed canvas, giving a slightly three dimensional effect.

Fig. 2. Evolved setup D cityscape scene, rendered with: block shapes; simulated pastels and pencils; and simulated acrylic paints.

In figure 6, we present artistic renderings of the two polar coordinate scenes. Using the Cartesian setup, we then ran the automatic invention of fitness function routine 10 times, but to produce scenes with only 50 elements, and we chose the four most interesting to show in figure 6 (an entirely subjective choice by the author). As with the invented cityscapes of figure 5, each of the four scenes clearly exhibits a pattern. However, of the six other scenes from the session (which are not shown), with four of them, we could discern no obvious scene structure. These scenes scored less than 0.8 for fitness, and on inspection, this was because the fitness functions needed to achieve contradictory correlations. With fewer attributes to seek correlations between in this application than in the previous one, the likelihood of generating such contradictory fitness functions was higher. We aim to get The Painting Fool to avoid such cases in future.
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Example Representation: Mathematical Function

(Machado et al. 2007)
Example Representation: Shape Grammar

(Machado and Nunes 2010)

```
startshape TREE
rule TREE 0.80 {
    CIRCLE {}
    TREE {size 0.95 y 1.6}
}
rule TREE 0.20 {
    CIRCLE {}
    TREE {size 0.95 y 1.6
          rotate 45}
    TREE {size 0.95 y 1.6
          rotate -45}
}
```

Made with Context Free (http://www.contextfreeart.org/)
Example Representation: Behavior of Artificial Life

(De Smedt, Lechat and Daelemans 2011)

Each creature is constructed randomly from a pool of components (heads, tails, cores, flippers and tentacles). The way a creature is constructed determines it's behavior later on in the survival game.
Example Representation: Behavior of Artificial Life

Made with NodeBox (https://www.nodebox.net/node/)
Images & Paintings: Representation

Use/devise a representation which helps you generate what you want!
Images & Paintings: Generation

• From scratch:
  – take the x and y coordinates of a pixel as input
  – Parameterize a curve or shape
  – Fill a composition plan

• From an input image:
  – Apply image filters
  – Apply paint strokes
  – Collage, Visual Operators (juxtaposition, fusion, replacement)

• Genetic Operators (in Genetic Algorithm & Genetic Programming)
Generation Example: Image Filters

DARCI (Digital Artist Communicating Intention) (Norton, Heath and Ventura 2011)

Source image

A ‘creepy’ version
Generation Example: Paint Strokes

The Painting Fool (Colton 2008)

Fig. 1.6 Example portraits using styles to heighten (L to R) sadness; happiness; disgust; anger; fear and surprise.

we asked them to express one of six emotions, namely happiness, sadness, fear, surprise, anger or disgust, which was captured in a video of roughly 10 seconds duration. The emotion detection software then identified three things: (i) the apex image, i.e., the still image in the video where the emotion was most expressed (ii) the locations of the facial features in the apex image, and (iii) the emotion expressed by the sitter – with around 80% accuracy, achieved through methods described by Valstar and Pantic (2006). It was a fairly simple matter to enable The Painting Fool to use this information to choose a painting style from its database of mappings from styles to emotions and then paint the apex images, using more detailed strokes on the facial features to produce an acceptable likeness. We found subjectively that the styles for surprise, disgust, sadness and happiness worked fairly well in terms of heightening the emotional content of the portraits, but that the styles for anger and fear did not work particularly well, and better styles for these emotions need to be found. Sample results for portraits in the six styles are given in Figure 1.6.

The combined system was entered for the British Computer Society's annual Machine Intelligence Competition in 2008, where software has to be demonstrated during a 15 minute slot. The audience voted for the Emotionally Aware Painting Fool as demonstrating the biggest advancement towards machine intelligence, and we won the competition. More importantly for The Painting Fool project, we can now argue that the software shows some degree of appreciation when it paints. That is, it appreciates the emotion being expressed by the sitter, and it has an appreciation of the way in which its painting styles can be used to possibly heighten the emotional content of portraits.

1.4.3 Scene Construction

Referring back to the creativity tripod described in the guiding principles above, we note that through the non-photorealistic rendering and the emotional modelling projects, we could claim that the software has both skill and appreciation. Hence, for us to argue in our own terms that the software should be considered creative, we needed to implement some behaviours which might be described as imaginative. To do so, we took further inspiration from Cohen's AARON system, specifically its ability to construct the scenes that it paints. It was our intention to improve upon AARON's scene generation abilities by building a teaching interface to The Painting Fool.
Generation Example: Collage

(Krzeczkowska et al. 2010)

Based on a news story about the war in Afghanistan
Generation Example: Visual Operators

(Xiao and Linkola 2015)

Original images for ‘electricity’ and ‘green’:

Juxtaposition

Fusion

Replacement
Images & Paintings: Intention

• Levels of artistic intentions

• State of the art:
  – Detect and express emotions (via stroke styles)
  – Represent the point of view (of a news story)
  – Express specific meanings

• Communicating intention (Framing)
Images & Paintings: Evaluation

• Self-evaluation
  – ‘General objective’ aesthetic measures in math (Birkhoff 1933)
  – Fitness functions in Evolutionary Computing (EC)
  – Learned mapping between image features and meanings

• External evaluation
  – Human curation
  – Human judge
  – Public exhibition
References


References


• De Smedt T., Lechat L. and Daelemans W. Generative art inspired by nature, using NodeBox. Lecture Notes in Computer Science, 6625:264-272, 2011.
Thank You!