

# Synthesizing emotive art

Konrad Cybulski

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## 1 Introduction

In the domain of creative artificial intelligence and evolutionary art, the desire exists for processes that produce imagery that is not only visually appealing, but images that exhibit abstract and emotive characteristics. There exists extensive research on the production of realistic, and target label accurate images. The use of quality-diverse (QD) algorithms in combination with deep neural network (DNN) image classifiers were used by Nguyen et al. (2015b) to generate images with high classification accuracy from pre-trained DNN. Bao et al. (2017) exemplifies recent use of variational generative adversarial network (GAN) architectures for the generation of realistic images from fine-grained target labels. GANs have shown their use in text-to-image synthesis (Reed et al., 2016; Zhang et al., 2017), producing realistic images reflecting the detailed description from which they are generated. With regard to creative image generation, Tan et al. (2017) explored techniques for synthesizing artwork with more abstract characteristics. Through the use of a target artist or genre, the generative network produced images that were highly abstract and stylistically accurate.

Little exploration however has been done on incorporating emotion into the process of art and image generation. Ali and Ali (2017) explored the idea of *emotion transfer*, using techniques such as image emotion assignment, and color/style transfer with the aim of altering image composition to reach a target emotion. Examples given use a target profile, with varying levels of emotions such as joy, anger, and fear, to alter the image’s color composition. The classification of an image’s affective emotion, the emotion with which a viewer classifies the image, has been explored in various works (Machajdik and Hanbury, 2010; Chen et al., 2015; Kim et al., 2018). Kim et al. (2018) produced a classifier for recognizing the emotion attributed to an image. This was done through the application of a DNN to decompose an image to a two-dimensional feature vector (valence and arousal) representing the image’s emotion mapped to a continuous plane (see Figure 2).

## 2 Aims

The aim of this research is to explore the synthesis of artwork with a target emotional profile. Primarily leveraging work by Tan et al. (2017) and Kim et al. (2018) to produce a generative architecture whose output not only has desirable abstract characteristics, but shows emotive capabilities. The proposed system would generate an image that satisfies a set of emotions provided. This will investigate both the efficacy with which a generative system can create emotive images, as well as give insight into the properties attributed to various emotions portrayed in image form.

In order to test, and verify the output of such a system, generated images will be exhibited to explore their emotional effect on humans, and any dissonance between the intended, and resulting emotional profile. This will further verify the accuracy with which an emotional profile can be synthesized into affective artwork with such an architecture.

## 3 Background

### 3.1 Unsupervised image synthesis

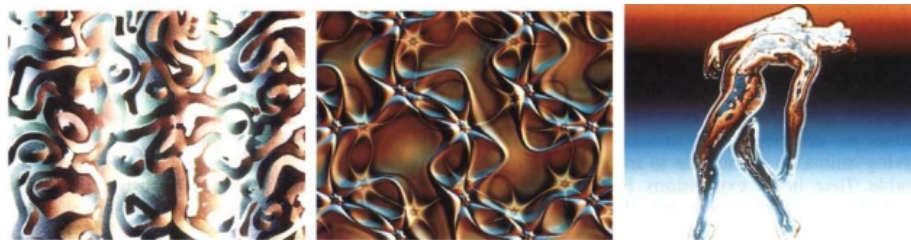


Figure 1: Images generated through the process of interactive evolution introduced by Sims (1993)

The area of evolutionary art and image generation has been explored for many years. Some of the first *human-in-the-loop* systems such as *NEvAr* (Machado and Cardoso, 2000) produced greatly impressive images leveraging methods introduced and exemplified by Sims (1993) such as those shown in Figure 1. Sims (1993) proposed using *Lisp* expressions for genotype definitions, which accepted a coordinate  $(x, y)$  which could be evaluated into a grayscale or RGB value, thus producing images. This genotype expression has been used in numerous further research into the process of both supervised and unsupervised image synthesis (Machado and Cardoso, 2000; Sims, 1993; den Heijer and Eiben, 2011, 2013; Ross et al., 2006).

Sims (1993) and Machado and Cardoso (2000) were able to produce images with visually striking characteristics, despite the slow nature of the interactive process. Ross et al. (2006) investigated the use of measures of aesthetics for

fitness evaluation in artificially evolving images. This research primarily used the observation of Ralph (2006), that the distribution of colour gradients in fine art tend towards normal. While the images produced through this method did not meet the level of intricacy and detail as the results of Sims (1993) or Machado and Cardoso (2000), it represented a self-contained system able to generate appealing art without human interaction.

The introduction of the generative adversarial network architecture (GAN) by Goodfellow et al. (2014) allowed the process of image generation to be completely unsupervised. Common GAN application has involved the generation of realistic images, such as has been done by Bao et al. (2017), where images have been synthesized to fine-detailed target labels such as bird species' and actors. Zhang et al. (2017) and Reed et al. (2016) have recently explored text to image synthesis, in which detailed descriptions of birds and flowers have been converted into photo-realistic images using the GAN model. Tan et al. (2017) has explored the generation of art according to target genre and artist.

### 3.2 Generative adversarial networks

Deep neural networks (DNN) have grown tremendously in popularity in the domain of image generation, and classification, and the accuracy with which they perform.

Research by Burton and Vladimirova (1998) showed that a genetic algorithm composing music benefited from fitness evaluation that relied on phenotype clustering, favoring those that showed diversity from existing clusters.

Recent work by Nguyen et al. (2015a) and Nguyen et al. (2015b) has used pre-trained DNN image classifiers for fitness evaluation throughout the evolutionary process.

### 3.3 Image emotion recognition

The area of image emotion and sentiment classification has been explored in a number of ways, primarily through image feature analysis derived from art and psychological factors (Machajdik and Hanbury, 2010); and more recently using techniques such as deep neural networks (Chen et al., 2015; Kim et al., 2018). Feature extraction and analysis has been used for various applications such as measuring aesthetic appeal (den Heijer and Eiben, 2010a,b, 2011) and as an emotional feature vector for sentiment classification (Machajdik and Hanbury, 2010). Due to the artistic and psychological underpinnings used by Machajdik and Hanbury (2010), the low-level features extracted from images can be understood at a high level. The relationship between an image's emotion and its core artistic components such as balance, harmony, and variety was further explored by Zhao et al. (2014), which uses a comparably small feature vector to Machajdik and Hanbury (2010), resulting however in a 5% classification increase to state-of-the-art approaches at the time.

Deep neural networks in this domain provide less transparency to the process with which emotions and sentiment are classified compared to feature analysis.

		High arousal 9				
		frustrated alarmed afraid angry	afraid angry distressed	astonished pleased excited	excited delighted glad	
1	Low valence	depressed afraid gloomy	afraid angry aroused	pleased content satisfied excited	happy excited glad delighted	9
		depressed gloomy annoyed	gloomy tense bored	tense at ease serene tired	serene glad delighted	High valence
		depressed bored gloomy	bored tired depressed	at ease tired serene	glad serene happy	
		1 Low arousal				

Figure 2: Distribution of emotions associated with levels of valence and arousal determined by DNN classifier produced by Kim et al. (2018)

## 4 Methodology

- ☐ Emotion profile representation
  - ☐ Discrete feature vector
  - ☐ Continuous valence-arousal space
- ☐ System architecture (training/evaluation method)
  - ☐ Generator: input type (related to emotion profile representation)
  - ☐ Generator: base architecture e.g. use ArtGAN (Tan et al., 2017)
  - ☐ Discriminator: use output image’s emotion classification and difference to target as part of accuracy evaluation
- ☐ Any interaction made between human and generator

## 5 Expected Outcomes & Contributions

The outcomes of this project will include a generative system with which art can be synthesized according to a target emotional profile. This system will be the combination of methods for the representation of emotion for use in a generative model, and an architecture with which such a model can be trained. Due to the exploratory nature of the project with respect to both system architecture and emotional profile representation, this research will have tested and analyzed various options and any comparative differences.

The proposed generative system will be used to create a collection of art, categorised by the target emotional profile with which they were seeded. The verification proposed involves the public exhibition of produced images, providing feedback to the generative process and pairing the generated images with a human assigned emotion label for use in any further system training.

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