A Study on Perceptually Coherent Distance Measures for Color Schemes

***Sandra Skaff*[1], *Luca Marchesotti*[2], *Gabriela Csurka*[2], *Craig Saunders*[2]**
[1] ***Xerox Research Center Webster, Webster, NY, USA;*** [2] ***Xerox Research Centre Europe, Meylan, France***
{***sandra.skaff, luca.marchesotti, gabriela.csurka, craig.saunders***} ***@xerox.com***

Abstract

*There has been extensive research on finding distance measures between individual colors which conform to the human visual system color perception. With the recent advent of using and naming color combinations by abstract concepts (*classic, romantic*), this paper addresses the new problem of computing distances between such combinations, which are referred to as color schemes. In addition, the paper proposes an algorithm to compute the distance measure which is shown to be competitive compared to various state of the art distance measures adapted to the problem at hand. In particular, the proposed distance measure, referred to as the Color-based Earth Mover's Distance (CEMD) embeds the CIEDE2000 color difference formula into the Earth Mover's Distance (EMD). The CEMD performance in computing distances is evaluated through a color scheme retrieval framework. Quantitatively, it is shown that the CEMD provides in general the highest precision at K as compared with the EMD and a distance based on Fisher Vector representations of color schemes, which we refer to as FD. Qualitatively, it is shown that retrieved color schemes are more similar to the query scheme when the CEMD is employed as compared with the EMD and FD. Qualitative results on image ranking by concept using the CEMD are shown to be better than those obtained using tags.*

Introduction

Color schemes or palettes, which are combinations of colors, are used in various applications. For example, image search using multiple colors or schemes has been introduced by IBM in their QBIC system [1] and by Flickr [2]. In image color transfer, a color scheme is used to transfer the colors of a given image to obtain an output image of colors resembling those of the input image [3]. A color scheme can be associated with a type of concept, whether emotion, mood, or aesthetic, and assigning concepts to color combinations has been a recent topic of investigation [4, 5]. More recently, color transfer approaches use concepts as compared with color schemes to indicate the desired transfer [6, 7, 8].

While employing color schemes, users might wish to replace a previously selected scheme with a similar one which still relates to the concept of the original scheme. In addition, more advanced users, such as graphic designers, may wish to either modify or create color schemes which adhere to a particular concept. If these users have one sample color scheme associated to a concept, they can then either create or retrieve similar schemes based on a distance measure which assesses the similarity between them.

There has been work in the literature on computing distances between color palettes, which are extracted from images such as in [9]. For Home Décor applications, there has been work on computing distances between object pixel colors and color palettes from a database designed by an interior designer [10]. Alternatively, there has been work which computes distances between color histograms [11, 12, 13]. These distance measures were used most commonly in the application of color-based image retrieval [11]. They take into account statistical properties of both the images as well as those of the color spaces used [12]. They can also take into account the spatial properties of images [14, 15, 16] or their salient regions [17]. The color schemes considered in this paper to compute and compare different distance measures are not extracted from images and therefore do not contain such information. Note that even though the schemes in the last section are extracted from images, they only use the representations of the colors in 3D space to compute the CEMD. In addition, these color schemes are not used in our study.

Most research in color science is focused on finding differences between individual colors. Over the years, the International Commission on Illumination (CIE) has devised several metrics, referred to as ΔE, to best represent the distance between two colors as would be perceived by the human visual system [18]. This paper has two main goals. First it proposes and addresses a new problem, which is that of finding differences between combinations of colors or color schemes. The paper starts by evaluating different distance measures, which are often used in computer vision applications, in the context of color scheme retrieval. The best performing distance measure, the Earth Mover's Distance (EMD), is thus selected. Second, the paper embeds the most recent ΔE metric, the CIEDE2000 color difference formula, into the EMD in order to render it more coherent with the human visual system color perception. This new distance measure is referred to as the Color-based EMD (CEMD). The paper then compares the CEMD to the EMD as well as to a distance defined on Fisher Vector (FV) representations of color schemes, which we refer to as FD. Such representations have shown state of the art performance when used for color schemes in categorizing them [5]. It is shown that similarities between color schemes are best captured using the CEMD. A color scheme retrieval framework is used in the paper for evaluation as it allows for both a quantitative and qualitative analysis of the distance measures.

The paper first starts with comparing different distance measures adapted to our problem. A quantitative evaluation of these distance measures through a color scheme retrieval framework is carried out. Next, the algorithm which computes the CEMD is presented. Quantitative and qualitative analyses are carried out to test its performance in a color scheme retrieval task. In these analyses the CEMD is compared to the EMD and the FD. It is shown that our proposed algorithm outperforms all the distance measures considered. Finally, it is shown that images retrieved by color schemes representing abstract concepts while using the CEMD are more visually coherent than those retrieved by tags in GoogleImages.

A Comparative Study of Distance Measures between Color Schemes

One of the goals of this paper is to introduce the problem of finding similarities between color schemes, as compared with individual colors. Several distance measures often employed in the computer vision literature are used. We adapt these measures to apply them to computing distances between color schemes. We first start with a description of the different distance measures used. We then show quantitative results within the considered evaluation framework.

Distance Measures

We describe the distance measures considered to assess the similarities and/or differences between color schemes. Denoting any two given color schemes by X_1 and X_2, each can be written as $X_1 = [S_{11}, S_{12}, ..., S_{1N}]$ and $X_2 = [S_{21}, S_{22}, ..., S_{2M}]$, where S_{ij} denotes the j^{th} swatch, or color, of scheme i. N and M are the number of swatches, or colors, of schemes X_1 and X_2 respectively. A swatch can be represented by a 3D vector in a given color space.

The Euclidean Distance

The Euclidean distance (ED) between two color schemes is the simplest distance measure which may be considered. It requires that $N = M$ and can be computed as follows:

$$d_{ED}(X_1, X_2) = \sum_{i=1}^{N} ||S_{1i} - S_{2i}||. \quad (1)$$

Note that this distance is dependent on the order of swatches in a color scheme.

The Levenshtein Distance

Color schemes can be interpreted as strings of symbols (see for e.g. [19]), which are swatches in our case. The Levenshtein distance (LD) between two strings is then taken to be the least number of operations needed to modify one string to obtain the other string. The cost of replacing one symbol by another is the ED between them and the insertion cost is left as a parameter. The algorithm pseudocode is:

begin
  Input: X_1, X_2; output: $d_{LD}(X_1, X_2)$
  for $i = 1$ **to** $N+1$ **do** $D_{i,1} = 0$; **od**;
  for $j = 1$ **to** $M+1$ **do** $D_{1,j} = 0$; **od**;
  for $i = 1$ **to** N **do**
    for $j = 1$ **to** M **do**
      $cost = D_{i,j} + ||S_{1i} - S_{2j}||$;
      $D_{i+1,j+1} = min(cost, D_{i,j+1} + c_{ins})$;
      $D_{i+1,j+1} = min(D_{i+1,j+1}, D_{i+1,j} + c_{ins})$;
    od;
  od;
  $d_{LD}(X_1, X_2) = D_{N+1,M+1}$;
end

where c_{ins} is the insertion cost. We consider in our analysis three values for c_{ins}, which are 0, 0.2, and 1. An advantage of the LD over the ED is that it does not require that $N = M$ although it does depend on the order of swatches.

The Permutation Distance

We propose the Permutation distance (PD) measure, which is based on the ED. This distance sums the EDs between swatches of one color scheme and corresponding swatches of a second color scheme. The swatch pairs are chosen without replacement in a greedy fashion according to the minimum ED between them. The algorithm pseudocode to compute this distance is:

begin
  Input: X_1, X_2; output: $d_{PD}(X_1, X_2)$
  $D = 0$, $I = \{1, 2, ..., M\}$.
  for $i = 1$ **to** $\min\{M, N\}$ **do**
    $j^* = \underset{j \in I}{\operatorname{argmin}} ||S_{1i} - S_{2j}||$;
    $I = I \setminus \{j^*\}$;
    $D = D + ||S_{1i} - S_{2j^*}||$;
  od;
  $d_{PD}(X_1, X_2) = D$;
end

The PD does not require the color schemes to be of the same length nor does it depend on the order between swatches unlike the LD and ED.

The Graph-based Distance

A drawback with the ED, LD, and PD is that they take into account the differences between individual swatches and not the relationship between successive swatches. For example, consider two color schemes which are identical apart from the fact that the identical swatches are translated from each other by a number of positions. The Euclidean distance in this case would penalize the translation distance cumulatively for each swatch. To remove this effect we propose a distance measure where the difference in the distance between successive swatches is taken into account and consequently such translations are not penalized. This is done by shifting each swatch in order to the same point in space, translating the successive swatches by the same amount and then taking a difference. As it is based on a distance measure between graphs, we refer to this distance as a Graph-based distance (GD). We include a parameter α which allows us to trade off the amount by which such translations are disregarded. For $\alpha = 1$ we recover the standard Euclidean distance. For $\alpha = 0$ we ignore the actual color values, and instead account for the differences in the transitions to successive swatches. The algorithm pseudocode is:

begin
  Input: X_1, X_2; output: $d_{Graph}(X_1, X_2)$
  $D = 0$;
  for $i = 1$ **to** $N-1$ **do**
    $D = D + ||(S_{1(i+1)} - S_{1i}) - (S_{2(i+1)} - S_{2i})||$;
  od;
  $d_{Graph}(X_1, X_2) = D$;
end

Finally, the two components are summed to obtain:

$$d_{GD}(X_1, X_2) = \alpha d_{ED}(X_1, X_2) + (1-\alpha) d_{Graph}(X_1, X_2). \quad (2)$$

The three values of α we consider in our analysis are 0, 0.8, and 1. When $\alpha = 1$, the ED is computed.

The Earth Mover's Distance

We also use the Earth Mover's Distance (EMD) to assess similarities between color schemes. The EMD [20] is computed as such:

$$d_{EMD}(X_1,X_2) = \frac{\sum_{i=1}^{N}\sum_{j=1}^{M} f_{ij}||S_{1i}-S_{2j}||}{\sum_{i=1}^{N}\sum_{j=1}^{M} f_{ij}}, \tag{3}$$

where f_{ij} is the flow between S_{1i} and S_{2j} and it is computed such that it minimizes the following cost, denoted by C:

$$C = \sum_{i=1}^{N}\sum_{j=1}^{M} f_{ij}||S_{1i}-S_{2j}||, \tag{4}$$

subject to the constraints:

$$\begin{aligned}
f_{ij} &\geq 0 && 1 \leq i \leq N, 1 \leq j \leq M;\\
\sum_{j=1}^{M} f_{ij} &\leq w_{S_{1i}} && 1 \leq i \leq N;\\
\sum_{i=1}^{N} f_{ij} &\leq w_{S_{2j}} && 1 \leq j \leq M;\\
\sum_{i=1}^{N}\sum_{j=1}^{M} f_{ij} &= min(\sum_{i=1}^{N} w_{S_{1i}}, \sum_{j=1}^{M} w_{S_{2j}}).
\end{aligned}$$

The weight vectors $\mathbf{w}_{S_1} = [w_{11}w_{12}...w_{1N}]$ and $\mathbf{w}_{S_2} = [w_{21}w_{22}...w_{2M}]$ are assumed to be equal. We experiment with three weight vectors, W_1, W_2, and W_3:

$$\begin{aligned}
W_1 &= [0.33\ 0.33\ 0.33];\\
W_2 &= [0.5\ 0.3\ 0.2];\\
W_3 &= [0.4\ 0.3\ 0.3].
\end{aligned} \tag{5}$$

As described in the next section, the color schemes we use comprise three swatches each and the weights vector is consequently three-dimensional. The weights allow us to put different emphasis on the swatches of the schemes. For example, we can choose equal weightings of the different swatches of a scheme. We can also assume that the first swatches are more important and thus assign higher weights to them. One of the advantages of using the EMD is that it can also be applied to compute distances between two schemes of different lengths.

Quantitative Analysis

We compare the different color scheme distance measures in the context of a retrieval task. The database of color schemes are obtained from the book "Communicating with Color" [21] and contains 360 color schemes, each comprising three swatches. Each of the schemes is representative of one of 15 abstract concepts: *capricious*, *classic*, *cool*, *delicate*, *earthy*, *elegant*, *luscious*, *playful*, *robust*, *romantic*, *sensual*, *serene*, *spicy*, *spiritual*, and *warm*. The colors of schemes pertaining to one concept for clusters in the RGB color space are shown in Fig. 1 for the concepts *romantic* and *serene*. Selecting each scheme, we compute the distance between it and the remaining 359 schemes. We can then rank the 359 color schemes in order of increasing distance to the selected color scheme. The schemes which belong to the same abstract concept as the selected color scheme are considered relevant, while the schemes which belong to other concepts are considered non relevant. Hence the precision is computed by dividing the number of relevant schemes amongst the top K retrieved color schemes. The average of the precisions from 1 to K was then taken to obtain the mean precision at K. This precision obtained while employing the different distance measures is shown in Fig. 2. We conclude that the best precision in color scheme retrieval is obtained in the case of the EMD. Note that the scheme swatch colors are represented in the Lab color space in our computations.

The Color-based EMD

We take the best performing measure, the EMD, and embed into it a perceptually coherent color difference formula as a metric. The formula we use is the CIE DeltaE2000 metric [22], which is widely used in the color science literature as it reflects a better perceptually coherent distance between colors represented in Lab space than the Euclidean distance. We refer to this distance as the Color-based EMD (CEMD). We first start by describing the algorithm used to compute the CEMD. We then compare it to the EMD and to the FD, both quantitatively and qualitatively.

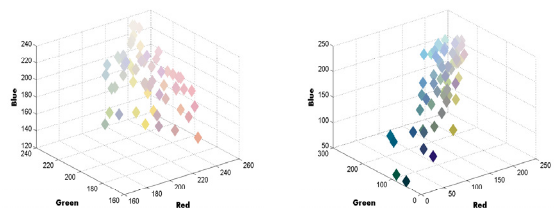

Figure 1. *Swatch colors for the schemes* romantic *(left) and* serene *(right) in the RGB space.*

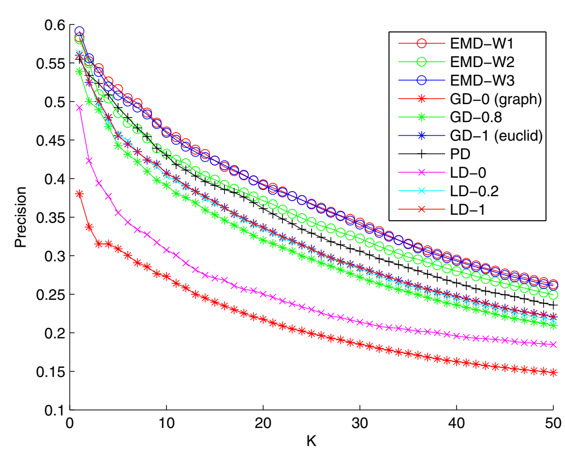

Figure 2. *Precision at K for the task of retrieving color schemes from our dataset. The precision shown is averaged over the precisions computed from 1 to K using each of the 360 available color schemes as a query. The distance measures used in retrieval are d_t, where $t =$: EMD with the Euclidean metric and weights W_1, W_2, and W_3 as given in Eq. 5; GD with α set to 0, 0.8, and 1; PD; LD with c_{ins} set to 0, 0.2, and 1.*

The CEMD algorithm

The CEMD is computed as such:

$$d_{CEMD}(X_1,X_2) = \frac{\sum_{i=1}^{N}\sum_{j=1}^{M} f_{ij}\Delta E(S_{1i},S_{2j})}{\sum_{i=1}^{N}\sum_{j=1}^{M} f_{ij}}, \quad (6)$$

where $\Delta E(S_{1i},S_{2j})$ is the distance between S_{1i} and S_{2j} according to the CIE DeltaE2000 color difference formula [22], and f_{ij} is the flow between S_{1i} and S_{2j}. S_{1i} and S_{2j} are the i^{th} and j^{th} swatches, or colors, of the color schemes. The flow $F = [f_{ij}]$ is computed such that it minimizes the following cost:

$$C = \sum_{i=1}^{N}\sum_{j=1}^{M} f_{ij}\Delta E(S_{1i},S_{2j}), \quad (7)$$

subject to the same constraints listed in Eq. 5. Since the highest precision at K is attained for the EMD with the weights vector W_1 (Eq. 5), we set $\mathbf{w}_{S_1} = [w_{11}w_{12}...w_{1N}]$ and $\mathbf{w}_{S_2} = [w_{21}w_{22}...w_{2M}]$ to W_1.

Analysis

In order to evaluate the performance of the CEMD at assessing similarities between color schemes, we compare it to the EMD and also to the FD. This distance is computed using the FV representations of color schemes. We choose to compare the CEMD to the FD since the FVs have shown to be state of the art representations of images in retrieval and classification tasks [23]. Consequently, state of the art performances on scheme categorization have also been achieved using FV representations [5]. The FV's are computed as described below.

Using the colors of the schemes over all the concepts as observations, we can estimate a GMM where each Gaussian i corresponds to one of the main colors of the concept [5]. Let $\lambda = \{w_i,\mu_i,\Sigma_i, i = 1...R\}$ denote the parameters of the GMM where w_i, μ_i and Σ_i denote respectively the weight, mean vector and covariance matrix of Gaussian i and R denotes the number of Gaussians. Let p_i be the distribution of Gaussian i such that we have $p(x) = \sum_{i=1}^{R} w_i p_i(x)$, where x denotes an observation of a color in this case. Let $\gamma_i(x_k)$ denote the occupancy probability that the color x_k[1] is assigned to Gaussian i. This quantity can be computed using Bayes' formula and then normalized as such: $\gamma_i(x_k) = w_i p_i(x_k)/\sum_{j=1}^{R} w_j p_j(x_k)$. The color swatch x_k is then transformed into the high-level R-dimensional descriptor: $\gamma(x_k) = [\gamma_1(x_k),\gamma_2(x_k),\dots,\gamma_R(x_k)]$. The representation of scheme X_s is then obtained by summing $\gamma(x_k)$ over the M color swatches:

$$X_s = [\sum_{k=1}^{M}\gamma_1(x_k), \sum_{k=1}^{M}\gamma_2(x_k),\dots,\sum_{k=1}^{M}\gamma_R(x_k)]. \quad (8)$$

The FV representation of one swatch of a color scheme is computed by concatenating the gradients of $\log p(x_k|\lambda)$ with respect to only the mean and standard deviation parameters assuming diagonal covariance matrices [23]:

$$\begin{aligned} f_{\mu_i^d}(x_k) = \frac{\partial \log p(x_k|\lambda)}{\partial \mu_i^d} &= \gamma_t(i)\left[\frac{x_k^d - \mu_i^d}{(\sigma_i^d)^2}\right], \\ f_{\sigma_i^d}(x_k) = \frac{\partial \log p(x_k|\lambda)}{\partial \sigma_i^d} &= \gamma_t(i)\left[\frac{(x_k^d - \mu_i^d)^2}{(\sigma_i^d)^3} - \frac{1}{\sigma_i^d}\right]. \end{aligned} \quad (9)$$

where the superscript $d = 1...L$ denotes the d-th dimension of the vector in an L-dimensional space. The dimensionality of the FV representation of the swatch S_{1k}, denoted by $f(S_{1k})$, is the concatenation of the above partial derivatives leading to a $2*L*R$ dimensional vector. The color scheme X_1 is then represented by taking the sum over the FVs from all the swatches as such $f(X_1) = \sum_{k=1}^{M} f(S_{1k})$. We then assess the similarity between two FVs by the following equation:

$$FD(X_1,X_2) = \frac{1 - f(X_1).f(X_2)}{2}, \quad (10)$$

where $f(X_1).f(X_2)$ is the dot product of the FVs of color schemes X_1 and X_2.

Quantitative

Using the color scheme retrieval task as an evaluation framework, we compute the precision at K in the cases of the CEMD, EMD, and FD as shown in Fig. 3. The weights vector W_1 is used for the CEMD and EMD. Two main conclusions can be drawn from the figure. First, the CEMD and the EMD, in general, result in higher precision at K as compared with the FD. Second, in comparison with the EMD, the CEMD provides higher precision for smaller K's. This result is also evident in the next section which shows the first six color schemes retrieved when using the CEMD and when using the EMD. Retrieving schemes at smaller K's is of particular importance in ranking applications. For example, similar to the case of images, users usually focus their attention and browse through the first few retrieved schemes.

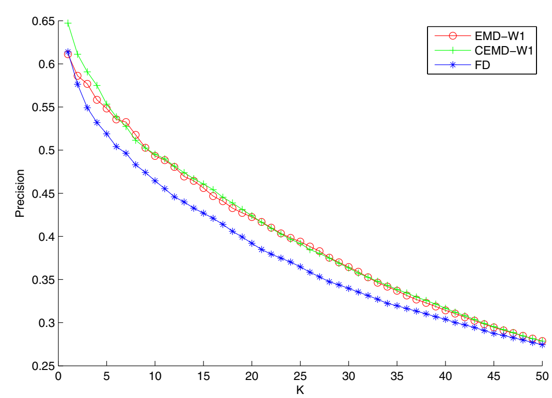

Figure 3. *Precision at K in the task of retrieving color schemes from our dataset. The precision shown is averaged over the precisions computed from 1 to K using each of the 360 available color schemes as a query. The distance measures used in retrieval are: the EMD with W_1 ((Eq. 5)); the CEMD with W_1; the FD.*

[1]For simplicity of notation in this section we use x_k instead of S_{1k} to denote a swatch.

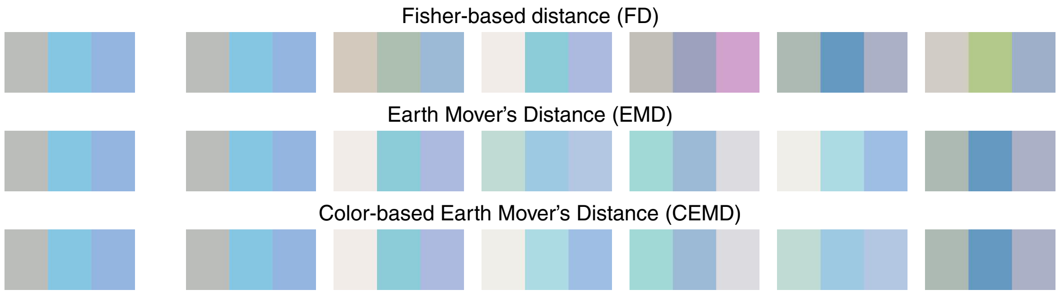

Figure 4. *Each row comprises the query color scheme in the first column and then the 6 color schemes with the smallest distances from the query scheme. The first retrieved scheme shown in the second column is the query scheme itself. The schemes are placed in order of increasing distance. Each row corresponds to one of three distance measures: the FD, the EMD, and the CEMD.*

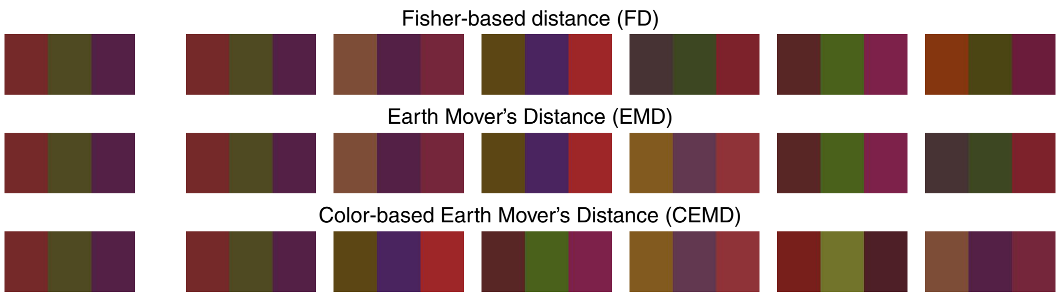

Figure 5. *Each row comprises the query color scheme in the first column and then the 6 color schemes with the smallest distances from the query scheme. The first retrieved scheme shown in the second column is the query scheme itself. The schemes are placed in order of increasing distance. Each row corresponds to one of three distance measures: the FD, the EMD, and the CEMD.*

Qualitative

In order to visualize the results obtained above, we show the first six color schemes retrieved and ranked given a query color scheme when the FD, EMD, and the CEMD measures are used. Figs. 4 and 5 show that the schemes retrieved using the CEMD and EMD better match the query than the ones retrieved using the FD. In addition, the schemes retrieved using the CEMD as compared with the ones retrieved using the EMD better match the query scheme in brightness. The better matches in brightness are expected as the ΔE metric takes into account brightness differences between colors as would be perceived by the human visual system. These results are conforming with the quantitative results obtained in the previous section. For example, in Fig. 4, the third retrieved color scheme in the CEMD case better matches the query scheme than its counterpart in the EMD case, where it is the fifth scheme. The better matches for the CEMD can be also be seen in Fig. 5. The second retrieved scheme in the EMD case is considered to least match the query scheme in the CEMD case among the six retrieved schemes. The scheme referred to has no color which is close to the olive-green color which is that of one of the swatches of the query scheme. In addition, the fifth retrieved scheme in the EMD case is the third in the CEMD case while it does better match the query scheme than the third retrieved scheme in the EMD.

Image Ranking using the CEMD

Color schemes can represent emotions or concepts [4, 5], and these have been used in image retrieval [24, 25]. By computing distance measures between color schemes images can be ranked by abstract concepts. If the color schemes are extracted from images, it can be assumed that the images have the same concepts as the schemes. Based on the ranking of color schemes using the CEMD, the corresponding images can also be ranked. Given a color scheme query which represents a concept, the color schemes, and consequently the images from which they were extracted, can be ranked.

We compare images ranked using the CEMD to images ranked using textual queries on GoogleImages. To this end, we downloaded 220 images from GoogleImages for each of our 15 considered concepts. The query used in each case is the name of the concept concatenated with "colors". In the case of the concept *romantic* the query is "romantic colors", for example. Color schemes are extracted from the images by estimating a GMM on the pixel colors as described in [5]. We then select color schemes estimated given all the colors of a concept as described earlier. Fig. 6 shows two schemes of the concepts *capricious* and *playful*. Figs. 7 and 8 show results of our experiment for these two concepts. The color schemes extracted from all the images (220x15) are ranked in increasing order of distance from the concept scheme as shown in the first row of each figure. The corresponding images are shown in the second row. The third row depicts the images downloaded from GoogleImages for the concept. The figures show that the images ranked by computing the CEMD between color schemes provide more visually coherent results than those obtained using GoogleImages, which uses tags.

Figure 6. *Color schemes representing the concepts:* capricious *(left) and* playful *(right).*

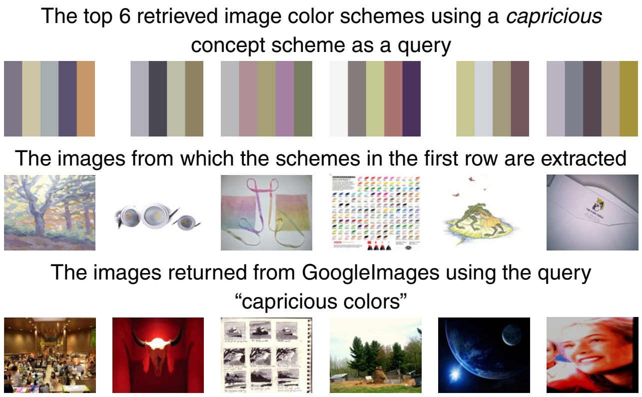

Figure 7. *The first row shows the top 6 color schemes of the 3300 schemes which are ranked in order of increasing distance from the query scheme shown in Fig. 6 (left). The distances are computed using the CEMD measure. The second row shows the 6 images from which the color schemes of the first row are extracted. The third row shows the top 6 images retrieved from GoogleImages with the query "capricious colors".*

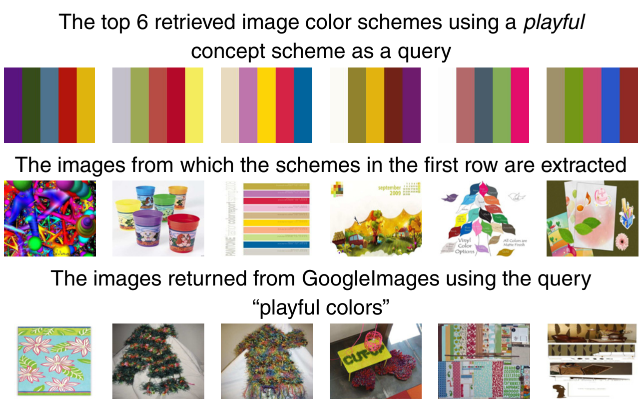

Figure 8. *The first row shows the top 6 color schemes of the 3300 schemes which are ranked in order of increasing distance from the query scheme shown in Fig. 6 (right). The distances are computed using the CEMD measure. The second row shows the 6 images from which the color schemes of the first row are extracted. The third row shows the top 6 images retrieved from GoogleImages with the query "playful colors".*

Summary

This paper proposed and addressed the new problem of computing distances between color schemes as compared with individual colors. It provided a comparative study of different measures adapted to compute distances between color schemes. The results of the study were used to propose a new measure, the Color-based EMD (CEMD), to compute distances between color schemes. This measure was shown to outperform state of the art measures such as the EMD and the FD in the color scheme retrieval framework. The analysis within this framework was performed both quantitatively and qualitatively. The application of the CEMD to rank images by abstract concepts is also shown.

Acknowledgments

We would like to thank Florent Perronnin for providing the code used to compute the Fisher Vector representations of the color schemes.

References

[1] http://www.hermitagemuseum.org/fcgi-bin/db2www/qbicColor.mac/qbic?selLang=English.
[2] http://labs.ideeinc.com/multicolr/.
[3] G.R. Greenfield and D.H. House, A Palette-Driven Approach to Image Color Transfer, Proc. CAe Workshop, pg. 91 (2005).
[4] L.-C. Ou, M.R. Luo, A. Woodcock, and A. Wright, A Study of Colour Emotion and Colour Preference, Part II: Colour emotions for two-colour combinations, Color Research And Application, 29, 292 (2004).
[5] G. Csurka, S. Skaff, L. Marchesotti, and C. Saunders, Learning Moods and Emotions from Color Combinations, Proc. ICVGIP (2010).
[6] C.-K. Yang and L.-K. Peng, Automatic Mood-Transferring between Color Images, IEEE Computer Graphics and Applications, 28, 52 (2008).
[7] B. Wang, Y. Yu, T.-T. Wong, C. Chen, and Y.-Q. Xu, Data-Driven Image Color Theme Enhancement, ACM Transactions on Graphics (SIGGRAPH Asia 2010 issue), 29, 146 (2010).
[8] N. Murray, S. Skaff, L. Marchesotti, and F. Perronnin, Towards Automatic Concept Transfer, Proc. NPAR (2011).
[9] L.-M. Po and K.-M. Wong, A New Palette Histogram Similarity Measure for MPEG-7 Dominant Color Descriptor, Proc. ICIP, pg. 1533 (2004).
[10] J. Marguier, N. Bhatti, H. Baker, and S. Süsstrunk, A home Décor Expert in Your Camera, Proc. CIC, pg. 85 (2009).
[11] M. Swain and D. Ballard, Color Indexing, International Journal of Computer Vision, 7, 11 (1991).
[12] L. Tran and R. Lenz, Compact Colour Descriptors for Colour-Based Image Retrieval, Signal Processing, 85, 233 (2005).
[13] O. Pele and M. Werman, The Quadratic-Chi Histogram Distance Family, Proc. ECCV, pg. 749 (2010).
[14] C. Colombo and A. Del Bimbo, Color-Induced Image Representation and Retrieval, Pattern Recognition, 32, 1685 (1999).
[15] L. Cinque, G. Ciocca, S. Levialdi, A. Pellican, and R. Schettini, Color-based image retrieval using spatial-chromatic histograms, Image and Vision Computing, 19, 979 (2001).
[16] B. Prasad, K. Biswas, and S. Gupta, Region-based image retrieval using integrated color, shape, and location index, Computer Vision and Image Understanding, Special issue on color for image indexing and retrieval, 94, 193 (2004).
[17] N. Sebe, Q. Tian, E. Loupias, M. Lew, and T. Huang, Color indexing using wavelet-based salient points, Proc. CBAIVL Workshop (2000).
[18] M.D. Fairchild, Color Appearance Models, 2nd edition, Wiley-IS&T (2005).
[19] D. Gusfield, Algorithms on Strings, Trees and Sequences, Computer Science and Computational Biology Computer Science and Computational Biology Publisher (1997).
[20] Y. Rubner, C. Tomasi, and L. J. Guibas, A Metric for Distributions with Applications to Image Databases, Proc. ICCV, pg. 59 (2000).
[21] L. Eiseman, Pantone Guide to Communicating with Color, Grafix Press, Ltd. (2000).
[22] http://www.ece.rochester.edu/ gsharma/ciede2000/.
[23] F. Perronnin and C. Dance, Fisher Kernels on Visual Vocabularies for Image Categorization, Proc. CVPR, pg. 1 (2007).
[24] M. Solli and R. Lenz, Color Emotions for Image Classification and Retrieval, Proc. CGIV, pg. 367 (2008).
[25] M. Solli and R. Lenz, Color Semantics for Image Indexing, Proc. CGIV, pg. 353 (2010).