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Saliency-Based Artistic Abstraction With Deep Learning and Regression Trees

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Abstract. *Abstraction in art often reflects human perception—areas of an artwork that hold the observer's gaze longest will generally be more detailed, while peripheral areas are abstracted, just as they are mentally abstracted by humans' physiological visual process. The authors' artistic abstraction tool, Salience Stylize, uses Deep Learning to predict the areas in an image that the observer's gaze will be drawn to, which informs the system about which areas to keep the most detail in and which to abstract most. The planar abstraction is done by a Random Forest Regressor, splitting the image into large planes and adding more detailed planes as it progresses, just as an artist starts with tonally limited masses and iterates to add fine details, then completed with our stroke engine. The authors evaluated the aesthetic appeal and effectiveness of the detail placement in the artwork produced by Salience Stylize through two user studies with 30 subjects. © 2017 Society for Imaging Science and Technology.*
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INTRODUCTION

Throughout history, artists have made attempts to mimic human perception in their creations. For example, the Cubist art movement gave rise to works such as Jean Metzinger's *Femme au miroir*[1] and Albert Gleizes' *Femme au gant noir*[2] where the background detail is far more abstract than the foreground detail, reflecting the Gestalt psychology observation of greater salience in the foreground.

Zeki discusses art as an externalization of the brain's inner workings, bringing up mental abstraction as a solution to the overwhelming sensory task of attending to every detail and the limitations of the human memory system.[3] The artist's approach to abstraction, Zeki claims, holds many similarities to the physiological visual process. Visually salient areas of the art will be detailed (either in color and tonal values, texturing, size, or complexity of shapes), while "peripheral" or non-salient areas will be more abstracted.

The artist's approach to emphasizing detail in salient areas is an iterative process, as explained by well-known portraitist John Howard Sanden in his book *Portraits from Life*.[4] The first pass on the creation of art usually starts with a small number of large, tonally limited masses. With each iteration, the artist creates smaller details and more varied tonal values in salient areas. Sanden describes this as a two-stage process, where the subject is first visually reduced to three or four large masses, and secondly the smaller details within each mass are painted while keeping the large mass in mind.[4]

With the advent of the Artificial Intelligence subfield of Deep Learning Neural Networks (Deep Learning) and the ability to predict human perception to some extent, this process can be automated, modeling the process of abstract art creation. This article discusses a novel artistic abstraction tool that uses a Deep Learning visual salience prediction system, which is trained on human eye-tracking maps of images of common objects. Given an input image, this system generates a predicted eye-tracking salience heatmap of the image, which is then used by our tool to segment the image into abstraction levels. While our technique is applicable to many forms of modernist fine art painting and abstraction, in this article we concentrate our generated output techniques on one form of artistic abstraction which is planar abstraction most notated in the art field of Analytical Cubism popularized by Picasso and Braque.

The abstraction process itself, similar to the human artist, starts with a high level of abstraction and iteratively adds more detail to salient areas. This is done with a Random Forest Regressor, which splits the abstraction planes into polygons of smaller and smaller sizes. The process is repeated at different depths, or levels of detail, for each of the abstraction levels from the generated salience "heatmap," which are then combined into one cohesive image.

The end output of our tool is an abstract art rendition of the input image, with higher levels of planar detailing around areas of visual salience and large, tonally simple planes in the visually "peripheral" areas of the image. We envision Salience Stylize mainly as an intelligent non-photorealistic rendering (NPR) technique for artists to use in the creation of digital art. However, there are other uses as well, such as anonymization. An example of this is Kadir et al's work, which explores the use of artistic processing as an anonymization practice in documentaries in order to preserve the integrity of the image and to avoid victimizing subjects through the blurring of their faces.[5]

RELATED WORKS

Our research, being at the intersection of NPR, cognitive science, and machine learning, builds on works in each of these fields. Within NPR research, a number of painterly rendering techniques were developed in the early 1990s, starting

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with Haeberli's pioneering work,[6] introducing stroke-based painting, and Litwinowicz's[7] fully automated algorithm producing paintings by using short linear paint strokes tangent to Sobel edge gradients. Hertzmann[8,9] advanced the field by using a multi-pass system of coarse-to-fine curved *b*-spline strokes aligned to a layered coarse-to-fine image difference grid with multiple styles. This was inspired by his observation that artists begin a painting with a first pass of large broad strokes and then refined the process with smaller strokes to create detail. Inspired by Hertzmann's work, DiPaola[10] moved away from a multi-pass coarse-to-fine grid for stroke placement choices and toward tonal masses based on lighting and drawing types. DiPaola created a color system that samples the tone (grayscale value) first, then with that tone remaps into a color model of choice, which differs from typical NPR color choice algorithms.

A number of NPR methods specific to abstract art have been developed as well, one example being Collomosse's[11] cubist rendering technique. This technique takes as input two-dimensional images of a subject from different perspectives, and after identifying the salient features in the images, combines them in one rendering to create the illusion of depth and motion. Finally, an image rendering algorithm pass gives the piece the textural appearance of a painting.

Many cognitive scientists have asserted and given varying degrees of evidence that visual artists exploit the properties of the human cognitive and visual systems.[12–17] For all humans, researchers have shown that vision is an active, or a constructive process.[16,18,19] We "construct" the internal model based on the representation of these experiences.[13,14,18,19] This emphasizing the salient is what Zeki[3] refers to as the Law of Abstraction, in which the particular is subordinated to the general, so that it can represent many particulars. Ramachandran and Hirstein[20] proposed eight principles in their cognitive model of art most notably the peak shift effect, which is similar to the theory of exaggerating the salient features that distinguish a given object of interest from other objects.

An automatic system for salience adaptive painting, driven by machine learning, was presented by Collomosse and Hall.[21] Collomosse, Gooch and others[21,22] described a major problem of most NPR approaches—they implemented local not global techniques and therefore restricted "attention to local image analysis, by independently examining small pixel neighborhoods" and these local techniques "can give no real indication of salience in an image."[23] Given that blind local processing/analysis especially in image-based NPR was a major impediment to provide artistic salience in NPR, he and several other researchers looked for efficient global solutions.[21,22,24–26]

Process

The development of this tool started with the analysis of *stylize*, a planar abstraction system created by Github user Alec Radford.[27] This system uses a regression tree-based approach, specifically using the scikit-learn library's ensemble learning Random Forest Regressor.[28] This system begins by simplifying the image into a single-tone polygon, and as the regression tree's depth increases (up to a terminal max_depth value), "child" polygons are created by splitting the "parent" into smaller, more detailed polygons and varied colors.

Figure 1. A picture of a woman abstracted at a single depth value.

We approached this analysis by thinking of the system as an artificially intelligent abstract artist. As we tested this system we realized an opportunity for improvement in the fact that it was applying a single depth value to the whole image (Figure 1). We noted that abstraction in art is a tool for reducing unnecessary detail, and not generally applied equally to all areas of the work.

Another significant improvement we aimed to make in this system was to consider from a cognitive viewpoint the approach that a human artist takes when deciding where to add detail in an image. As a result, we decided to determine the salient areas of an image using the deep convolutional network saliency prediction system (SalNet) introduced by Pan et al.[29] SalNet was developed on Caffe and was trained with the SALICON (Salience in Context) dataset, which is eye-tracking salience data for the MS COCO (Microsoft Common Objects in Context) image database. Given an input image, this system generates a black and white salience heatmap of the predicted eye-tracking data (Figure 2).

We processed the images in a vector format, as this gives more flexibility for future work built on this tool, as well as the ability to scale images easily. We used the *potrace* svg tool to handle this conversion.

METHOD

Our tool, *Salience Stylize*, generates planar abstract art by creating three abstraction levels in an input image by referring to a salience heatmap of predicted eye-tracking data (Figure 3). First, the input image is passed through the SalNet system in order to generate the saliency map, which has white areas for highest saliency, black areas for lowest saliency, and gray tones for mid-range values. The generated map has the same dimensions as the input image, and generally has best results for input images where there is a clearly dominant subject, such as portraits.

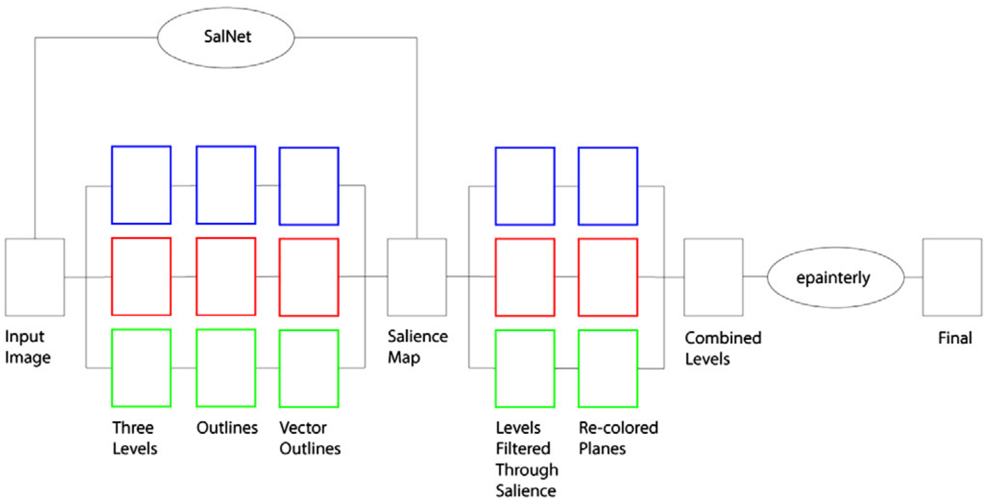

Figure 2. The Salience Stylize art creation process.

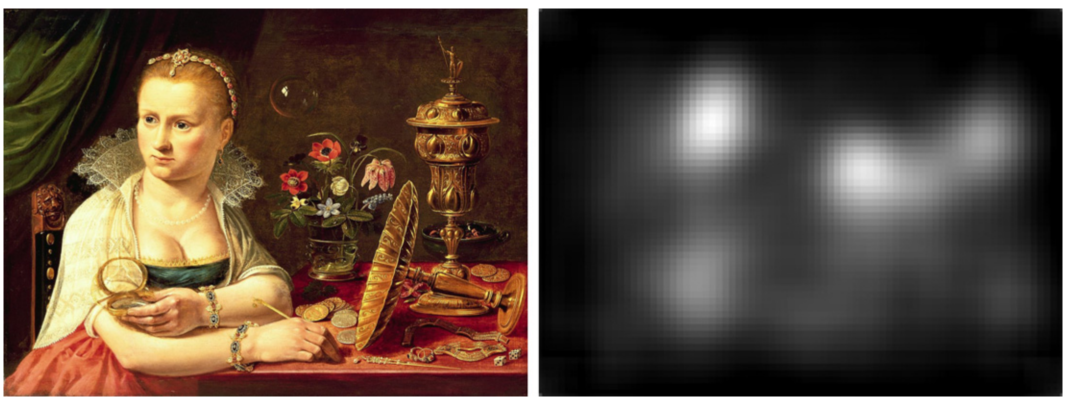

Figure 3. An input image (left) and the generated saliency heatmap (right).

Next, the image is passed through the *stylize* tool at the following depth values:

1. 5 (very abstract, large planes)
2. 10 (mid-level abstraction, slightly smaller planes)
3. 20 (detailed, very small planes).

The resulting abstract renders are then converted to black and white outlines, as the potrace svg system works only in black and white. This outlining process divides the planes into groups of black pixels which will then be treated as paths by potrace. This grouping happens as follows:

$$\text{group} = \{P | P \subset A, \quad C_{p_x p_y} = C_{p_{x+1} p_y}, \quad C_{p_x p_y} = C_{p_x p_{y+1}}\} \tag{1}$$

where P is a pixel, A is the abstract image, and C is the color of P at x and y coordinates. The resulting outline images are then passed through the potrace program to get three vector images, where each path is one abstracted plane.

The next step is to filter the saliency areas based on the generated saliency map, deciding which paths to keep in the area and which to delete:

$$\text{high} = \{G | G \subset svg, 115 \leq M_{G_x G_y} \geq 255\} \tag{2}$$

$$\text{mid} = \{G | G \subset svg, 30 \leq M_{G_x G_y} < 115\} \tag{3}$$

$$\text{low} = \{G | G \subset svg, 0 \leq M_{G_x G_y} < 30\} \tag{4}$$

where G is a path or plane, svg is the vector image of the outlines, and M is the saliency map at the x and y locations of the paths. Since the saliency map is monochrome, the full range of values is from 0 to 255. 0 is fully black and non-salient, while 255 is fully white and salient.

For the most detailed outlines, any path that is not in the *high* set defined above is removed, and the same is done for the mid-detail outlines and the *mid* set, as well as the most abstract outline image and the *low* set. This leaves large, abstract planes in the non-salient areas, mid-sizes planes in the mid-saliency areas, and small, detailed planes in the most salient areas of the map.

At this stage, the planes are all black and must be colored. For each abstraction level, the color of the plane is copied from the related plane in the original abstract renders. The three levels of paths are all then appended to one array of paths, which result in one cohesive svg image with all three abstraction levels.

The image is then passed through our NPR painterly toolkit known as *ePainterly*, which uses several passes to

Figure 4. The post-painterly image before (top) and after (bottom) color correction with close-ups.

achieve a hand painted style including (1) natural looking "hand" distortion of the planes, (2) an "ink line" (painted dark thin line) on some edges that is correlated with the natural distortion, and (3) lastly we use a sophisticated cognitive- and particle-system-based painterly brush stroking system to repaint (brush stroke) all parts of the image which give texture and detail to the planes.

We do this with two modules of our ePainterly NPR system which was adapted from its typical use to work specifically with the style attributes and color toning of analytic cubism. The first takes the solid colored planes from the Salience Stylize system as source, analyzes it, and perturbs the straight edges to be more natural looking, with a slight distortion of the planes based on two Perlin noise functions (one for each coordinate). To achieve the hand painted look, we have experimented with "roughness" of the Perlin noise which is relative transparency of the octaves the noise is composed of (the number of octaves is controlled by the *Details* parameter) to achieve the best effect. We then achieve correlated ink lines to the noise by producing this noise process twice and merging the results—the lines show up where there is a difference in the two functions which occurs on some edges as seen on many cubists works by Picasso.

We then repaint the whole image using our cognitive-based painting system, Painterly,[10,30] which models the cognitive processes of artists, uses algorithmic, particle system and noise modules to generate artistic color palettes, stroking and style techniques. We applied this three-stage ePainterly process on all our generated output.

Finally, the resulting image is color-corrected, as the colors were oversaturated in order to preserve the details when passed through ePainterly. In order to inform the choice of color palette, we used the pyCaffe-based implementation of style transfer,[31] with one of our output images as the content image, and a work of professional cubist art as the style image. As this process added noise or at times distorted the image, we did not use this in our final work, but instead learned from its output and shifted the tones of our image toward the output of the style transfer. This resulted in a more muted color palette (Figure 4).

Study 1: Evaluation of Aesthetic Appeal

Method

Leder et al.[32] introduce a model for aesthetic appreciation of art, in which previous experience as well as the style and content of the artwork are factors in aesthetic liking and aesthetic emotion. Style and content were judged by their interestingness and emotional arousal. We evaluated these factors of aesthetic appeal of the artwork produced by Salience Stylize through a user study on the Amazon

Mechanical Turk platform, using a combination of jsPsych[33] and Psiturk[34] to facilitate the study. Psiturk provides ad-serving for psychological studies running on Mechanical Turk, and also the backend server to run the ads, and has been generally found to be a reliable mechanism for conducting experiments.[35] JsPsych is a JavaScript-based library for providing a wide range of psychological instruments for measuring participant response, while controlling the flow of the participants' stimuli and responses.

One Human Intelligence Task (HIT) with 30 assignments was loaded onto Amazon Mechanical Turk. 30 unique workers completed both trials. We denied the use of mobile or tablet devices for this work, in order to maximize the image quality and size when viewed by participants.

Instruments

We designed two questionnaires. The first was presented to each participant before the study, and asked the participant to rate their expertise with art in general, as well as with analytical cubist art. The second questionnaire included a web-based interactive form that presented a total of 34 paintings, one at a time, to the participant, along with a set of questions and Likert scales next to the image to be answered for each painting. Before starting the questionnaire, the participants were asked to consider each image independently without reference to previous images, and to evaluate them as works of fine art. These questions remained the same for every painting:

(1) How well do you think this artwork depicts the essence of the subject? (On a scale of 1–9)
(2) How pleasing is the style of this painting? (On a scale of 1–9)
(3) How interesting is this painting? (On a scale of 1–9)
(4) Rate this painting out of 5 as a work of art (in terms of style, content, and sophistication).

The images presented to the participants included two variations of four paintings produced by Salience Stylize (including the saliency-based abstraction, and either only high detail, only low detail, or randomized abstraction) and 19 works of professional and amateur cubist art (Figure 5). Three of the professional paintings and three of the amateur pieces were repeated in order to avoid bias caused by similarity between variations of Salience Stylize output. This artwork was collected as the top results from a Google Images search for "analytical cubism," that is from this search the 9 to 10 of first images that were by professional artists and the first top 9 to 10 images that were from non-professional artists were used. The first 10 professional paintings ended up being 5 from Picasso and 5 from Braque, the masters of this field. The total imageset was shuffled before being presented to the user.

Results

Of the 30 participants, one was removed as their completion time of five minutes was much shorter than expected for the

Figure 5. Four variations of different images—low detail, saliency-based, random abstraction, and high detail (left to right, top to bottom).

number of questions. Of the 29 remaining, 16 identified as males and 13 as females. They were aged between 21 and 64 ($M = 34.48$, $SD = 10.45$). 10 had very little or no familiarity with art in general, 16 had some previous familiarity, and 3 considered themselves experts in art.

In order to assess how the different kinds of artwork compared to each other, we examined each aggregate category: our saliency-based abstraction, our non-saliency-based abstraction, the amateur cubist set, and professional cubist set. We wanted to determine whether the saliency-based model produced work that was more similar to professional cubist or amateur cubist work. For all the artwork that was rated, we asked four questions, rating its Essence, Style, Interest, and Artistic Quality (Figure 6). The comparisons we were mainly interested in were saliency versus amateur, saliency versus professional, and saliency versus non-saliency. To compare these means, we used homoscedastic 2-sample t-tests, testing at the 0.05 significance level. We first successfully conducted an f-test to ensure that the assumption of equal variances was acceptable.

First, we wanted to establish that the amateur and professional artworks were perceived differently. This would be the baseline, as it would show that the sets of confederate artwork used alongside our generative artwork were distinct. When comparing the amateur versus professional artworks' Essence ratings, there was a significant difference between their means; $t(723) = 1.96$, $p = 0.036$. When comparing the amateur versus professional artworks' Style ratings, there was a significant difference between their means; $t(723) =$

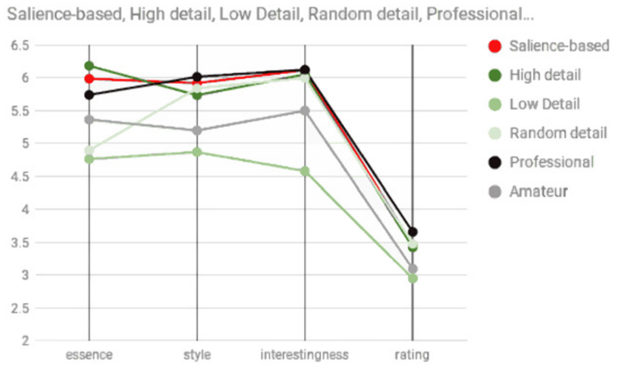

Figure 6. Performance of each art category on the four questions (the rating category was out of 5).

1.96, $p < 0.0001$. When comparing the amateur versus professional artworks' Interest ratings, there was a significant difference between their means; $t(723) = 1.96$, $p = 0.00037$. When comparing the amateur versus professional artworks' Artistic Quality, there was a significant difference between their means; $t(723) = 1.96$, $p < 0.0001$. This seems to support our hypothesis that our amateur and professional pools of artwork are visually distinct.

Next, we wanted to compare our saliency category of generative artwork to the set of amateur artworks. This would allow us to determine if they were perceived similarly to that kind of artwork. When comparing the saliency versus amateur artworks there was a significant difference between their means of all four questions: Essence ratings ($t(462) = 1.97$, $p = 0.0076$), Style ratings, ($t(462) = 1.97$, $p = 0.0037$), Interest ratings, ($t(462) = 1.97$, $p = 0.0075$), and Artistic ratings ($t(462) = 1.97$, $p = 0.0016$). This supports the hypothesis that our saliency category of generative artwork is visually distinct from the amateur artworks.

Next, we wanted to compare the saliency category of generative artworks to the set of professional (i.e. Picasso and Braque) artworks. When comparing saliency versus professional artworks' ratings, we did not find significant differences between the means of any of the four ratings. This means that we can support a hypothesis that our generated saliency artworks are not separate from the professional artworks. To our participants, as a category, these works received similar ratings.

Lastly, we wanted to compare our saliency and non-saliency generative artworks. This would let us see whether they were distinct categories of work. When comparing the saliency versus non-saliency artworks' Essence ratings as well as the Artistic Quality ratings, there was no significant difference between their means. When comparing the saliency versus non-saliency artworks' Style ratings, ($t(260) = 2.11$, $p = 0.036$) and Interest ratings ($t(260) = 2.11$, $p = 0.0085$), there was a significant difference between their means. This means that in two of the ratings (Style and Interest), we find support for these categories being different, however, for two of the ratings (Essence and Artistic Quality), we cannot support that hypothesis. There seems to be some distinctiveness to these two categories of artwork.

Table I. Number of participants who selected each version.

Image #	High detail	Saliency-based	Low detail	Random detail
Image 1	24	0	3	2
Image 2	16	7	3	3
Image 3	16	7	3	3
Image 4	11	8	6	4
Image 5	15	8	3	3
Image 6	12	8	5	4
Image 7	14	5	2	8
Image 8	13	5	4	7

Study 2: Evaluation of Detail Placement

Method

This study was presented as the second part of the Study 1, with the same participants. The purpose of this part was to ascertain that the placement of highest detail on the most salient areas of an image creates the most aesthetically pleasing artwork. We tested this by presenting eight output paintings (four of which were shown in Study 1), but this time with four variations of each painting.

Instruments

For each painting, we juxtaposed the following variations, in different orders:

1. Only high detail
2. Only low detail
3. Three levels of detail, most detailed at high saliency areas
4. Random detail, generated with a false saliency map of Perlin noise.

On each page, the user was asked to select the variation that created the most aesthetically pleasing work of abstract art (Figure 7).

Results

When analyzing the responses of all participants, the high detail images were always selected more often than the other variations (Table I). However, when limiting results to only those who identified as art experts, high detail and saliency-based images were each selected 7 times in total, while low and random detail images were each selected 5 times (Table II).

When limiting the results to only male participants, saliency-based images were selected a total of 29 times, while high detail images were selected 68 times, which is a ratio of approximately 0.43–1. When limiting to only female participants, saliency-based images were selected a total of 19 times, and high detail images were selected 53 times, which is a ratio of approximately 0.36–1.

DISCUSSION

The results of Study 1 confirm that the quality and aesthetic appeal of the art produced by Salience Stylize are perceived

Figure 7. Four variations of abstraction, including: 1—random abstraction, 2 —saliency-based abstraction, 3—low detail, and 4—high detail.

Table II. Number of expert participants who selected each version.

Image #	High detail	Saliency-based	Low detail	Random detail
Image 1	2	0	0	2
Image 2	1	2	0	0
Image 3	2	0	1	0
Image 4	1	0	2	0
Image 5	0	1	1	1
Image 6	0	2	1	0
Image 7	0	2	0	1
Image 8	1	0	0	1

as better than both non-saliency-based abstraction and amateur cubist artwork, scoring relatively close to the professional cubist artwork for each of the questions. For every question, there was a significant difference between the mean responses for saliency-based abstraction and amateur cubist artwork, while there was no significant difference between the mean responses for saliency-based abstraction and professional cubist artwork. This provides support for the quality and aesthetic appeal of our art pieces being high.

The results of Study 2 did not support our hypothesis that saliency-based detail placement would produce the most appealing art pieces, as participants were overall more likely to select the entirely high detail images. This finding is in line with previous research[36] showing that for viewers with no expertise in cubist art, the preference is for those images in which objects are most recognizable. Hekkert and Leder[37] claim that "we like to look at patterns that allow us to see relationships or create order." However, this preference for high detail was not as strong when considering only the participants with an expertise in art, as an equal number selected the saliency-based images. This discrepancy between expert and non-expert participants' responses for aesthetic appeal evaluation has been explored previously by researchers such as Lebreton et al.[38] Male and female participants did not have significantly different preferences. This suggests that when creating generative artwork, it is still crucial to keep one's audience in mind, along with the impact this has on evaluation.

Future Directions

While Salience Stylize mimics an artist's abstraction process by simplifying the areas of least visual salience, an argument can be made that this does not fully reflect the intricacies of the artist's design decisions. Rather than being a way of recognizing where an observer's gaze will fall and increasing the detail there, artistic abstraction and detailing sometimes serves as a tool for an artist to intentionally guide the observer's gaze to another area of the artwork.

An eye-tracking study by DiPaola et al.[17] provides support for this, as they found that the gaze of participants was drawn to areas of finer textural detail in Rembrandt-style portraits, and suggested that "portrait artists, perhaps even as early as Rembrandt, guided the viewer's gaze through their selection of textural detail."

This variation in the abstraction process is not addressed in our work, but this provides an interesting opportunity for improvement in future works. In order to create a true digital abstract artist, it is necessary to accommodate the option to create abstract art that is not influenced by saliency, but rather acts as an influencer of saliency. Perhaps this effect could even be approximated through Deep Learning, by training a Neural Network on variations in detailing in artwork, and using that to predict the areas that an artist would select for finer textural detailing. This could replace the saliency prediction system (SalNet) which is currently used in our work. Alternately, the use of a Neural Network for the generation of saliency maps could be replaced or enhanced by a human user. In such a setup, the user would have greater creative influence over the output, and would be able to select the areas of the artwork in which greater detail is required.

Another possible solution to this is to model the traditional art-studio setup of a painter observing a subject. By interacting with the subject, a painter will gain a better understanding of their personality or "essence," which they can then reflect in the portrait. This process could be automated by capturing on camera the unique facial expressions and gestures of an individual over a short span of time before taking their photograph. The detail placement of the portrait could then be influenced by this process, emphasizing the subject's most expressive facial features for a truly personalized portrait.

Currently, Salience Stylize is limited to the style of traditional Analytical Cubism; however, in future works this can be generalized to other art styles as well. For example, we have experimented with the use of Google's Deep Dream (an image processing approach for visualizing Deep Learning Neural Networks)[39] in conjunction with saliency maps for stylizing the images, which creates a less traditional look. In this variation, we also explored the use of different detailing techniques in salient areas, such as the number of "iterations" in Deep Dream, which can create more saturated colors and sharper edge lines in salient areas.

CONCLUSION

We propose a novel method of abstract art creation based on predicted human saliency of images using Deep Learning and a Random Forest Regressor. Abstraction in art often reflects human perception, and we aimed to reflect that by omitting details in the peripheral image areas and emphasizing details in the areas that a viewer would be most likely to look. Similar to a human artist's method of starting with a few large tonally limited masses and adding increasingly refined detail with each iteration, our tool, Salience Stylize, starts by splitting the image into large planes and adding more detailed planes as it progresses. We evaluated the aesthetic appeal and detail placement in the artwork produced by Salience Stylize through two user studies with 30 subjects, and found that our artwork was considered by participants as having a quality close to professional cubist artwork; however, we found that our artwork did not perform as well as images of entirely high detail when assessing the effectiveness of the detail placement. Finally, we recommend further developing this method in order to address the need for artist-driven saliency, where intelligent decisions about detail placement guide the viewer's perception rather than modeling the detail placement on a prediction of viewers' gaze.

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