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Aesthetic Rating and Color Suggestion for Color Palettes

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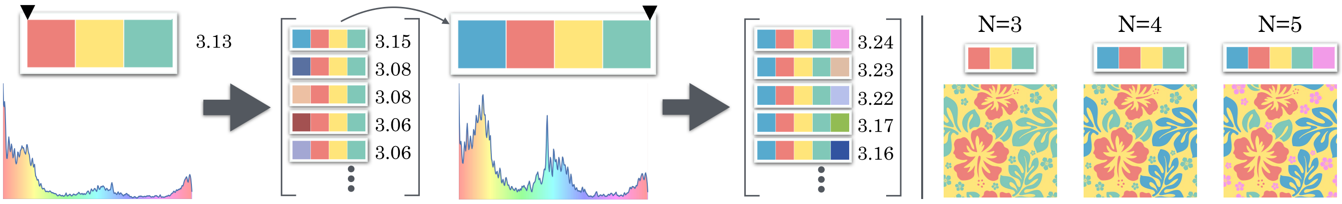


Figure 1: *The proposed method can rate a given color palette with any number of colors relative to human aesthetic preferences. The proposed method suggests a compatible color for the given palette, which allows us to expand the palette while retaining color harmony to support user exploration of color design.*

Abstract

A model to rate color combinations that considers human aesthetic preferences is proposed. The proposed method does not assume that a color palette has a specific number of colors, i.e., input is not restricted to a two-, three-, or five-color palettes. We extract features from a color palette whose size does not depend on the number of colors in the palette. The proposed rating prediction model is trained using a human color preference dataset. The model allows a user to extend a color palette, e.g., from three colors to five or seven colors, while retaining color harmony. In addition, we present a color search scheme for a given palette and a customized version of the proposed model for a specific color tone. We demonstrate that the proposed model can also be applied to various palette-based applications.

Categories and Subject Descriptors (according to ACM CCS): I.3.0 [Computer Graphics]: General—

1. Introduction

Color palettes and patterns are used in various fields, such as graphics, web, packaging, fashion, and interior design. Such design elements are also used in business, e.g., illustrations in documents and presentations, and play an important role in scientific visualizations. In addition, individuals make personal decisions about aesthetics and harmonious color combinations (e.g., the color of curtains and wallpaper, room theme colors, or even cushions and other decorative objects in a room). Therefore, evaluating the aesthetics and color harmony of color combinations is not only important for design professionals, it is also important for many people. However, creating and evaluating a set of colors (i.e., a color palette) is difficult for most people.

Many books, such as [Kob91], that help a user select a color palette based on a *color image* (e.g., *casual*, *elegant*, or *romantic*) have been published. Such books illustrate the relationship between a color image and a three-color palette. On the web sites, such as Adobe Color (formerly known as Adobe Kuler) [Col16a] and COLOURlovers [COL16b], users can share the color palettes and patterns with other community members. These services are useful for novices and designers because they can use others' palette designs as references or customize palettes to suit personal requirements and taste. However, customizing a palette composed of N colors that can be expanded to $N+\alpha$ while retaining the original color harmony remains difficult because choosing a color that is compatible with the original palette from many possible colors is challenging and tedious.

We propose a color palette rating model that considers human aesthetic preferences. In addition, we propose a compatible color suggestion method, which is based on the color palette rating model, to expand a given palette while retaining color harmony (Fig. 1). First, we construct a model that predicts the ratings of a given palette composed of any number of colors by learning from a large dataset of human-rated color palettes. Here, we propose a feature extraction method that does not depend on the size of color palette, which enables us to rate a color palette composed of any number of colors. We also propose a color suggestion method, wherein we employ a sampling method to search color candidates efficiently from a large color space.

In summary, we present the following:

- a model that can evaluate a given color palette aesthetics regardless of size, i.e., the number of colors in the palette;
- a feature extraction method to learn the weights of the model;
- a method to suggest a compatible color for palette expansion, i.e., a color that retains color harmony;
- a sampling method to search the compatible color from a color space.

2. Related Work

Color Harmony Theory. Color harmony theory as a research topic did not begin until after Newton reported his experiments with the light spectrum in 1672. Various color harmony theories, such as Goethe's thought-provoking color theory [Goe71], were proposed near the end of the 18th century and throughout the 19th century. In the early 20th century, the first practical *color-order-system* were derived from the color theories proposed by Munsell [BC69] and Ostwald [OB69]. The color theory proposed by Moon and Spencer [MS44], which was based on the mathematical analysis of a user study, represents the beginning of modern color harmony theory. Following Moon and Spencer, Itten proposed a color theory which is defined on a hue wheel [Itt74].

Color Harmony Model. Many color harmony models based on the mathematical analysis of user study results have been proposed [OL06,SBS10,OCLM11,ORLS*12]. However, such models only evaluate two or three color combinations with a small number of participants (fewer than one hundred), which restricts the generalization of the model. On the other hand, O'Donovan et al. collected 327,381 human ratings of 22,376 color themes (palettes) using Amazon Mechanical Turk (MTurk) and proposed a model trained using a machine learning algorithm [OAH11]. Lin et al. also collected 1,600 data items relative to how people extract color themes from images from 160 MTurk participants [LH13].

These models can only rate two-, three-, or five-color palettes, which is too limited because color palettes are typically composed as many as seven colors. In contrast to previous approaches, the proposed method is not limited to a specific number of colors in a palette, i.e., our feature extraction method and machine learning method can handle a color palette composed of any number of colors, which allows us to rate any color palette. Therefore, the proposed method can be applied to a wide range of applications, such as compatible color suggestion, 2D pattern coloring, and other fields of color design.

Applications. Cohen-Or et al. proposed a method that employed a *harmonic template* on a hue wheel to harmonize the target image colors [COSG*06], and Li et al. proposed a fast image recolorization algorithm by employing geodesic distance-based color harmonization [LZNH15]. Sawant et al. applied color harmonization for videos [SM08], and Zhang et al. employed a color scheme replacement method in their video stream abstraction method for stylization [ZLHM11]. Wang et al. proposed a data-driven approach to convert a target image based on a given color theme [WYW*10], while Chang et al. proposed a method for recoloring a photograph based on a color palette [CFL*15]. Lin et al. proposed a probabilistic factor graph model to color 2D patterns automatically [LRFH13], and Kim et al. proposed a method based on color perception theories to assign color to 2D patterns automatically [KYKL14]. Employing the color compatibility rating model proposed in [OAH11] as the one of the terms to be optimized in the optimization problems they formulated, Yu et al. proposed outfit synthesis (fashion design) [YYTC12], and, as mentioned previously, Lin et al. employed the model ratings as a global aesthetic term for 2D pattern coloring [LRFH13]. Chen et al. proposed automatic material suggestion for indoor digital scenes [CXY*15].

Since [YYTC12,LRFH13,CXY*15] employed the rating model proposed in [OAH11], their method is limited to only five-color palettes in their methods, which limits the scope of application. In contrast, we propose a feature extraction method that does not depend on the number of colors in a given palette. Therefore, we can suggest a compatible color for a given palette with any number of colors. For example, given a three-color palette as input, the palette can be expanded to four-, five-, or even seven-color palettes using our color suggestion method while maintaining color harmony.

3. Model Training for Color Palette Rating

We employ a machine learning approach to learn the weights of a model for rating a color palette. First, we extract features from palettes in a dataset. Then, multivariable regression analysis is applied to learn the weights for each feature vector.

3.1. Dataset

We use a MTurk dataset from O'Donovan et al. [OAH11]. In the dataset, 10,743 color palette ratings by MTurk users are available. The palettes were collected randomly from the Adobe Kuler website. Each palette was rated on a scale of 1-5 by 40 participants.

3.2. Feature Extraction

O'Donovan et al. extracted 334 features from a palette [OAH11]. We extract 118 equivalent features from a palette. These include palette colors, mean, standard deviation, median, max, min, and max minus min across a single channel in each color space, i.e., RGB, CIELAB, HSV, and CHSV[†]. We also extract plane-fitting features, i.e., a 2D plane is fit to 3D color coordinates using PCA in RGB, CIELAB, and CHSV color spaces, while in the HSV color space, we extract hue entropy and hue joint/adjacent probabilities. Please refer to the original paper for the details. On the other hand, we exclude features that depend on the number of colors in a palette, i.e., we do not extract colors sorted by lightness, by differences between adjacent colors, and by color differences. Using such features, the total length of the feature vector varies based on the number of colors in a given palette. This is why O'Donovan's

† A space where hue θ and saturation s are remapped to Cartesian coordinates: $d_1 = s\cos(\theta)$ and $d_2 = \sin(\theta)$.

model can only be applied to a five-color palette. However, our proposed model does not suffer such restrictions.

In addition, we include a color harmony term [OL06]. In addition, a "gradation of lightness" and a "gradation of hue" of colors in a palette are included in our feature extraction method. These are based on the fact that as the order of colors in a palette becomes increasingly linear, human ratings tend to increase. The details of feature extraction are described in the supplemental material. In total, 121 features were extracted and used as for learning and rating.

3.3. Learning Model Weights

We use LASSO regression [Tib96] in the same way as [OAH11, LH13] for learning the weights of each feature. The equation for rating color palette $\mathbf{t}$ is given by $r(\mathbf{t}) = \mathbf{w}^\top \mathbf{f}(\mathbf{t}) + b$, where $\mathbf{w}$ is a weight vector, $\mathbf{f}$ is a feature vector, and b is a bias term. Then, the weight vector and the bias are leaned with L_1 regularization:

$$\min_{\mathbf{w},b} \sum_i (\mathbf{w}^\top \mathbf{f}_i + b - r_i)^2 + \lambda \|\mathbf{w}\|_1, \tag{1}$$

where r_i is an actual user rating (1-5) from the dataset described in Section 3.1 and λ is a regularization parameter ($\lambda = 2.2 \times 10^{-6}$ by 10-fold cross validation). The dataset is split into learning and test datasets at a ratio of $6:4$. Due to the L_1 regularization, the extracted features are expected to have adequate weight even if there are similar features in the extracted feature vector.

4. Suggesting Compatible Colors

Using the proposed model, we can suggest a compatible color for a given color palette, while in [OAH11], they can only suggest a fifth color for a given four-color palette.

Given a color palette with any number of colors, an index position the user would like to insert a color in the palette (e.g., the i-th index from the left of the palette), and optionally the number of colors M to be suggested, the proposed method can suggest compatible colors. First, we search a compatible color and add the color to a given palette. Then, the palette is rated by the rating prediction model. The top M high-rated colors are suggested to the user. To avoid suggesting overly similar colors for the given palette to the human eye, we calculate CIEDE2000 (ΔE_{00}) [SWD05] for each color in the palette and the candidate color, and we collect only candidates with ΔE_{00} values greater than a threshold τ. Similar to the τ thresholding, we calculate the ΔE_{00} for each two candidate color combinations out of M. Note that we collect only candidates with ΔE_{00} values greater than a threshold κ. We explore the color space with those constraints and select candidate colors by rejection sampling, which allows us to suggest various colors to the user.

4.1. Compatible Color Suggestion

Given a color palette $\mathbf{t} = [\mathrm{c}_1, \mathrm{c}_2, \ldots, \mathrm{c}_n]$, we calculate the following equation for a compatible color candidate $\mathrm{c}^{\mathrm{cand}}$ with the given palette:

$$\begin{aligned} \max_{\mathrm{c}^{\mathrm{cand}}} \quad & r(\mathbf{t}) \\ \text{subject to} \quad & \Delta E_{00}(\mathrm{c}^{\mathrm{cand}}, \mathrm{c}_i) \geq \tau,\ \forall i \in \{1, 2, \ldots, n\}, \end{aligned} \tag{2}$$

where, $r(\mathbf{t})$ is a color palette rating by the learned model, $\Delta E_{00}(\mathrm{c}_1, \mathrm{c}_2)$ is CIE Delta E of c_1 and c_2, and τ is the user-defined threshold to suggest colors that are substantially different from the colors in the given palette.

4.2. Color Space Exploration

Since the color space is vast, it is necessary to search color candidates efficiently in order to suggest compatible colors to the user. It took 12 hours to brute-force search a candidate in the RGB color space with a Core i7 2.3 GHz, 16 GB RAM machine. Therefore, we perform the following procedure to sample candidates in the HSV color space.

First, we calculate an adjacent hue probability distribution of a color c. Here, $\mathbf{p}_{\mathrm{c}}^{\mathrm{joint}} = [P_{h_{\mathrm{c}},0}^{\mathrm{joint}}, P_{h_{\mathrm{c}},1}^{\mathrm{joint}}, P_{h_{\mathrm{c}},2}^{\mathrm{joint}}, \ldots, P_{h_{\mathrm{c}},359}^{\mathrm{joint}}]$, where $h_{\mathrm{c}} \in [0, 360)$ is the hue of c and $P_{h_1,h_2}^{\mathrm{joint}}$ is the probability of co-occurrence of colors with its hues h_1 and h_2 in the same palette, i.e., $P_{h_1,h_2}^{\mathrm{joint}} = \frac{\text{\# of occurrence of hues } h_1 \text{ and } h_2 \text{ in the same palette}}{\text{\# of palettes in a training dataset}}$. The adjacent hue probability distribution of color c denoted by $\mathbf{p}_{\mathrm{c}}^{\mathrm{adj}}$, which is the probability of co-occurrence of the adjacent hues h_1 and h_2 in the same palette, is calculated in the same manner. With this configuration, we perform rejection sampling using a hue probability distribution function to select a candidate hue $\mathrm{c}^{\mathrm{cand}} = (h, s, v)$ depending on the index position at which the candidate is to be inserted.

A case whereby the specified index in a palette is the head or tail of the palette, we compute the following as the hue probability distribution function:

$$\alpha \cdot \mathbf{p}_{\mathrm{c}_i}^{\mathrm{adj}} + (1 - \alpha) \cdot \frac{1}{n-1} \sum_{\mathrm{c}_k \in \mathcal{C} \setminus \{\mathrm{c}_i\}} \mathbf{p}_{\mathrm{c}_k}^{\mathrm{joint}}, \tag{3}$$

where c_i is a color adjacent to c^{cand}, n is the number of colors in the given palette, c_k represents non-adjacent colors to $\mathrm{c}^{\mathrm{cand}}$, and α is a balancing parameter of the two terms ($\alpha = 0.5$ in this study). We compute P^{adj} with the adjacent color and P^{joint} with the remaining non-adjacent colors. When a candidate is to be inserted between two colors in a palette, we compute the following hue probability distribution function:

$$\alpha \cdot \frac{\mathbf{p}_{c_i}^{\mathrm{adj}} + \mathbf{p}_{c_j}^{\mathrm{adj}}}{2} + (1 - \alpha) \cdot \frac{1}{n-2} \sum_{c_k \in \mathcal{C} \setminus \{c_i, c_j\}} \mathbf{p}_{c_k}^{\mathrm{joint}}, \tag{4}$$

where c_i and c_j are adjacent colors of c^{cand}, and c_k represents non-adjacent colors of c^{cand} in the palette. Figure 2 shows the hue probability distribution function calculated for various color palettes where a candidate is to be inserted at ▼.

We also sample the candidate's saturation s with $s \sim \mathcal{N}(\mu_s, \sigma_s)$ and the value v with $v \sim \mathcal{N}(\mu_v, \sigma_v)$ from the given color palette, where $\mathcal{N}(\mu, \sigma)$ is a normal probability distribution with mean μ and standard deviation σ.

In addition, we constrain the color differences of any two color combinations from M candidates by computing the following constraint, which ensures the diversity of the suggested colors:

$$\Delta E_{00}(\mathrm{c}_{\mathrm{j}}^{\mathrm{cand}}, \mathrm{c}_{\mathrm{k}}^{\mathrm{cand}}) \geq \kappa,\ j \neq k,\ \forall j, k \in \{1, 2, \ldots, M\}, \tag{5}$$

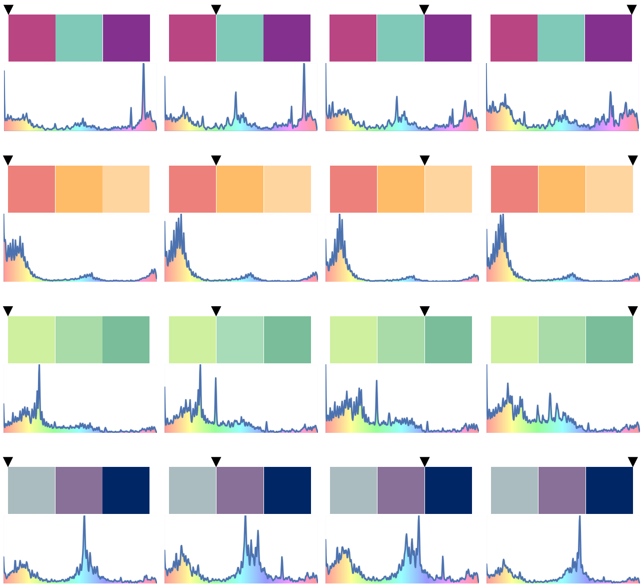


Figure 2: *Hue probability distribution functions for various color palettes when a color is to be inserted between the index specified by ▼.*

where κ is a user-defined threshold. The proposed sampling method results in few seconds to several tens of seconds depending on the number of samples (a few thousand to 100,000), and we also find that the rejection sampling algorithm is approximately 10 times faster than naive random hue sampling. The pseudo code of the rejection sampling algorithm is provided in the supplemental material.

5. Customizing the Model to a Specific Color Tone

We use the general-purpose dataset described in Section 3.1 rather than a dataset with a specific concept. Therefore, it sometimes does not give the user a satisfactory rating or color suggestion with the model if the given palette has specific context, such as *pastel colors*. The suggested colors tend to be relatively dark with low saturation.

To address this issue, we customize the model based on the idea proposed by Chen et al. [CXY*15], i.e., we rerate the all color palettes in the dataset using an additional dataset:

$$r'(\mathbf{t}) = \delta \cdot r(\mathbf{t}) + (1-\delta) \cdot e^{-\min_{\mathbf{t}' \in T} d(\mathbf{t},\mathbf{t}')}, \tag{6}$$

where $\mathbf{t}$ is a color palette in the dataset described in Section 3.1 and $\mathbf{t}' \in T$ is a color palette in the new dataset composed of a specific color to be used for customization. δ is a balancing parameter for the two terms ($\delta = 0.6$ in this study).

In [CXY*15], they employed a weighted sum of the squared Euclidean distance of all five colors in a HSV space palette to calculate $d(\mathbf{t},\mathbf{t}')$. Note that their method can only deal with five-color palettes; however, since our method is not restricted to five-color palettes, we must be able to compute the distance of two palettes with different numbers of colors (e.g., the distance between a three-color palette and a five-color palette). To do so, we use the following distance function:

$$d(\mathbf{t},\mathbf{t}') = \mathrm{EMD}_{\Delta E_{00}}(\mathbf{t},\mathbf{t}'), \tag{7}$$

where $\mathrm{EMD}_{\Delta E_{00}}(\mathbf{t},\mathbf{t}')$ is the Earth Mover's Distance (EMD) [RTG98], and we employ ΔE_{00} as the distance metric. The EMD with ΔE_{00} is defined as follows:

$$\mathrm{EMD}_{\Delta E_{00}}(\mathbf{t},\mathbf{t}') = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} f_{i,j}\Delta E_{00}(\mathbf{t}_i,\mathbf{t}'_j)}{\sum_{i=1}^{m}\sum_{j=1}^{n} f_{i,j}}, \tag{8}$$

where $f_{i,j}$ is a flow from t_i to t'_j, and t_i and t'_j are the i-th and j-th color in each color palette with m and n colors, respectively. The flow $F = [f_{i,j}]$ is computed by solving the following optimization problem:

$$\begin{aligned} \text{minimize} \quad & \sum_{i=1}^{m}\sum_{j=1}^{n} f_{i,j}\Delta E_{00}(\mathbf{t}_i,\mathbf{t}'_j) \\ \text{subject to} \quad & f_{i,j} \geq 0, 1 \leq i \leq m, 1 \leq j \leq n, \\ & \sum_{j=1}^{n} f_{i,j} \leq w_{\mathbf{t}_i}, 1 \leq i \leq m, \\ & \sum_{i=1}^{m} f_{i,j} \leq w_{\mathbf{t}'_j}, 1 \leq j \leq m, \\ & \sum_{i=1}^{m}\sum_{j=1}^{n} f_{i,j} = \min\left(\sum_{i=1}^{m} w_{\mathbf{t}_i}, \sum_{j=1}^{n} w_{\mathbf{t}'_j}\right), \end{aligned}$$

where $\mathbf{w_t} = \mathbf{w_{t'}} = [\frac{1}{3}, \frac{1}{3}, \frac{1}{3}]$ is the weight vector.

After rerating all palettes in the original dataset, we then combine the additional and original datasets by giving full-rate to all new color palettes to build a customized dataset for *pastel* colors and so on.

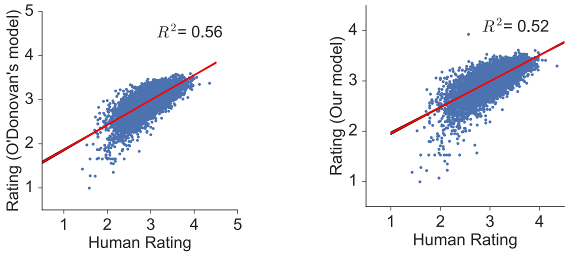
6. Results

6.1. Model Analysis

Here, we compare our learned model with a previously proposed model [OAH11]. The mean absolute errors (MAE) and mean squared errors (MSE) are shown in Table 1. The baseline was computed by the difference between the test and training data calculated by the proposed method [OAH11]. For [OAH11], the MAE decreased by 33% and MSE decreased by 55% compared to the baseline. For the proposed method, MAE and MSE decreased by 30% and 51%, respectively. We also performed correlation analysis of ratings for both models (Fig. 3). As can be seen, $R^2 = 0.56$ in [OAH11] and $R^2 = 0.52$ for the proposed method. Although the proposed method is less accurate than [OAH11] in both cases, the MAE and MSE values are reduced compared to the baseline and R^2 is greater than 0.5, which indicates that the proposed model can still rate color palettes with respect to human aesthetic preferences with sufficient accuracy. In addition, the proposed model can rate color palettes with any number of colors, while the model proposed in [OAH11] can only rate a five-color palette. As the learning result with L_1 regularization shows, 19 features out of 121 received zero weights, and the other 102 features received nonzero weights. The Color Harmony (CH) and Gradation (Grads) terms added to

Table 1: *Comparison of MAE and MSE for [OAH11] and the proposed model.*

	Fixed (baseline)	[OAH11]	Proposed model
MAE	0.267	0.180	0.187
MSE	0.116	0.052	0.057



(a) [OAH11] (b) Ours.

Figure 3: *Comparison of correlation coefficient R of human ratings for [OAH11] (a) and the proposed model (b).*

Table 2: *Comparison of correlation coefficient of predicted rating by the proposed model and human ratings. The R value was calculated with and without the CH and Grads terms.*

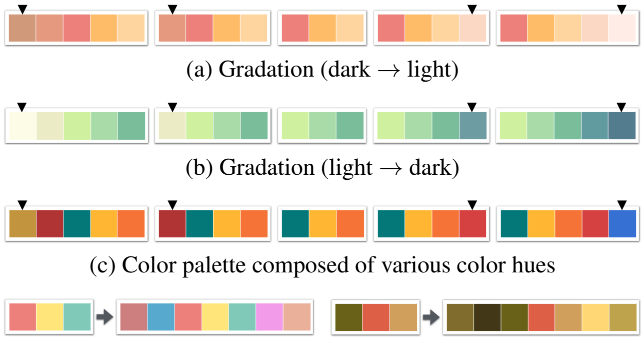
	[OAH11]	w/o	w/ CH	w/ Grads	w/ both
R value	0.76	0.71	0.71	0.72	0.72

the feature extraction method receive nonzero weights, which contributes to increased correlation. We further analyzed these features and found that, although the CH term received nonzero weights, it does not sufficiently contribute to correlation. On the other hand, the correlation coefficient R increases by 0.01 due to the Grads term (Table 2). A more detailed analysis is provided in the supplemental material.

6.2. Analysis of Compatible Color Suggestion

Figure 4 shows the results of the color suggestions for the given palettes. The proposed method can suggest appropriate colors for the gradation color palettes (Figs. 4a and 4b) and can suggest well-chosen colors for a palette that includes various hues (Figs. 4c and 4d). Using the proposed color suggestion method, the input three-color palettes are expanded to four-, five-, or seven-color palettes while retaining color harmony.

We conducted an experiment to evaluate the performance of the palette expansion algorithm. For 10 three-color palettes and 10 five-color palettes, we applied our compatible color suggestion method (*Ours(Best)*) to expand these palettes to four-color and six-color palettes, respectively. For comparison, we generated palettes using the *incompatible* color suggestion method (*Ours(Worst)*), in which we sampled the lowest rated hue by our model in HSV color space, and the saturation and value were sampled in the manner described in Section 4.2. We also generated palettes with additional colors sampled randomly in RGB color space (*Random*). For 20 cases, we asked 17 participants (four females) with normal color vision to rank the three palettes generated by the different methods relative to *Naturalness (“expansion with additional color is natural”)*



(a) Gradation (dark $\rightarrow$ light)

(b) Gradation (light $\rightarrow$ dark)

(c) Color palette composed of various color hues

(d) Palette expansion from 3-color to 7-color

Figure 4: *Palette expansion results of the proposed method. Rows 1-3: a suggested color is added at the index specified by ▼. Row 4: two types of palettes are expanded from three-color to seven-color palettes by adding suggested colors side-by-side. $\tau = 5$ for all results.*

and *Compatibility (“the expanded palette has compatibility to the original palette”)*. In the experiment, each participant was shown an original three-color palette at the top of the display, and three expanded palettes with four colors were displayed at the bottom, side-by-side in a random order.

We applied Friedman's test and if a significant difference ($p < 0.05$) was observed, we proceeded to perform Wilcoxon tests with Holm corrections for multiple comparison. The results showed that, for 12 of the 20 cases, the palettes expanded by our method were statistically significant for both the *Ours(Worst)* and *Random* methods. In addition, even in cases where our method had no statistical significance, Fig. 5 shows that the palettes generated by our method were most frequently chosen by participants as the best palette, which demonstrates the effectiveness of the proposed method.

6.3. Palette Index for Variations of Color Suggestions

As shown in Fig. 6, the suggested colors can vary depending on where the color is to be inserted because the rating model considers the order of colors in a palette. One may consider a color palette as simply a set of colors that is independent of the order of the colors in the palette, however, we must consider color order because such sets of colors should be arranged to form a single group. Therefore, we consider that the order is important for us to evaluate the aesthetics of a color palette.

We also apply a palette re-ordering to a palette $\mathbf{t}$, where we select the highest rated palette from all possible permutations; $\mathbf{t} = \arg\max_{r \in \mathcal{P}(\mathbf{t})} r(\mathbf{t})$, where $\mathcal{P}(\mathbf{t})$ denotes the $7! = 5{,}040$ possible permutations of a palette in the results shown in Table 3.

In addition, we conduct a user study to analyze user preferences of a color order of a palette. In the study, we show a participant a pair of color palettes (an original and the re-ordered) listed in Table 3 except for #6 since it is not re-ordered. We shuffle the left or right side of the two palettes randomly and ask “*Which color palette is more harmonius?*” to 48 participants (36 males and 12 females), 27 of them major in design. The age of the participants lies in 20 – 25. The result is shown in Fig. 7. According to the

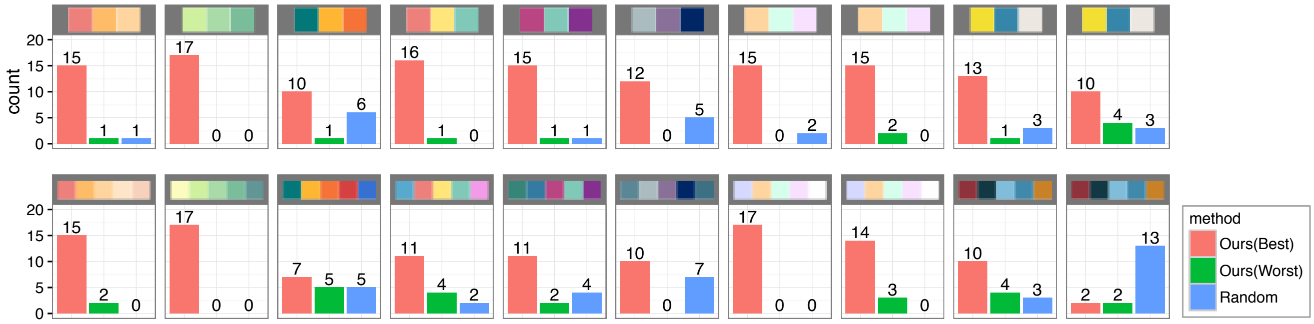


Figure 5: *Number of times that palettes generated by three different methods were chosen by participants as the best compatible palette. (Top) Color suggestions for three-color palettes to be expanded to four-color palettes. (Bottom) Color suggestions for five-color palettes to be expanded to six-color palettes. We expanded the palettes listed at the 8th and 10th columns with pastel and retro customized models, respectively.*

Figure 6: *The suggested colors (▼) are varied depending on the index of the palette ($\tau = 5$).*

Table 3: *Comparison of ratings for original and re-ordered palettes.*

	original palette		re-ordered palette	
#1		3.40		3.41
#2		3.43		3.49
#3		3.41		3.45
#4		3.37		3.37
#5		3.09		3.21
#6		3.52		3.52

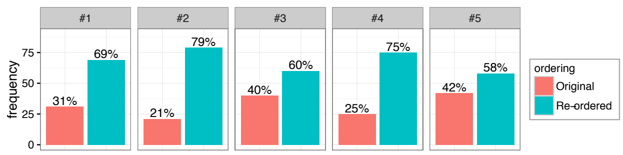


Figure 7: *Preference analysis from a user study. For each palette, the participants selected either an original or the re-ordered palette. The palettes used in the study were taken from #1 – #5 shown in Table 3.*

histogram, the re-ordering approach is effective for improving color palette evaluation of human aesthetics preferences.

6.4. Choice of τ.

Figure 8 shows the results of choosing different τ values in Eq. 2. Although Fig. 6 does give color suggestion results with $\tau = 5$ and sufficient hue variations while maintaining overall color compatibility, it does not always suggest sufficient hue variation, as shown

(a) $\tau = 5$

(b) $\tau = 20$

Figure 8: *τ affects the color suggestion results. With a small τ value, the results can be similar to the colors already in the given palette. With a greater τ value, perceptually different but compatible colors can be suggested. For a three-color palette with different τ values ((a) $\tau = 5$ and (b) $\tau = 20$), the suggested colors are marked as ▼.*

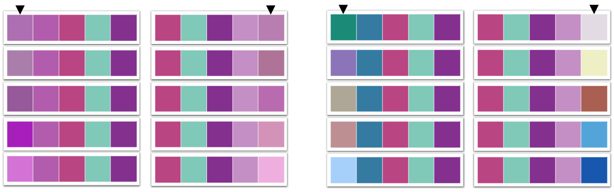
in Fig. 8a. When the user desires a variety of colors that differ sufficiently from the colors in the original palette, the proposed color suggestion method can suggest various colors that are sufficient to perceive the differences for the human visual system by setting τ to a larger value. As can be seen in Fig. 8a, $\tau = 5$ does not give sufficient differences because the value is close to a just-noticeable difference (the value around 2.3 [MVEO94]). With a larger value, e.g., $\tau = 20$, in Fig. 8b, the proposed method can suggest a wide variety of colors.

6.5. Choice of κ.

As shown in Fig. 9a, the color candidates tend to be similar to the colors in the given palette if κ in Eq. 5 is small. To avoid this, greater κ will suggest colors with more variety (Fig. 9b) while the palette maintains color harmony.

6.6. Analysis of Model Customization

For the model customization, we collected 1,403 *pastel* color palettes from Pastel_L♥vers [COL16d] and 3,176 *retro* color palettes from the Retro group [COL16e], and we customized the model with these additional datasets by applying the method described in Section 5.



(a) $\tau = 5,\ \kappa = 5$ (b) $\tau = 20,\ \kappa = 20$

Figure 9: *κ affects the color suggestion results. Given a four-color palette with different τ and κ, the suggested colors are inserted at both ends (the ▼ columns). Top to bottom is higher to lower ratings. $N = 4$, $M = 5$.*

Table 4: *Comparison of color suggestions with and without the model customized with pastel colors. The suggested colors are listed in the columns marked ▼, and the rating is shown next to it. $N = 3$, $M = 5$, $\tau = 5$, and $\kappa = 20$.*

	w/o custom model		w/ *pastel* model	
#1		3.16		4.47
#2		3.14		4.35
#3		3.10		4.35
#4		3.07		4.23
#5		3.07		4.18

Table 4 shows a comparison of the color suggestion results with and without the *pastel*-customized models. As can be seen, the customized model can suggest more compatible colors than the model without customization.

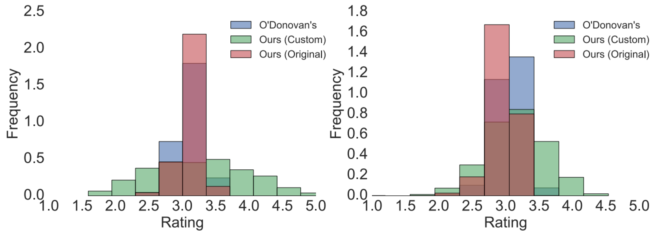
Table 5 shows a comparison of the ratings results with and without the *pastel* and *retro* customizations. We rated various three-color palettes using these models. As can be seen for the *pastel*-customized model, the ratings are higher than those obtained without the customized model for the palette shown by (a) in Table 5.

In addition, the *pastel* model gives higher ratings to gradation palettes, as shown in Table 5b and c, while the palette shown by (e) – (i) in Table 5 obtained lower ratings. On the other hand, the *Retro* model rated the palette shown in Table 5h higher, and the *pastel* color palette shown in Table 5a was also rated higher, which suggests that the *retro* model gives higher ratings to palettes comprising colors where saturation values are very similar. We also found that the *pastel* model rates were lower for Table 5i, while the *retro* model rates it with nealy the same rating as the non-customized model.

Furthermore, we compared our *pastel* and *retro* customized model to our original and O'Donovan's model [OAH11]. For the comparison, we collected 664 *pastel* color palettes and 1,222 *retro* color palettes from P a s t e l C u t i e s [COL16c] and RETROpolis [COL16f], respectively. Then, we rated the *pastel* dataset by our *pastel*-customized and original model, and O'Donovan's model (Fig.10a), and the rated *retro* dataset by our *retro*-customized and original model, and O'Donovan's model (Fig.10b). These means

Table 5: *Comparison of ratings for various color palettes with and without model customization.*

	color palette	model customization w/o	*pastel*	*retro*
(a)		2.90	4.24	3.50
(b)		3.18	3.73	2.75
(c)		2.95	3.20	3.12
(d)		3.01	3.16	2.85
(e)		3.21	3.02	3.23
(f)		2.76	2.45	2.94
(g)		2.95	2.24	3.07
(h)		2.84	2.63	4.02
(i)		2.65	1.57	2.66



(a) *Pastel* dataset (b) *Retro* dataset

Figure 10: *Histograms of ratings of pastel dataset (a) and retro dataset (b) of our pastel-customized and retro-customized and original model, and O'Donovan's model [OAH11].*

Table 6: *Mean and StdDev for Fig. 10.*

Dataset		[OAH11]	Ours (Original)	Ours (Custom)
Pastel	Mean	3.11	3.13	3.24
	StdDev	0.197	0.166	0.719
Retro	Mean	3.06	2.95	3.15
	StdDev	0.207	0.198	0.452

and standard deviations (StdDev) are listed in Table 6. They showed that, the customized model obtained higher mean ratings in both cases, and larger StdDevs are considered to these abilities to rate the specific colors in detail, while O'Donovan's and our original model can not capture the differences of the specific colors well since these models have smaller StdDevs. Although the original model has a less correlation to human ratings in Table 1 and Fig. 3, the customized version of the proposed models compare favorably to O'Donovan's model [OAH11].

6.7. Applications.

Coloring 2D Patterns. We applied the proposed color suggestion method to a 2D pattern template from COLOURlovers (Fig. 13). First, we selected a three-color palette with color images (e.g., *mysterious*, *noble*, *dreamy*, and *progressive*) [Kob91]. Then, the three-color palette was expanded to a five-color palette using the

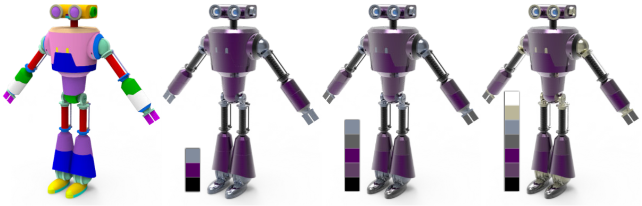


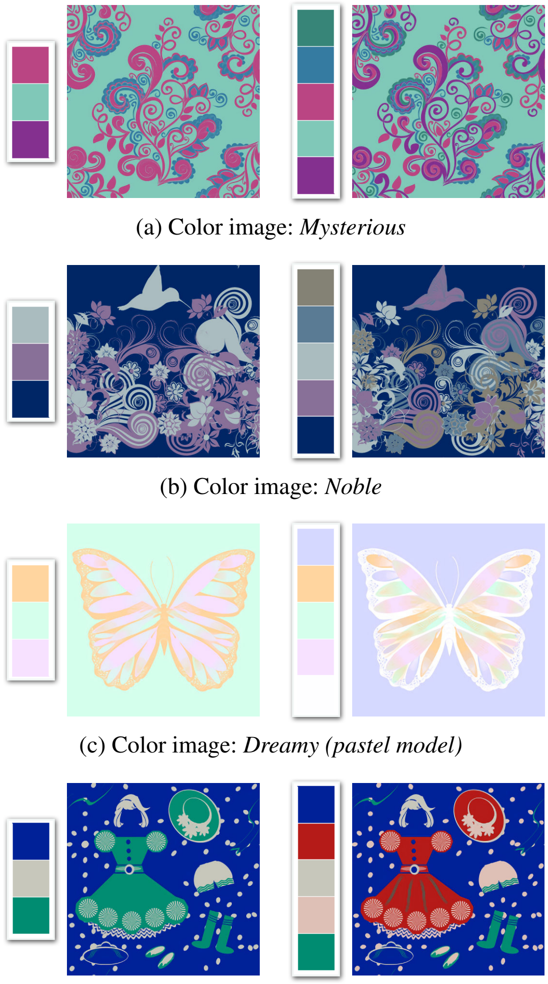
Figure 11: *Robot color design. Left to right: segmented model, model colored by a three-color palette, model colored by a five-color palette, and model colored by a seven-color palette while retaining the color image.*

proposed color suggestion method. We performed pattern coloring with three-color (Fig. 13, left) and five-color palette (Fig. 13, right). As can be seen in the five-color palette and its pattern coloring results, the color image does not change from that of the original three-color palette. Since the pattern coloring with the five-color palette has $5! = 120$ possible pattern coloring combinations, we employed the color assignment method proposed in [KYKL14] for coloring and selected the top-ranked results in Fig. 13.

Coloring segmented 3D model. We also applied the method to 3D model coloring. Given a segmented model, we group these segments into three to seven group, and color them with three-color, five-color, or seven-color palettes (Fig. 11). It can be noted that such color variations are useful, for example, a user already has a basic color concept (e.g., three basic colors) and would like to refine the color design while retaining the color image.

Photo recoloring. A user can produce enhanced photo-editing results by incorporating a palette-based photo recoloring method [CFL*15] with our palette expansion method. First, we prepare a three-color palette with a target color image. Such a palette with a certain color image can be obtained from the Internet (e.g., by searching for *Pastel* or *Retro* palettes) or from a book [Kob91]. Second, we apply the palette expansion method to the palette to obtain additional compatible colors. We also prepare a target photo to be recolored and apply the palette-based photo recoloring method to extract a source palette from the photo. Then, each color in the source palette is replaced with our palette colors using the color transfer function to recolor the photo. Figure 12 and Fig. 17 show the results. Using our palette expansion method, a user can obtain more colors in the palette while retaining its color image when the colors of the collected palette are limited, which provide more flexibility.

Figure 12: *Recoloring results with Mysterious palettes. The original photo (left) is recolored using the palette-based photo recoloring method with three- (middle) and seven-color palettes (right). Photo courtesy of Tommie Hansen (Flickr).*



(a) Color image: *Mysterious*

(b) Color image: *Noble*

(c) Color image: *Dreamy (pastel model)*

(d) Color image: *Progressive (retro model)*

Figure 13: *Coloring pattern templates. The original three-color palette color image (left) was expanded to a five-color palette using the colors suggested by the proposed method while retaining its color image.*

Figure 14: *Pen set*

Adding items. A user can add items with different colors to a set according to the color suggestions. For example, for a set of pens with different colors (Fig. 14 (left)), the additional pens with different yet compatible colors are added to the set (Fig. 14 (right)). This is useful when providing color variations. Another example is provided in Fig. 15, in which additional objects (e.g., a blind and a sofa) with colors that are compatible with the room's color theme are added to the room. Here, we assign the color to a diffuse color of the object.

7. Conclusions and Limitations

Conclusions. In this paper, we have proposed a rating prediction model for a given color palette that can comprise any number

Figure 15: *For a bedroom with an associated color theme (left), a window blind and a sofa with colors assigned according to the extended palette are added to the room (right). Model courtesy of 3D Bar.*

(a) Template (b) *Merry* (c) *Noble*

Figure 16: *Coloring pattern templates using two color palettes with different color images.*

of colors. We have also proposed a compatible color suggestion method for palette expansion while retaining color harmony, as well as a method to explore color space to select color candidates. With the proposed model, we can evaluate simple palettes, such as gradations, and we can rate palettes comprising various color tones and hues.

Limitations. Since the proposed method employs a machine learning approach, the rating prediction of the model depends strongly on the quality of the dataset. We specialized our model by collecting *pastel* and *retro* palettes from COLOURlovers with relatively little effort. However, if only a few datasets are available or it is difficult to collect datasets from the Internet, it is difficult to customize the model. It is also difficult to determine how many palettes need to be customized for sufficient rating accuracy. In addition, we have demonstrated coloring pattern templates as an application; however, the color harmony of a palette is not directly related to the target pattern mood, which can result in mismatched coloring. Figure 16 shows an example, in which we prefer Fig. 16c over Fig. 16b relative to the mood of the target content in the pattern template (Fig. 16a).

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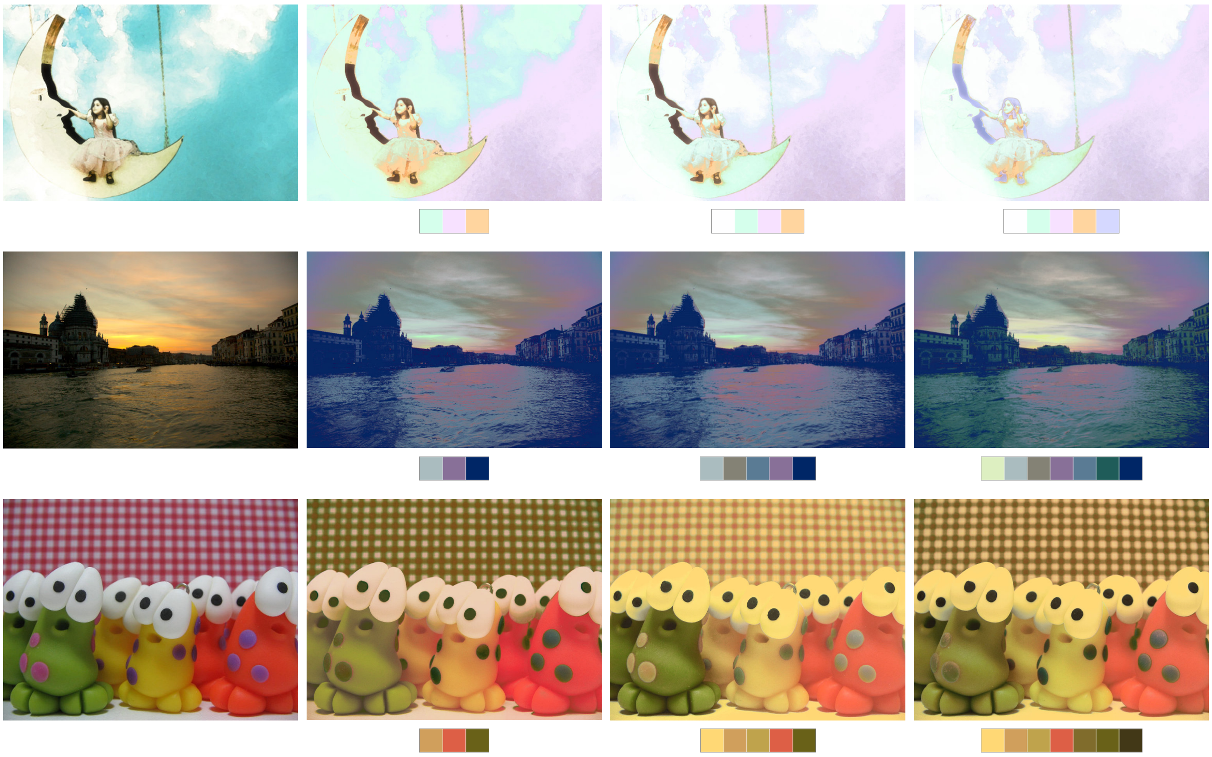

Figure 17: *(Top) Recoloring results with Dreamy palettes. (Middle) Recoloring results with Noble palettes. (Bottom) Recoloring results with Retro palettes. The first column shows the original images. Photos courtesy of Celine Nadeau (top) and Ana Kuhnen (bottom) (Flickr), and the MIT-Adobe FiveK Dataset [BPCD11] (middle).*

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