Associating Colors with Mental States for Computer-Aided Drawing Therapy:
Beyond Color Psychology

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***Abstract* - The aim of a computer-aided drawing therapy system in this study is to associate drawings which a client makes with the client's mental state in quantitative terms for psychological diagnosis. To perform such association through colors, we translate a drawing to a color feature by measuring its representative colors as primary color rates which are defined from psychological primary colors. To estimate how closely a color feature is associated with a concurrent mental state, we propose a method of utilizing machine-learning classification. A practical way of making a classification model through training and validation on a very small dataset is presented. The classification accuracy reached by the model is considered as the degree of association of the color feature with the mental state data. Experiments were carried out on given clinical data. Several kinds of color feature were compared in terms of the association with the same mental state. As a result, we found out a good color feature with the highest degree of association in the range of experiments. Also, primary color rates proved more effective in representing colors in psychological terms than RGB components. The results provide evidence that colors can be related quantitatively with states of human mind.**

Keywords - drawing therapy, psychological primary colors, color analysis, machine-learning classification

I. INTRODUCTION

Drawing therapy is a kind of clinical practice of art therapy [1], where psychological treatment is provided by a psychotherapist to a client via drawings. Here, let us refer to a psychotherapist as a therapist for short. The client is encouraged to make any drawings there. Such creative activities are expected to have therapeutic effects on the client. Thus, drawing therapy is recently considered a simple and effective way of psychological treatment.

The therapist observes the drawings while interpreting them in psychological terms to deduce the client's emotions. Different therapists are likely to make their respective interpretations of the same drawing because a drawing can be observed by different persons from their respective viewpoints. Besides, the interpretations may depend on clinical experiences and/or knowledge of a therapist. Accordingly, drawing therapy is subject to therapist's subjective judgments.

Objective features of an image are effective in reducing the difference in subjective interpretations of the image. Such features are provided by computer image analysis [2]. The analyses are given numerically, and so they can be used in further computer processing. Image features are also helpful to those therapists who have still short-term experiences. The effectiveness of such quantitative analysis has been also reported in the field of painting arts [3]. However, no ongoing studies on computer-aided psychotherapy systems, to our knowledge, except our work have ever been reported.

The aim of our computer-aided drawing therapy system is to analyze drawings by computer and make the results useful for psychotherapeutic diagnosis. Focusing on colors based on color psychology, in our earlier work [4], we proposed a practical method of analyzing pastel drawings which a client made in a clinical setting so that a therapist can interpret the drawings in terms of simple colors. Then, we defined a measure of colors against psychological primary colors [5], which we refer to as primary color rates here. A primary color rate measures a color as a rate of properties of the corresponding psychological primary color [6]. In addition, we proposed making a color feature of a drawing from primary color rates of its representative colors [5]. However, the effectiveness of the color feature in representing a concurrent mental state has been left unconfirmed. Also, the appropriateness of using primary color rates instead of original color values should be verified.

Following the previous studies, the present paper deals with the association between colors and mental states in detail. To find out which color feature can be most closely associated with a mental state, it is necessary to evaluate a color feature from the viewpoint of the effectiveness in representing a mental state. As an evaluation method, we build a classification model by training it on a given dataset to learn the relationship between a color feature and mental state classes, and consider the classification accuracy reached by the model as the degree of association of the color feature with the mental state. Hence, our computer-aided drawing therapy system requires another psychotherapy which should be conducted in parallel with the drawing therapy to the same client, and also where the client's mental state is evaluated as numerical scores. Using experimental data which were obtained in the clinical setting with the requirements satisfied, we carry out the case study in this work.

The experimental data we actually obtained for the case study were only 47 pairs of a pastel drawing and a mental state score; this data shortage may be a common situation in psychotherapy practice. To make the resulting classification-accuracy reliable as a measure of association, we will present a practical way of making a color-classification model on such a very small dataset.

The rest of this paper is organized as follows. In Sec. II, the scheme of computer-aided drawing therapy in this study is explained. The clinical setting of the case study and clinical data for experiments are also described. Section III explains the color analysis method in brief. Section IV deals with color classification for evaluating the association with mental states. In Sec. V, the results of experiments using the clinical data are shown and discussed. Lastly, Sec. VI concludes the paper.

II. A Scheme of Computer-Aided Drawing Therapy

A. An Approach to Computer-Aided Drawing Therapy

Fig. 1 illustrates an approach to computer-aided drawing therapy by extending a conventional (non-computer-aided) process of drawing therapy that a psychotherapist usually gives a client. In the drawing therapy, a client makes drawings at will. Then, a psychotherapist observes the drawings trying to read the client's emotional cues according to the therapist's knowledge and experience. The observations may be rather descriptive than quantitative, and also rather subjective than objective. Then, the therapist makes a diagnosis.

Our system supposes another psychological therapy as Fig. 1 indicates. This therapy is conducted in parallel with the drawing therapy, and the client's mental state is evaluated as numerical scores. Thus, both drawings and mental state scores are to be obtained from the same client in the same period of therapy.

Now, a computer-aided path can be added parallel with the data path from the drawing therapy to the diagnosis as shown in Fig. 1. Drawings are analyzed to extract image features such as color usage by using image processing techniques by computer. These features are based only on image signals and hence, expressed in objective quantity. Thus, the features can be processed together with the numerical mental state scores for psychological evaluation.

B. A Case Study

To develop the above system, we conducted a case study using experimental data which had been obtained at a clinical site. In the clinical setting, both drawing therapy and cognitive behavioral therapy were given to the same client during almost four years of therapy program. The client was a male in his 50s and suffering kind of depression.

In the drawing therapy, the client made a drawing with color pastels every month. In the cognitive behavioral therapy, the therapist provided a counselling treatment to the client to mitigate his psychological problem and then, the therapist evaluated how much the client's mental state had improved as numerical scores [7], [8], [9]. This therapeutic practice had been conducted once a month. In the end, we collected 47 monthly pairs of a pastel drawing and a mental state score.

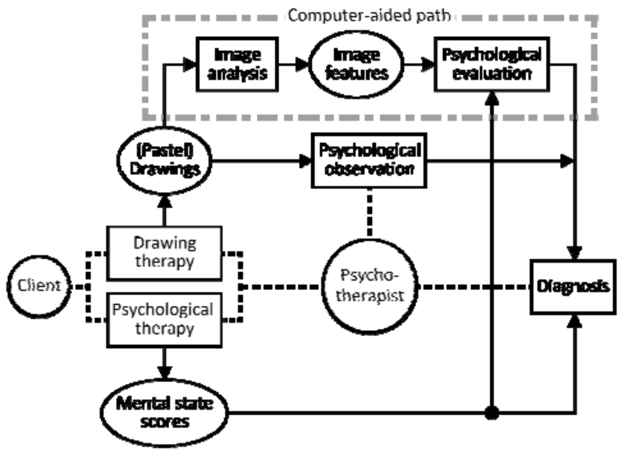


Figure 1. A system concept of computer-aided drawing therapy.

Both the drawing and the mental state score in the same month could express the same mental state of the client. Hence, we consider that these two data have close relations. On the other hand, a practice of drawing therapy specifies source data of the following image analysis. Hence, in this case study, the analysis must involve the processing of digital images with characteristics of pastel drawings.

III. Extracting and Measuring Representative Colors

A. Image Digitization and Segmentation

Pastel drawings on sheets of drawing paper are converted to 24-bit RGB color images on a computer with a digital scanner. Each digital image is low-pass filtered and reduced to a source image for the subsequent processing. Then, a source image is segmented into a drawing region and a background region by the algorithm previously proposed [4]. The drawing region is treated as the contents which the client seems to have intended.

B. Determining Representative Colors

To describe colors used in a source image, we define two kinds of representative color.

1) Approximate colors: We make the contents of a source image approximately colored by using a few colors, which we call approximate colors of the image. A way of obtaining such approximate colors is to reduce the colors used in the drawing region. We use the k-means clustering algorithm [10], [11] for color reduction. Being applied to the drawing region with k, the algorithm classifies the pixels into k clusters in the 3-d color space. Each cluster has a set of pixel positions and the average of the pixel colors there, which is considered an approximate color of the cluster.

While iterating k-means with increasing the value of k one by one from 1 and with adjusted initial points, we decide on a small k so that the k clusters can approximate moderately to the drawing region. We refer to this way of implementing k-means as the increasing k-means. The resulting clusters are arranged in descending order of cluster area. Thus, an ordered set of k approximate colors is determined for each source image. We refer to the approximate colors in this order: the first approximate color is that of the widest cluster, for instance. The number of approximate colors varies by image.

2) Area-averaged colors: As another kind of representative color of a drawing region, we define an area-averaged color by averaging colors over the whole or partial area of the drawing region. They are calculated from the above ordered clusters. By accumulating the clusters in descending order of area one by one, area-averaged colors over the respective accumulated proportions of the drawing region are obtained in ascending order of area rate up to 100%.

Also, an average color over a proportion of any area rate can be estimated from the ordered area-averaged colors [5]. This estimation method makes it possible to obtain an average color of the same area rate from all the source images. We call the average color at an area rate r an r-area color, for example, a 50%-area color. Note that area-averaged colors in themselves are invisible on a drawing. Also, only a 100%-area color is determined regardless of the clustering result for each drawing.

C. Psychological Color Measurement

To evaluate colors from a psychological viewpoint, we define a measurement of the relationship between a color c and a psychological primary color p, $pcr(c, p)$ [5]: Letting d_c and d_0 denote the Euclidean distances $\|p - c\|$ and $\|p - p_0\|$, respectively, in the 3-d color space,

$$pcr(c,p) = \begin{cases} 1 - d_c/d_0 & \text{if } d_c < d_0, \\ 0 & \text{if } d_c \geq d_0 \end{cases} \tag{1}$$

where c, p and p_0 are all represented in the L*a*b* uniform color space, and p_0 is a constant color mentioned below. We call $pcr(c, p)$ a primary color rate, for instance, a primary *red* rate for p of the psychological primary red.

As seen from Eq. (1), if c is located inside a sphere which has its center at p and a radius of d_0 in the 3-d color space, $pcr(c, p)$ is larger as c is closer to p, and $pcr(c,p) = 1$ only if c is coincident with p. In contrast, if c looks different so much from p that c is outside the sphere, $pcr(c,p) = 0$. Thus, $0 \leq pcr(c,p) \leq 1$. It means that c has a rate of $pcr(c, p)$ of the psychological properties associated with p.

The point p_0 performs the origin of psychological primary colors. It must be of no emotion and accordingly be at least an achromatic color. Hence, we will locate it at the 3-d coordinate origin in the experiment later.

IV. MAKING A COLOR EVALUATION MODEL

A. Datasets for Color Classification

Both drawings and mental state scores are obtained as timeseries data in a therapy period. Mental state scores obviously have properties of time-varying variables depending on a human mental state. Accordingly, it is proper to treat the colors of drawings as timeseries data to classify.

Making timeseries samples is as follows: Each drawing is translated into its representative colors by the color analysis. Then, we decide on one or more kinds of representative color to use through all the drawings, and measure the colors as primary color rates. As a result, each drawing is represented in a vector of a fixed number of primary color rates, which is referred to as a color feature vector, or simply a color vector.

Samples to classify are made from the timeseries of color vectors. A sample consists of consecutive vectors of a certain length, denoted by *N_STEPS*. Each sample is extracted from the timeseries at every timestep from the first, as illustrated in Fig. 2. Thus, given N color feature vectors, we obtain $(N - N\_STEPS + 1)$ samples.

Labelling samples for machine learning is as follows: A mental state class can be evaluated from the corresponding mental state score every timestep. From a timeseries of the mental state classes, a label associated with a timeseries sample can be determined. In this paper, we simply use the mental state class at the last timestep of each sample, as also illustrated in Fig. 2.

B. A Neural Network Architecture

To process samples as timeseries data, we use a neural network architecture with recurrent layers for a classification model.

1) Neural network layers: A model is composed of Long Short-Term Memory (LSTM) layers with input dropout and recurrent dropout, and Dense layers with input dropout.

2) Network configuration: We build a sequential model by stacking network layers on top of each other. The first layer is an LSTM layer whose input dimensionality corresponds to that of a color feature vector. The last layer is a Dense layer with output units corresponding to mental state classes.

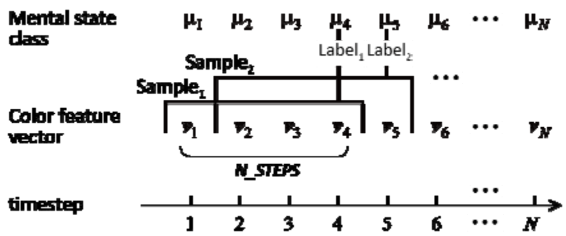


Figure 2. Relationship between samples and labels on timesteps for an example of *N_STEPS* = 4.

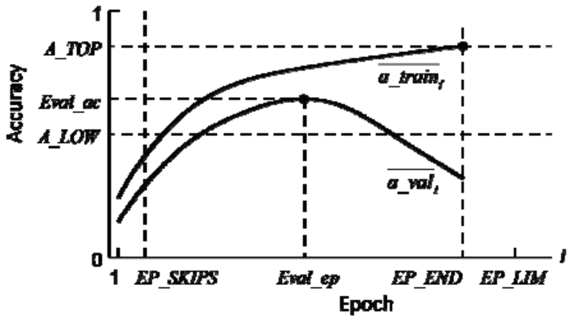


Figure 3. Evaluating a result of training.

C. Training and Evaluating a Neural Network

Considering that only a few dozen samples are available for machine learning, training and validating a neural network is conducted as below (also see Fig. 3).

1) Training a network: Training a network is conducted on given samples in every epoch. Every time an epoch of training is completed, an accuracy for the training samples, denoted by *a_train*, and that for the validation samples, *a_val*, are evaluated. If $\overline{a\_train} > A\_TOP$, where $\overline{a\_train}$ is an average of *a_train*'s and *A_TOP* is a predefined constant, the training is ended. Otherwise, if *EP_LIM* epochs are completed, the training is also ended. After the end, we find out the largest value of $\overline{a\_val}$, which is expressed as *Eval_ac* in Fig. 3, under the condition that $\overline{a\_val} > A\_LOW$, where $\overline{a\_val}$ is an average of *a_val*'s and *A_LOW* is a predefined constant. We consider *Eval_ac* as a validation score for the model in this time of training.

2) Evaluation protocol: To evaluate a network trained on a small dataset, we use *K*-fold cross-validation [12]. *K* being considered as an integer value, first, the available data are split into *K* partitions. Then, by using one partition for validation and the other partitions for training, the network is trained and its validation score is evaluated. This process is carried out repeatedly with the partition for validation changed. Thus, *K* validation-scores for the network are obtained from the dataset. The average of them is considered as the result of one time of *K*-fold cross-validation.

Furthermore, to make the evaluation more reliable, we iterate *K*-fold cross-validation on the same network and the same dataset multiple times. The whole dataset is randomly shuffled every time. By iterating *N_KFOLD* times, *N_KFOLD* results of *K*-fold cross-validation are obtained. Then, we consider the average of them as the final validation score for the network.

V. EXPERIMENTS AND DISCUSSION

A. Color Analysis of Pastel Drawings

Fig. 4 shows an example of the process of extracting representative colors from a pastel drawing by the color analysis. The source image of Fig. 4(a) is 549 by 445 pixels of 24-bit RGB colors. First, the whole image was segmented into a drawing region and a background region which Fig. 4(b) depicts in black and white, respectively.

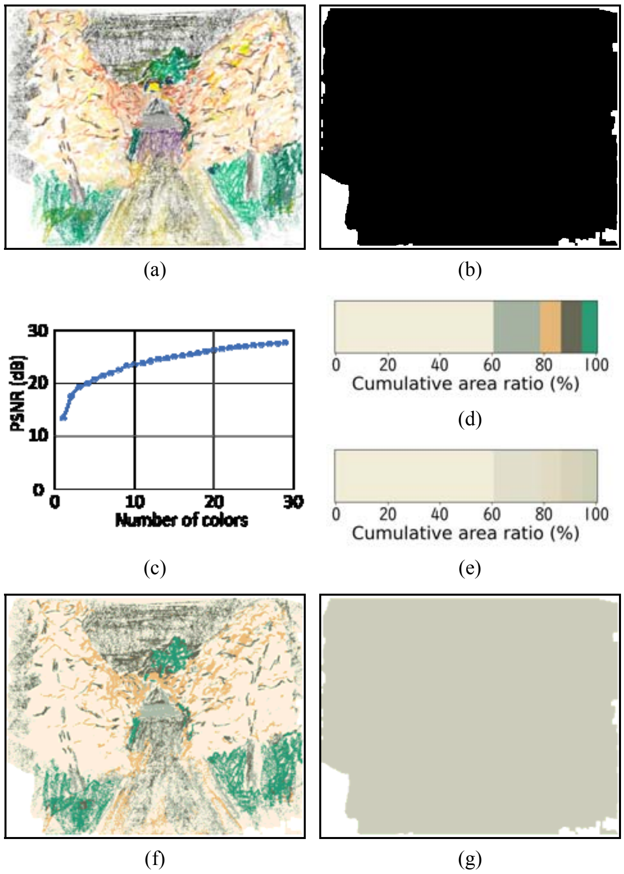
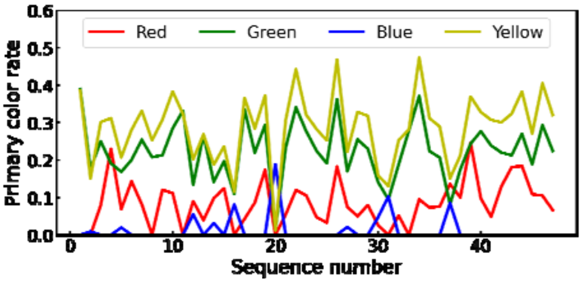


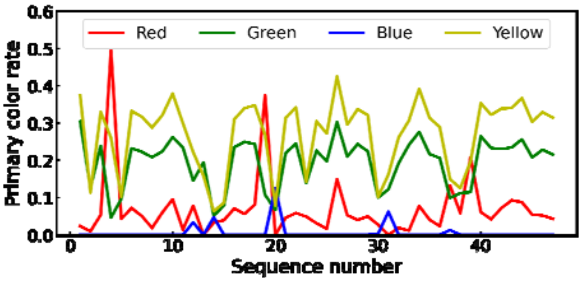
Figure 4. An example of the process of color analysis of a pastel drawing.

Next, the increasing *k*-means algorithm was applied to the drawing region. Fig. 4(c) shows the results of color clustering by plotting the approximation qualities in terms of peak signal-to-noise ratios (PSNRs) against the number of colors. It demonstrates that the algorithm produces a sequence of cluster sets such that the approximation quality increases smoothly with the number of clusters. From the results for various drawings including this one, we figured out a criterion for deciding on the number of colors. The details are omitted here. In the case of Fig. 4(c), we determined the number of approximate colors to five. The five colors are arranged in descending order of cluster area, as illustrated in the area chart of Fig. 4(d). In addition, the approximate image with these five colors is depicted in Fig. 4(f).

From the above ordered five approximate colors, area-averaged colors were evaluated. The area chart of Fig. 4(e) shows the five evaluated colors in order. Also, Fig. 4(g) depicts the drawing region by painting it in the 100%-area



(a) 100%-area colors



(b) First approximate colors

Figure 5. Measurements of primary color rates.

color so that we can see a kind of subliminal color which the image presents as a whole impression.

B. *Psychological Color Measurements*

Each of the representative colors obtained from a drawing was measured as primary color rates in the following way: We used four psychological primary colors for the primary color rate function: red denoted by *PP_R*, green *PP_G*, blue *PP_B* and yellow *PP_Y*, which are considered most effective in representing human emotions in color psychology. Whereas numerical values of these colors are undefined, we used the following values: (1, 0, 0) as *PP_R*, (0, 1, 0) as *PP_G*, (0, 0, 1) as *PP_B* and (1, 1, 0) as *PP_Y* in (*R*, *G*, *B*) coordinates. The primary color rates with these four psychological primary colors are denoted by *pcr_r*, *pcr_g*, *pcr_b* and *pcr_y*, respectively.

Fig. 5 shows examples of the measurements of primary color rates for the sequence of 47 drawings. Fig. 5(a) shows four primary color rates of the 100%-area color of each drawing. The measurements are considered to be a representation of each color in terms of psychological primary colors. As another example, Fig. 5(b) shows the measurements for the first approximate colors. The difference between these two figures seems to imply a difference between the two kinds of color in psychological terms. In particular, the difference between the sequences of primary red rates is noticeable.

C. *Color Evaluation Through Classification*

1) Datasets for training a classification model: Mental state classes were determined simply by thresholding mental state scores. Taking account of the distribution range of the score, we classified the 47 scores into three categories by using two thresholds. As a result, 19 class 0s, 14 class 1s, and 14 class 2s were obtained.

TABLE I. EXPERIMENTAL COLOR-FEATURE VECTORS

Vector	Dim.	Description of elements
*CV*1	4	*pcr_r*, *pcr_g*, *pcr_b* and *pcr_y* of a 100%-area color
*CV*2	4	*pcr_r*, *pcr_g*, *pcr_b* and *pcr_y* of a 50%-area color
*CV*3	4	*pcr_r*, *pcr_g*, *pcr_b* and *pcr_y* of the first approximate color
*CV*4	5	*pcr_r*, *pcr_g*, *pcr_b* and *pcr_y* of a 100%-area color, and *pcr_r* of the first approximate color
*CV*5	3	*pcr_r*, *pcr_g* and *pcr_b* of a 100%-area color
*CV*6	3	*r*, *g* and *b* of a 100%-area color in RGB

We used three kinds of representative color to make up color feature vectors: a 100%-area color, a 50%-area color and the first approximate color. All the colors were measured as primary color rates. Using the measurements, we defined several color-feature vectors for comparative evaluation, which are listed in Table I.

Datasets for making classification models were generated from the sequences of color feature vectors with a value of *N_STEPS* changed (see Table II). The number of timeseries samples generated from 47 drawings for $N\_STEPS = 2$, 4 and 6 was 46, 44 and 42, respectively.

2) Building classification models: Building color-classification models was carried out on the datasets. *K*-fold cross validation was implemented with $K = 4$ and iterated over 20 times ($N\_KFOLD \geq 20$) to evaluate each configuration of a neural network in the process of finding out a model of the best validation score for each dataset. The resulting models and scores are included in Table II.

3) Discussion of experimental results: We now discuss the experimental results according to Table II.

a) Timeseries of color feature vectors: We discuss the appropriateness of dealing with color feature vectors as timeseries for classification. A timeseries of four vectors of *CV*1 was flattened to a 1-d vector and used to train a two-Dense-layer network in Experiment I, while the same timeseries was used to train a baseline recurrent network in Experiment J. Comparing these two resulting scores indicates that it is more appropriate to associate colors as timeseries data with mental states than as set data.

The length of a timeseries sample, *N_STEPS*, was examined in Experiments A, B, and C where the datasets were made from the same vector set with different numbers of *N_STEPS*. A comparison of the three scores indicates that color feature vectors need somewhat long timeseries to represent the association with a mental state. As for *CV*1 and the mental state scores, timeseries of four or more vectors are required.

b) Effectiveness of primary color rates: We conducted Experiments G and H to examine the classification

TABLE II. RESULTS OF COLOR EVALUATION

Expt.	Dataset		Classification Model	
	Vector	***N_STEPS***	**Configuration†**	**Score**
A	*CV*1	2	$L_4^{20} L_{20}^{20} D_{20}^{20} D_{20}^{20} D_{20}^{3}$	0.500
B		6	$L_4^{16} L_{16}^{8} D_8^8 D_8^8 D_8^3$	0.721
C		4	$L_4^{20} L_{20}^{10} D_{10}^{8} D_8^3$	0.728
D	*CV*2			0.633
E	*CV*3			0.552
F	*CV*4		$L_5^{16} L_{16}^{16} D_{16}^{16} D_{16}^{3}$	0.748
G	*CV*5		$L_3^{20} L_{20}^{15} D_{15}^{8} D_8^3$	0.723
H	*CV*6		$L_3^{12} L_{12}^{6} D_6^6 D_6^3$	0.665
I	*CV*1		$D_{16}^{n} D_n^3$	0.466‡
J			$L_4^{n} D_n^3$	0.569‡

†L_m^n denotes an LSTM layer with *m* inputs and *n* outputs; D_m^n denotes a Dense layer with *m* inputs and *n* outputs.
‡An averaged score over various *n*'s of configuration.

performance of the measurements of *pcr_r*, *pcr_g* and *pcr_b* by comparison with that of the source values *r*, *g* and *b* of the same color. The result shows that primary color rates are obviously more effective in representing the relationship to the mental state scores than RGB components.

c) Association of color features with a mental state: Experiments C, D and E examined the respective kinds of representative color, by using the same four kinds of *pcr* and the same model. These three colors yielded much different validation scores; *CV*1 of 100%-area colors showed the best. In addition, the color feature vectors *CV*4 that were composed of *pcr*'s obtained from two kinds of representative color were examined in Experiment F. The resulting validation score showed that *CV*4 performed better than *CV*1 in learning the relationship between color features and mental state scores.

From these results, we found out that a degree of association with the given mental state scores varies substantially by color feature. Also, making up a color feature from more than one representative colors can improve the degree of association.

VI. CONCLUSION

In the experiments, we extracted representative colors from the given drawing sequence, and made some kinds of color feature from them by using primary color rates based on four main psychological primary colors. As for a color feature made from one color, the 100%-area color showed closer association with the mental state scores than the first approximate color. On the other hand, the color feature composed of two colors showed even closer association. The fact that a degree of association with the same mental state scores varies by color feature just offers evidence that appropriate colors can represent human mental states.

Also, the experimental results showed that measurements by primary color rates were more closely associated with mental state scores than RGB color-components, just as expected. Primary color rates can specify in quantitative terms emotional properties which psychological primary colors describe in psychological terms. Using primary color rates is expected to make drawing therapy fine-tuned to an individual beyond color psychology.

Considering the nature of psychotherapy, the experimental results must have been specialized to the given clinical data. The association between colors and mental states probably varies according to various personal factors: a client's psychological problem and/or personality, his/her way of making drawings colored, mental state scores used, and so on. Accordingly, it is necessary to find out effective color features in each therapy situation. Primary color rates based on other psychological primary colors such as brown may be also preferable. Personalized therapy is more important to a troubled mind than common psychology. Good color features could achieve it.

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