Affective Color Palette Recommendations with Non-negative Tensor Factorization

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***Abstract*—Color is an essential factor that influences human perception, and thus, the proper selection of color sets is crucial in creating informative and appealing visual content. Furthermore, the choice of such color palettes often reflects the underlying emotional intention of creators, especially when they want to introduce specific affective styles. This paper presents a color palette recommendation system that facilitates preferred colors and affective expressions in visual content. This is accomplished by introducing *non-negative tensor factorization* (NTF), which extends the conventional matrix-based collaborative filtering for recommending items through ratings of multiple users. In our approach, we composed a rating tensor that constitutes the scores for colors in terms of affective factors provided by participants in the user study. With this rating tensor, we explored the meaningful relation between affective expression and color preference. Our experiments exposed that we can successfully apply a tensor-based approach to recommending convincing sets of colors in several possible cases by predicting the underlying emotional intentions in the visual content design.**

***Index Terms*—Color palettes, affective factors, recommendation systems, non-negative tensor factorization**

I. Introduction

Color has a strong influence on what we perceive through our eyes and thus plays a vital role in creating compelling visual media, including illustrations and advertisements. A critical role of color is to assign different labels to objects according to their quantities or categories, which helps us extract important information according to our demands. Furthermore, we perceive such visual content not only cognitively but also emotionally, and, among possible visual characteristics, colors and their combinations can effectively reflect emotional factors [1], [2]. Again, such affective color choices can promote specific preferences in making good design decisions [3]. This observation naturally suggests the need to select proper combinations of colors that can enhance the affective value of visual media.

However, it is still a technical challenge to simulate the high-level choice of color palettes based on emotional factors according to individual preferences. For this purpose, we need to understand the various relations between the underlying affective intention and actual color selection for each user. This consideration leads to a desperate need to develop recommendation systems for color palettes that sufficiently respect the preferences of individual users; otherwise, we can only pursue major trends in color expressions that are commonly accepted. For this purpose, we employ a collaborative filtering technique that predicts the proper choice of items based on

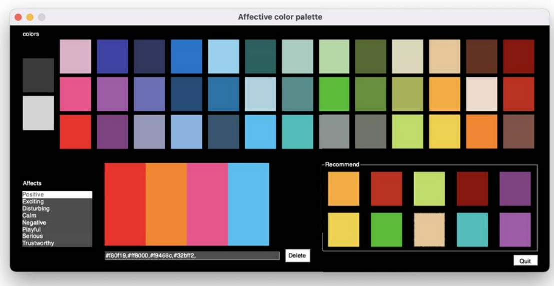

Fig. 1. Snapshot of our color palette recommendation system.

the preferences of users, which is commonly employed in contemporary e-commerce sites. We implement this idea by introducing a variant of the conventional matrix factorization method so that we can explicitly incorporate affective factors to understand the major trends in color choice.

The objective of this research is to implement a color palette recommendation system that simultaneously considers individual color preferences and affective intentions. This is accomplished by employing *non-negative tensor factorization* (NTF) [4], a high-dimensional enhancement of the conventional *non-negative matrix factorization* (NMF). We first composed a rating tensor of three dimensions spanned by the affective type, color, and user. We then factorized the tensor into factor matrices to analyze important trends over the three attributes. We conducted an online questionnaire to compose such a rating tensor, where we asked participants to answer their ratings of representative colors in terms of affective categories. We also implemented a prototype system for predicting color choices according to the underlying emotional context in the choice of colors.

Fig. 1 shows our prototype system for recommending color palettes based on affective factors. First, our system assumes that the user selects a specific emotional expression from the list of eight primary emotions on the left of the user interface before starting the color recommendation phase. Each time the user selects a new color from the color samples at the top of the interface or the candidate colors, the system updates a set of the harmonious colors it is expecting next that respects the underlying trends in the color selection. Alternatively, our system can infer the underlying emotional intention only from

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initially selected colors and propose the next candidate colors.

The remainder of this paper is structured as follows. Section II provides a brief survey on related research topics. Section III reviews the necessary prerequisites for NTF. Section IV describes how we composed the rating tensor for NTF through the user study. Section V presents our prototype color recommendation system to demonstrate the feasibility of our approach in different scenarios. Finally, we conclude this paper and refer to possible future extensions in Section VI.

II. Related Work

This section provides a brief survey on the following relevant research topics: color harmony design, tools for color design, and recommendation systems.

A. *Color Harmony Design*

Research on color design has been conducted both from theoretical and application aspects to tackle cognitive and perceptual issues. Ou et al. [1] first studied theoretical perspectives in their research for a color harmony model for two colors, and then they extended this idea to that for three colors [2]. On the application side, Cohen-Or et al. [5] presented a pioneering work for enhancing the color harmony of images in the context of computer graphics. Wang et al. [6] developed a knowledge-based system for introducing established color design rules. Color harmonization techniques have been further developed by introducing a saliency-driven mechanism for adjusting colors in photographs [7] and automatically selecting semantically-resonant colors in data visualization [8]. Lindner et al. [9] proposed a computational model that associates colors with words and extracts color palettes from words.

B. *Tools for Color Design*

Several tools for aesthetically designing colors have been developed by advancing techniques for color visualization. The famous online tool called ColorBrewer [10] was developed specifically for selecting color palettes in thematic maps. Setlur et al. [11] explored how to generate meaningful color palettes using linguistic information in data to exploit concept–color association. Fang et al. [12] developed an algorithm for maximizing the perceptual distances among a set of given colors to better discriminate between visual elements. Smart et al. [13] focused on the characteristics of the color lamps created by designers using machine learning techniques. Recently, Misue facilitated understanding of the degree of color difference by displaying cross-sectional contours in the color space [14] and further incorporated color ramps to clarify the difference in the associated quantitative values [15].

C. *Recommendation Systems*

Recommending items based on the rating of previous users facilitates proper decision-making that respects common preference patterns. *Collaborative filtering* is one such technique in which we can predict the favorites of a new user by simulating the behavior of some existing user who has the same preference. Adamopoulos and Tuzhilin [16] developed a probabilistic approach for recommending items in the neighborhood-based collaborative filtering framework to avoid over-specialization and concentration bias problems. Hassan and Hamada [17] devised multi-criteria recommendation systems by introducing the neural network model. Afoudi et al. [18] formulated a hybrid recommendation scheme that combines collaborative filtering with a content-based approach and a self-organizing map. Readers can refer to the recent survey [19] on collaborating filtering techniques.

As for the systems for recommending color palettes, O'Donovan et al. [20] predicted preferences of color aesthetics by learning from a large dataset of rated color themes/palettes. Recently, Linping et al. [21] developed a sophisticated data-driven recommendation system for suggesting color palettes with deep learning techniques.

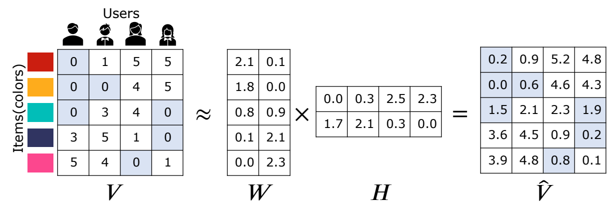


Fig. 2. NMF lets us factorize a data matrix $\boldsymbol{V}$ into matrices $\boldsymbol{W}$ and $\boldsymbol{H}$. $\widehat{\boldsymbol{V}}$ is the reconstructed matrix as the product of $\boldsymbol{W}$ and $\boldsymbol{H}$ and approximates the original matrix $\boldsymbol{V}$.

III. Non-negative Factorization

This section first reviews NMF commonly employed in current recommendation systems and then describes NTF as its high-dimensional version.

A. *Non-negative Matrix Factorization (NMF)*

In the collaborative filtering technique, we need to identify meaningful preference trends in the behavior of previous users. NMF is often employed for this purpose as a mathematical tool for extracting essential components from the given co-occurrence matrix [22]. Here, the co-occurrence matrix corresponds to a rating matrix in which rows and columns correspond to items and the choices made by users, respectively. The rating matrix is generally sparse because users do not evaluate every item due to time constraints. Thus, the preference trends should also be represented as sparse feature vectors.

NMF allows us to approximate this rating matrix $\boldsymbol{V}$ with the product of the two matrices $\boldsymbol{W}$ and $\boldsymbol{H}$, as shown in Fig. 2, by minimizing the error $\| \boldsymbol{V} - \boldsymbol{W}\boldsymbol{H} \|$. The unique characteristic of NMF is to preserve the elements of $\boldsymbol{W}$ and $\boldsymbol{H}$ as non-negative, assuming that the input data matrix $\boldsymbol{V}$ has non-negative elements only. Furthermore, non-negative factorization maximally respects the underlying sparsity in the elements of the factor matrices. We can specify the number of essential factors as k, which corresponds to the numbers of columns in $\boldsymbol{W}$ and rows in $\boldsymbol{H}$. Thus, after this matrix decomposition, we can represent the latent component factors

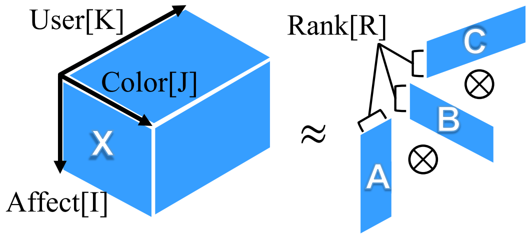


Fig. 3. NTF allows us to factorize a tensor $\boldsymbol{X}$ into the three factor matrices $\boldsymbol{A}$, $\boldsymbol{B}$, and $\boldsymbol{C}$.

of items as the column vectors in $\boldsymbol{W}$ and their weights as the row vectors in $\boldsymbol{H}$. In Fig. 2, the first column vector of $\boldsymbol{W}$ indicates that the first two items (i.e., red and orange), probably with the third one (i.e., green), will be selected simultaneously. In contrast, the second column vector of $\boldsymbol{W}$ reveals that the previous users are relatively likely to select the third item (i.e., green) if they like the fourth and fifth ones (i.e., blue and pink).

To recommend the next preferred items, we define the approximation of $\boldsymbol{V}$ as the product of two decomposed matrices, $\widehat{\boldsymbol{V}} = \boldsymbol{W}\boldsymbol{H}$. The approximate rating matrix $\widehat{\boldsymbol{V}}$ provides predicted rates of items that have not been evaluated in $\boldsymbol{V}$. This means that we limit our next choice to unrated items whose scores vanish in $\boldsymbol{V}$ and search for those having higher values in $\widehat{\boldsymbol{V}}$. In the case of Fig. 2, we recommend the third item (i.e., green) as the next item for the first user because the corresponding element 1.5 is the highest among the unevaluated items in $\widehat{\boldsymbol{V}}$. On the other hand, we do not highly recommend the first and second items because their corresponding scores are low in $\widehat{\boldsymbol{V}}$.

Once we obtain the factor matrix $\boldsymbol{W}$ from the rating matrix, we keep the column vectors of $\boldsymbol{W}$ unchanged as the latent component factors that reflect the crucial trends in the color selection. Thus, given the rating vector by a new user, we compute the k non-negative weights for the fixed column vectors of $\boldsymbol{W}$. This allows us to better approximate the rating vector and guide the next colors for the users.

B. *Non-negative Tensor Factorization (NTF)*

Although matrix factorization successfully facilitates labeling colors according to the likes and dislikes of previous users, it does not accommodate other possible factors that influence such preferences in the color selection. This led us to the need to introduce an additional dimension to promote a more detailed categorization of colors in terms of such preference factors. We implemented this idea by extending the conventional NMF to NTF, which was one higher dimensional version of NMF because we took as input a three-dimensional rating tensor.

Fig. 3 presents such an example where the input tensor corresponds to the array of rating matrices in terms of another factor, such as time or place. In practice, NTF helps us extract features in analyzing various problems, including purchasing behaviors and social networking. This third dimension indicates the affective modes assumed to be the background condition for selecting colors in our study.

Fig. 4. The set of 41 representative color samples proposed in [23]. Color IDs are used consistently in this manuscript.

The rating tensor for color evaluation is defined as an $I \times J \times K$ tensor $\boldsymbol{X} = [x_{ijk}] \in \mathbb{R}_+^{I \times J \times K}$, where $I = \#\{\text{affects}\}$, $J = \#\{\text{colors}\}$, and $K = \#\{\text{users}\}$. Here, $\mathbb{R}_+$ represents the set of non-negative real numbers. Moreover, we decompose the three-dimensional tensor $\boldsymbol{X}$ into the three factor matrices $\boldsymbol{A}$, $\boldsymbol{B}$, and $\boldsymbol{C}$, each consisting of R column vectors as the basis factors. Let us denote the product of $\boldsymbol{A}$, $\boldsymbol{B}$, and $\boldsymbol{C}$ as $\widehat{\boldsymbol{X}}$ that approximates the original tensor $\boldsymbol{X}$ as

$$\boldsymbol{X} \approx \widehat{\boldsymbol{X}} = \boldsymbol{A} \otimes \boldsymbol{B} \otimes \boldsymbol{C}. \tag{1}$$

This lets us denote the elements of the tensor $\widehat{\boldsymbol{X}} = [\widehat{x}_{ijk}]$ by multiplying the elements of $\boldsymbol{A}$, $\boldsymbol{B}$, and $\boldsymbol{C}$ as

$$\widehat{x}_{ijk} = \sum_{r=1}^{R} a_{ir} b_{jr} c_{kr}, \tag{2}$$

where $\boldsymbol{A} = [a_{ir}] \in \mathbb{R}_+^{I \times R}$, $\boldsymbol{B} = [b_{jr}] \in \mathbb{R}_+^{J \times R}$, and $\boldsymbol{C} = [c_{kr}] \in \mathbb{R}_+^{K \times R}$. NTF is a method of finding matrices $\boldsymbol{A}$, $\boldsymbol{B}$, and $\boldsymbol{C}$ that minimizes the error $\| \boldsymbol{X} - \boldsymbol{A} \otimes \boldsymbol{B} \otimes \boldsymbol{C} \|$ while preserving the non-negativity of these three factor matrices. The Euclidean distance is generally employed for this error if the rating tensor consists of scores, and thus we follow this convention because we will collect the elements for the tensor through a Likert-type scale questionnaire in this study.

IV. Composing the Rating Tensor

As described earlier, we need to compose a rating tensor by collecting the color preferences of multiple users according to the expected emotional conditions. For this purpose, we conducted an online questionnaire in which participants selected their favorite color samples for each affective category.

A. *Choice of Affects and Colors*

Our first step was to select a proper set of affects that primarily influence color choices in creating visual expressions. We based our approach on the research by Bartram et al. [24], who studied how color properties contribute to the various emotional expressions in information visualization. To determine the primary set of affects, they focused on how

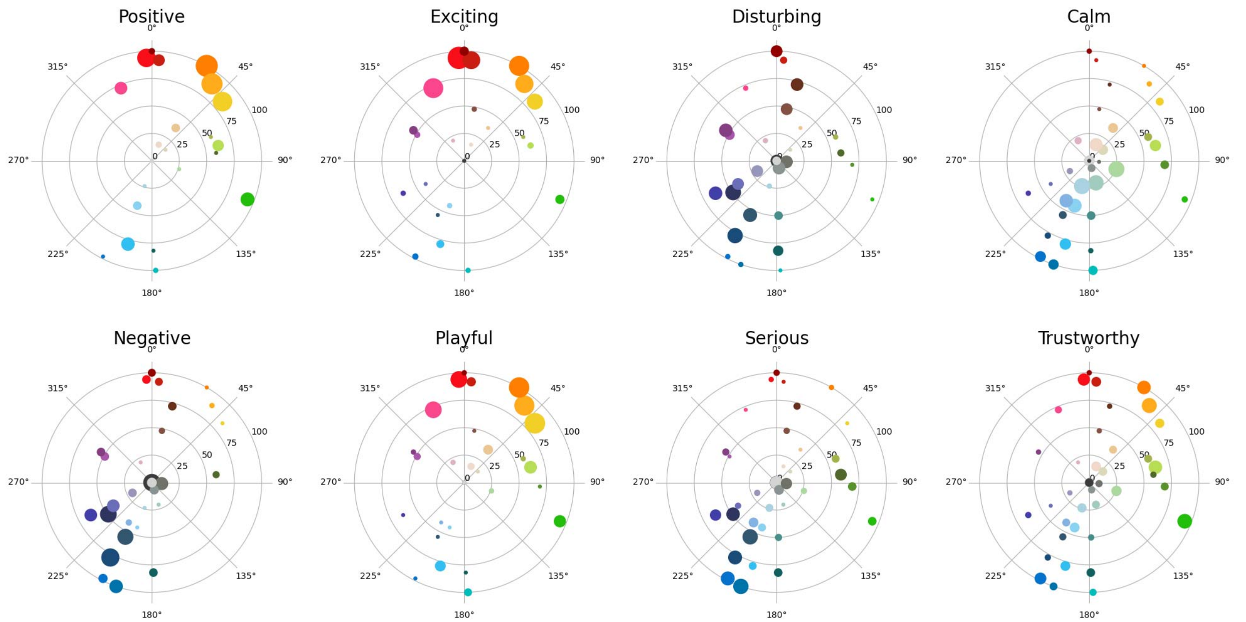


Fig. 5. Colors selected for each affect in the questionnaire. Each color sample is plotted on a hue wheel, while the distance from the center corresponds to the saturation. The size of each dot indicates the selection frequency of the corresponding color.

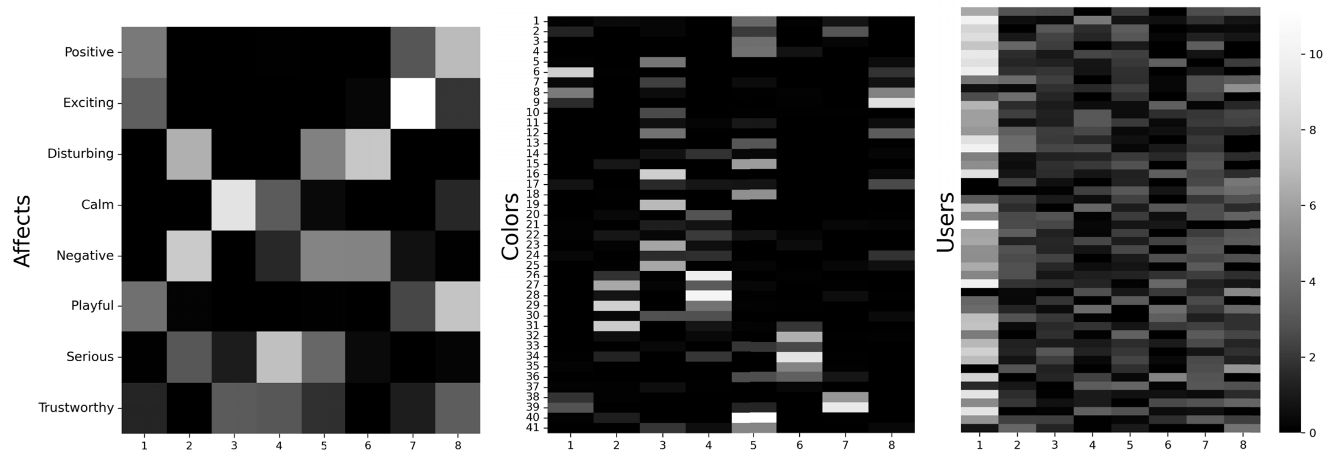
color emotion associations correspond to the *PAD space* [25], a well-known model for plotting emotions in space spanned by the axes of *valence* and *arousal*. Note that valence reflects the pleasure range from Positive to Negative, and arousal reflects the intensity from Calm to Exciting. Furthermore, they added four practical affects— Serious, Playful, Trustworthy, and Disturbing — to compose the emotional space with the set of eight primary affects in the communication of visual content. This study employed these eight primary affects as the crucial impacts on color choices in visual media design.

We also needed to limit the choice of colors so that the participants in the online questionnaire could select their favorite colors for each affect within a fixed period. We employed the color set derived from the experiments by Bartram et al. [24] again in this case. They first collected images associated with the eight affective modes in image databases built upon major social networking services and calculated the statistics of hue, saturation, and lightness of the image set. They then classified similar colors by k-means clustering and selected the representative color for each group. Fig. 4 exhibits the final set of 41 representative color samples, as detailed in [23].

B. *Collecting Color Scores in the Online Questionnaire*

To recommend affective color sets, we needed to compose the rating tensor that retained the color preferences of multiple users according to required emotional conditions. As described in Section III, we composed the three-dimensional data tensor in terms of affects as well as colors and users, and thus the size of the tensor was $I \times J \times K$, where $I = \#\{\text{affects}\}$, $J = \#\{\text{colors}\}$, and $K = \#\{\text{users}\}$. In our approach, we set $I = 8$ and $J = 41$ by following the choice of affects and colors made by Bartram et al. [24]. We obtained this data tensor through an online questionnaire. In the questionnaire, we asked participants to select five colors out of the 41 representative color samples for each of the eight affective categories. In addition, we requested them to order the five colors according to their preference so that we could assign the different scores to the selected colors in the data tensor. This was achieved by introducing the five point Likert scale, where we assigned the scores 5–1 to the five selected colors in that order and 0 to the other unselected colors. Before they answered the main questions, participants could practice by selecting their favorite colors in the questions, which also helped us understand how much each participant understood the contents of the questionnaire. We recruited 50 participants (12 females and 38 males) for this questionnaire, and their ages ranged from 19 to 64. More than half of the participants were university students (ages 19–24) majoring in computer science and relevant fields. From the results of this questionnaire, we composed a three-dimensional data tensor of the size $I \times J \times K = 8 \times 41 \times 50$.

As shown in Figure 5, the results obtained through the questionnaire reveal differences in the choice of colors for each affective category. For example, the affective categories Positive, Exciting, and Playful correspond to warm hues with high saturation. In contrast, Negative, Serious, and Disturbing cover many cold hues, such as blue, and low lightness colors, such as dark red, brown, black, and gray, along with achromatic colors. For the affective category Calm, cold colors with low saturation were selected. Although the color distributions for Positive and Playful were similar in hue and saturation, the colors selected for Playful were more widely distributed along the hue wheel than Positive. These



Factor matrix $\boldsymbol{A}$
(a)

Factor matrix $\boldsymbol{B}$
(b)

Factor matrix $\boldsymbol{C}$
(c)

Fig. 6. The three factor matrices obtained by factorizing the data tensor with NTF. (a) Factor matrix $\boldsymbol{A}$ ($I \times R$). (b) Factor matrix $\boldsymbol{B}$ ($J \times R$). (c) Factor matrix $\boldsymbol{C}$ ($K \times R$). Here, $I = \#\{\text{affects}\} = 8$, $J = \#\{\text{colors}\} = 41$, and $K = \#\{\text{users}\} = 50$. The grid cell becomes bright according to the magnitude of the corresponding elements in each factor matrix.

trends in the choice of colors for the respective affective emotions are surprisingly consistent with those obtained in the previous experiments conducted by Patra et al. [23], in which they demonstrated a strong relationship between emotional expressions and color palette design. In this work, we used the set of scores obtained through the questionnaire as the rating tensor for NTF-based color palette recommendations.

V. Results

This section presents experimental results to demonstrate the applicability of the proposed approach. We implemented our recommendation system on a PC laptop with an Intel Core i5 CPU (2.0 GHz, quad-core) and 16 GB RAM, and the source code was written in Python using the PySimpleGUI library. The matrix and tensor factorization was implemented using a combination of general Python external libraries and the Tensorly library [26]. Specifically, we employed the CANDECOMP/PARAFAC (CP) decomposition, one of the typical NTF approaches to decomposing the three-dimensional tensor $\boldsymbol{X}$ into three matrices consisting of R basis factors.

A. *Factorization Results*

We decomposed the rating tensor obtained through the online questionnaire described in Section IV. In this study, we compared the results for the number of basis factors $R = 3, 4, 5, 6, 7$, and 8, respectively, and empirically selected $R = 8$ because this choice maximally retained important trends in the color selection. Figure 6 presents the three factor matrices A, B, and C obtained using NTF, where the brightness of each grid cell represents the magnitude of the corresponding non-negative elements in the factor matrices. The distribution of the bright cells exposes the underlying trends of color selection based on emotional conditions.

In Figure 6, the first column of $\boldsymbol{A}$ indicates that Positive, Exciting, and Playful share the choice of colors represented as high scores in the first column of $\boldsymbol{B}$. This means that highly saturated colors with warm hues, including orange and red, are likely to be selected for the three affective categories. Moreover, the first column of $\boldsymbol{C}$ indicates that this tendency was supported by the majority of the participants in the online questionnaire. We can justify the observation that most users choose a set of warm colors for Positive, Exciting, and Playful, as already presented in Figure 5.

Another notable trend appears in the second and fourth column vectors for all the three factor matrices, which reflect the common preference in the color choices for Negative, Serious, and Disturbing. First, the second and fourth columns in $\boldsymbol{A}$ have relatively high values for the three affective types. In $\boldsymbol{B}$, on the other hand, bluish and greenish colors in the second and fourth columns have relatively high scores, respectively. This specific bias suggests that the low-saturated cold colors are preferred for Negative, Serious, and Disturbing, but we cannot find apparent differences in their tendencies. Nonetheless, we can still claim that the sixth columns in $\boldsymbol{A}$ and $\boldsymbol{B}$ disclose that Disturbing and Negative are commonly associated with dark blue and purple, independently of Serious.

B. *Case Studies for Recommending Affective Sets of Colors*

To assess the usefulness of our approach, we tested our prototype system in three case studies for recommending affective color palettes. A demonstration video is available at https://youtu.be/RemPRNZmlKw.

Case I: Predicting colors individually for each affective category: In the first case study, our system recommends possible color candidates individually for each of the eight affective conditions. The system proposes such colors by referring to

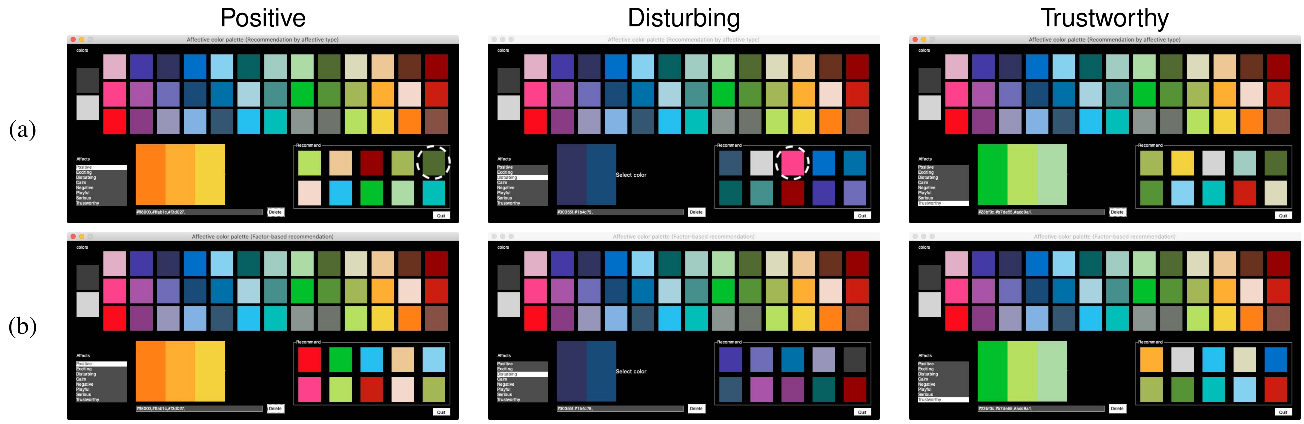


Fig. 7. Recommending colors by affective type. Results in (a) Case I and (b) Case II for the affective types Positive, Disturbing, and Trustworthy. The tensor-based recommendation approach (Case II) proposes a better set of colors than the matrix-based approach (Case I) because it effectively captures the overall trend of color preference concerning the affective type.

the rating tensor obtained through the online questionnaire. However, in this case, we first decompose the tensor into eight matrices concerning the affective types and then employ NMF to reconstruct the approximate rating vector individually for each type. Thus, this case study helps us to assess the capability of the conventional matrix-based recommendation system in the context of affective color palette compositions and later compare the results with those obtained using our proposed approach.

In this case, we expect users to start by specifying the affective category and select initial color samples from the 41 prepared samples according to their preference with our system (Fig. 1). This lets us reconstruct the J-dimensional rating vector individually for the specified emotional condition. Regarding actual color recommendations, we compare the original and reconstructed rating vectors for the 41 representative colors and select color samples that have not yet been chosen while receiving higher scores. The users can repeat this alternating iteration between recommendation and selection until they compose the complete palette of colors.

Fig. 7(a) demonstrates actual scenarios for composing color palettes for the three affective types, Positive, Disturbing, and Trustworthy. Since colors for Positive primarily constitute warm hues and high saturation in the color space, color samples such as red and orange are likely to be recommended. However, the predicted color set contains an unwanted dark gray color (circled by the broken white line), which is less critical for Positive. The unwanted color suggestion also occurs for Disturbing. The color palette should mainly consist of dark colors but unexpectedly contains a relatively light pink color (circled by the broken white line). The preferred colors for Trustworthy are widely distributed over the color space, including both high and low saturated colors. After taking such color samples as the initial choices, the recommendation system faithfully reproduces highly saturated colors.

Case II: Predicting colors taking all affective categories into account: In the second case study, we take full advantage of the NTF-based approach to respect the trends in color choice for all affective categories. In this case, the users are asked to select their preferred color samples for multiple affective types at once. Thus, the system inputs the provided $I \times J$ rating matrix and reconstructs the approximate matrix of the same size using NTF. It then compares the reconstructed scores of the unrated colors in the approximate matrix and proposes the colors of higher scores. This scenario also helps us predict the preferred colors for a specific affective category by referring to previous color selections for the other categories.

Comparison between results in Cases I and II allows us to confirm the feasibility of the proposed approach. Fig. 7 exhibits such a comparison, where Fig. 7(b) corresponds to the results obtained in Case II. For the affective type Positive, we could fully respect the tendency of the initially selected colors because we could entirely exclude low-saturated colors from the proposed palette. As for Disturbing, our system successfully limited the proposed colors to dark colors, compared with the results obtained in Case I. For Trustworthy, the system kept a well-balanced distribution in candidate colors as obtained through the questionnaire.

As mentioned above, the color choices of the other affective categories in this case study help us predict even further choices. Fig. 8 presents such a case, in which the system tried to propose candidate colors for a specific affective type by reflecting the choice made for the other types. We first provided warm colors as the samples for Positive and Exciting, and then we looked for the candidate colors for Trustworthy. The system yielded relatively warm and vivid colors for the potential palette, as shown in Fig. 8(a). Conversely, as observed in Fig. 8(b), the system produced cold and light colors instead, if it took dark and bluish colors as samples for Disturbing and Calm. In this way, the system could arrange the color recommendation for Trustworthy by referring to color samples for other affective types because the preferred colors for this category were widely spread over the color space. Thus, we could successfully make sound

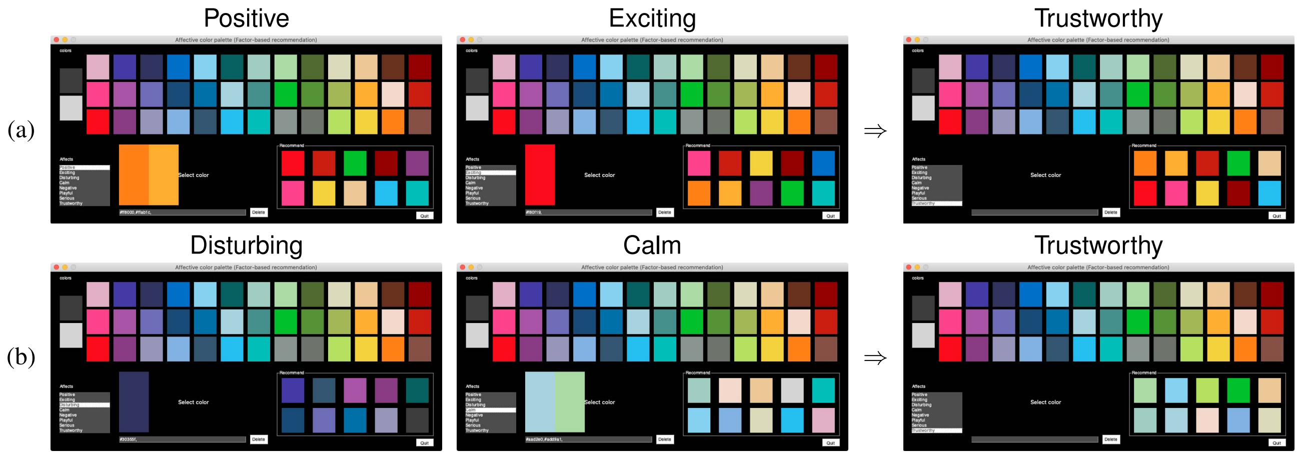


Fig. 8. Recommending colors from the preference for other affective types in Case II. (a) Proposing colors for Trustworthy when warm colors are selected for Positive and Exciting. (b) Proposing colors for Trustworthy when cold colors are selected for Disturbing and Calm. Preferred colors for Trustworthy are widely spread over the color space, and thus the proposed colors are dependent on the color choice made for other affective types.

recommendations that respect the underlying trends of color preference for all the affective categories with the NTF-based analysis.

Case III: Predicting colors while inferring the corresponding affective category: We could also employ NTF to infer the corresponding affective category from the preliminary selection of color samples because it allowed us to understand mutual relations between different affective types in color selection. In Case III, we implemented this type of affective inference in the color palette composition. By taking initially selected color samples, our system tried to infer the corresponding affective type. The actual affective prediction was achieved by duplicating the scores for the representative 41 colors for all the affective types to compose the $I \times J$ rating matrix and by reconstructing its approximate matrix using NTF. This was followed by computing the squared differences between the original and reconstructed matrices for the already selected colors. The best affective type was obtained by finding the corresponding J-dimensional score vector that minimized the squared difference.

Fig. 9 demonstrates several results in which we could identify the affective category that best matched the set of selected colors in an early stage of the color palette composition. Our system also displayed the inferred affective types in ascending order of error between the original and reconstructed matrices. In this case study, the system updated the sorted list of affective types whenever it took a new color sample as input. Per this update, the system also provided a set of next candidate colors for the identified affective category through the interface.

VI. Conclusion

This paper has presented an approach to color palette recommendation that considers emotional expressions and color preferences. The goal behind our approach was to represent the affective color choices of multiple users as the three-dimensional tensor and decompose it into factor matrices using NTF. The factor matrices allowed us to successfully characterize significant relationships between affective emotions and color preferences. The rating tensor of affective color choices was obtained through an online questionnaire, in which 50 participants selected their favorite colors from the 41 representative color samples for each of the eight affective categories. We conducted three case studies for color palette composition by considering affective types and demonstrated the applicability of our approach through interactions with the prototype system.

Our future work includes improving our algorithms to accommodate more extensive evaluation data. We also plan to develop an interactive tool for adjusting color parameters, including saturation and lightness. We need to assess color harmony in composing color palettes for more practical color design. Incorporating additional attributes/conditions for recommending colors will be another interesting theme for future research. For this purpose, we need to develop our approach to implementing recommendation systems with multiple attributes [27]. Extending the proposed ideas to accommodate visual expressions such as shapes/patterns and their layouts remains to be further explored.

Acknowledgments

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Fig. 9. Proposing colors while inferring the corresponding affective category in Case III. The most suitable affects for the color palettes were inferred to be Positive, Playful, Exciting, Disturbing, Calm, and Trustworthy, in this order. The system displayed the list of inferred affective modes in ascending order of error, where each error value was parenthesized.

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