Liminal Scape, an interactive visual installation with expressive AI

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Abstract

Liminal Scape is a visual art installation with an expressive AI system that has been trained to recognize human emotion and generate abstract images at will. The proposed system receives an image (photographic portrait) and labels it based on the recognized emotional valence. Our system takes this initial photo and paints it red, yellow, or blue depending on the recognized emotions (from the facial expression) using a painterly algorithm which in turn becomes an input for a two modified Deep Convolutional Neural Network (CNN) models known as Deep Dream and Neural Style. These systems along with a final particle system pass generate a range of latent images that convey the initial emotion, unique to the given input (photographic portrait) and the labeled category (R, Y or B). Our system combines emergent and arbitrary behavior and breeding aspects of CNNs (in the low level) with a hybrid ML/particle stroking system to explore art creation within a high complexity space of artificial creativity.

Keywords

Convolutional Neural Networks (CNNs), Style Transfer, Deep Learning, Emotive Art, Expressive AI, Pastiches, Generative Art

Introduction

The impact of art on emotional state has been studied in brain research and neuroscience (Silvia, 2007). For instance, Neuroesthetics studies the neural bases behind aesthetic experiences such as art creation or contemplation (Chatterjee, 2011).

Moreover, emotional responses to art known as aesthetic emotions have been the topic of interest in philosophy, psychology, and art criticism (Robinson, 2004). In particular, the field of color psychology showed how hues evoke human emotions (Whitfield & Whiltshire, 1990).

Humans respond differently to color stimuli dependent on their past experiences and biological traits (Hurlbert and Ling, 2007). For example, the color red is widely used to describe emotions such as rage, warmth, energy, passion and love (Wright, 1995; Carruthers et al., 2010).

Scientific studies validated that emotions such as awe (Shiota et al., 2007) and wonder (Zentner et al., 2008) are frequent while contemplating artworks. More recent studies emphasized that emotional responses to art are very diverse (Silvia, 2012), including Sadness (Vuoskoski and Eerola, 2012), Nostalgia (Barrett et al., 2010), and Anger (Silvia & Brown, 2007).

More notably, the emotional responses of perceiving artworks are not always cognitive (or in detached mode), but often lead to affective congruent states (i.e. facial expressions, postures, etc.) on a subjective and bodily level (Freedberg and Gallese, 2007; Azevedo and Tsakiris, 2017; Ishizu and Zeki, 2017). For example, audience show frowning in response to artworks with negative emotional content and smiling in front of artworks with emotionally positive content (Cacioppo et al.1986; Lang et al. 1993). Moreover, the physiological synchrony (with the observed or experienced emotion) depends on a few important factors: the empathic accuracy and the intensity of the emotional experience (Dimberg et al. 2011; Sato et al. 2013; Korb et al. 2014; Künecke et al. 2014).

There is an emerging interest in artificial emotions or otherwise mediated emotional life to produce expressive and empathic media such as music, poetry or paintings (McStay, 2018). Behavioral or interactionist AI have shaped the discourse between AI and cognitive science with the core assumption that intelligence is a property of embodied interaction with the world. Interactionist AI is concerned with creating intelligent systems that exhibits the essential properties of intelligence. Expressive AI (or creative AI) focus on the authoring of AI system as cultural artifacts and performance (Kolker, 2006).

In generative art in particular, some artists conduct research using AI to stimulate emotions. Most of these studies focused on non-aesthetic stimuli (e.g., geometrical shapes) and broad aesthetic preferences instead of specific emotions (Jacobsen & Höfel, 2002) or emotional soundscape (Fan et al., 2018).

Here, we focus specifically on the aesthetic representation of emotions (derived from facial expressions) to create an emotive AI model that is capable of generating expressive emotional artworks.

Our preliminary results (Figure 6) present features from generated images that are commonly associated with the underlying emotion of the content images such as the representative colors, and styles (strokes, textures).

Background

Facial Recognition

Psychological, anthropological and neuroscientific research employs a particular definition for basic emotion. For example, Paul Ekman introduced Facial Action Coding System (FACS) to describe facial expression. FACS is based on Action Unit detection and temporal dynamics analysis system, each corresponding to a particular muscle group in the face (Ekman & Friesen, 1971).

Many researchers proposed to use convolutional neural networks (CNNs) as an appearance-based classifier to detect facial expression (Dailey et al., 2002; Zhao et al., 2004). Moreover, artists began using facial expressions as a tool to create empathic art, Colton et al. (2008) proposed emotionally aware portrait painting, a non-photorealistic rendering (NPR) system. They used a machine vision system that recognizes emotions to produce enhanced emotional portraits.

Augello et al. (2013) proposed a cognitive architecture originated from the model of blending or conceptual integration (Fauconnier & Turner, 1998) linking the representational spaces (i.e. color perception), and emotions.

DiPaola et al. (2019) proposed an empathy based affective portrait painter using cognitive based empathy in AI conversational agents and a cognitive-based creativity AI painterly system, and art analysis tools (i.e., texture and palette synthesis) to parameterize a generative artistic painting process based on mood, conversation and emotion.

Deep Generative Image Modeling

From the artificial intelligence perspective, automatic generation of art has been a long-standing objective (DiPaola & Gabora, 2009). Recent advances in generative models have been successfully applied to the artistic domain. There are several frameworks for image generation, using recurrent neural network (Gregor et al., 2015), auto-regressive models (Oord et al., 2016), generative adversarial networks (GANs) (Goodfellow et al., 2014), and more (Ma et al., 2018; Xu et al., 2018).

Outstandingly, GANs have achieved the most impressive visual quality and is the most popular technique among artists for generating photorealistic and non-photorealistic visuals. GANs have also been applied to style transfer, for example Elgammal et al. (2017) proposed a method to generate art by learning about styles and deviating from style norms.

Mordyintsev et al. (2015) presented Deep Dream which uses a guide-image mode, back propagation and gradient ascent, to analyze the strong features from one “guide” image and emphasize the best-matching features from a second source image by transforming the pixels in this second image. This results in the emphasis of pre-existing shapes and patterns as well as the appearance of hallucinated patterns in which the network gravitates towards “seeing” patterns it has learned to recognize.

Gatys et al. (2016) then presented style transfer, called Deep Style (DS) by matching features in convolutional layers of VGG-19. In a follow-up study, they proposed ways to control the color preservation, the spatial location, and the scale of style transfer (Gatys et al., 2017). Ruder et al. (2016) improved the quality (i.e. consistent and stable stylized) of video sequence transfer by imposing temporal constraints. Alvarez-Melis and Amores (2017) proposed using style transfer for creating emotional art using Generative Adversarial Network (GAN) trained on a dataset of modern artworks labeled with emotions.

Concept and System Description

Liminal Scape is a multi-screen interactive visual installation that fills the interior of a gallery space across 6 screens (same size) as shown in Figure 1. The screens portray the stylized paintings of our AI system. The visuals are reflected back in the space and the viewers, creating a sense of intimacy. A viewer is then on a journey through a landscape of colors, textures and compositions that expresses and evokes cognitive and bodily emotions. The front wall (screens) display the most immediate results of the system and the screens on the back walls present the more abstract results (generated from the evolving system after a few runs) as shown in Figure 1.

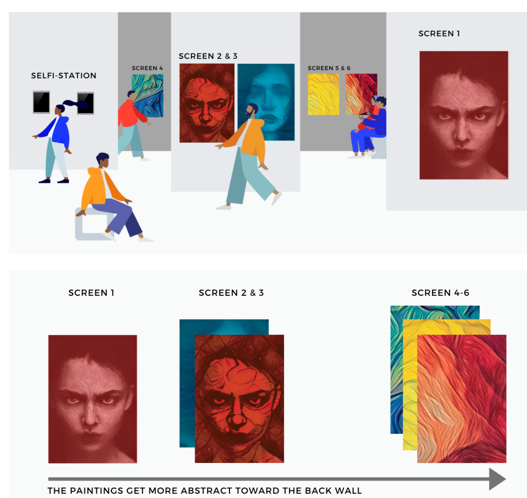

Figure 1. An overview of *Liminal Scape* installation layout

Interaction Scenario

Upon stepping into *Liminal Scape*, a viewer encounters 6 visual screens, each displaying a temporal series of abstract visual feeds (varying in colors, textures and compositions). The artwork invites visitors to take their participation further through an Apple iPad or Tablet, where they can take a selfie (expressing different emotions) which will be "painted" and added to the existing pool of faces (the contents of the artwork) as shown in Figure 2.

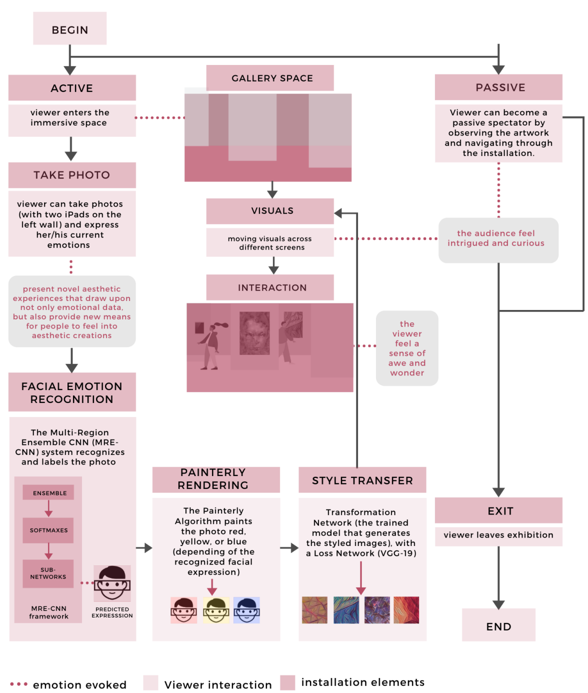

Figure 2. An overview of *Liminal Scape* interaction diagram

Our Approach/ Architecture

-Facial Recognition

We use a Multi-Region Ensemble CNN (MRE-CNN) for facial expression recognition (adapted from Fan et al., 2018). We take three sub-regions of the human face: the left-eye, the nose and the mouth, combined by its corresponding whole facial image, to form a double input subnetwork. We adopt 13 CNN layers and 5 max pooling layers and an output layer of 3 neurons, one for each emotional category grouped together: R: anger, rage, wrath, resentment, passion, lust, love, Y: happiness, joy, delight, pleasure, bliss, and B: sadness, sorrow, despair, grief, melancholy. The networks then generate labels and colorize (red, yellow, or blue) the photographic portraits as shown in Figure 3.

-Modified Deep Dream and Neural Style Transfer

We use a two-phase approach starting with our modified Deep Dream and Deep Style (or Neural Style) pass. Our modified Deep Dream system specifically trains new CNN models with creative art generation (style recognition) as its goals as opposed to more typical object recognition, using paintings and drawings as training data. We now have amassed a specific to fine art painting data set of 160,000 labeled and categorized paintings from 3000 labeled artists for a total size of 67 gigabytes of artistic visual data.

Since in our system, detecting and identifying regular objects 'within' an image is less important than the overall artistic style of the entire image (e.g. style of stroke, texture and color palette), we develop a "hierarchical tight style and tile" process (DiPaola et al., 2018) which uses a more art based texture and style based labeling syntax as well as hierarchical stochastic tiling method to produce a training set that is more conductive to painterly style over object recognition. This method is combined with our neural style transfer model as proposed by Elgammal et al. (2017) to make abstract emotional paintings influenced by the given photographic portrait (facial expressions).

The style transfer architecture has two different CNNs in the training phase: An Image Transformation Network (the trained model that generates the styled images), and a Loss Network (pre-trained VGG-19 classifier) to compute the Style-Loss and the Content-Loss and in turn train the Image Transformation Network (Dumoulin at al., 2016). Our goal is to generate abstract novel images from the infinite possibilities in the creative space and emphasizing semantic and/or stylistic qualities to highlight certain emotions as shown in Figure 5. The training process is as follows: stylized paintings are produced by feeding a content image (emotionally labeled face) through the style transfer network. The content image, along with a fitted style image (selected from one of the 18 abstract paintings of Joan Miró, Wassily Kandinsky, and Mark Rothko), are passed through the Loss Network (VGG-19) as shown in Figure 5 and generates a series of abstract paintings dependent of the intensity of the emotional valance and the selected labeled category.

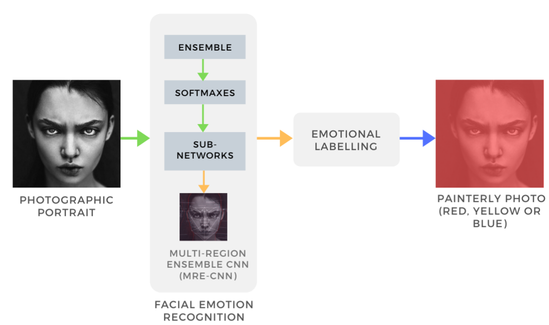

Figure 3. An overview of our Facial Recognition phase using Multi-Region Ensemble CNN (MRE-CNN) framework (adapted from Fan et al., 2018)

-Adaptive Instance Normalization (AdaIN)

We use adaptive instance normalization (AdaIN) for the interpretation adapted from Huang and Belongie (2017) model. Given a content image and a style image, AdaIN simply adjusts the mean and variance of the content image to match those of the style image by transferring feature statistics. Then the decoder network learns to generate the stylized images by inverting the AdaIN output back to the latent image space.

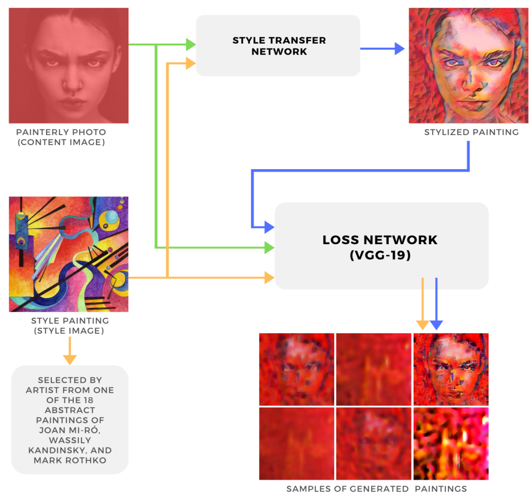

Figure 4. An overview of our style transfer. We use VGG-19 network to encode the content and style images. An AdaIN layer is used to perform style transfer in the feature space. A decoder is learned to invert the AdaIN output to the image spaces

-Final Rendering (EPainterly)

In the last phase, the source image created from the previous steps is further manipulated by our hybrid AI/particle system, ePainterly system, which is an extension to our cognitive painting system (DiPaola and McCaig, 2016) and models the cognitive processes of artists based on years of research in this area. It uses additional Deep Style, algorithmic, particle system and noise modules to generate artistic color palettes, stroking and style techniques. It is the NPR subclass of stroke-based rendering that is used as the final part of our process to realize the internal Deep Style models with stroke-based output informed by historic art making. Specifically, aesthetic advantages of this additional system include reducing noisy artifacts of the generated Deep Style output via cohesive stroke-based clustering as well a better distributed color space.

Conclusion and Future Work

The notion of Sentient AI, capable of feeling and perceiving emotion (sentient) sounds promising, since we live with technologies that feel and are sensitive to human life in ways that until now not seen. Moreover, empathic art presents novel aesthetic experiences that draws upon not only emotional data, but also provide new means for people to feel aesthetic creations. Our intention behind the Liminal Scape is to create an exploratory AI system in the form of an installation to present abstract emotional paintings, in which users will reveal and explore their affective states. We aim to create expressive/emotional experience, and are curious to know what is the overall experience of the users while interacting with the system. We recognized the potential of artificial creativity for creating novel artworks supported via interactive environments in the future. Our initial results (Figure 6) show the potential of creating emotive paintings that will evoke a range of emotions/aesthetic reactions such as pleasure, anger and arousal. To this end, we will explore expressive AI by mimicking human emotions (facial expressions) and mapping them into low level features such as colors, strokes, intensity. These features are most effective in steering the emotional state of the artworks in the desired direction. We hope that with this work and future research we are getting closer to the design of an emotive AI capable of perceiving and expressing emotions.

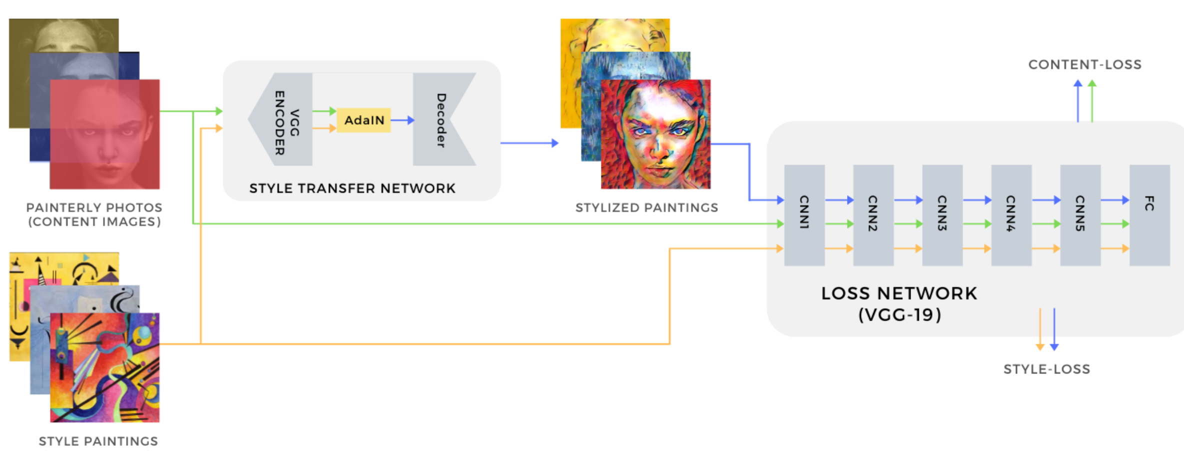

Figure 5. The overview of arbitrary style transfer in real-time with Adaptive Instance Normalization (AdaIN) and Deep CNN (VGG-19) (adapted from Elgammal et al., 2017; Huang & Belongie, 2017)

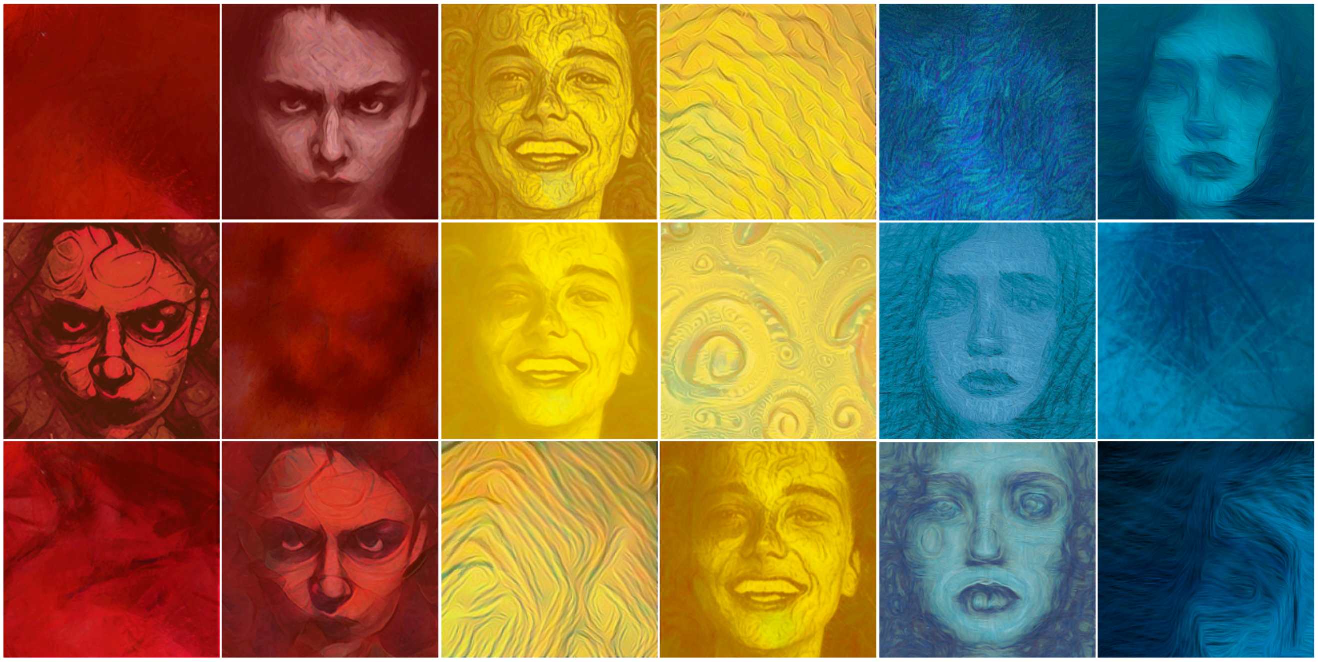

Figure 6. Artworks generated by the *Liminal Scape* resulted from different emotional detection, from left to right: categories R, Y, and B. (R: anger, rage, wrath, resentment, passion, lust, love, Y: happiness, joy, delight, pleasure, bliss, and B: sadness, sorrow, despair, grief, melancholy)

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Mahsoo Salimi: is a Ph.D. Candidate at Simon Fraser University and interdisciplinary researcher interested in artificial creativity and Expressive AI. Her current research is bridging swarm intelligence and robotics to create dynamic and visceral relationships between human, robots, and AI.

Nouf Abukhodair: is a Ph.D. Candidate at Simon Fraser University and interdisciplinary researcher, her background is in Computer Science, she is interested in AI, Image Processing and Visual Perception. Her current research is looking at computational creativity, to learn how Deep Learning AI systems can understand visual art. Her work uses modern AI machine learning systems to understand goals and processes, to dynamically adapt the system for best results for art, entertainment and health applications.

Steve DiPaola: active as an artist and a scientist, he is the past director of the Cognitive Science Program at Simon Fraser University, and leads the iVizLab (ivizlab.sfu.ca), a research lab that strives to make computational systems bend more to the human experience by incorporating biological, cognitive and behavior knowledge models.

Carlos Castellanos: is an interdisciplinary artist and researcher whose work bridges science, technology, education and the arts, developing a network of creative interaction with living systems, the natural environment and emerging technologies. His artworks have been exhibited at local, national and international events such the International Symposium of Electronic Art (ISEA), SIGGRAPH & ZERO1 San Jose.

Philippe Pasquier: in his artistic practice, focused primarily on generative arts, he is bringing forward forms that are exploring the nonverbalisable dimensions of the sublime. Philippe has been acting as a performer, director, composer, musician, producer and educator in many different contexts. He also serves, or has served, as an active member and administrator of several artistic collectives and companies (Robonom, Phylm, Miji), art centers (Avatar, Bus Gallery) and artistic organizations (P: Media art, Machines, Vancouver New Music) in Europe, Canada and Australia. Philippe was director of ISEA2015.