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Emotion-Inspired Painterly Rendering

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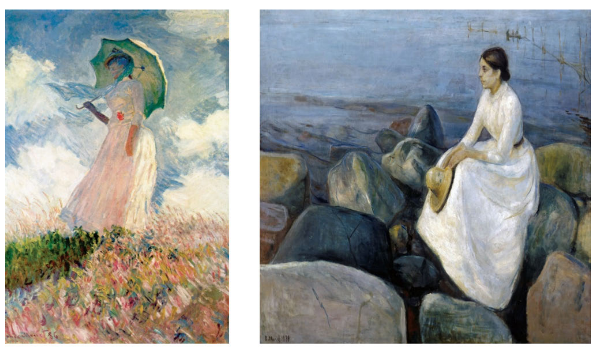
ABSTRACT When painters draw, they do not draw what they see; they reflect their emotions through specific forms of artistic expression. Through this empathy, humans derive aesthetic satisfaction. Psychological studies on art and emotions have been extensively conducted since the 20th century, and it has been found that artistic activities such as painting and writing have a positive effect on human emotions. However, it is difficult for a non-professional painter to express human emotions in a picture using artistic elements. The aim of this study was to propose a ''user emotion-inspired painterly rendering process'' to help non-professionals reflect their emotions through painting. To accomplish this aim, a painter-rendering system that automatically creates digital paintings with parameterized painting features was used. We analyzed the correlation between human emotions and the rendering parameters affecting the painting style through a user study, and we estimated the rendering parameter values for specific emotions. The results showed that colors and emotions were closely linked, and color scheme was an influential factor in the paintings. Furthermore, we developed a recoloring algorithm based on Kobayashi's three color systems classified as human emotions, and we created paintings that better reflect specific emotions. The proposed algorithm was validated through a user satisfaction survey. Hence, the proposed system can improve a user's understanding of painting and create paintings that reflect specific emotions.

INDEX TERMS Affective computing, emotion analysis, image stylization, painterly rendering, recoloring.

I. INTRODUCTION

Paul Klee, the founder of modern abstract art said, ''Art does not reproduce the visible but makes invisible.'' That is, artists do not paint things as they see, but they draw feelings from the visual experience through specific artistic expressions. Painters use painting elements to express their feelings, as shown in Fig. 1. Fig. 1(a) portrays a lively, youthful emotion with vibrant brush strokes, bright colors, and direction. On the other hand, Fig. 1(b) depicts calm and depressing emotions with dark colors and static brush strokes. In the two paintings, a woman is the object; however, it can be seen that the mood of painting and the emotions people feel differ according to the elements of painting by stroke properties.

Painting and emotions have been extensively researched, and the interest in human emotion has been an important research subject. Particularly, studies are being conducted to analyze the elements of painting and predict painting emotions. Yanulevskaya *et al.* [1] completed an emotional classification model using IAPS images by analyzing color and texture information among the physical features of painting. This model was used to classify famous paintings into eight kinds of emotions. Lee *et al.* [2] extracted three representative colors of painting and defined emotional



(a) (b)

FIGURE 1. Example of paintings that have same objects but different emotion. (a) ''Woman with a parasol facing left'' by Claude Monet, Painted in 1886. (b) ''Summer night, inger on the beach'' by Edvard Munch, painted in 1889.

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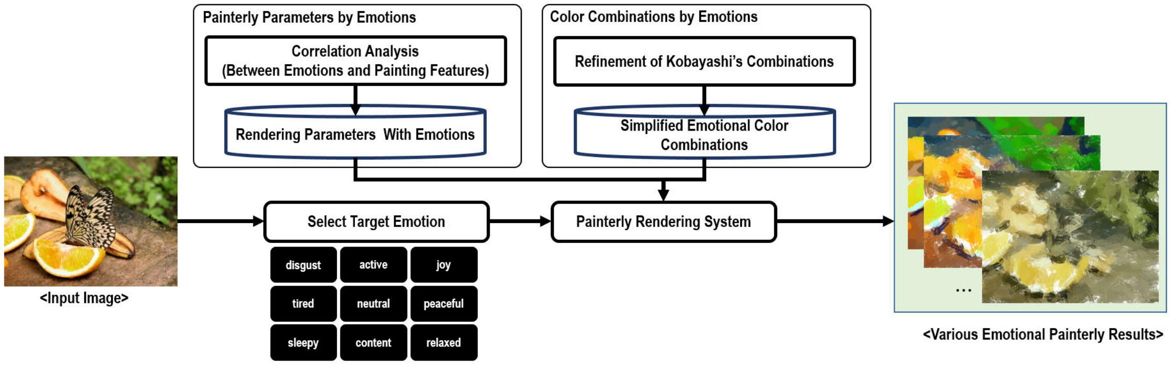

FIGURE 2. Overview of the system; The output image is generated through color transfer and painterly rendering system.

values of painting by matching emotional adjectives with the three colors defined by Kobayashi. And Lee's work [3] presented a learning tool that increases the ability to analyze the sensibility of paintings based on CNN. Through this system, non-experts can improve their understanding of painting's emotions by repeated learning to choose the picture that is closest to a given picture and emotion. While various studies have been conducted, most studies on emotion in painting have focused on predicting the value of emotion; thus, the research on creating painting that reflect human emotions are insufficient.

As fig. 1 shows, artist express their feelings in paintings through various painting elements. On the other hand, non-experts who are not related to art may not be proficient in painting. Artists know how to draw using painting elements and can skillfully express desired emotions in works. On the other hand, it is difficult for non-experts to handle painting elements adequately as they require considerable time and effort to fully understand the elements. In addition, as several studies have been conducted mainly to predict the emotions of painting, there are insufficient studies to understand the relationship between painting characteristics and emotion. Therefore, a study that pays attention to the emotion of painting is necessary from the human point of view, and this study intends to pioneer the research on painting that focuses on the emotion of the user.

The process of the proposed emotional painterly rendering system for creating paintings based on human emotion is shown in Fig. 2. The core approach of this process is to define painting elements and color themes based on emotional values and apply them to the rendering system to create paintings.

The first step in creating a painting that reflects an emotion is to find a correlation between the painting features and emotion. The painting features are defined and controlled as parameters in the rendering system, which can generate various styles of paintings.

We performed a user study using various painting results obtained from the rendering system. The user study was conducted by administering questionnaires, and the correlation between emotion and the parameters was analyzed. The correlation obtained in this step was applied in inverse linear regression to estimate the values of painting parameters for nine standard emotions. Furthermore, the estimated rendering parameter values were set in the rendering system to generate a painting about each emotion.

The proposed algorithm requires a second step to compensate for the difficulty in creating a painterly image that completely expresses a particular emotion by using only the painting parameters. In the second step, the color model is constructed based on the emotion, and the recoloring algorithm is applied to convert the color of the input image according to the desired emotion. The recolored image synergizes with the effect of the painting rendering parameters to produce a painting that better represents the target emotion.

Through the above process, we achieved various painting outputs based on emotions by building a painterly rendering process that helps users understand the painting elements. The result of this study is to help users express their feelings more skillfully like an artist.

II. RELATED WORK

NPR(Non-photorealistic rendering) was initiated in 1963 based on Johnson's study [4] on developing sketch pads that allow interaction between humans and computers. Since the 1990s, NPR has been an important research subject in the field of computer graphics and has been extensively studied. In this present study, we used stroke-based painterly rendering to generate images, such as oil paintings, among NPR fields.

Stroke-based rendering is a technique for expressing oil paintings in stroke units rather than pixel units to generate the resulting image. Haeberli [5] developed an image abstraction rendering system that can interact with the user. The painting elements received abstraction style images by receiving the brush position, stroke order, brush shape, and direction through interaction with the user. Litwinowicz [6] proposed a method of expressing impressionist styles by applying painterly rendering to videos and images. The optical flow field is used to enhance visual coherence and to maintain and apply the position of the stroke for frame-to-frame coherence, thereby enabling the painterly rendering of videos. However, the existing painterly rendering used shapes such as circles, polygons, and straight lines as strokes, thus making it difficult to make them resemble human drawings. Hertzmann [7] proposed brush strokes with curves to create an image that resembled hand paintings. In addition, multiscale algorithms were used to generate richer strokes and to simulate the expression methods artists pursue. Various stroke-based rendering techniques have been studied. A real-time video artistic stylization system was presented and demonstrated a variety of painterly styles [8], [9]. Since then, studies and algorithms for creating various painting styles have been continuously introduced [10], [11]. Recently, research has been conducted on robot painting system. Reference [12] studied a robot painting system using palette knife, and has generated various painting through painting parameters. Reference [13] proposed a robot interactive system that produces artwork with acrylic paint.

With the development of painterly rendering, further studies have been conducted on the application of human emotion. Conton *et al.* [14] introduced the first system to apply emotion to painterly rendering. The study extracted human emotions using action units of facial action coding system (FACS) based on the six commonly performed basic emotions defined by Ekman *et al.* [15]. The researchers defined the parameters of the painterly rendering system according to emotions to create portraits that maximize the emotions of users.

Shugrina's work [16] also used the action units of FACS to extract the emotions; however, it is possible to directly select the target image for painterly rendering. Seifi *et al.* [17] proposed a method to increase the intensity of emotion on the face in an animated character using various color palettes depending on the user's emotion.

All these studies produced paintings from images. In this study, we added emotional conditions while creating paintings. However, as each emotion had a corresponding painting style, it was difficult to accurately define the correlation between the painting elements and emotions, except for the colors.

Studies that apply emotion to images have been conducted more extensively with recoloring than in the field of painterly rendering. Reinhard *et al.* [18] first proposed an automatic color transfer algorithm that matches the mean and variance between the original and input images. First, the color space of two images was converted from RGB to lab, and the mean and standard deviation of each color axis were calculated. The pixel value of the input image was transformed according to the average and standard deviation of the reference image. Furthermore, the color space was converted to RGB to generate a color-converted image.

Several color transfer and recoloring algorithms have been proposed. Inspired by Reinhard's approach, several studies have presented methods for color transfer in various 3D color spaces. Neumann and Neumann [19] proposed a 3D histogram matching technique in HSI color space that transfers hue, saturation, and intensity. This method achieved an exact match of the gamut of the target image by transferring the source image's 3D color distribution to the target image. Reference [20] transferred the distribution of images in various color spaces through histogram matching in lab space. In addition, various methods of color transfer studies were conducted. Reference [21] presented a selective color transfer of image and video with color mixture map. Seo *et al.* defined color templates and introduced recoloring techniques using the templates [22]. Wu *et al.* [23] focused on analyzing the content of high-level scenes, unlike conventional methods that rely on image color statistics. Reference [24] also proposed the new method of color transfer with moving last squares. Reference [25] has proposed a new recoloring algorithm that complements the limitations of existing palette-based color transfer methods. The automatic palette extraction approach, which preserves inherent color characteristics of the source image, was able to create more natural results than previous works. Color transfer studies are being studied through various methods, such as [26]–[28].

Color is the most important component of human visual information. References [29], [30] conducted a study of these colors to define the relationship between color and emotion. This shows that color is the most powerful tool for conveying moods or feelings by greatly influencing human vision. Artists express their emotional feelings by effectively using colors in creating works of art. Studies have also been performed to transfer color with emotion. Yang and Peng [31] first devised an emotional color transfer method. In this work, the user selects a list of colors representing various moods and selects a reference image from the list. The image is then applied to a histogram matching algorithm to produce a more accurate and justifiable resulting image. However, there are cases where the color cannot be transferred naturally by applying a single color scheme. He *et al.* [32] proposed a color transfer framework to evoke different emotions for images based on color combinations. This framework, which uses pantone color combination instead of single color, was able to create more accurate results than previous work. Liu and Luo [33] proposed an emotional color theme extraction framework incorporating color psychology theory. When the user selects the emotional color theme, the emotional value distribution of the color theme is delivered to the target theme, and the image that is color-transferred is output by applying the target theme optimized for emotion. Su and Sun [34] developed another framework that delivers targeted emotions based on dynamic, adjustable color combinations. The number of main colors is determined according to the complexity of the image. The color transfer was achieved using the reference image from the predefined color emotion model. Kim *et al.* [35] proposed an algorithm that automatically selects segments that semantically match the input image for the target emotion and performs color transfer for each region. This way, an image following the target emotion was generated while maintaining the meaning of the target input image. Liu and Pei proposed a new emotion estimation method for extracting the target emotion of reference images and applied them to their color transfer method [36]. Recently, various emotion-based color transfer and recoloring techniques using deep learning technology have been extensively introduced [37], [38].

All recoloring studies mentioned above are emotion-based color transfer algorithms that can be applied only to photographs. We employed a basic recoloring algorithm but propose an emotion-based recoloring process that can be combined with the painting parameters used in the painterly rendering system.

III. THE PROPOSED PAINTERLY RENDERING SYSTEM

To create a painting that reflects an emotion, it is essential to find a correlation between the painting features and the emotion. Therefore, in this study, a painterly rendering system having painting features as parameters was used. The rendering system was used to generate various paintings using painting features that were used in the user survey to determine emotional values. Correlations were obtained from the response values using linear regression, and painting features parameter values for specific emotion values were obtained through inverse linear regression.

A. GENERATING PAINTING USING PAINTING FEATURES

In this study, the stroke-based painterly rendering system proposed by Seo *et al.* [39] was used. This system is based on an image retrieval method and uses a stroke database, and it produces painting-like images composed of predefined brush strokes. The stroke database consists of transformed copies of the several brush stroke profiles obtained from an actual brush stroke [40]. This rendering system is a flexible system that can provide various rendering parameters and obtain various styles of painting results by changing parameter values. We extended this system in the process of creating paintings by painting features. The stroke database, rendering parameters, and results of the painterly rendering system are shown in Fig. 3. The painterly rendering system analyzes the input image and generates strokes by determining attributes such as color, material, direction, and length of the brush based on the analyzed data. We created a painting rendering image that expresses various emotions by applying various parameter values to the rendering system.

The painting features applied in our painting rendering system can be classified into three categories. The first is the brush color component, which is a post-processing factor. The second is the brush information factor, which includes straight line, curve, length, thickness, and direction. The third includes brush positioning factors such as contour, density, and level of detail (LOD). The painting elements for the three factors reflect in the twelve control parameters, as shown in Table 1, to achieve various results. In this study, to obtain a clear relationship between painting elements and emotions, we used the rendering parameters that influence the rendering results the most.

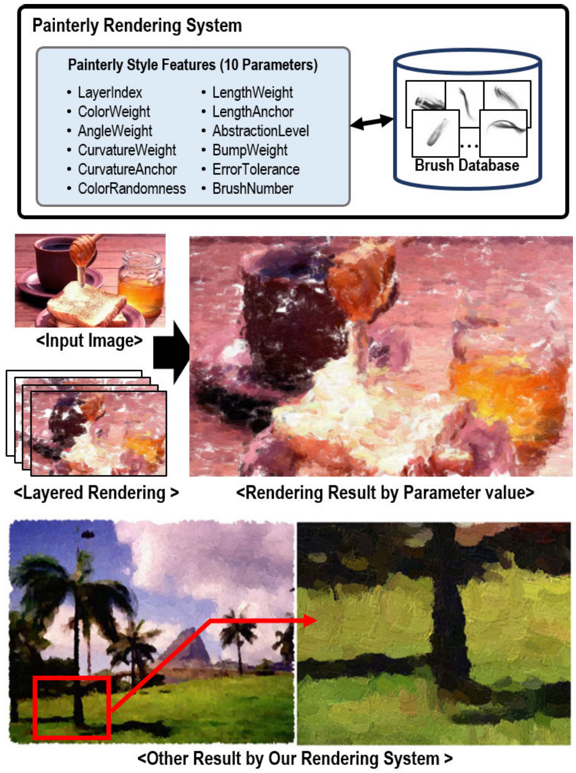

FIGURE 3. The overview of our painterly rendering system.

TABLE 1. Rendering parameters in painterly rendering system.

Painterly Parameter	Description
layerIndex	Number of layers that relates to the expressed brush size
colorWeight	Selection of a brush with color difference between the canvas and the original image
angleWeight	Selection of a brush that has a similar angle with edge direction
curvatureWeight, curvatureAnchor	Selection of a brush with its curvature
lengthWeight, lengthAnchor	Selection of a brush with its length value
bumpWeight	Extent of brush texture application
colorRandomness	Scope of color diversity
abstractionLevel	Degree of abstraction of the painting
errorTolerance	Application of a brush based on the image loss
brushNumber	The number of brushes used in the brush selection process

In the case of the brush information factor parameter, an objective function score was applied to optimize the stroking of the brush. The score function is calculated as shown in (1). The value of the score function produces a final value based on the color, length, curvature, and angle values of the area to be brushed.

$$\begin{aligned} score = {} & W_{color} * colorDifference \\ & + W_{length} * (lengthAnchor - brushLength) \\ & + W_{curvature} * (curvAnchor - brushCurv) \\ & - W_{angle} * dot(ETF, brushangle). \end{aligned} \tag{1}$$

The brush stroke with the highest score is selected from the stroke database, and the brush stroke is painted at the corresponding position. The optimal stroke selection function adopts the color difference value as a basis, and the condition of stroke selection can be changed using weight parameter values (lengthWeight, curvatureWeight, angleWeight) for stroke length, curvature, and angle.

Finally, we analyzed emotion by selecting four parameters (layerIndex, angleWeight, abstractLevel, and colorRandomness) that have the most influence on the painting result among painting element parameters. The four parameters were selected through a simple survey using paintings created by setting each parameter value to extreme.

Our painterly rendering system creates a canvas, divides it into a grid of brushes of a certain size, draws an optimized brush on the canvas, and then redraws the canvas by the number of layers [39]. Each time you move to the next layer, you reduce the size of the brush for more details. However, if the number of layers used is minimal, a painting that does not adequately represent the objects in the image would be produced. Applying a large number of layers will produce a detailed image like a photograph. Therefore, we defined the number of layers between 3 and 5. LayerIndex is a parameter for the number of layers to use, which directly affects brush size. The application of the brush, according to the number of layers, is shown in Fig. 4. As the number of layers increases, small brushes are drawn on the canvas for more details. The final result is obtained by overlapping all the layers.

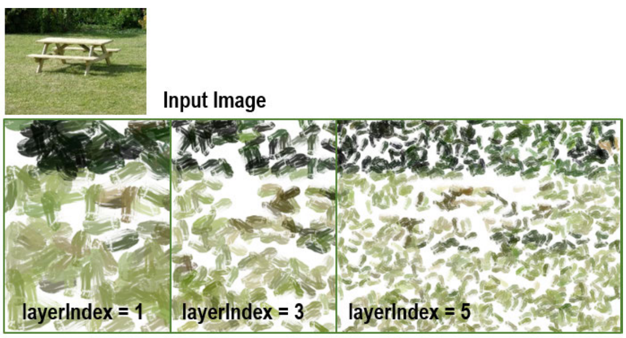

FIGURE 4. Result image for each layer affected by layerIndex; left top image is input.

The direction of the brush is determined by the angleWeight parameter, and the direction of the input image is computed locally by the edge tangent flow (ETF) [41]. The dot product is obtained between the gradient vector of the ETF and the direction vector of the brush, and the brush having the closest angular value is selected. At this point, the angleWeight value is used. As the angleWeight value increases, the final brush is selected by considering an angle more than the color difference, curvature, and length during the optimal brush selection process. Therefore, when the value of the angleWeight parameter increases, the brush is further drawn along the directional information of the input image.

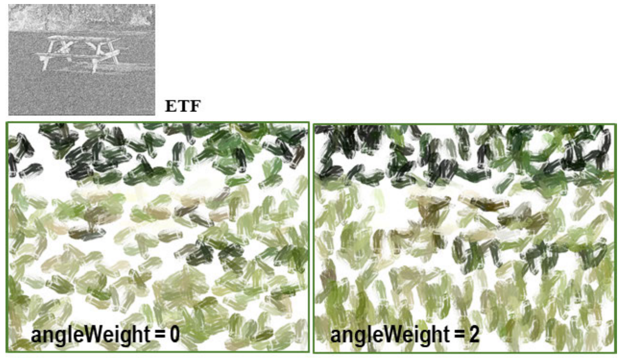

FIGURE 5. Stroking outputs obtained by different values of angleWeight; left top is ETF image.

A part of the rendering process based on the value of angleWeight is shown in Fig. 5. If the angleWeight parameter is set to a value higher than 0 or 2, the brushes with similar orientation to the contour of the input image can be seen.

The AbstractLevel parameter indicates the abstraction of the painting by setting the size of the SuperPixel, which is a large area that groups adjacent pixels together with perceptually similar information, such as color and brightness. The SuperPixel algorithm proposed by Achanta *et al.* [42] is based on graph theory. The algorithm compensates for the drawback of a slower computational speed due to the larger graph in proportion to the image size. As shown in Fig. 6, a large AbstractLevel parameter value produces a larger set of pixels, resulting in a simplified painting result.

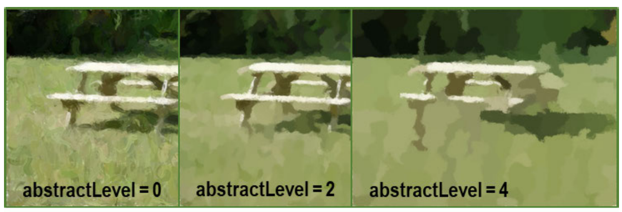

FIGURE 6. Output examples obtained by different values of abstractLevel.

Finally, the colorRandomness parameter is used to determine the color of the brush stroke and to provide various results. In this study, the LCH color model was used. The LCH color space is a space created based on lab color space, and it is a model that can intuitively understand the color information recognized by the human eye [43]. This model consists of lightness L, chrom C, and hue H. colorRandomness gives variability to the H color channel of the LCH model, resulting in a painting with various colors. As shown in Fig. 7, the larger parameter value results in the higher variety of stroke colors in the painting.

B. USER STUDY: ESTIMATING CORRELATION BETWEEN EMOTION AND PAINTING FEATURES

We selected four parameters that produced the most change in the style of the resulting image. We then looked at the

FIGURE 7. Brush color variation according to colorRandomness.

rendering example to see how the selected parameters produced various results. This section evaluates how the various painting results generated by each parameter affect human emotion. The first process is to create a painting expressed in different styles by setting various values for the four parameters. When a person observes the results of various styles, the user's emotional change is evaluated through user studies. It is essential to maintain the characteristic consistency of the input image used for the test and the assumption that the diversity of the image has a different effect on human emotion.

The IAPS is a database of 956 color photographs from everyday objects and scenes, which was designed to provide a standardized set of pictures for studying emotion and attention, and it has been widely used in psychological research [44]. An essential property of the IAPS is that the stimulus set is accompanied by a detailed list of the average ratings of the emotions elicited by each picture. The normative rating procedure for the IAPS is based on the assumption that emotional assessments can be accounted for by three dimensions, namely valence, arousal, and dominance.

We selected a total of 10 landscape and still images with the same compression ratio as input images from the IAPS image database. As shown in Table 2, a total of 160 paintings were created by modifying the values of the selected parameters. Each parameter is set to two values that produce a reasonable painting, with sufficient difference in the results of the painting.

TABLE 2. Rendering parameter for user study.

Painterly Parameter	Value1	Value2
layerIndex	3	5
abstractLevel	0	2
angleWeight	0	2
colorRandomness	0	0.7

We conducted a user survey using 160 rendering results as shown in Fig. 8. Emotional values were answered based on the two axes (arousal, valence) of the circumplex model defined by Russel *et al.* [45]. The circumplex model is an extension of an unidimensional emotional model to a two-dimensional model.

Russell developed the circumplex model to generalize multi-dimensional emotion models, and it is now used for various studies on emotions. This model allows a visual identification of the similarities and differences between neighboring emotions. The user survey was conducted on 144 non-specialists who were not related to art to receive emotional responses. First, the respondent's occupations, ages, and genders were answered. The respondents were college students, teachers, service workers, office workers, and IT, and their ages ranged from 20 to 50. Also The male:female ratio was 4:3. Then, emotional value, five levels of arousal and valence, were responded to each of the 160 paintings.To calculate the correlation between painting parameters and emotions, regression analysis was performed using survey data. We analyzed the influence of each painting parameter and emotion by a regression process using the following equation.

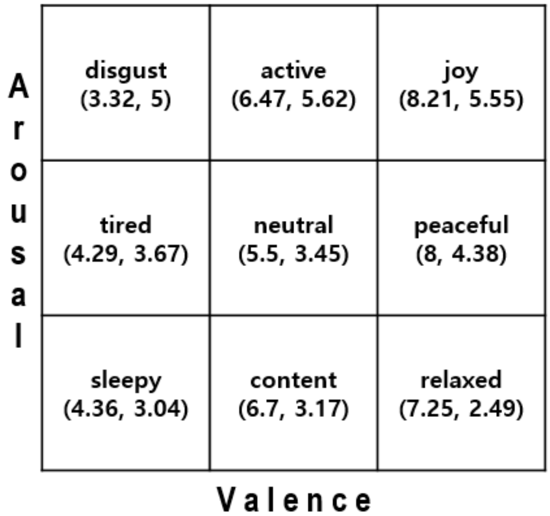

FIGURE 8. Our nine-emotions model and its AV values.

$$y = \beta_1 x_1 + \cdots + \beta_n x_n + e \tag{2}$$

Here, x_n is the painting parameter value pairs (value1, value2 in Table 1) applied to generate 160 paintings, where n is 4 (1: layerIndex, 2: abstractLevel, 3: angleWeight, 4: colorRandomness); y is the VA values assigned to the painting by the survey subject; β_n is obtained from the regression analysis of x_n and y, and it is a regression coefficient value corresponding to valence and arousal, which indicates how much a parameter affects emotion; and e is the prediction error of the regression model. The regression coefficient (R. coef.) β_n is shown in Table 3. After this process, the correlation coefficients (C. coef.), shown in Table 1, are calculated, and the values reveal the relationship between the two variables (painting parameter and emotion). In this study, the regression analysis showed that layerIndex and abstractLevel have a positive correlation with emotion, and angleWeight and colorRandomness have a negative correlation with emotion. The regression coefficients will be used to predict painting parameters according to specific emotion.

TABLE 3. Regression and Correlation coefficients of painterly parameters.

	Valence		Arousal	
	R.coef	C.coef	R.coef	C.coef
layerIndex	0.068	0.194	0.279	0.153
abstractLevel	0.068	0.126	0.073	0.170
angleWeight	-0.051	-0.152	-0.033	-0.151
colorRandomness	-0.321	-0.163	-0.613	-0.164

C. INVERSE LINEAR REGRESSION FOR DEFINING PARAMETERS

Using the regression model obtained through the linear regression analysis, a rendering parameter prediction model for emotion was produced. We first defined nine standard emotion models for parameter extraction according to emotions. For the emotional space model used in this study, we referred to the emotional models of [46] and [47] based on Russell's circumplex model. It consists of nine emotional spaces. Representative adjectives that represent each space were selected heuristically based on the commonly used adjectives in daily life. The nine proposed emotional adjectives and their arousal and valence values in 2D AV emotion space are shown in Fig. 8.

We extracted the rendering parameter values for nine standard emotions using the inverse linear regression method by Biswas and Biswas [48]. This approach performs an inverse function based on the results established through regression analysis to obtain independent variables. Equation (3) is for predicting a paramter value about nine emotions and is an example of layerIndex. The prediction values for the remaining three rendering parameters can also be calculated using eq (3).

$$x_1 = \frac{[y-(e+\beta_2 \times x_2\_mean+\beta_3 \times x_3\_mean+\beta_4 \times x_4\_mean)]}{\beta_1} \tag{3}$$

x_n represents four painting parameter values that we want to obtain for the nine emotions. y is a VA value corresponding to nine emotions in Fig. 8. β_n is the regression coefficient value obtained in the previous section in table 3 and x_1_mean is the normalized VA mean value for each emotion obtained from the user study. This allowed us to extract four rendering parameters for nine emotions. The results of the rendering parameters are shown in Table 4.

The results of applying the above four parameter values to our rendering system are shown in Fig. 9. "Joy" is characterized by a high abstraction, which gives a cartoon-like feel. "Sleepy" has a pronounced color variation and direction, indicating a distinct difference between the two paintings. However, if the emotional values, such as "active," "neutral," and "tired," "sleepy" are near, there would be slight differences in the painting results. We observe that different results were generated for each of the nine emotions; However, there was no significant difference in visual expression.

TABLE 4. Painterly parameter value for The nine-standard-emotion model.

	disgust	active	joy	tired	neutral	peaceful	sleepy	content	relaxed
layerIndex	4.99	4.78	5	3.14	4.59	4.36	3.72	3.91	3
abstractLevel	1.13	0.65	2	1	0.55	1.69	0.55	0.4	0.93
angleWeight	1.16	0.96	0	1.34	0.81	1.22	2	1.22	1.34
colorRandomness	0.31	0.22	0	0.41	0.21	0.44	0.7	0.49	0.62

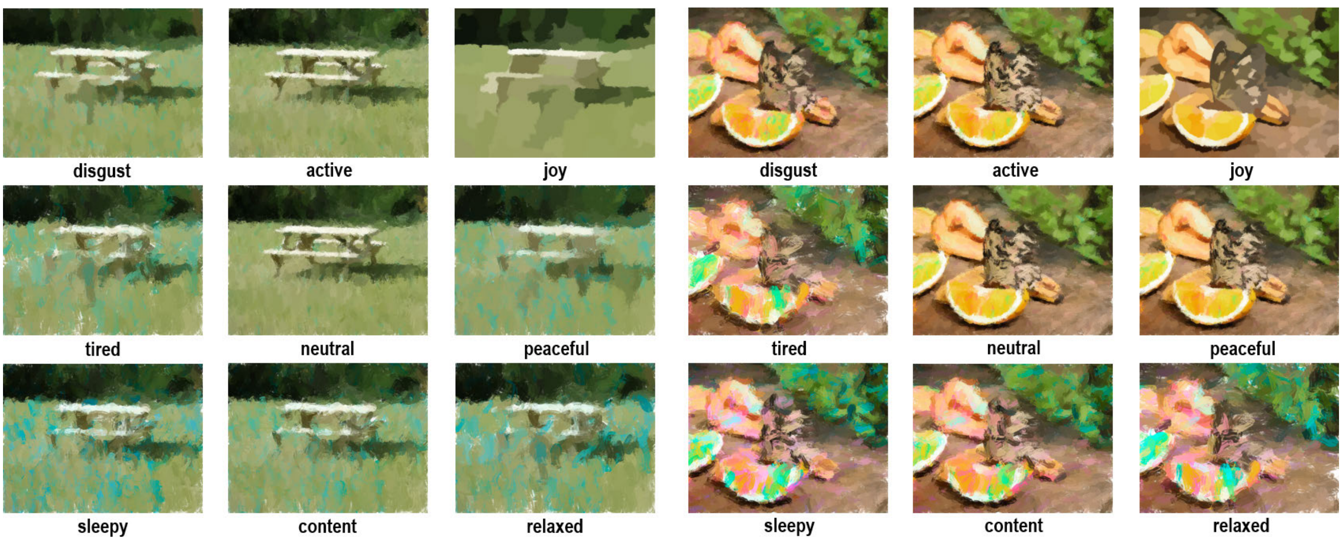

FIGURE 9. The paintings generated using painterly parameter of specific emotions.

IV. RECOLORING WITH EMOTION

The recoloring algorithm is applied to increase the accuracy of the target emotion of the painting created through the four parameters. As shown by the correlation coefficient obtained through correlation analysis, each parameter has a weak correlation with emotion. This problem also appears in the generated paintings, and each of the nine paintings in Fig. 9 does not show a significant visual difference. In addition, there is difficulty in confirming a marked difference that can sufficiently express the target emotion. To compensate for this, this study considered the color that occupies the most to human visual stimulus.

A. ESTABLISHING COLOR MODEL

To apply the recoloring algorithm to the emotion-based painterly rendering, we used a database that defined 460 three-color schemes of Kobayashi that matched 174 emotional adjectives [49]. To apply three-color schemes to specific emotions, the 460 color schemes were classified based on emotional adjectives. First, adjectives existing on the Kobayashi two-dimensional emotional space (warm-cool, soft-hard) were placed in Russell's two-dimensional AV emotional space.

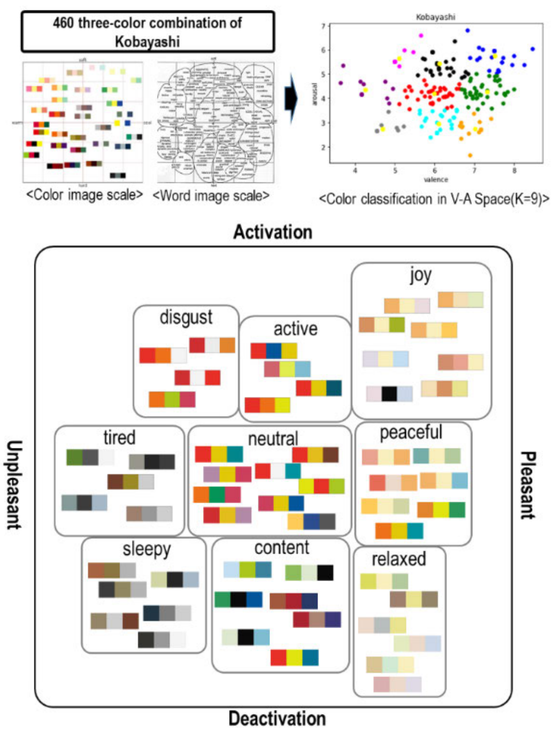

FIGURE 10. **Color classification results in two-dimensional emotion space.**

Subsequently, the weighted k-means algorithm was applied to classify the emotional space into 9 areas, as shown in Fig. 10. The k-means algorithm is a basic algorithm for grouping data with similar properties. In the general k-means algorithm, all data points have the same weight around the cluster center. Weighted k-means algorithm weighs specific data points. The weights can control the likelihood that each object will belong to a cluster and affect the process of finding a cluster center. In this study, the weighted k-means algorithm was used for color classification optimized for the nine emotion spaces defined above. The weight was determined in inverse proportion to the VA Euclidean distance squared with the adjective position representing the emotional region.

As classified emotional adjectives are located in a specific part of the emotional space, there are cases where the tricolor scheme is not classified at the optimized position. To eliminate this case, emotional adjectives with an AV Euclidean distance value between the cluster center and classified emotional adjectives greater than 0.7 were excluded from each cluster. Fig. 10 is a color model classified according to nine standard emotions by clustering emotional adjectives. A set of colors classified for each emotional space can be observed in the figure. For sleepy emotions, several dark achromatic colors are included. On the other hand, it can be seen that active emotion is mainly distributed with bright and vibrant colors.

B. RECOLORING WITH COLOR MODEL

Before recoloring using clustered color combinations based on emotion, color selection was performed to select the colors to be used for recoloring from the candidate color combinations of each cluster. First, the k-means algorithm was applied to the input image to obtain the main three colors of the image. Secondly, for the six cases of candidate color combination, the color distance score was calculated and the minimum value was set to the representative score value. Finally, one color combination was chosen by comparing the minimum color division score of each candidate color combination. Equation (4) was used as the objective function for selecting colors. minLuminanceDistance is the minimum distance of luminance between the main color of input image and kobayashi's color combination and MaxHueDistance is the max distance of hue. Therefore the luminance distance was minimized, the hue distance was maximized. The weight values were determined heuristically after rendering several images in various cases. Then three color combination were selected by assigning a higher weight to the hue distance.

$$\begin{aligned} \textit{Color distancer score} &= 0.3 * \textit{minLuminanceDistance} \\ &\quad - 0.7 * \textit{maxHueDistance}. \end{aligned} \tag{4}$$

Finally, the selected color combination was applied to the recoloring algorithm to obtain a result image reflecting the target emotion. Xiao and Ma [20] studied an algorithm that generates natural color transfer images while maintaining the visual quality of the original image by calculating the color regression line between the original image and the colors of the template in lab color space. This study used this algorithm, and the process is illustrated in Fig. 11. The recoloring results for the nine emotions obtained by the proposed

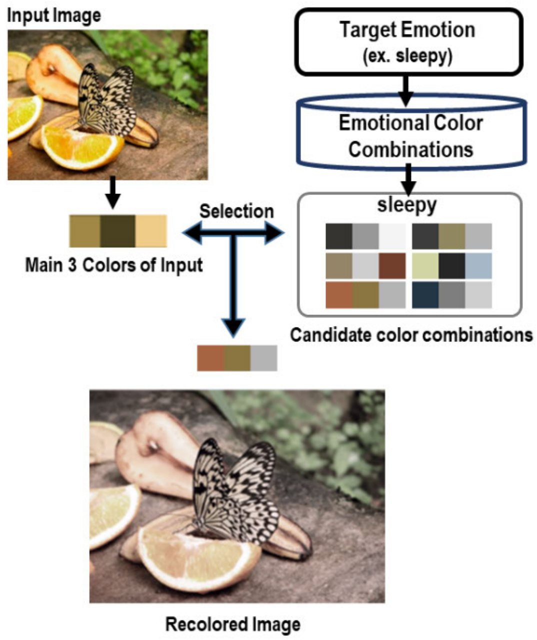

FIGURE 11. Color selection and recoloring process according to emotion.

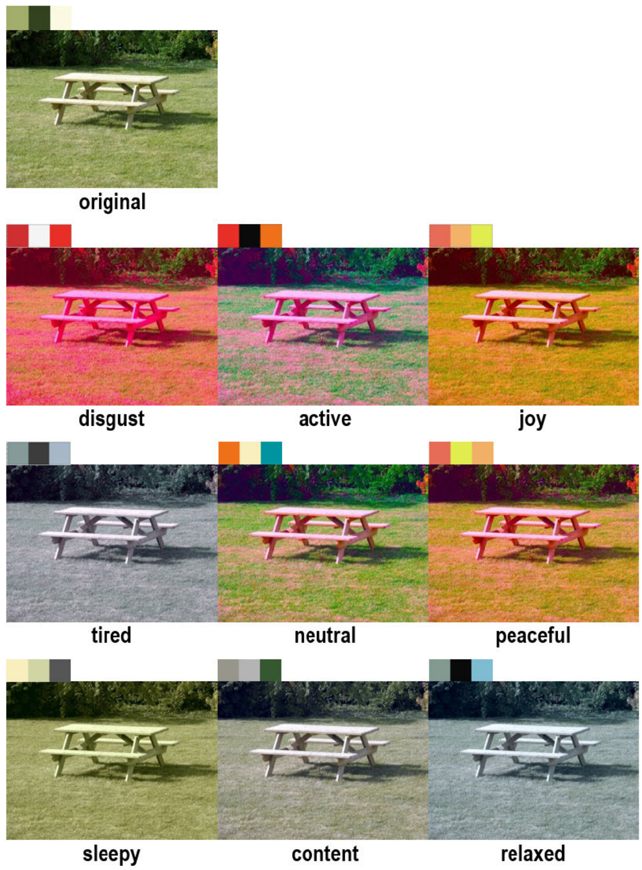

FIGURE 12. Emotional recoloring results.

method are shown in Fig. 12. The three colors in the upper left of each resulting image are the best matching results obtained from each color selection process. When "disgust" emotion was applied to the input image, the adjective "forceful" color combination was applied, and the "active" color combination was applied to "childlike" emotion. The image at the top left of each result shows the color combination chosen for each emotion.

V. RESULTS AND DISCUSSION

This study produced the final painting by applying four painting parameter values defined for a specific emotion, together with the recoloring of three color combinations for a target emotion.

We tested our process on a PC equipped with an Nvidia GTX 970 display card, 10G RAM. On average, the entire process for an image with resolutions of 1024 × 768 took around 15 seconds, including 10 seconds for recoloring with color selection and 5 seconds for rendering painting.

These results are shown in Fig. 13. For each result, the rendering parameter values for each emotion in Table 4 were applied. This shows a more advanced result of the emotions compared to the result of Fig. 9, which reflects the application of only four parameters. In Fig. 9, it is difficult to identify several differences in each painting expressing nine emotions. Particularly, "active," "neutral," and "tired," "sleepy" appear similar as the painting control parameter values were similar. It seems reasonable to compare "joy" and "sleepy," which show the most difference in parameter values, to illustrate different emotions.

On the other hand, in Fig. 13, which is the result of adding the recoloring process to the four parameters, the color that takes the largest proportion of the human visual information is changed to produce a result that shows the target emotion well. In Fig. 9, "active" and "neutral," which have minor differences, produce target emotions that are more clearly expressed.

By analyzing the parameters of the painting elements and Kobayashi's three color schemes for emotions, we created a painting that fully expresses nine emotions from one image through a color model obtained by clustering. When the user selects the "joy" emotion, the image is abstracted by four parameters, and a vivid color is displayed. In the case of the "sleepy" emotion, the direction is prominent by the parameter, and dark colors are obtained. Hence, the colors, textures, and brush sizes of paintings optimized for nine standard emotions were applied to confirm the result of expressing a specific emotion.

Questionnaires were administered to confirm whether the result of the painting represented a specific emotion better than the original image. The results of nine emotional paintings on 6 input photographs used in the survey are shown in Fig. 16. 103 people participated in this survey,

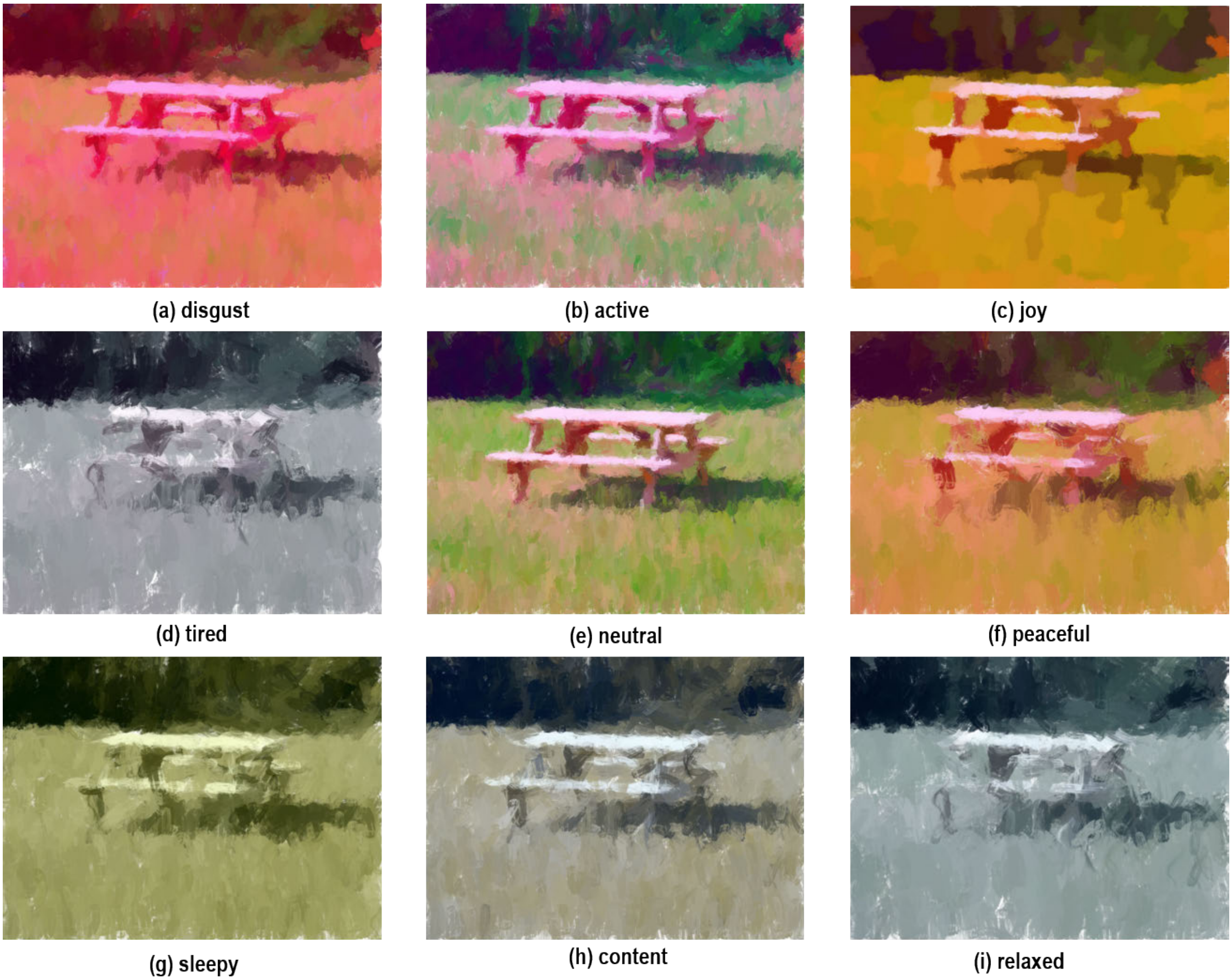

FIGURE 13. **Painting using painterly parameters and color.**

some of which were included in the user study of section 3. We received their occupations, ages and genders. Their occupation were office workers, service workers, ect. Their ages ranged from 20 to 50 and the male:female ratio was about 1:1. The participants were shown 25 sets of paintings made for the original images and the paintings created for specific emotions. And they responded with a value between 1 and 5 to indicate how well the painting expresses the target emotion compared to the original image. The data obtained from the survey showed the results as shown in Figure 14 after data preparation. In all nine standard emotions, a score of 3 or more was given. In the case of "tired" and "sleepy," it is observed that a score of 4 or more was received. After verifying the research, we applied this algorithm to the general photo, not the IAPS image, to obtain the results as shown in Figure 15. (a) and (b) represent the painting results for the

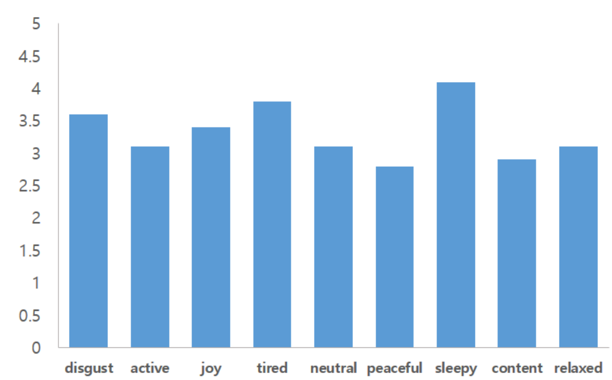

FIGURE 14. **Use study about emotion accuracy.**

input image. (c) is a result of reflecting the 'sleepy' emotion, and the expression with lifeless colors and aromatic brushes

FIGURE 15. Emotional painting result of general images. (a) and (b) are the general rendering results of the input. (c) reflects the 'sleepy' emotion. (d) reflects the 'joy' emotion.

stands out. On the other hand (d) reflects the 'joy' emotion, with vivid colors and expressions such as cartoons. As a result, we have confirmed that specific emotions are well reflected in the image through painting elements and recoloring algorithm.

Although this study is not the first attempt in the field of painterly rendering that reflects emotions, it is meaningful as the first painterly rendering attempt to apply an emotion color theme based on a user's emotional response analysis without heuristically determining rendering parameters.

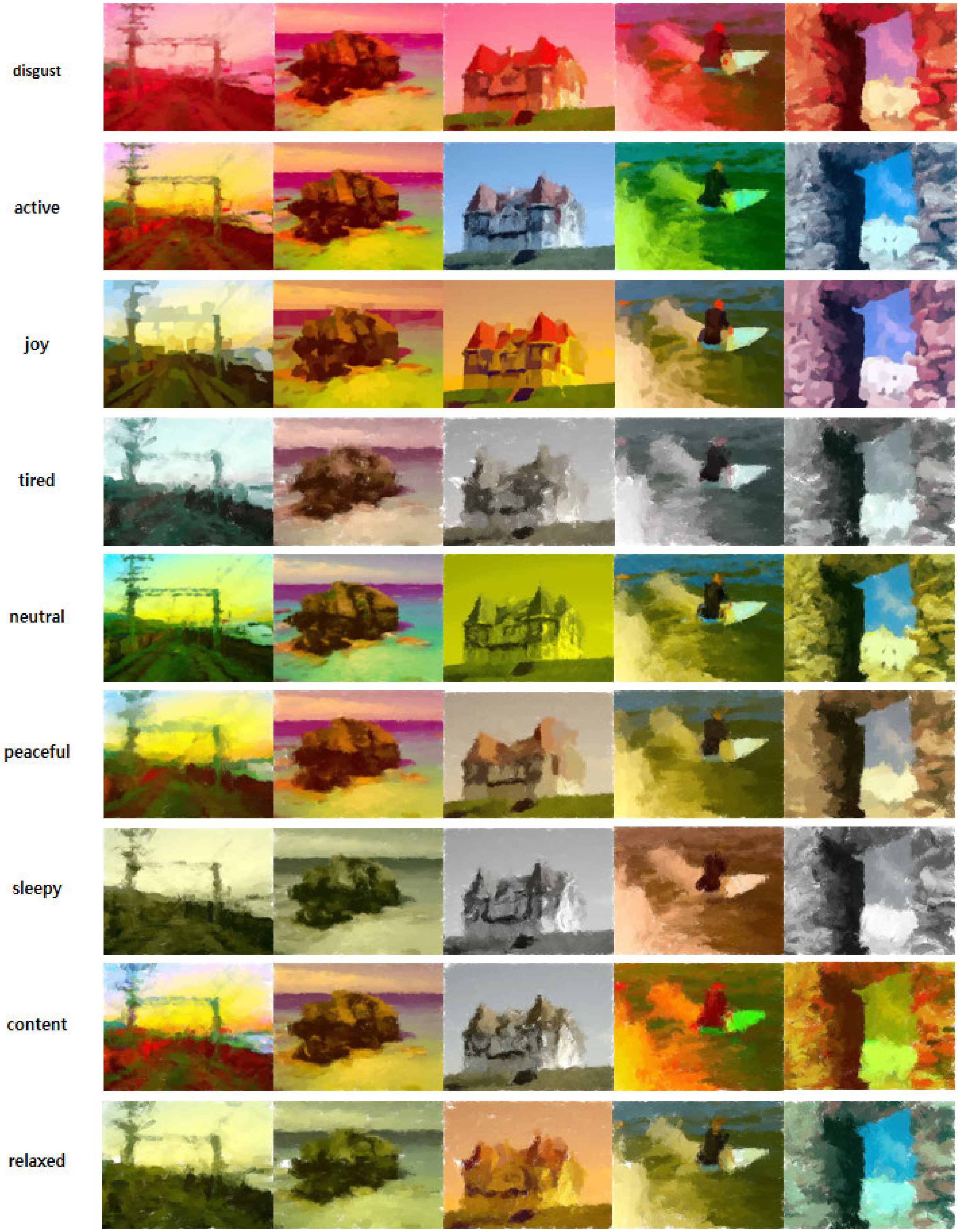

FIGURE 16. Emotional painting result of various input images.

VI. CONCLUSIONS

In this paper, we report a study conducted to create a painting that reflects a user's emotion. First, to analyze the correlation between painting elements and emotions, we used a painterly rendering system with various painting elements as parameters. In the rendering system, we extracted four rendering parameters that produced the largest change to the resulting image. Furthermore, various painting results were generated for the four parameter values, and a user study was conducted to analyze the relationship between painting elements and specific emotions. A regression model was obtained from the response of the user survey, and the model was applied to inverse linear regression to define the parameter values for the nine standard emotions we designed. However, as it was difficult to create a sufficiently expressive painting based on the painterly rendering parameter values, recoloring techniques according to specific color emotions were applied. This was premised on the considerable influence of color on the human visual system.

Finally, four rendering parameters and a recoloring algorithm were applied to create a painting that reflects a particular emotion. In addition, through a user study, it was confirmed that the target emotion was better expressed than the original image. Furthermore, by analyzing the correlation between painting and emotion, we could improve the understanding of the user's painting elements, and by applying this to painting, we could help the user create a painting for a specific emotion.

This study has the following contributions. First, this study analyzed the relationship between painting and emotion from a human perspective. Until now, the research on painting emotion has been conducted only to analyze the emotions that appear in actual paintings, but we conducted a research to create the paintings by investigating the effects of the changes in painting elements on human emotions. Second, various emotional color schemes are arranged to be suitable for painterly rendering, and a consistent algorithm is proposed, in which the emotional color scheme is effectively selected based on the input image and applied to the rendering. This can improve the understanding of the correlation between painting and emotion, and it can help the user express their feelings more skillfully.

This study analyzed color-emotion correlations by selecting only four rendering parameters that are most likely to affect emotion. This is part of our rendering parameters, defined in twelve. Due to capacity, time, and cost constraints, a multi-dimensional analysis of all the parameters will be required in the future. For the same reason, the study on color schemes for emotion was simplified to define nine representative emotional spaces. In the future, the types of emotions provided by the system will also need to be expanded and diversified.

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