Received: 4 August 2023 | Revised: 31 January 2024 | Accepted: 12 March 2024

DOI: 10.1002/col.22927

RESEARCH ARTICLE

COLOR RESEARCH AND APPLICATION WILEY

A computational method for predicting color palette discriminability

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Abstract

Automatic analysis of images is increasingly being used to generate color insights and this has led to various methods for generating palettes. Several studies have recently been published that explore methods to predict the visual similarity between pairs of palettes and these methods are often used to evaluate different generative methods. This work is concerned with being able to predict visual similarity between color palettes. Three data sets (two of which were previously published) are used to evaluate two methods for predicting visual similarity between palettes. A novel palette-difference metric (based on the Hungarian algorithm) is compared to the previously published minimum color difference model (MICD) and was found to agree better with the visual data for two of the three data sets. Agreement between models and visual data was also better for CIEDE2000 (1, 2) than for CIELAB metrics.

KEYWORDS

color difference, color palette, modeling, psychophysics

1 | INTRODUCTION

According to Afifi,[1] color palettes are "finite sets of representative colours for image colours" that are used to encode and represent color relationships and typically contain a set of discriminable and harmonious colors.[2] According to Kim and Choi,[3] a color palette is "one of the simplest and most intuitive descriptors that can be extracted from images or videos" and they have many applications in design. For example, in one study color palettes were used to explore cultural differences in meaning and preference for interior environments.[4] Color palettes can also be a useful step in the image recolouring problem[5] and for color image quantization[6] and those that are extracted from art work often have a certain aesthetic.[7] When color palettes have an aesthetic or symbolic dimension then they are sometimes referred to as color schemes.[8,9] In some cases, a color palette may be derived from an image or from a word and the colors may not be harmonious but simply representative.[10] Some color palettes are more harmonious or more aesthetically pleasing than others. In this work the term color palette is used in a general sense to mean a number of colors that together form a set for some purpose irrespective of any perceived harmony, symbolism, or aesthetic. In many practical applications the number of colors in a palette is small; in one study, for example, 3-, 5- and 8-color palettes were investigated.[11] Several authors have tried to predict the visual

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aesthetic rating of color palettes; for example, one study found an r^2 value between model prediction and visual ratings of 0.56[12] whereas another study found an r^2 value of 0.52.[13] However, the work in this study is not concerned with aesthetics and is not restricted to palettes that may be considered to be harmonious or aesthetically pleasing nor even those that contain discriminable colors; rather, we explore the general problem of predicting the visual similarity between two N-color palettes where N is the number of colors in each palette and where N is relatively small (e.g. $1 < N < 50$). Note that when $N = 1$ we have 1-color palettes and the traditional color-difference problem that has been extensively explored[14] and when N becomes very large the problem becomes one of image similarity rather than palette similarity.

Automatic analysis of images is increasingly being used to generate color insights and this has led to various methods for generating palettes.[15] Many researchers focus on generating color palettes that are harmonious[16,17] but others focus on generating color palettes that are simply representative of an image,[18] movie,[19] or word.[20] The website Colorgorical[11,21] is an example of an online tool that can generate color palettes whereas ColorBrewer provides access to pre-configured palettes.[22] Simple unsupervised machine learning methods (most notably k-means) have often been used to derive a color palette from an image though more complex variants of cluster analysis (sometimes with a supervised machine learning component) have also been used.[18,23,24] Colormind is a website that generates a color palette or color scheme from images, artwork, or movies using deep learning.[25]

This work is concerned with being able to predict visual similarity between color palettes. Methods for predicting visual similarity between color palettes are useful in that they can be used to quantify the performance of various methods for generating color palettes by comparing the similarity of these palettes to ground-truth data (often these are palettes that have been generated by humans where the goal of any palette-generating algorithm to is generate palettes that are as similar as possible to these ground-truth data). Imagine that we have two methods for generating a color palette from an image and we want to know which method is best; by best, we mean which method produces a color palette that is most similar (visually) to a palette (or palettes) generated by humans. Of course, we could evaluate the visual similarity by asking participants to scale the visual similarity or difference between two palettes. However, such scaling experiments may be laborious and it is valuable to have a computational method that can predict the visual similarity between two palettes (so that a psychophysical or scaling experiment is not needed). Exactly, the same rationale was used over the second half of the 20th Century to develop color difference metrics that can predict visual differences between pairs of colors.

The simplest method to compare two N-color palettes is to compare (using color difference) each patch in one palette with each patch in the other palette and to average the N^2 color differences.[3] Pan and Westland evaluated this method, called the mean color difference (MECD) model, using a set of psychophysical data whereby 30 participants rated the visual similarity between 96 pairs of 25-color palettes.[26] The same authors also evaluated a method where each patch is compared to the closest match in the other palette and the average of the $2N$ color differences was calculated. The term "closest" means the smallest color difference using whatever color difference formula is being applied. This method is known as the minimum color difference (MICD) model and when the CIELAB color difference formula was used the r^2 value between this model and the psychophysical data was 0.61 whereas the r^2 value for the naive MECD model was 0.12.[26] The MECD and MICD models were also evaluated by comparison with psychophysical similarity data obtained from 20 participants who rated 95 pairs of 5-color palettes and the r^2 values were 0.35 (MECD) and 0.82 (MICD) using the CIELAB color difference formula.[27] With both of these methods it is possible to use any color-difference metric; in both studies[26,27] better correlation with visual color differences was obtained using the CIEDE2000 (1, 2) metric than using the CIELAB equation. A different approach for developing a palette-difference metric based on palette sorting was developed by Kim and Choi.[3]

This study introduces a new method for calculating a visual difference between two N-color palettes that is based on N color differences and evaluates this using three sets of data; two of these data sets (5-color palettes[27] and 25-color palettes[26]) have been previously published but the third (45-color palettes) has not been widely published. The performance of the new method is evaluated using all three data sets and is compared with two previously published methods (MECD and MICD).

2 | METHODS

2.1 | Psychophysical similarity data

Table 1 lists the properties of the three data sets that have been used in this study. The 5-color[27] and 25-color[26] datasets were previously published whereas the 45-color dataset has only been published in a PhD thesis[28] and is therefore described in more detail in this manuscript.

Table 2 lists the 30 words that were used to generate the palettes for the 45-color data set. Each was entered into Google image search and 50 images extracted for each word. A k-means clustering algorithm was used to extract 45 colors from the combined 50-image data for

TABLE 1 Summary of details for three psychophysical palette-similarity data sets.

Name	Number of pairs of palettes	Number of participants	Source of the palettes	Similarity rating method
5-color set	95	20	Selected by observers from landscape images	10-point scale
25-color set	96	30	Generated from landscape images using k-means	Magnitude Estimation
45-color set	30	15	Generated from images obtained from Google in response to key words; for each word a palette was selected by the participants and a palette was generated using *k* means	11-point scale

TABLE 2 List of words used to generate the 45-color palettes.

Words used to generate images		
Active	**Good**	**Poor**
Bad	Healthy	Powerful
Clean	Hot	Religious
Cold	Lucky	Rich
Culture	Male	Safe
Dangerous	Married	Sweet
Dead	Medical	Traditional
Female	Modern	Unlucky
Fresh	Natural	Urban
Future	Old	Young

FIGURE 1 Example palette from the 5-color data set.[27]

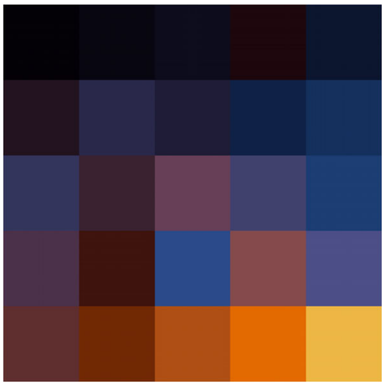

FIGURE 2 Example palette from the 25-color data set.[26]

each word. A second palette was generated for each word from a psychophysical experiment in which each of 15 participants used a color-picker tool to select three colors to represent each word.

Figures 1 and 2 show example palettes from the 5-color and 25-color data sets, respectively. Figure 3 shows an example image pair from the 45-color data set. In Figure 3, the human-generated palette was generated with a psychophysical experiment in which each of 15 participants selected three colors (using color-picker GUI) to represent each word.

2.2 | Psychophysical experiments

Two of the data sets were obtained from previously published studies but some details are repeated here. For the 5-color palette data, 90 pairs of palettes were presented to each of 20 participants (9 males and 11 females, aged 25–56) and the similarity was evaluated using a 10-point scale. For the 25-color palette data, 96 pairs of palettes were presented to each of 30 participants (15 males and 15 females, aged 21–35) and the similarity was evaluated using magnitude estimation (each participant entered a number between 0 and 100, representing minimum and maximum visual difference between the palettes). In both cases a mean visual difference (ΔV) was calculated for each pair of palettes and these will be the ground-truth data against which algorithms will be evaluated.

The 45-color palette experiment was carried out as part of a PhD programme and is therefore described in more detail. The human- and computer-generated 45-color palettes were used to constitute an image pair; these image pairs were presented to 15 participants (8 males and 7 females, aged 18–35) who rated their similarity using an 11-point scale from -5 (most different) to $+5$ (most similar). The difference between this scale and the 10-point scale using in the previous study is that this scale was an integer scale from -5 to $+5$ including a zero point whereas the previous study did not include a zero. The decision to include a zero or not in such experiments is debated in the literature (e.g.[29]). However, in this case, the two experiments are independent and made different decisions in this regard. Participants viewed the 96 pairs of palettes (presented in random order) on a neutral gray background at a distance of about 100 cm in a darkened room. All participants passed an Ishihara color test before taking part in the study and each participant spent about 30 min making the evaluations of the 30 pairs of palettes. The data were processed to generate Z scores and these were used to represent the magnitude of visual difference (ΔV) between the pairs of palettes. The experiments were carried out in a darkened room with a display configured to the sRGB specification (white point CIE $x = 0.3115$, $y = 0.3299$, max luminance 118.6 cm/m^2, gamma ~2.4). Table 3 shows measurements of the display made using a

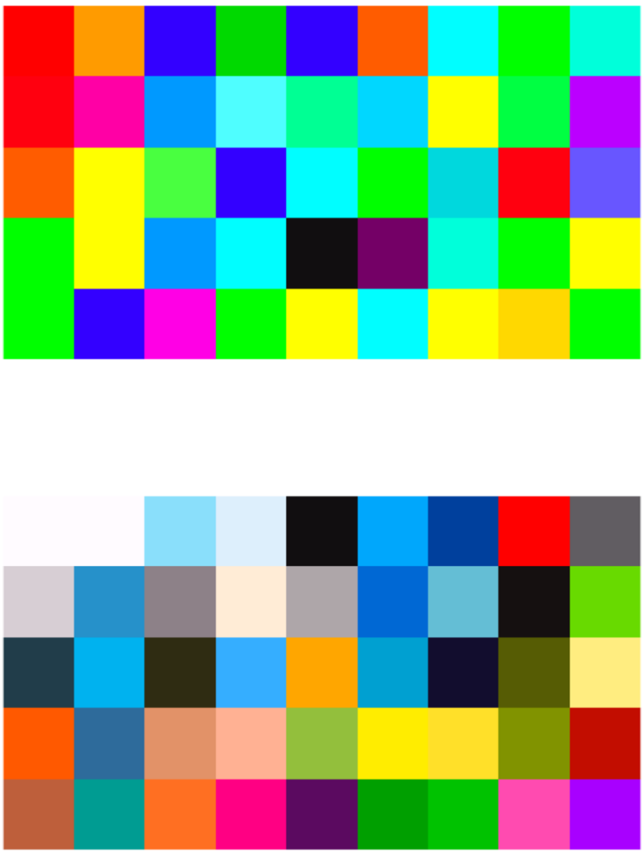

FIGURE 3 Example pair of palettes from the 45-color data set[28] showing the human (upper) and computer (lower) generated palettes for the word "active."

Minolta CS2000 tele-spectroradiometer from a distance of 80 cm. The compliance to sRGB allows the standard sRGB relationship to be used to convert the display RGB values (0–1) selected by the participants to CIE XYZ values (D65/1931) using Equations 1 and 2.

$$\begin{aligned} &\text{If RGB} > 0.04045 \\ &\text{RGB\_linear} = ((\text{RGB} + 0.055)/1.055)^{2.4} \\ &\text{Else} \\ &\text{RGB\_linear} = \text{RGB}/12.92 \end{aligned} \tag{1}$$

$$\mathrm{X} = \mathrm{MR} \tag{2}$$

where R is a $3 \times N$ array of RGB_linear values for N colors, X is a $3 \times N$ array of CIE XYZ values, and M is a transfer matrix; thus,

$$M = \begin{matrix} 0.4124 & 0.3576 & 0.1805 \\ 0.2126 & 0.7152 & 0.0722 \\ 0.0193 & 0.1192 & 0.9305 \end{matrix}.$$

Although the stimuli were presented based on their RGB values, it was possible to calculate CIELAB values for each color in each palette using the sRGB model. The data from the other two experiments are also available as CIELAB values. In all three experiments, the data consists of a pair of color palettes (specified in terms of CIELAB) and a value of ΔV (representing the ground-truth visual difference between the palettes).

For the 25- and 45-color palettes the palettes were generated from images using a k-means algorithm whereas the 5-color palettes were selected by humans. We note that k-means is an algorithm that has many parameters and where the choice of these parameters likely affects the colors that are selected. For example, an important parameter is how the initial colors (or centroids) are selected. For the generation of 25- and 45-color palettes the initial centroids were randomly selected. This means that running the algorithm again would likely generate different results. This is considered to a problem by some researchers who have developed alternative initializations that mean that the same color palette always results from

TABLE 3 Measurements of the display used in the laboratory experiment.

Stimulus	Luminance cd/m^2	CIE x	CIE y
White [255 255 255]	118.62	03115	0.3299
Red [255 0 0]	24.70	0.6397	0.3294
Green [0 255 0]	85.36	0.2969	0.6011
Blue [0 0 255]	8.70	0.1528	0.0606

the same image.[18] In the context of this study, however, it is irrelevant that changing the parameters in the *k*-means algorithm would have generated different color palettes. The algorithm was used as "means-to-an-end" to generate pairs of palettes and it was those palettes that were generated that were visually assessed in terms of visual palette difference. Likewise, different words (Table 2) could have been used to generate the images from which the 45-color palettes were derived and this would have generated a different set of images and then different palettes. Of course, it is an open question whether this manuscript contains sufficient psychophysical data (derived from a sufficient number—and sufficiently varied—pairs of palettes); however, one of the strengths of this work is that is takes data from three separate studies to allow a more robust analysis of the algorithms than would have been possible by analyzing any one of those studies alone. The fact that different approaches were used to generate the palettes in the three studies arguably contributes to this robustness.

It is important to note that generally when comparing palettes this involves some large color differences. For example, in Figure 3 if each color in one palette is compared to each color in the other palette then the majority of color differences will exceed 5 CIELAB units. An analysis for the data in this study showed that the mean color differences between individual patches from pairs of palettes were 62.2, 46.4, and 93.3 CIELAB units for the 5-color, 25-color, and 45-color palettes, respectively. These mean values were based on an average of 2250 (5-color palettes), 60000 (25-color palettes), and 66750 (45-color palettes) color differences. There is no particular bias in terms of differences in hue, lightness, and chroma but further work could consider this in more detail.

3 | PALETTE DIFFERENCE METRICS

Figure 4 illustrates a pair of palettes from the 5-color data set and the 5×5 color-difference matrix that shows the CIELAB color differences between each of the possible 25 paired comparisons.

With respect to Figure 4, the MECD model is calculated as the average of the 25 ΔE values in the 5×5 matrix. The MICD model is calculated as the average of the five smallest values in each column and the five smallest values in each row. The new method presented in this manuscript treats the problem as an assignment task where the matrix shown in Figure 4 is a cost matrix. An algorithm is sought that pairs the colors from one palette with the colors from the other palette so that the sum of the five elements in the cost matrix is smaller than the sum of the five elements that represents any other assignment or pairings. In the example shown, the optimal pairings are 1 v 3 ($\Delta E = 34.5$), 2 v 4 ($\Delta \mathrm{E} = 32.6$), 3 v 2 ($\Delta \mathrm{E} = 27.1$), 4 v 5 ($\Delta \mathrm{E} = 63.9$), and 5 v 1 ($\Delta \mathrm{E} = 45.1$) and this results in the pairings shown in Figure 5.

The assignment problem can be solved using the Hungarian method known as the Kuhn-Munkres algorithm[30] and an open-source MATLAB implementation[31] was used in this work. This method will be referred to as the Hungarian method. The rationale for using this method is that the naïve method (which involves N^2 color differences) has been shown to be ineffective. The MICD model only considers pairs of colors that are similar but this is asymmetric so that 2N pairs need to be considered (see Figure 4). The Hungarian method is a way that allows the colors from the two palettes to be optimally paired to allow the calculation of only N color differences. Note, however, that pairs of palettes are possible where the average of the 2N color differences (from the MICD model) would be identical to the average of the N color differences (from the Hungarian model) but this is certainly not guaranteed.

FIGURE 5 Optimal assignment (pairings) of the two palettes shown in Figure 4.

	1	2	3	4	5
1	68.7	36.3	34.5	45.4	108.8
2	72.0	45.6	54.6	32.6	123.4
3	59.5	27.1	39.9	49.1	65.1
4	100.5	98.7	114.6	104.0	63.9
5	45.3	31.1	11.9	42.1	98.1

FIGURE 4 Example pair of palettes from the 5-color data set and the 5×5 color-difference matrix that shows the CIELAB color differences between each of the possible 25 paired comparisons.

We note that there is a relationship between the Hungarian method and the earth-mover's distance.[32] However, the important property of the Hungarian method that is useful in this study is that it makes a binary assignment; that is, each color in one palette is assigned to one color in the other palette and no color is assigned to more than one color in the other palette.

3.1 | Performance metric

For each of the three psychophysical data sets interval scale values that represent palette similarity (ΔV) are available. Each of the three algorithms (MECD, MICD, and Hungarian method) predict palette similarity by calculating the average of N^2, 2 N, and N color differences, respectively. The algorithms are implemented using both CIELAB and CIEDE2000 (1, 2) color difference equations. In previous work [26,27] both MECD and MICD were implemented using a range of different color difference equations. However, calculations using CIEDE2000 (1, 2) always gave the best correlation with the visual data. In this study CIEDE2000 (1, 2) is used but CIELAB is also used for comparison. The goodness of fit between the model predictions of similarity and visual similarity are calculated using the coefficient of determination r^2 (the square of the correlation coefficient).

4 | RESULTS

Figure 5 shows the correlation between the model predictions of palette difference and the visual data.

It is evident from Figure 6 that the MICD and Hungarian models fit the visual data better than the MECD model. However, this can be quantified by calculating r^2. Table 4 shows the performance (r^2) for each of the three algorithms using two different equations and for each of the three psychophysical data sets. All of these produced significant correlations with the exception of the MECD

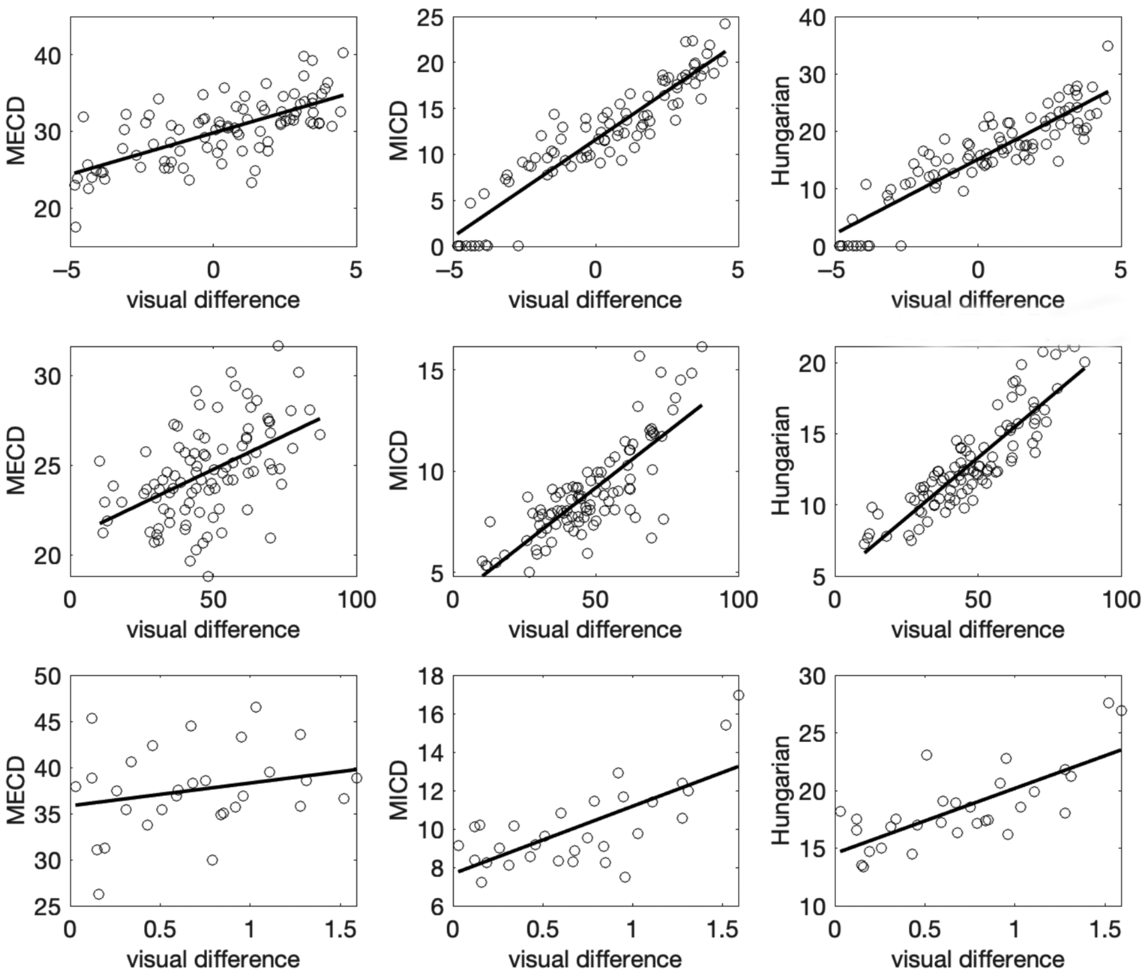

FIGURE 6 Correlation of algorithms using the CIEDE2000 (1, 2) color difference equation with visual data for the 5-color (top row), 25-color (middle row), and 45-color (bottom row) palettes, respectively.

TABLE 4 Agreement (r^2) between each of the three algorithms and the visual data for each of the three psychophysical data sets.

	MECD		MICD		Hungarian	
	CIELAB	CIEDE2000	CIELAB	CIEDE2000	CIELAB	CIEDE2000
5-color data	0.307	0.466	0.821	0.864	0.768	0.804
25-color data	0.119	0.251	0.607	0.636	0.598	0.769
45-color data	0.061	0.056	0.431	0.487	0.391	0.528

Abbreviations: MECD, mean color difference; MICD, minimum color difference model.

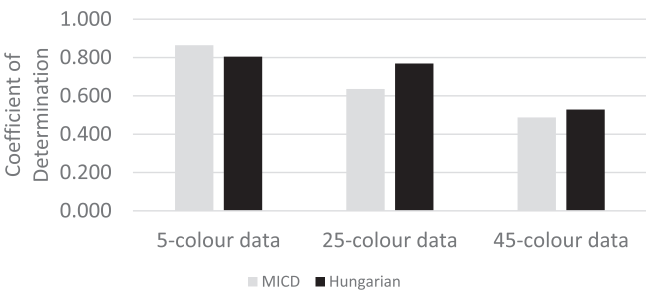

FIGURE 7 Comparative performance of MICD and Hungarian algorithms using the CIEDE2000 (1, 2) color difference equation. MICD, minimum color difference model.

model for the 45-color data using both equations ($p > 0.05$). It is evident that agreement with visual data declines with increasing number of patches N in the palettes for all three algorithms. Note that the coefficient of determination for the naïve MECD method is <0.1 for the 45-color data. This is intuitive since as N increases the palettes will essentially become images at which point the order or arrangement of the patches in the palettes (or images) will become important. None of the three algorithms considers the order of colors in the palettes. Figure 7 shows a comparison of the MICD model and the Hungarian method using the CIEDE2000 (1, 2) equation. The decline in performance with increasing N is less steep for the Hungarian method than for the MICD method. Although performance of the MICD model exceeds that for the Hungarian method when N is small ($N = 5$), the Hungarian method gives better agreement with the visual data than the MICD method for the other two conditions ($N = 25$ and $N = 45$).

A statistical analysis of the data illustrated in Figure 6 was carried out to see if there was any significant difference between the correlations of the MICD and Hungarian models. The p values were 0.1901, 0.0636, and 0.8227 for the 5-color, 25-color, and 45-color datasets, respectively. This indicates that there is no significant difference in performance of these two models. However, both of these models were statistically better at fitting the visual data than the MECD model in all cases ($p < 0.05$).

5 | DISCUSSION

This work is concerned with methods that can predict visual similarity between pairs of palettes where each palette contains N color patches. Three algorithms—MICD, MECD. and the Hungarian model—were evaluated using both CIELAB and CIEDE2000 (1, 2) metrics. The correlation between the algorithms and the visual data is better when N is small; that is, for palettes with only a few colors. This is probably because as N increases, the spatial arrangement of the colors may become important but none of our algorithms considers spatial arrangement. We have unpublished data that show that spatial arrangement does not affect visual color difference when N is very small; but clearly, when N become very large we effectively have an image so that spatial arrangement would become critical. It makes sense that our results show that our algorithms (which do not consider spatial arrangement) should fit the visual data better when $N = 5$ than when $N = 25$ or 45. However, in practical use, the majority of color palettes tend to contain relatively few colors and therefore the algorithms may be useful. Note that when $N = 1$ we simply have two color patches and all three algorithms are identical since we have a regular color difference between two patches. Thus, in this sense, we can see that regular color difference (which has been the topic of many decades of research of course) can be viewed as a special case of comparing two N-color palettes where $N = 1$.

All of the algorithms can be used with any color difference equation and our data show that correlation between algorithm prediction and visual data is much stronger for CIEDE2000 than for CIELAB. This is interesting because the color differences that are being considered in this case are often very large; much larger than five CIELAB units for example. Whereas CIEDE2000 is generally preferred for small color differences the work in this paper provide some indirect evidence that CIEDE2000 may perform well even for large color differences.

Both the Hungarian and MICD models have been shown to be effective. Note that although the Hungarian model calculates an average of N color differences rather than $2N$ color differences (used by the MICD model) it is not necessarily quicker. This is because for both the MICD model and the Hungarian model all N^2 color differences needed to be calculated in order to determine which N or which $2N$ differences should be averaged. The MICD model also has an advantage in that, in principle, it could be used to compare the visual similarity between an N-color palette and an M-color palette where $N \neq M$ whereas the Hungarian method requires that $N = M$. However, to our knowledge no studies have been carried out that explore the visual similarity of palettes where the number of colors is not the same.

6 | CONCLUSION

This work considered three psychophysical experiments in which the magnitude of color difference between pairs of color palettes was measured. Three models were evaluated that aim to predict color difference; two of these (MICD and MECD) were previously published, but the other (the Hungarian model based on the Kuhn-Munkres algorithm from the 1950s) had never been applied to this problem before. It was shown that both the MICD and Hungarian models were statistically better at fitting the visual data than the MECD model. It was also shown that the MICD and Hungarian models were statistically indistinguishable. These models can be used to predict color similarity between color palettes. Fairly recently various automated methods (often based on machine learning) are being used to derive color palettes from images or words; the color palette difference metrics described in this work are useful for evaluating the similarity of such palettes with ground-truth data (e.g., palettes generated by humans) as a way of discriminating between the usefulness of various palette-generation methods.

AUTHOR CONTRIBUTION

Graham Finalyson conceived the idea for the paper and critically reviewed the manuscript. Qianqian Pan, Yun Chen and Jie Yang collected and analysed data. Stephen Westland and Peihua Lai undertook data analysis and wrote the manuscript.

ACKNOWLEDGMENTS

We would like to thank the reviewers for their helpful comments on the submitted manuscript.

FUNDING INFORMATION

No funding was received for this work. The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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How to cite this article: Westland S, Finlayson G, Lai P, Pan Q, Yang J, Chen Y. A computational method for predicting color palette discriminability. *Color Res Appl*. 2024;1-9. doi:10.1002/col.22927