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A Computational Tool for Recoloring Based on User Emotions

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Abstract

This work describes a system to recolor a user's painting based on the perceived emotional state of the viewer. An automatic palette selection algorithm is used to generate color palettes for a set of emotions. A user can create a painting using one of the generated palettes. To notify the end of the painting, the user clicks on the DONE button. Once the button is pressed, the colors of the user's painting change as the facial expression of the user changes. Facial emotion recognition is used in this process to classify the emotional status of the user's face.

Introduction

A key type of information included in visual data is the emotions embodied in an image or video. Throughout human history, artists have used color as an instrument to express their feelings (Nesterov and Fedorova 2017). Eugène Delacroix, a French artist stated, "[a] picture is nothing but a bridge between the soul of the artist and that of the spectator." As such, creating image-based artwork naturally involves emotional communication. While artists can express desired emotions in their artwork, it is difficult for non-experts to express their feelings in paintings using available art elements (e.g. line, shape, and color) as they require considerable time and experience to fully understand these elements.

There have been a lot of research projects in computer graphics that recolor images to evoke different emotions for the average users who have less skills for properly selecting and modifying colors (Kim, Kang, and Lee 2016; He, Qi, and Zaretzki 2015). More specifically, painterly renderings of photorealistic images have been widely explored by the non-photorealistic rendering (NPR) community. For example, the "empathetic painting" is an interactive painterly rendering whose appearance adapts in real time to reflect the perceived emotional state of the viewer (Shugrina, Betke, and Collomosse 2006). The Painting Fool, generative art software with decision making abilities, was integrated with a machine vision system that recognizes emotions to automatically produce portraits which heighten the emotion displayed by the sitter (Colton 2012). It reacts to emotional keywords by rendering portraits with different line styles, colors, and shape transforms. Although these systems are capable of generating various styles of painting by controlling various painting features, they do not consider individual user's choice of affective expressions.

As emotion includes subjective feelings in addition to physiological reactions and cognitive appraisals (Scherer 2005), we follow an interactional approach, which we review in the following section. In addition, whereas the goal of The Painting Fool program was to be taken seriously as a creative artist, our goal is to understand human emotions and artist-viewer interactions rather than producing autonomous creativity in software. Therefore, we created a computational tool which recolors the user's paintings based on their emotions.

Fig. 1 summarizes the steps of the process — we give a detailed description of the system design. The core approach of this process is to let users define their own color palettes for each emotion (happy, angry, sad, and relaxing) and apply them to the rendering system to create paintings.

Related Work

This work has been inspired by and made possible by progress in several different areas, which we review below.

Palette-Based Image Recoloring

Image recoloring methods can be classified into three types: stroke-based, palette-based (Chang et al. 2015), and example-based recoloring (Kim, Kang, and Lee 2016). Of particular relevance to our work is the palette-based approach, where the system recolors the source image by palettes. In example-based approaches, on the other hand, the system recolors the source image such that it matches the color statistics of an example image. Although we use example images as the reference to extract palettes, users paint using the generated palettes, which allows palette-to-palette color mapping.

Palette design requires a selection of a small set of colors that represents the original image colors (Celebi 2011). There are various algorithms for a palette selection, such as k-means (Celebi 2011), minmax (Xiang 1997), median-cut (Heckbert 1982), octree (Gervautz and Purgathofer 1988), and fuzzy c-means (Bezdek 2013). We chose k-means, since

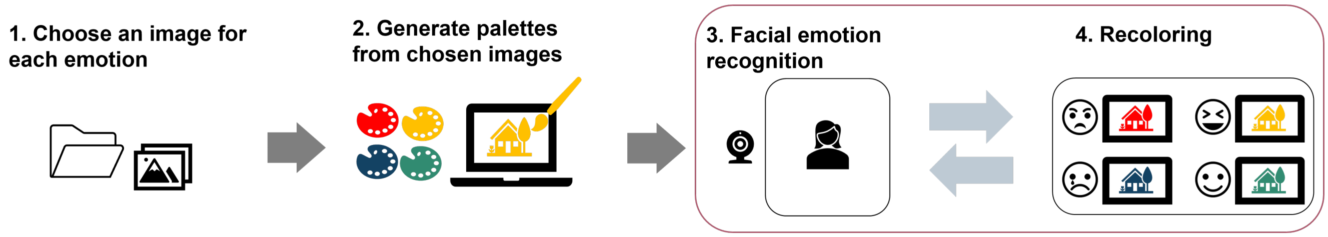

Figure 1: Schematic diagram of our computational tool for recoloring based on user emotions.

the performance of it as a color quantizer has been proven effective.

Applying Emotion to Painterly Rendering

There exists a lot of prior research in NPR which tries to produce painterly renderings of a given image in various styles of elements of art reflecting different emotions. As mentioned in the introduction, the ”empathetic painting” (Shugrina, Betke, and Collomosse 2006) recognizes users' facial expressions through the detection of facial actions units defined under the Facial Action Coding Scheme (FACS) (Ekman and Friesen 1978) and the action units are mapped to vectors within a continuous 2D space representing emotional state. The result was a digital canvas capable of smoothly varying its painterly style at approximately 4 frames per second. They then deployed this system in a live installation, allowing users to experiment with their interaction method. They reported that the user feedback was broadly positive in terms of method of interaction.

Lee et al. (Lee, Choi, and Seo 2020) also demonstrated a painterly rendering system that automatically creates painterly images with defined painting parameters. The aim of their study was to propose a “user emotion-inspired painterly rendering process” to help non-professionals reflect their emotions through painting, which bear similar motivation to our work. Correlations between the painting features and the emotion were obtained from the response values using linear regression, and the final painting was produced by applying four painting parameter values defined for a specific emotion, together with the recoloring of three-color combinations for a target emotion.

These systems are capable of generating various styles of painting by controlling the painting features such as types of strokes and color combinations as parameters. However, both of these works focus on automatically producing paintings from photographs and do not consider individual user's choice of affective expressions, i.e. mappings of tonal variation to the valence-arousal space. Since our objective is to allow users, instead of the system, to interpret the emotional meaning of the output, we built a system that integrates emotion detection and a painting tool.

Interactional Approaches to Affective Computing

Our method is most closely aligned with the idea that emotions are not only mediated through physiological signals but also largely constructed through culture and social interactions, which is known as an interactional approach (Boehner et al. 2007).

Affector (Sengers et al. 2008), for example, is a video window between the adjoining private offices of two colleagues. This system supports user-defined rules, which can support human experiences as open-ended and emergent. eMoto (Sundström, Ståhl, and Höök 2005), a mobile service for sending affective messages to others, with the explicit aim of addressing such sensing, is another example of the interactional approach. Instead of relying on the physiological measures, eMoto uses affective gestures for input. Through using such gestures, the user navigates the expressions that make use of colors, shapes and animations for the background of messages.

Although we focused on expressing emotions through facial expressions, we support a more diverse range of communication acts (Boehner et al. 2007) by allowing users to map their own color palettes to the emotional space. The palettes are generated from user-chosen images. By incorporating arousal and valence values from facial emotion recognition, the system can combine real-time measures with subjective expressions of emotion, which are defined by the user-chosen palettes.

Design Goals

Based on our background research, we outlined a set of four design principles in detail below:

- **Easy to use.** The tool should be easy enough to learn and use, even for non-expert users. For example the interaction should be natural so that it does not require formal knowledge of art to understand the application.
- **Expressive.** The tool should offer sufficient degrees of freedom that it supports a diverse range of communication acts.
- **Balanced support for objective and subjective measures.** The tool should support primary subjective accounts while preserving the objective accounts of emotion.
- **Reflective.** The tool should give users the opportunity to understand and experience their own emotions.

System Design

In this section, we first describe the model of facial emotion recognition that we used and then explain the process by which the recognition results are connected to the user's painting.

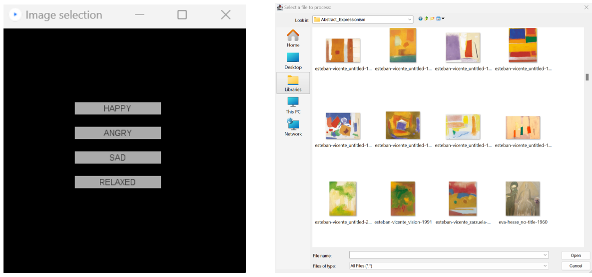

Figure 2: GUI window for selecting images.

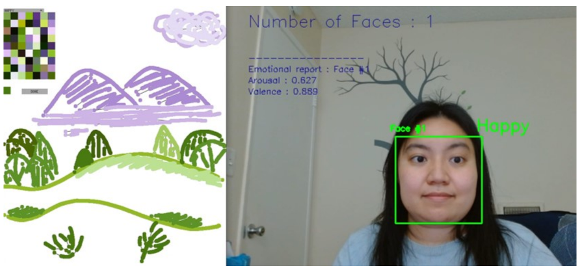

Figure 3: GUI for the recoloring tool.

We have adapted Maël Fabien's real-time facial emotion recognition (Bradké et al. 2019) model and the Drawing Manager external processing Library (Jennifer Jacobs 2021) for our computational tool, under which estimated valence and arousal values are used to express control over color combinations of the user's painting (Fig. 3). The purpose of this system is to allow users to both explore the design space of a recoloring tool connected to facial emotion recognition, and to interact with their own artwork. A GUI shown in Fig. 2 allows users to choose images from the WikiArt dataset (Tan et al. 2019). After the user chooses an image for each emotion, the system extracts the color palettes from the images and displays them in the top left corner of another window (Fig. 3).

Emotional State Estimation

Maël Fabien's facial emotion recognition utilized the FER2013 dataset (Goodfellow et al. 2013), which makes a prediction on the face using an XCeption model (Chollet 2017). For the sake of simplicity, we adopted Yang's four emotion classes (Yang et al. 2008) defined according to the four quadrants of the emotion plane, as shown in Fig. 4. As the data set consists of images of faces in seven emotion classes, valence and arousal values are first calculated by taking the expected value (see Appendix) using prediction probabilities and then used for classifying the facial expression into one of the four emotion classes (happy, angry, sad, and relaxing).

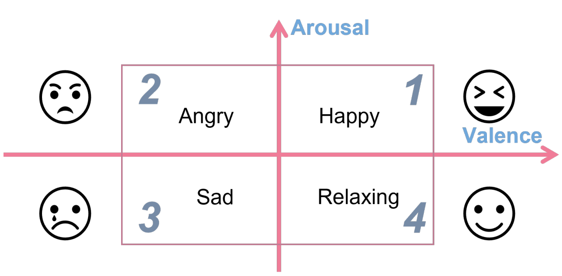

Figure 4: Four quadrants of the emotion plane. (Yang et al. 2008)

Automatic Palette Selection and Recoloring

For the automatic palette selection, we used Chang et al.'s algorithm (Chang et al. 2015). The algorithm selects a set of k colors that distill the main color groups in the image. Our target number of colors for the palette selection was 63. When user-chosen images are loaded into the application, palettes are automatically generated. By choosing four images (one for each emotion class), a user defines the color combinations that they think correspond to their emotions. Fig. 5 demonstrates some examples of the automatic palette selection results from images chosen by a user.

The user then uses one of the defined palettes to make a painting on the interface. The system saves strokes with the index of the color chosen from original palette. To notify the end of the painting, the user clicks on the DONE button. Once the button is pressed, the colors of the user's painting change as the facial expression of the user changes. Since the palette colors are arranged in descending order of color density (normalized frequency), the system maps the original colors of the saved strokes to the corresponding colors at the same position in a new palette for recoloring (Fig. 6). The recoloring results for the four emotion classes obtained by the proposed method are shown in Fig. 7.

User Study Design

Study Design and Procedure

The user study was completed online with the participant using a remote control for the experimenter's laptop on Zoom meeting. The stream frame rate for the online participants was 30 frames per second. A total of 7 participants (all women between the ages of 25 and 34) participated in the study. After filling out the consent form and collecting their basic background information, we briefly demoed the process of using the tool and given instructions for the study

Figure 5: Examples of automatic palette selection.

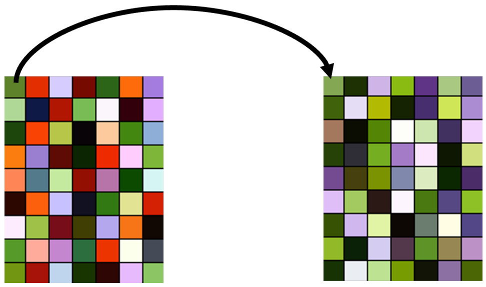

Figure 6: One-to-one mapping for recoloring.

task. Five of the seven participants indicated that they have experiences in painting less than one year.

Before experiencing the recoloring tool, the participant first filled out the pre-study survey (see Appendix). Then, the participant was asked to choose images from a dataset comprising of painting from 195 different artists in 13 styles, which correspond to each of the four emotions (happy, angry, sad, relaxed). The participant was guided to paint using one of the palettes generated from the chosen images. Right after the painting is done, the experimenter interacted with the participant's painting utilizing facial emotion recognition. After the end of the session, participants filled out post-survey, which includes questions about the reason why they chose certain images and the categories in which they are grouped. A short semi-structured interview was then conducted to evaluate their experience with the tool. See the Appendix for the survey and interview questions. The total time commitment to participate in the study was about 30-40 minutes.

Results

Overall results indicate that participants found the recoloring tool interesting and inspiring. Figure 8 shows some paintings made by participants in the study. Most of the participants who have tried raster graphics editors for digital painting prior to the study felt that the recoloring tool is easy to use. Participants who found it difficult to choose images mentioned that there were too many categories. Some of the participants mentioned that for them, the content of an image is more important than colors for perceiving emotions. In the following section, we describe these results in detail in the context of our design principles.

Ease of Use. All participants were able to follow our instructions for using the recoloring tool. These observations were elaborated by survey and interview responses: all participants agreed that they thought the system was easy to use, and they were able to find corresponding images for each emotion. One participant (p3) answered that the interface is very interactive and straightforward to use. In addition, she mentioned that it could be deployed to other domains as people are familiar with facial expressions and use them in daily life.

Expressiveness. All participants agreed that the images were sufficient for creating color palettes corresponding to each emotion. Participants showed a variety of responses regarding the amount of images; some participants preferred to go through all the images, while others thought there were too many categories.

In survey and interview responses, participants indicated they struggled with searching images by category keywords. Three participants (p4, p5, p6) suggested showing thumbnail images for each category. In addition, one participant (p1) was not satisfied by not enough colors being extracted from the chosen images.

Despite the lack of background information in art styles, participants were able to choose categories based on their familiarity with the style. Three participants (p1, p2, p7) stated that they had candidate colors in mind, and five (including the first three) stated that their priority consideration was the colors of an image. The participants who had a museum experience or interest in art were able to clearly describe the reasons for choosing certain images and their categories. For example, a participant (p2) who had experience in painting at least one year mentioned that she chose 'pop art' for searching 'happy' images (Figure 8-b). She explained that it is because she finds bright colors such as pink and orange as happy, which are likely to be found in pop art. In addition, she chose 'abstract expressionism' for searching 'relaxed' images because colors are more muted.

Balanced support for objective and subjective measures. Because of the limited conditions of our study (online), only two participants (p6, p7) were able to interact using their own facial expressions, while other participants watched the experimenter interacting with their painting. The participants who tried facial emotion recognition mentioned that it was helpful in realizing their own facial expressions such as 'relaxed', as they did not know how to make such expressions.

All participants, except one, found that the facial recognition combined with the designated palettes can help them interact well with their painting: one participant (p2) stated that having the extra component of an emotion estimator for the interaction was confusing to her, while the rest of the participants found it novel and entertaining.

Another participant (p5) mentioned that she discovered how her emotions can be expressed visually while the experimenter interacting with her painting. For her, happiness is a part of her everyday life, which was the reason for choosing an image with achromatic colors to generate the corresponding palette. When strong colors appeared with a negative facial expression, she realized that it is a special event for her. Although she was not confident when choosing images for generating her own palettes (subjective measures), she was surprised to see facial expressions (objective measures) matched well to the emotions of recolored images.

Reflectiveness. Five participants answered that using the system helped them to understand and experience their own emotions, which is one of the goals of interactional approach; two other participants (p2, p3) described that the content and sound respectively are more important modalities for them to express emotions.

During the interview, one participant (p1) shared that she

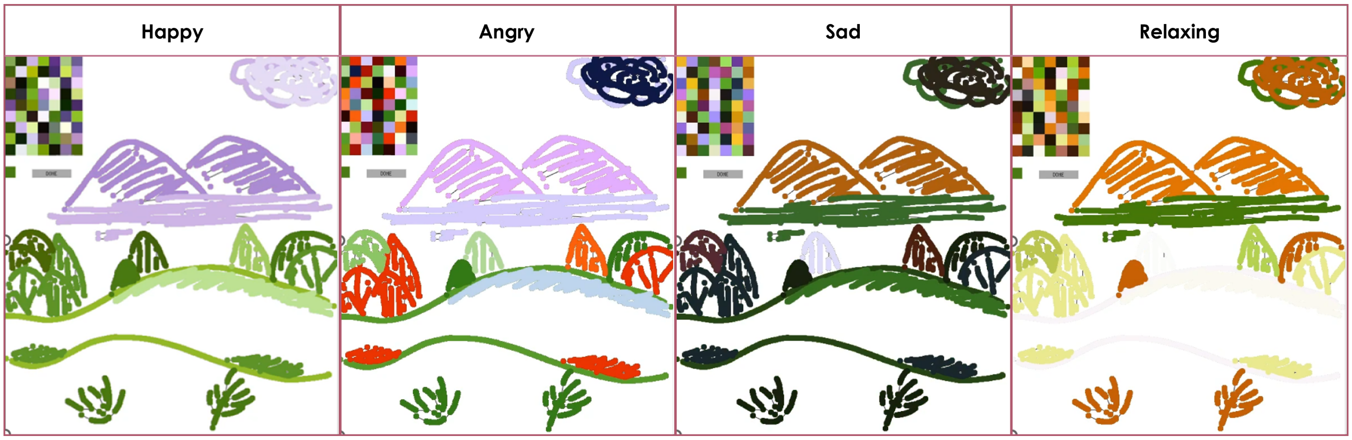

Figure 7: Emotional recoloring results of a painting.

sometimes finds it hard to express her emotions verbally since English is not her first language. She felt that painting is easier for communicating emotions. Another participant (p4) expressed about the difficulty of expressing emotions as she used to try to hide them for personal reasons; however, while using the tool, she thought about what she can draw that would make herself and other people happy (Figure 8-d). The other participant (p5) said that the tool was helpful for reading changes in emotion by visualizing them through color changes, and said she thinks it is very important to be able to communicate emotions visually. These examples demonstrate that the participants had an opportunity to think about how to express their emotions by using the recoloring tool.

Discussion

The psychological effect of colors has always been an interesting topic. How could we generate images that arouses certain feelings through color? This question has been answered by many applications using deep learning and computer vision techniques (Kim, Kang, and Lee 2016; Kim et al. 2018). Most of these applications involve recoloring photographic images. Instead, I aimed to allow users to be more engaged in the process by creating their own paintings.

The design of the recoloring tool was partially based on Josef Albers's perspective that color is the most relative medium in art (Albers 2013). Albers was a German-born artist and educator who taught at the Bauhaus among established artists. He mentioned in his book that color is always seen in relation to its neighbors, and it connects and relates to other colors. Through our computational tool, users can create their own color palettes and use them for expressing the subjective experience of emotion.

Although we acknowledge that small sets of colors are extracted from photographs, the original dataset used for creating palettes contains paintings by artists, many genres of which already incorporate a limited number of colors, i.e. abstract expressionism, color field painting and fauvism. In addition, the participants in our study mentioned that they found the extracted palettes useful because the main color groups in the image were distilled by the algorithm.

The interactional approach of the recoloring tool is important because, aside from providing more options, interactional approach allows users to ponder upon and understand their own emotions. As the ultimate objective of interactional approach is to find a better way to appreciate the interplay between objective and subjective accounts of emotion (Boehner et al. 2007), we tried to connect an objective measure (facial emotion recognition) and a subjective measure (user-defined mappings of palettes). From the study, we learned that some people value the content for emotional expression more than formal elements such as colors and lines, which would be reflected in future by automatically analyzing user-chosen images. In the same context, the software can also use sketch-based emotion recognition and provide related contents to the user's painting.

The recoloring tool also offered new ways of interaction by supporting user choice and expressions. A participant (p2) described that she liked artwork sorted in categories. She also mentioned that this could be a good inspiration tool. Overall study results and participant feedback demonstrate how the combination of facial emotion recognition and the mapped palettes generated from user-chosen images can help users interact well with their painting.

Although psychology and art theory can inform us about (Machajdik and Hanbury 2010; Shugrina, Betke, and Collomosse 2006) which combinations of colors can evoke particular emotions, following such rules strictly can limit individual expressions. Using the recoloring tool, some participants struggled with making decisions from too many choices. However, they still preferred to apply their own color palettes to their painting. Participants also found the extracted palettes useful since colors in the palettes were ordered by the frequency, which represent the majority of the colors, therefore the overall impression, presented in an image.

While the facial expression can be faked or exaggerated, it also is one of the most frequent ways that people communicate emotions. Healey et al. showed that on average, spontaneous facial expressions have less intensity than in-

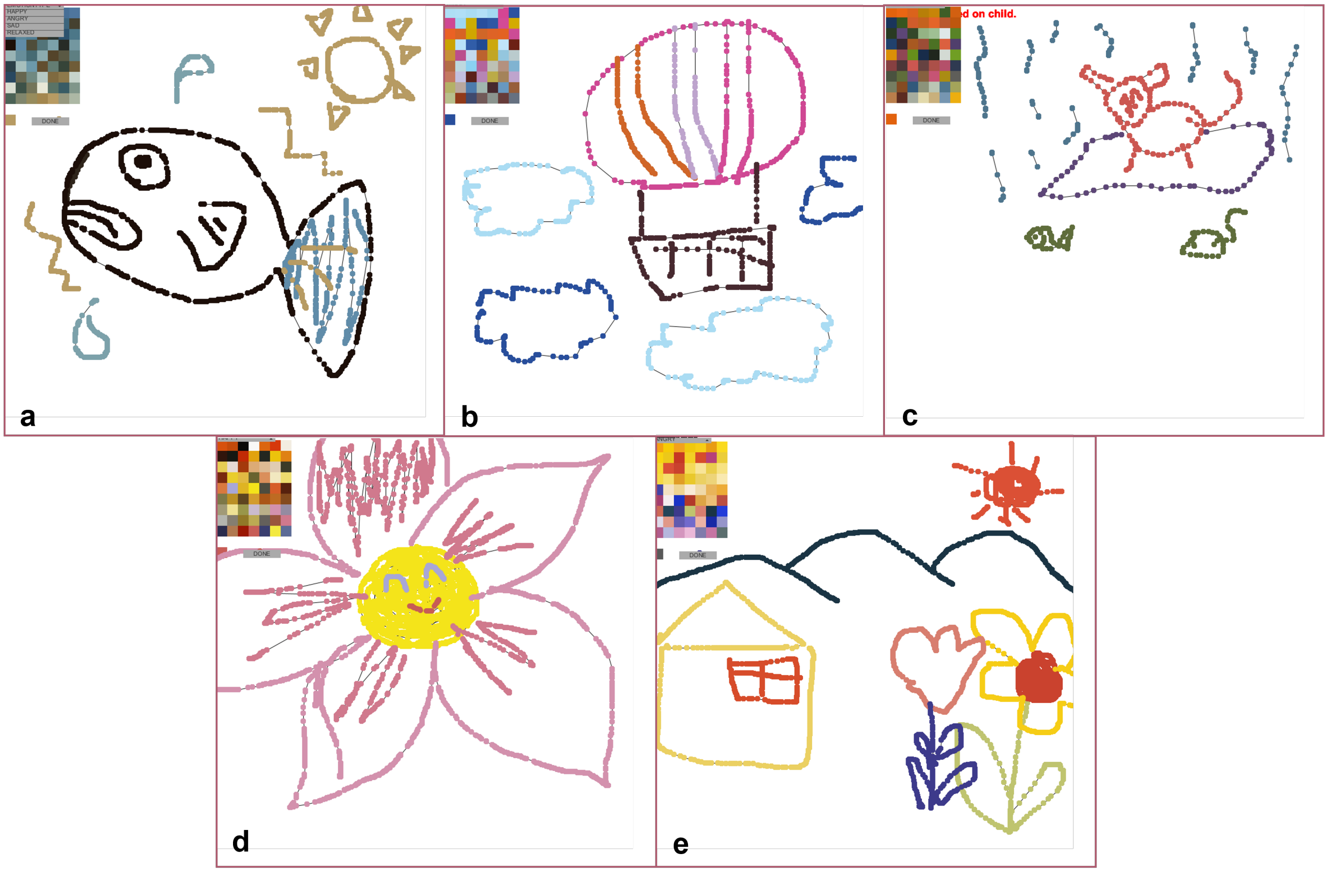

Figure 8: Happy paintings from study. a) p1; b) p2; c) p3; d) p4; e) p6.

tentional expressions of (Healey, Wang, and Chhaya 2020). Despite these findings in the discrimination between fake and genuine emotion, we observed that participants enjoyed the interactions most when they were purposefully displaying facial expressions with higher intensity from our pilot study. Therefore, we found that better recognition accuracy for genuine emotion would not necessarily lead to more enjoyable interactions.

We have worked with a small number of participants, but feel that prior work (Rajcic and McCormack 2020; Höök 2002; Sengers et al. 2008) adequately shows that the qualitative findings to be the most insightful and constructive for affective interfaces. What got us convinced about the result was not the objective conclusions, but individual effectiveness to gain further input into the design process.

Overall we believe the recoloring tool built with the interactional approach can open up new possibilities for emotional expression and experience of users. As the participants enjoyed using the tool, we would like to improve the current system by adding more dynamics to the users' painting.

Conclusions and Future Work

The most common approach in the design of affective computing systems is to model affect in a similar way to cognition and make it available in a system that recognizes a user's emotional state using sensors (Fagerberg, Ståhl, and Höök 2003). Based on the perceived emotional state of the user, the system can be designed to adapt to it and influence it through the use of various affective expressions like changing the environment in virtual reality (Kim and Lee 2003), or suggesting the painting for emotional health-care (Lee et al. 2020).

In this paper, we presented an affective computing system that matches the user's emotions with their painting and allows them to experience emotional interactivity. Through development and evaluation of a recoloring tool, we demonstrated that the tool is helpful for producing expressive paintings and interacting with them using facial expressions.

We believe that using deep learning technology and stroke-based rendering to build a computational tool opens new ways for users to express their emotions. In future work we hope to explore more rigorously the extension of our system to be context aware so that the application can provide more sophisticated palettes and mappings of color variation to the valence-arousal space.

Expected Value

The expectation of random variables with finitely many outcomes is defined in the book *Probability and measure* (**?**).

Consider a random variable X with a finite list $x_1, ..., x_k$ of possible outcomes, each of which (respectively) has probability $p_1, ..., p_k$ of occurring. The expectation of X is defined as

$$E(X) = x_1p_1 + x_2p_2 + ... + x_kp_k. \quad (1)$$

Since the probabilities must satisfy $p_1 + ... + p_k = 1$, it is natural to interpret $E(X)$ as a weighted average of the x_i values, with weights given by their probabilities p_i.

Pre-Study Survey Questions

1. What is your age?
2. What is your gender?
3. Do you have experience in painting?
4. Have you ever tried (more than 15 minutes) digital media? If yes, which ones have you used? (*Note: what you tried today does not count)
5. What is your profession? (major/field)

Post-Study Survey Questions

1. I thought the system was easy to use.
2. In our recoloring tool, were you be able to find corresponding images for each emotion, which were used for creating color palettes? (Did you think that the materials were sufficient?)
3. I think the facial recognition combined with the designated palettes helped me interact well with my painting. (i.e. emotional interaction)
4. I think using the system helped me to understand and experience my own emotions.
5. What emotion have you tried to express in your painting?
6. If you could add more words for emotions to our recoloring tool, what types of emotions would you like to add? Why?
7. Do you have additional comments or suggestions for helping improve our recoloring tool?

Interview Questions

1. What did you like about it? Were the images provided plenty enough for creating the color palettes corresponding to your emotions?
2. What did you not like about our application?
3. How would you improve it? & what do you think could be done differently?
4. Do you think the facial emotion recognition combined with the mapped palettes helped you better produce expressive paintings? (i.e. paintings embodying emotional qualities)
5. Did you find it helpful to create your own palettes by choosing images for creating paintings that communicate emotions? Was it easy or difficult?
6. What are the reasons for you to choose certain images when mapping them for creating palettes? (e.g. happy - your favorite color)
7. Did using the tool give you an opportunity to think about how to express your emotions? If it did, could you elaborate more on your idea?
8. Is it important for you to be able to communicate emotions visually? Why or why not?

Ethical Statement

With the advancement of affective technology, there have been concerns about systems that can manipulate media based on user emotions. They are due to the possibility of such systems being used for harmful purposes, even with the best of intentions. For instance a gambling company could use such technology to alter the visual media in a gambling system to make a profit based on their emotional state.

In such cases. we would expect the Government to have appropriate policies to deal with potential negative applications. If the application is used for entertainment purposes, there should be regulations which prohibit this kind of practice. For example, the accuracy of emotion recognition they use might need to be maintained at a certain level and specified explicitly.

As with any new technology, emotion-related applications regularly face ethical challenges (Cooney et al. 2018; McStay 2020). As it is almost impossible to delay the development of artificial intelligence that produces significant economic benefits, we believe not only regulations but also education on affect-sensitive technologies to raise public awareness is necessary.

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