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# Feature Extraction From Oriental Painting for Wellness Contents Recommendation Services

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**ABSTRACT** As the interest in health increased, people are more interested in mental health as well as physical health. Predominantly, due to the development of IT technology and digital contents, production of wellness contents through fusion with digital contents is increasing. Although many types of research that pursue wellness through the satisfaction of the visual sense are increasing, they were dealing with the western painting that emphasizes color and saturation. On the other hand, oriental painting is different from western painting in color and composition, and the expression is also very subjective. In addition, due to the material characteristics and composition of oriental painting, it is often used for mental health treatments such as mental health and self-growth. In this paper, we analyze characteristics of materials and composition of the oriental painting and propose the feature extraction method suitable for them. We also suggest the oriental painting recommendation approach that can provide users with customized digital contents to support wellness. In the experiment, feature extraction results are compared and the appropriateness of the recommendation results is evaluated. The results of the proposed approach are expected to be utilized as a personalized digital contents recommendation service for mental health management of people in the future.

**INDEX TERMS** Recommender system, wellness, feature extraction, oriental painting, information retrieval, data analytics.

## I. INTRODUCTION

Recently, many people have been taking an interest in active health care through life satisfaction for the prevention of disease. As the treatment-oriented healthcare paradigm shifts to preventive focus, wellness for improving the quality of life is emerging as a concern. Wellness is important for optimal health, it means a well-being state that conceptually consists the three-dimensional space of body, mind, and soul [1]. In 2006, the World Health Organization (WHO) defined wellness as ‘‘the optimal state of health of individuals and groups,’’ which includes the realization of potential in the physical, mental, spiritual, and economic realms [2].

Individuals in modern society are increasingly interested in health promotion, but lack of research on the definition and measurement of these concepts. In addition, people are interested in well-being, social and cultural trends that pursue a healthy life regardless of general health care.

On the other hand, Computer vision and imaging technology is one of the essential technologies in a modern society [3]. The analysis of key information from the images and recognition of objects (ex: Detection of unusual movements in security CCTV footage, detection of disease in MRI pictures, face/license plate recognition in camera images, etc.) are the traditional research topics in computer vision. As computer vision technology develops and evolves, its application has gradually expanded into an art sector as well as conventional applications. Conventional vision technology is aimed at accurately detecting and recognizing objects of images. In the arts, however, they aimed at not only detecting objects but also extracting features to grasp the meanings of images. There have been researches on the classification of painting styles and painters using image information after analyzing famous painting images, quick search of user-wanted illustrations through analysis on illustration styles and even

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prediction of the first emotions that users can feel from the paintings or photos [4]–[6].

People have tried to pursue individual's psychological stability and health by the visual sense. Therefore, research on healthcare or wellness technology and contents that can provide visual satisfaction is increasing. However, most of researches are focused on western painting that emphasizes color and saturation. On the other hand, oriental painting is different from western painting in color and composition, and expression is also very subjective. In addition, due to the material characteristics and composition of oriental painting, it is often used for mental health treatments such as mental health and self-growth. The proposed approach extracts features of materials and composition of oriental painting and provides wellness contents recommendation service. Despite its long history, there have been few studies on the analysis of oriental painting using computer vision technology. The proposed method extracts low-level features such as color, brightness, and saturation as well as high-level features that could reflect characteristics of orientations such as stroke, tone, and space. As a result, clustering is performed based on the features to analyze the correlation between oriental paintings. In addition, we suggests wellness contents recommendation that can help users' psychological stability. In this paper, Section 2 presents related works, and section 3 describes the proposed feature extraction approach. In Section 4, experimental analysis and concluding remarks in Section 5.

## II. RELATED WORK

The concept of health has been considered important to maintain harmony between body, mind and spirit since ancient times [1]. In the nineteenth century, a variety of alternative medical remedies focusing on preventive care, including self-healing and natural therapies. Then it have become widespread in Europe and America. On the other hand, the concept of modern well-being has developed in the direction of maximizing the potential of individuals since the middle of the 20th century. It leads to a variety of health care technologies and wellness content to support a healthy life.

Recently, with the advancement of advanced technology, development of AI(Artificial Intelligence) and the spread of digital devices, we have interested in a ways to change the lifestyle and maintain well-being. It is an important research issue for modern people whose medical expenses are continuously increasing due to chronic diseases and obesity. In addition, as the aging society progresses gradually, caring for the elderly becomes a very important social problem. Therefore, evaluation methods for well-being are derived, and it is looking for ways to improve from the emerging technologies such as big data, artificial intelligence, and cyber physics system which are becoming a recent issue. As a result, various tools, services, and evaluation methods are being developed to monitor and improve people's daily life and improve their quality of life.

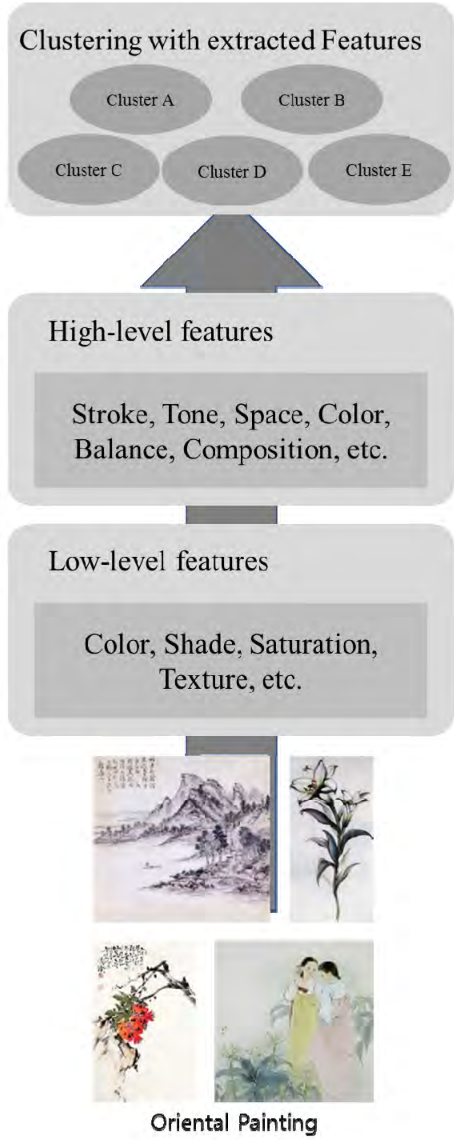


**FIGURE 1. The procedure of the proposed feature extraction approach.**

The concept of wellness that has been suggested with happiness and life satisfaction. The factor that surrounds these factors is considered as the quality of life and well-being. The reason why we regard happiness and life satisfaction as sub-factors of subjective well-being and subjective quality of life [10], [11]. Poor mental health is the most common cause of cardiovascular disease, cancer and diabetes. It is associated with increased risk of illness, and mental health is known to prevent disease risk.

There are many researches for providing the wellness contents with data mining algorithm [12]. They proposed the prediction model with a wellness score. It is based on the features such as weight and activity level.

## III. PROPOSED APPROACH

In this section, we proposed the approach which is for extracting features in oriental painting (Figure 1). The characteristics of oriental paintings are divided into 2 levels and clustered to find out how they are associated with each other. First, for this, low-level image characteristics (ex: Color, shade, saturation, texture, etc.) were extracted from oriental painting images. We could analyze the high level features (ex: Stroke features, tone, space, color balance, composition, etc.) for representing the unique characteristics of oriental painting based on these low-level characteristics. Then, a personalized wellness contents recommendation prototype system with oriental painting for users' psychological stability and health.

### A. COLOR-RELATED ORIENTAL PAINTING CHARACTERISTICS EXTRACTION

Color is the basic feature of images. It is a fundamental element which makes a human perceive an object in the image or have a certain emotion. In the oriental painting images handled in this study as well, color is the major feature which classifies each oriental painting's style [7]. Therefore, [8] proposed a method to extract the colors which constitute the input oriental painting images as the features. In image processing and computer graphics, diverse color models have been used depending on purposes in order to handle colors in the images. Among them, an RGB color model is the most widely used model which uses three primary colors. The RGB color which can be obtained by extracting red, green and blue values in each pixel from the images is a model good which can be expressed in diverse display devices such as a monitor. Because the RGB color model does not consider human's color perception, however, it is inappropriate in calculating color difference.

In contrast, CIELAB in (Figure 2) is a color model which is matched with human's color perception the best. In this model, difference (distance) between two different colors is calculated very similar to the color difference perceived by human. Therefore, CIELAB is widely used in many studies where color difference is numerically calculated and utilized. In this study, CIELAB-based color features are calculated from the input oriental painting images and used as the characteristics of oriental paintings. CIELAB has three dimensions: $a$ describes the color ranging from green to red while the layer $b$ ranges from blue to yellow. This study attempted to derive the averages of $a$ and $b$ in each pixel from input oriental painting images and use them as the characteristics which reflect the colors widely used in input oriental painting images.

In oriental paintings, however, an achromatic color is frequently used with a lot of achromatic spaces. If the averages are calculated using a common method, however, $a$ and $b$ often converge to zero. This kind of result occurs because of failure to consider the characteristics of oriental paintings.

Even though there is colors which have been frequently used, this kind of aspect is not reflected on the characteristics. Hence, this study calculated weighted average on $a$ and $b$ by taking the degree of color intensity in each pixel as weight as

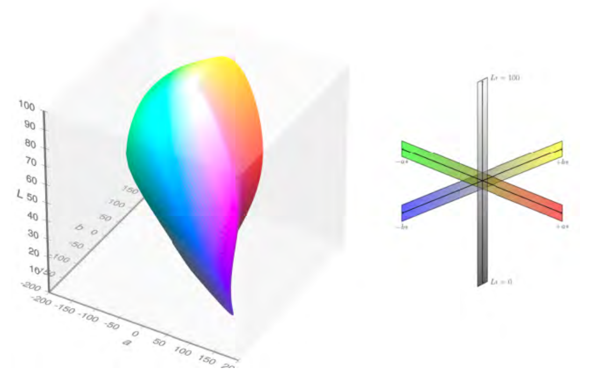

FIGURE 2. CIE lab color model.

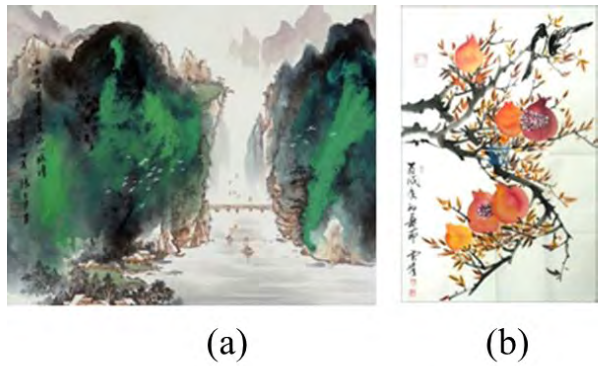


FIGURE 3. Comparisons with Color-related characteristics: (a) Avg.a: -0.25, Avg.b: 0.08 (b) Avg.a:0.31, Avg.b: 0.49.

shown in the (Equation 1).

$$f_1 = \sum_{i}^{N} s_i a_i \tag{1}$$

Then, the results are used as the characteristics. $s_i$ represents the saturation of the pixel $i$ while $a_i$ and $b_i$ refer to the $a$ and $b$ components of the pixel $i$ respectively. To figure out color distribution in input oriental painting images, furthermore, the standard deviation of $a$ and $b$ of the pixels in the images in (Equation 2) is used as the characteristics.

$$f_2 = \sqrt{\frac{1}{N} \sum_{i}^{N} (s_i a_i - f_1)} \tag{2}$$

In the proposed approach, we analyzed color-based characteristics which are average value, standard deviation, and color histogram in oriental painting (Table 1).

### B. SHADE-RELATED ORIENTAL PAINTING CHARACTERISTICS EXTRACTION

Color harmony is a theory on a harmonious combination among colors. In the beginning, color researchers have interested in harmony color relations in a color circle [7]. In particular, [8] have revealed that harmonious color matches are restricted with several patterns as shown in (Figure 3). Hence, it is able to specialize the characteristics of color harmony

**TABLE 1. Definitions for color-based characteristics.**

| No. | Feature | Definition |
|---|---|---|
| 1 | avg. a value | The degree of green-redness of imag e pixels. Calculated as the average of a values in lab color space |
| 2 | avg. b value | The degree of blue-yellow in the ima ge pixels. Calculated as the average of b values in lab color space |
| 3 | Std. dev. a value | Green-red distribution of image pixel s. Calculated as the standard deviati on of a values in lab color space |
| 4 | Std. dev. b value | Blue-yellow distribution of image pix els. Calculated as the standard devia tion of b values in the lab color spac e |
| 5 | type of color histogram | The most similar type among seven harmony types of color harmony the ory |
| 6 | avg. L value | The brightness of image pixels. Calc ulated as the average of L values in l ab color space |
| 7 | Std. dev. L value | The distribution of brightness of ima ge pixels. Calculated as standard de viation of L value in lab color space |
| 8 | avg. S value | The average saturation of image pixe ls. Calculated as the mean of the s va lues in the HSV color space |
| 9 | Std. dev. S value | The distribution of saturation of imag e pixels. Calculated as the standard deviation of the s value in the HSV co lor space |

in the images by investigating the pattern of color relation. This study classified the patterns of the colors used in oriental painting images, using the color harmony pattern calculation algorithm proposed [9]. (Equation 3) refers to get color histogram.

$$f(X,(m,\alpha)) = \sum_{v\equiv X} \left\| H(p) - E_{T_{\mathrm{in}(\alpha)}}(p) \right\| S(p) \tag{3}$$

After all, it was able to classify the color harmony characteristics of oriental paintings into 8 different types after selecting the most properly matched pattern among the 8 patterns in (Figure 4).

In oriental paintings, shade is one of the most important properties, and it is available as a great criterion to classify oriental paintings. In our approach, a method to calculate the shade of pixels used in the images and specialize the results was adopted.

First, the shade-related characteristics refer to the average shade values of the pixels used in the input oriental painting images. As stated in (Equation 4), it is able to get the characteristics with which a degree of the oriental painting image shade can be estimated by calculating the average of $L$ which represents a brightness of color in the CIELAB. (Equation 5) calculates the standard deviation of $L$, it is able to calculate a

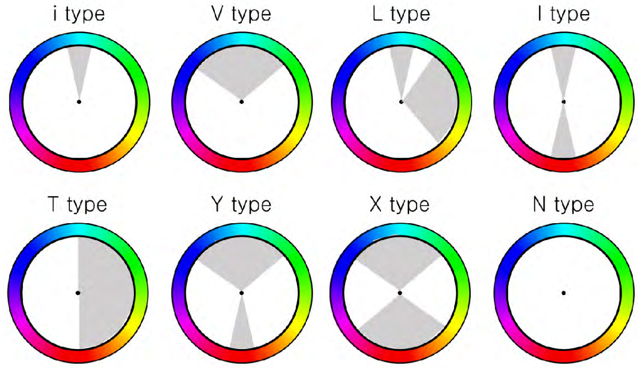


**FIGURE 4.** Color Harmony Theory: 8 color patterns in harmony.


**FIGURE 5.** Comparisons with Shade-related characteristics: (a) Avg. L: 0.32, SD.L: 0.28 (b) Avg. L:0.58,SD.L: 0.61.

degree of changes in the shade.

$$f_3 = \sum_{i}^{N} s_i L_i \tag{4}$$

$$f_4 = \sqrt{\frac{1}{N}\sum_{i}^{N} (s_i L_i - f_6)} \tag{5}$$

(Figure 5) reveals the results of the calculation shade-related characteristics using input samples. Since the painting on the right is relatively brighter than the left one, $f_3$ is higher. Furthermore, the characteristics $f_s$ of the painting on the right having a wider range of shade are higher.

### *C. SATURATION-RELATED ORIENTAL PAINTING CHARACTERISTICS EXTRACTION*

A degree of color intensity in oriental paintings can be a critical aspect in the classification of oriental printing. In terms of the characteristics of oriental paintings, therefore, it should be able to calculate color intensity. In this study, it was calculated by measuring color saturation in the images. Instead of previous color models, HSL was adopted for color saturation.

As shown in (Figure 6), HSI is a color model which expressed color with color, saturation and brightness. In this study, saturation was only measured. Then, average saturation and standard deviation in the oriental painting images were calculated as stated in (Equation 6) and (Equation 7) used as

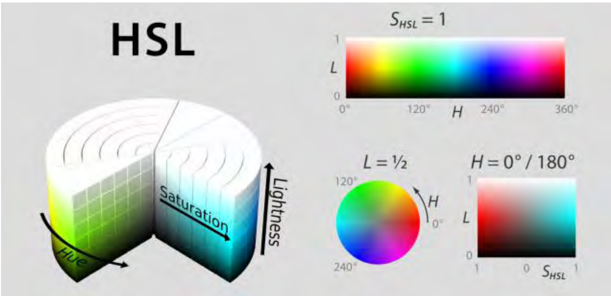


**FIGURE 6.** HSL color model.

(a) (b)

**FIGURE 7.** Comparisons with Saturation-related characteristics: (a) Avg. S: 0.21, SD.S: 0.19 (b) Avg. S:0.44,SD.S: 0.42.

**TABLE 2.** Characteristics related to Gradient for oriental painting.

| No. | Feature | Definition |
|---|---|---|
| *1* | *avg. gradient magnitude* | *The average variation of image pixels. Calculated as the average of pixel gradient values* |
| *2* | *Std. dev. gradient magnitude* | *Distribution of variation of image pixels. Calculated as the standard deviation of pixel gradient values* |

the characteristics of oriental paintings.

$$f_5 = \sum_{i}^{N} s_i \tag{6}$$

$$f_6 = \sqrt{\frac{1}{N}\sum_{i}^{N}(s_i - f_5)} \tag{7}$$

(Figure 7) reveals the results of the calculation on the proposed saturation characteristics in the input oriental painting samples. In terms of coloring, the figure on the left is lower than the right one. Therefore, the former appears to be lower the latter in terms of average saturation as well. It was also confirmed that the figure on the left is lower in the standard deviation of saturation.

### *D. GRADIENT-RELATED ORIENTAL PAINTING CHARACTERISTICS EXTRACTION*

A gradient is one of the image characteristics which are critical in image processing and imaging (Table 2).

The image gradient can be calculated by estimating changes with the brightness of surrounding pixels [10]. In general, images are expressed in 2D space. Therefore, an image gradient can be calculated by estimating the partial differential of brightness in x- and y-axis directions in 2D space as well (Equation 8).

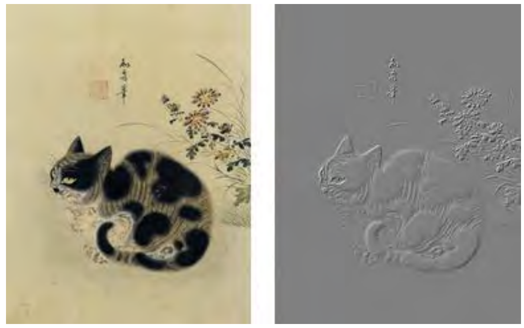

**FIGURE 8.** Example of gradient in an oriental painting.

(a) (b)

**FIGURE 9.** Comparisons with Gredient characteristics: (a) Avg.gradient: 0.35, SD.gradient: 0.28 (b) Avg.gradient:0.03,SD.gradient: 0.05.

$$\nabla f = \frac{\partial f}{\partial x}\hat{x} + \frac{\partial f}{\partial \mu}\hat{y} \tag{8}$$

(Figure 8) shows the images which expressed a gradient size using (Equation 8) in brightness. The gradient size was large at the point where image brightness rapidly changed, or where texture was emphasized.

Based on these properties, this study numerically expressed the characteristics of texture in these input oriental painting images by calculating the average and standard deviation of the gradients in the images as stated in (Equations 9) and (Equation 10).

$$f_7 = \sum_{i}^{N} \|\nabla f\| \tag{9}$$

$$f_8 = \sqrt{\frac{1}{N}\sum_{i}^{N}(\nabla f - f_7)} \tag{10}$$

(Figure 9) shows the calculation of the proposed characteristics in the two input oriental painting images. The figure on the left, in which texture is relatively more emphasized was higher than the left one in terms of the calculation values.

### *E. TEXTILE-RELATED ORIENTAL PAINTING CHARACTERISTICS EXTRACTION TECHNOLOGY*

Texture is one of the elements used as image characteristics. In various studies, texture characteristics have been developed and used. Among them, the characteristics of the commonly used Haralick texture [11] were used as one of

**TABLE 3.** Definitions for textile-related characteristics.

| No. | Feature | Definition | |
|---|---|---|---|
| 1 | *Angular Second Moment* | *The texture moment of the texture used (physical quantity + distribution)* | $f_9 = \sum_i \sum_j p(i,j)^2$ |
| 2 | *Contrast Feature* | *Contrast of brightness of texture used* | $f_{10} = \sum_{n=0}^{N_g-1} n^2 \left\{ \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i,j) \right\}, \; \lvert i-j \rvert = n$ |
| 3 | *Correlation Feature* | *Correlation of used textures* | $f_{11} = \frac{\sum_i \sum_j (i,j)p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y}$ |
| 4 | *Variance Feature* | *Variety of used textures* | $f_{12} = \sum_i \sum_j (i-\mu)^2 p(i,j)$ |
| 5 | *Inverse Difference Moment(IDM) Feature* | *Affinity of used textures* | $f_{13} = \sum_i \sum_j \frac{1}{1+(i-j)^2} p(i,j)$ |
| 6 | *Sum Average Feature* | *Total texture of texture used* | $f_{14} = \sum_{i=2}^{2N_g} i p_{x+y}(i)$ |
| 7 | *Sum Variance Feature* | *Total amount of varieties of texture used* | $f_{15} = \sum_{i=2}^{2N_g} (i - f_8)^2 p_{x+y}(i)$ |
| 8 | *Sum Entropy Feature* | *The total sum of the randomness of the material distribution of the texture used* | $f_{16} = -\sum_{i=2}^{2N_g} p_{x+y}(i) \log\{p_{x+y}(i)\} = f_8$ |
| 9 | *Entropy Feature* | *The randomness of the material distribution of the texture used* | $f_{17} = -\sum_i \sum_j p(i,j) \log(p(i,j))$ |
| 10 | *Difference Variance Feature* | *Random distribution of material distribution of used textures* | $f_{18} = \sum_{i=0}^{N_g-1} i^2 p_{x-y}(i)$ |
| 11 | *Difference Entropy Feature* | *Variance in the randomness of the material distribution of the textures used* | $f_{19} = -\sum_{i=0}^{N_g-1} p_{x-y}(i) \log p_{x-y}(i)$ |
| 12 | *Measure of Correlation Feature 1* | *Correlation between textures Evaluation value 2* | $f_{20} = \frac{HXY - HXY1}{\max HX, HY}$ |
| 13 | *Measure of Correlation Feature 2* | *Correlation between textures Evaluation value 2* | $f_{21} = (1 - \exp[-2(HXY2 - HXY)])^{\frac{1}{2}}$ |
| 14 | *Max. Correlation Coefficient* | *The coefficient of the principal component having the greatest correlation value* | $f_{22}$ *=square root of the first largest eigenvalue of* $Q$ *where* $Q(i,j) = \sum_k \frac{p(i,k)p(j,k)}{p_x(i)p_y(k)}$ |

the texture characteristics for oriental painting images in this paper. We summarize the equations for extracting features related to the textile of oriental painting in (Table 3).

### *F. COMPOSITION-RELATED ORIENTAL PAINTING CHARACTERISTICS EXTRACTION TECHNOLOGY*

Composition is one of the key features which are essential in evaluating aesthetics in art works, especially in painting. It is also important in oriental painting where the beauty of space is emphasized. Depending on where it is positioned in a painting, it can create a different feeling. In other words, it can be a key feature affecting user preference. However, it is extremely difficult to find the primary target in the image. After all, it can vary depending on a user's perspective, and it could be obtained through semantic analysis on the target image. Therefore, this study investigated the position of key targets using the user visual saliency estimation method and opened the characteristics as an alternative.

Visual saliency is an algorithm designed to detect an area where users watch by calculating major characteristics in an image. In this algorithm, visual saliency is high compared to other areas when the difference compared to the color or brightness of pixels in the images and pixels in a gradient direction is high. (Figure 10) shows saliency values on input oriental paintings in brightness. The visual saliency is mostly high in the areas where primary targets are positioned. In this study, input images were divided into a 5x5 grid, and visual saliency in each region was estimated after calculating the average of saliency in each grid. The 25 saliency average values are used as the leading compositional characteristics of oriental painting images.

### *G. EXPERIMENTAL RESULTS*

This section shows the experimental results with the proposed approach. In order to extract the characteristics from the input orientated image, feature values of the images in (Figure 11).

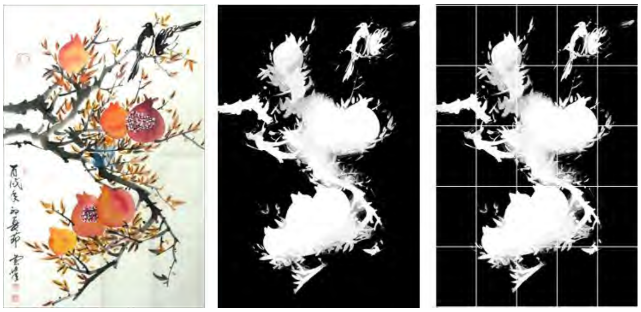

**FIGURE 10.** **The result of calculation of the salience in the oriental painting. As shown on the right, divide the grid into 5x5 steps to calculate the average value of the saliency for each grid.**

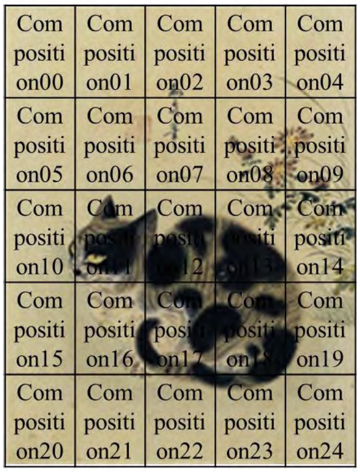


**FIGURE 11.** **Sample Oriental painting pictures for extracting features.**

We used OpenCV, a specialized image processing library. Experiments have been performed to recommend similar images for input images with 720p resolution, and on the average about 1 second of execution time is required.

We identified the identified characteristics not only the lower dimension, but also higher dimension of oriental painting. And the oriental painting having similarity with the query image was suggested. All images were converted to 300x300 to compare features. Also, we separated areas of image with 25 regions as (Figure 12). Each region is represented by a 25x3 feature vector, and then Euclidean distance is used to calculate the distance between each region. The Features of the suggested three query image in (Figure 11).

On the other hand, we evaluate the experiments with oriental painting query using Top-k results of similarity evaluation (Figure 13). As a result, the accuracy of top-5 was more than about 50%, and the result of Top-10 was about 46.67%. However, the accuracy is lowered when feature of the query image is a landscape painting with distinctive margins of oriental paintings.

In this experiment, we segmented and extracted the features of oriental painting. Furthermore we suggested the personalized wellness contents recommendation through analysis of the relationship between the features which are not only traditional computer vision such as color and saturation, but also the high level features such as stroke, composition. However, the results could be shown that accuracy is lowered in the process of expanding the recommendation results. This is due to the difficulty of expanding the recommendation results, which can reflect the aesthetic factors such as the beauty of the margin of Oriental painting.

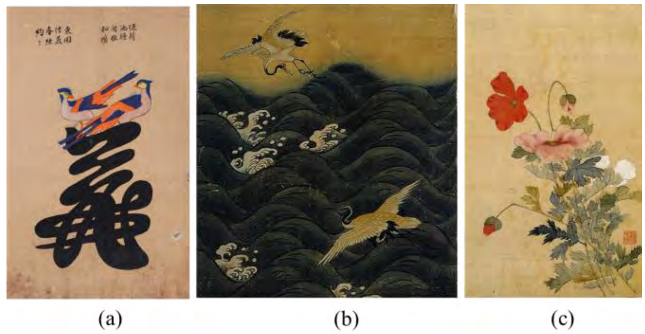


**FIGURE 12.** **Separated 25 regions for extracting features.**

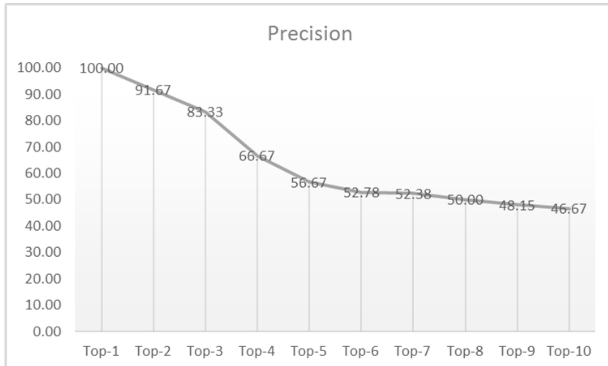


**FIGURE 13.** **Precision results with similarity Top-k.**

## IV. CONCLUSIONS

As IT technology develops and people's interest in well-being grows, there is a growing demand for the development of wellness contents that can support mental health as well as healthcare technology. In particular, Oriental painting is suitable as a subject of wellness contents due to the nature of materials and composition in psychological treatment such as mental health and self-growth. In this paper, we analyze and extract characteristics of materials and composition of oriental painting. We also recommend oriental contents to personal preferences for supporting wellness. The proposed approach extracts the two level characteristics of oriental painting and performs clustering using their characteristics. As a result, oriental painting considering user's preference is recommended. In order to evaluate the characteristics of art works in engineering, it is necessary to analyze not only the characteristics of objects but also various high-level characteristics that can extract the intention of the artist. Future research will analyze not only the enhanced feature extraction that can reflect the intention of the artist, but also the impact on people's mental health and develop personalized human care content recommendation service.

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